THE TRANSFORMATION OF SPATIAL EXPERIENCE IN NARRATIVE DISCOURSE

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ABSTRACT

This dissertation investigates the status of spatial information as a structural element of narratives of personal experience. Traditionally, event, temporal and rhetorical relation information are considered structural – i.e., minimally necessary to define local and textual elements of narrative discourse. However, while this information is readily apparent from surface linguistic forms, spatial information, and its status as structural, is less straightforward. To uncover correspondences between spatial information and structural elements of narrative discourse, I rely on a series of machine learning experiments to analyze morpho-syntactic, formal and cognitive semantically encoded spatial information indexed by spatial prepositions and verbs from a particular frame of reference, relative to events, rhetorical relations, tense, aspect, explicit temporal reference and text sequence in three corpora of narrative discourses (conversational, adventure travel, and criminal activity narratives).

Based on strength of prediction in the machine learning experiments – where statistical classifiers are able to predict spatial, temporal, event and rhetorical information to between 60 and 70% accuracy with an increase to over 80% when implicit spatial information and text sequence are considered – spatial information is argued to demonstrate structural patterns on clausal and textual levels. These structural patterns hold for all corpora despite contextual parameters, number of authors, length of text and density of spatial information. Further, the
results and analysis are compared to existing narrative analysis frameworks (Labov 1972, Herman 2001) where it is determined that a more nuanced, but non-contradictory, picture of spatial information in narrative discourse, based on both syntactic and semantic considerations, emerges from the presented research. Additionally, I engage in a discussion of environmental criminology to bridge interdisciplinary gaps between cognitively informed insights into spatial language and the linguistic conveyance of experiential discourse. In sum, spatial information exhibits structural patterns in narrative discourses that facilitate a deeper practical and theoretical understanding of the cognitive and linguistic organization, and analysis of, experiential discourses.
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INTRODUCTION

This dissertation evaluates the following primary research question:

(1) How does the spatial information of events relate to narrative discourse?

Narrative discourses of personal experience depict a series of events that build toward some central occurrence in the narrator’s past. Research on the formal linguistic structure of narrative discourses indicates that this “series of events” can be captured with temporal and event based primitives that define all narrative discourses. For example, the two-clause discourse in (2) depicts two events, inferred to occur in temporal sequence via the discourse sequence – i.e., (2a) occurs before (2b) in discourse, (2a) happened before (2b) in past time.

(2) a. Pascale finished her nap in the crib
    b. She ate some cereal at the table

As (2a) and (2b) depict two past time events linked in temporal sequence, the rhetorical relation of NARRATION obtains between (2a) and (2b). This can be tested by reversing the order of the clauses such that if (2b) is uttered before (2a) and a different series of events is depicted, then the NARRATION relation holds. The linguistic determination of events, temporal sequencing and rhetorical relations is based on clause level features. However, narrative discourses also exhibit text level features. For example, following Labov’s (1972) framework, Orientation (which sets the scene for the narrative events (who, what, when, where, etc.)), Evaluation (the narrator’s commentary on events and descriptions – e.g. good, bad, exciting, etc.), and Coda (returning from the past to the present) clauses are prominent features in addition to narrative clauses.
These clauses, and the rhetorical relations between them, require different types of information (e.g., states and events) and have different temporal implications (stopping or overlapping the sequence of narrated time). In addition to events, temporal and pragmatic (rhetorical) information, spatial information also exists, but is not strictly necessary for defining the event, time and rhetorical structure of narrative discourses. For example, if the locative prepositional phrases in (2) are deleted (in the crib, at the table), the ability to determine the NARRATION relation would not be disrupted. The spatial information is simply additional, optional information that supplements the total information of the discourse with specific spatial details. It is not a crucial component of what is considered necessary for structural components of discourse, at least, not as they emerge on the linguistic surface or can otherwise be inferred.

Whether or not this state of affairs is due to spatial information being a different type of information – say, compared to temporal information in narrative discourses which is iconic (i.e., the sequence of utterances corresponds to the sequence of past actions), where spatial information is more indexical or symbolic – where events are experienced is intuitively related to when events are experienced and what events occur. However, there is no obvious relationship between the content and sequence of utterances and the location of past action as it pertains to what one would consider a structural feature of narrative discourse. Although, there may be an indirect relationship between spatial and temporal reference; if temporal and event elements of experience play such an important structural role for narrative discourses, spatial elements of experience should be equally necessary. This perspective has been adopted in definitions of rhetorical relations. For example, the definition of the NARRATION relation has a spatiotemporal consequence, “where things are in space and time at the end of Event 1 is where they are at the
beginning of [Event 2]” (Asher and Lascarides 2003:462). However, a fuller demonstration and argument of the structural status of spatial information, if it exists at all, has largely eluded narrative research. The lack of such a demonstration is arguably due to the fact that spatial information is optional on the linguistic surface and, consequently, does not appear to participate in resolving the temporal, event and rhetorical details of discourse. Such a demonstration is tantamount to measuring the invisible.

Research by Herman (2001) has broken new ground in the understanding of the structural nature of spatial information in narrative discourses from both clause and text level perspectives. By focusing on ghost story narratives, which seemingly rely heavily on spatial details to locate and track supernatural entities, Herman demonstrates that narrative events can be grouped into larger “narrative domains” based on spatial information. Herman essentially argues that, when spatial information is available on the linguistic surface, there is an organization of structural elements, based on spatial cognitive insights, that is different from traditional time, event and rhetorical relation perspectives. As the spatial structure is tandem with time, event and rhetorical relations, there is a suggestion that spatial information is structural, but possibly in a way that is not readily resolved under traditional theories and analysis of linguistic discourse. This dissertation extends the work of Herman by presenting, in some detail, qualitative and quantitative motivations for accepting two hypotheses (3-4) that evaluate the research question posed in (1):

(3) Based on the strength of prediction in statistical machine learning classification tasks, spatial information is a structural element of the narrative discourse of personal experience
Certain types of spatial, temporal, rhetorical and event information conforms to a consistent structural profile based on text sequence that is generalizable to all narrative discourses of personal experience.

Overall, spatial information is shown to co-vary with temporal, event and rhetorical relation elements of discourse structure. Spatial information exhibits patterns at the clause level consistent with syntactic and formal semantic insights and on the text level consistent with spatial cognitive and cognitive semantic insights. I ultimately conclude that spatial information is indeed structural despite appearing not to be obligatory on the linguistic surface. “Obligatoriness” will come to mean constrained relationships between types of spatial information and temporal, event and rhetorical information in narrative discourses – i.e., when spatial information appears in certain environments, a particular type of spatial information is expected. Consequently, the answer to the central research question will be based on a combination of clause and text level observations.

This dissertation is arranged as follows. Chapter I provides the background on linguistic discourse structure from clause and text level features of spatial, temporal, event and rhetorical relation. In particular, I rely on Segmented Discourse Representation Theory (“SDRT”) (Asher & Lascarides 2003) to provide a semantic formalism to model narrative discourse structures. As SDRT is a generalized formalism, i.e., not specifically tailored to one type of discourse genre, I explore insights from Labov (1972, 1997, 2001) who provides narrative specific observations about clause and text level linguistic features. For example, narratives of personal experience are largely in the past tense and progress from Orientations (setting information) (BACKGROUND in SDRT) to Complicating Actions (NARRATION in SDRT) to Evaluations (evaluations are treated as
a type of elaboration in SDRT) of the narrative events, Resolutions of the narrative events, and Codas (returning to present time). Perspectives on spatial information from the clause and text level in general and narrative discourse are also considered. Ultimately, as indicated by the results and analysis of this dissertation, the spatial aspects of narrative are not inconsistent with the Labovian model. However, focus on the type of spatial information and its relationship to other temporal, event and rhetorical relation elements of narrative discourse structure reveals a more nuanced presentation and indicates a deeper structural than is considered by Labov, but are considered in Herman (2001) (which is not inconsistent with Labov’s framework).

Chapter II presents the linguistic perspective on spatial information beginning with a discussion of spatial information in discourse and the model of analysis proposed by Herman (2001). For purposes of this dissertation, “spatial information” broadly covers how physical space is referred to in language (with specific emphasis on English). The morpho-syntactic, formal and cognitive semantic representations of space will be developed, with an eye towards the consolidation of as many spatial phenomena as possible, into a single annotation scheme (which also includes temporal, event and rhetorical relation information). Several linguistic phenomena of spatial information are explored; in particular, figure and ground relationships (Talmy 2000), mereotopologically classified (i.e., region-based) prepositions (Asher & Sablayrolles 1995) and verbs (Pustejovsky & Moszkowicz 2008) that create figure and ground relationships, frames of reference (Levinson 1996), and granularity (or level of scale-based detail) of spatial description (Montello 1993).

Chapter III presents the underlying theory and elements of the annotation and machine learning methodologies. First, the data analyzed in this dissertation is presented. Specifically, a
sample of narrative discourses is extracted from three different corpora: (1) narratives from the American National Corpus’ Charlotte Narrative and Conversation Collection (Ide & Suderman 2007) – oral narratives in conversations; (2) narratives from serial and non-serial criminals – oral and written confession statements and guilty pleas; and (3) narratives from the Degree Confluence Project – written narratives of adventure travel. Second, the development and use of an XML-based annotation scheme are motivated and presented relative to inter-annotator agreement on the recognition and classification of not only the spatial information being modeled in discourse, but also the temporal, event and rhetorical relation information. The distribution of coded elements in the analyzed data is presented as well. Lastly, I discuss the use and theoretical parameters of several statistical machine learning classification methodologies and specific algorithms (Witten & Frank 2002) and justify their use in a series of classification experiments designed to address the research question in (1) and associated hypotheses (3-4).

Chapter IV presents the results of the machine learning experiments based on the annotated spatial, temporal, event and rhetorical information in all corpora combined. The results focus on the predictability of explicit spatial information types relative to other spatial information types (e.g., predictability of spatial verb types based on spatial granularities) and structural elements (e.g., predictability of spatial verb types based on event types). The higher the predictability, the closer the relationship is between spatial information and structural elements and the stronger the argument becomes that spatial information is itself a structural element. These experiments are then run again considering implicit spatial information, textual sequence and a collapsing of coding elements based on the results of the inter-annotator agreement discussed in Chapter III. All predictability results are discussed relative to morpho-syntactic, formal and cognitive
semantic insights, and the Labovian and Herman models of narrative discourse. In particular, information theoretic based perspectives on the overall distribution of the spatial, temporal, event and rhetorical relation elements, and statistical ranking of relationships between key elements relative to text-sequence, indicate clause and text level organization of spatial information contribute to a structural “template” that I argue is generalizable to all narrative discourses of personal experience.

Chapter V considers the prediction results of all corpora combined in light of individual corpora and individual narratives. Differences in performance between the three corpora are analyzed relative to contextual parameters, number of authors, types of activities narrated and the density of spatial information. Overall, the structural template of narrative discourses relative to text sequence does not significantly vary from narrative to narrative and does not appear to be affected by context, number of authors, subject matter or amount of spatial information. Further, as text level patterning of spatial information relative to temporal, event and rhetorical relation information is demonstrated, consistent with Herman (2001), deeper insights into the possible role of spatial cognition generally in narrative discourses is facilitated through a discussion of the narratives of serial and non-serial crime and environmental criminology (Brantingham & Brantingham 1984). In particular, variance in the spatial information of the serial crime narratives are predicted for in environmental criminology, which shares the spatial cognitive perspective of Herman (2001), and provides useful interdisciplinary analysis for spatial information in linguistic discourses and avenues of refinement in a practical application of environmental criminology known as geographic profiling (Rossmo 2000).
A summary conclusion of this dissertation’s findings will follow Chapter V and bring the dissertation to a close. Particular emphasis is placed on impacts to the Labovian and Herman models of narrative, limitations in the presented research and future directions.
CHAPTER I - DISCOURSE

1. INTRODUCTION TO CHAPTER I. Answering the research question posed in (1) of the Introduction – How does the spatial information of events relate to narrative discourse? – ultimately requires a model to represent spatial semantic relationships in narrative discourse.

“Spatial semantic relationships” is short for the different types of spatial relationships that can be linguistically depicted. For example, on relates two physical things in a spatial relationship (e.g., [Physical Thing 1] on [Physical Thing 2] – the apple is on the bowl) that is different from in (e.g., [Physical Thing 1] in [Physical Thing 2] – the apple is in the bowl). The specific spatial information that is attended to in this dissertation is the focus of Chapter II. Use of the term “model” indicates the development of generalizable formalisms that represent some observed phenomenon in the world. The model can then be used to test or predict unseen observable phenomena to support the model’s validity or to revise the model. For purposes of this dissertation, a model should not only include the semantic behavior of spatial information in a given data set, but the temporal, event and rhetorical relation information in narrative discourses as well. This chapter develops the larger discourse model that captures and formalizes the semantic and pragmatic aspects of narrative discourse structure.

Determination of the semantic and pragmatic aspects of narrative discourse structure (again, temporal, spatial, event and rhetorical information) is dictated largely by the semantic and pragmatic content of individual clauses and their interaction with adjacent clauses. These interactions comprise the local, or clause level, discourse structure. The local structures then, assuming more than two clauses, can group into text level discourse structures. For example, the NARRATION relation obtains on the local clause level, but *narratives* are a text structure defined
by groupings of the different elements of the local clause structures. The focus of this dissertation is on the relationships between spatial information and both local and text level structural features.

This chapter is structured as follows. Section 2 introduces narrative discourses and the semantic and pragmatic features that define the narrative text structure. The specific perspective explored is that of Labov and Waletzky (1967[1997]) and Labov (1972, 1997, 2001) who provide a wealth of insight into narratives of personal experience. This introduction to narrative discourse will serve to constrain the discussion of more generalized local discourse structure in Section 3. Emphasis is placed on event (e.g. Davidson 1967[1980]) and temporal (e.g. Reichenbach 1947) representations (Section 3.1) and rhetorical relations (Section 3.2) through the introduction of Segmented Discourse Representation Theory (henceforth “SDRT”) (Asher & Lascarides 2003). Section 3.3 consolidates information on time and event following the TimeML annotation scheme (Pustejovsky et al. 2003). The temporal, event and rhetorical relation elements discussed in Sections 3.1-3.3 are ultimately included in the annotation scheme presented in Chapter III. While spatial information is not thoroughly discussed until Chapter II, how spatial information fits into the temporal, event and rhetorical relation perspectives discussed in Sections 2 and 3, is presented throughout. Section 4 concludes Chapter I.

2. The semantics and pragmatics of textual discourse structure. Textual discourse structure is synonymous with terms such as genre (e.g. Swales 1990) or text-type (e.g. Virtanen 1992) and defines the descriptive, potentially typologizing, category that a given text falls into – e.g., news text, summaries, essays, letters, speeches and, for our purposes, narratives. For
example, Smith (2003: 19-20) defines five primary discourse modes based on the *Situations* (events and states) they describe, the overarching *Temporality*, and the type of text *Progression*:

- **The Narrative mode**
  - situations: primarily specific events and states
  - temporality: dynamic, located in time
  - progression: advancement in narrative time

- **The Report mode**
  - situations: primarily events, states, general statives
  - temporality: dynamic, located in time
  - progression: advancement anchored to Speech Time [as opposed to the reported or narrative time]

- **The Description mode**
  - situations: primarily events and states, and ongoing events
  - temporality: static, located in time
  - progression: spatial advancement through the scene or object

- **The Information mode**
  - situations: primarily general statives
  - temporality: atemporal
  - progression: metaphorical motions through the text domain

- **The Argument mode**
  - situations: primarily facts and propositions, general statives
  - temporality: atemporal
  - progression: metaphorical motion through the text domain

For Smith, narratives are a basic form of discourse (a view shared by others (Virtanen 1992)) and discourse modes in general tend to be defined contrastively based on categorizations of structural elements. As mentioned, structural elements are local (like those to be discussed in Section 3 – temporal and event semantics and rhetorical relations) and groups of local structural elements combine into textual elements. Relevant textual elements are introduced here with a presentation of Labov’s (1972, 1997, 2001) research on narratives of personal experience.
2.1 Narratives of Personal Experience. Narratives of personal experience (henceforth “narratives”) are a sociolinguistic construct born somewhat out of necessity in fieldwork performed by William Labov in New York and Philadelphia in the 1960s. By having interview subjects elaborate on a positive response to a “Danger of Death Question” in a sociolinguistic interview (e.g., *Were you ever in a situation where you were in serious danger of being killed, where you said to yourself – “This is it?”* (Labov 1972:354)), interviewers worked to ensure that the subject was speaking as naturally as possible and not modifying his or her speech for the formal interview setting. Such a modification by the interview subject gives rise to a type of Observer’s Paradox (i.e., attempting to capture “natural” speech in “unnatural” observational settings) and prevents an accurate, especially, phonetic picture of the interviewee’s dialect. As an independent linguistic phenomenon, Labov and Waletzky (1967[1997]:21) originally accounted for both the formal and functional definitions of narratives.\(^a\)

From a formal perspective, narratives crucially contain “[a]ny sequence of clauses that contains at least one temporal juncture” (Labov 1972:360). This minimal definition – mirroring the *Narration* rhetorical relation discussed in the Introduction, Ex. 2 – creates a distinction between clauses based on events and temporal sequence, which presumably corresponds to the temporal unfolding of events at the time of the narrator’s experience. Consequently, Labov and Waletzky (1967[1997]:15-17) draw distinctions between *narrative clauses* – strictly ordered

\(^a\) Methodologically speaking, alternative perspectives more closely consider and integrate contextual factors of everyday speech (e.g., conversations between friends or arguments between family members and how these factors influence the emergence and form of narrative). See generally Mishler’s (1995) narrative analysis typology, Ochs and Capps’ (2001) multi-dimensional approach, and ethnomethodological/conversation analytical approaches developed by Jefferson (1978), Sachs (1972) and Schegloff (1997)). Despite these analytical approaches differing from Labov (and Waletzky), they accept, nonetheless, a core temporal and event component to narrative (see e.g. Baynham’s (2003) discussion of conversation analytic (Zimmerman 1998) and literary perspectives (Rimmon-Kenan 1983)).
temporally such that they cannot be rearranged; *free clauses* – not strictly ordered temporally such that they can appear anywhere within the narrative; and *restricted clauses* – not strictly ordered temporally nor free to appear anywhere within the narrative. These clause designations set up a central chain of narrative events, unique to the narrator, which is the hallmark of the narrative text-type. Further, Labov and Waletzky (1967[1997]:17-22) indicate the overall tense make up of narratives. In particular, that the finite verb of the narrative clause (the *narrative head*) is typically preterit or present tense (with potentially progressive aspect).

From a functional perspective, narratives serve *referential* (i.e., relaying past experiences) and *evaluative* functions (i.e., there is a *point* to relaying the past experiences); consider (1):

\[(1) \quad \begin{align*}
\text{a.} & \quad \ldots \\
\text{b.} & \quad \text{and so we was doing the 50-yard dash} \\
\text{c.} & \quad \text{there was about eight or ten of us, … going down, coming back} \\
\text{d.} & \quad \text{and, going down the third time, I caught cramps} \\
\text{e.} & \quad \text{and I started yelling “Help!”} \\
\text{f.} & \quad \text{but the fellows didn’t believe me, you know} \\
\text{g.} & \quad \text{they thought I was trying to catch up} \\
\text{h.} & \quad \ldots \\
\text{i.} & \quad \text{Scoutmaster was up there} \\
\text{j.} & \quad \ldots \\
\text{k.} & \quad \text{but he didn’t pay me no attention either} \\
\text{l.} & \quad \text{and for no reason at all there was another guy…} \\
\text{m.} & \quad \text{he just jumped over} \\
\text{n.} & \quad \text{and grabbed me}
\end{align*}\]

\[(1) = \text{Labov and Waletzky (1967[1997]:17, Ex.6)}\]

In (1), (1b-c) are considered free clauses as they could appear anywhere in the narrative without disrupting the temporal progression of the events. (1e) is a narrative clause as it cannot appear anywhere else in the narrative without leading to a different representation and understanding of the narrative actions. For example, if (1e) appeared after (1n), it would still be a narrative clause,
but the progression of events would be different. (1f-g) are restricted clauses as they could be switched around and the overall temporal progression of the narrative chain would not be disrupted. However, they are restricted in that the temporal progression would be disrupted if they appeared somewhere else besides the (1f-g) slots; again, leading to a different reading of the narrative.

For Labov and Waletzky, structurally, narratives are a joining of both form and function. From a standpoint of observation, free, restricted and narrative clauses group together into text-structures in similar ways across different narratives (Labov & Waletzky 1967[1997]:17-35):

- **Orientation** – free clauses, typically at the beginning but possibly elsewhere, which serve a referential function of providing person, place, time and other background information;

- **Complication (Complicating Action)** – narrative clauses which serve a referential function of providing the past-time experiences of the narrator;

- **Evaluation** – (groups of) free or restricted clauses, multi-coordinate clauses (or possibly syntactically attached to a narrative clause) which suspend the narrative action and “reveals the attitude of the narrator towards the narrative by emphasizing the relative importance of some narrative units as compared to others”;

- **Resolution** – as the evaluation typically follows the complicating actions, the resolution is formally defined by narrative clauses which providing a referential function of relaying past-time experiences by continuing the “narrative sequence that follows the evaluation”; and

- **Coda** – the coda is simply a returning to the present time.

Following this overall structural progression constitutes a *normal form* for narratives. By normal form, I mean that a “canonical” narrative is a representation of the normal form – i.e., all elements are present. The Labovian normal form is also a specified form of Smith’s (2003)
Narrative Mode. From this normal form, a model or framework for the analysis of other narratives can be created. For example, returning to (1) above, (1b-c) would be an Orientation, (1d-f) would be Complicating Actions, (1i-k) would be Evaluations and (1l-n) would be the Resolution. While not included in (1) and example of a Coda would be *so now I always run with people I consider to be my friends* (also evaluative), which would return to the present time.

Overall, (1) is conveying past-time events as part of its referential function and the evaluative function is achieved in the evaluations in (1i-k) – providing a personal perspective on the *Boy Scouts* and *Scoutmaster*. In longer narratives, there can be multiple iterations of these elements and can appear, relative to the noted clausal restrictions, virtually anywhere in a given narrative.

Subsequent developments of Labov and Waletzky’s framework came with Labov (1972). First, the minimal definition of narrative became more concise – “a sequence of two clauses which are temporally ordered [such that] a change in their order will result in a change in the temporal sequence of the original semantic interpretation” (Labov 1972:360). Second, the structural element of *Abstract* – a brief summary of the narrative – was added (Labov 1972:363-64). Third, the linguistic forms which achieve the evaluative function are further developed and differentiated into external evaluations where “[t]he narrator can stop the narrative, turn to the listener, and tell him what the point is” (Labov 1972:371-372) or embedded (internal) evaluations where the narrator either “quote[s] the sentiment as something occurring to him at the moment rather than addressing it to the listener outside of the narrative” (Labov 1972:372) or the narrator can simply say what she did rather than what she said (Labov 1972:373). These observations about evaluations (and abstracts) led to a re-conceptualization of the overall narrative structure set out in Labov and Waletzky (1967[1997]).
Labov (1972) also discusses “departures” from the surface syntax of narratives. As mentioned, narratives are typically in simple past or present tense with information being conveyed by independent clauses linked in discourse sequence. With the inclusion of internal and external evaluations, room is made for more syntactic complexity (which also parallels age – i.e., narratives are more complex in older individuals). It is within the room for more syntactic complexity that spatial information makes it way into the structure of narratives of personal experience, at least as observed by Labov. In particular, Labov (1972) indicates eight departures from simple narrative syntax. One specific departure mentions spatial information: “Locative adverbials. Narrative syntax is particularly rich in this area” (Labov 1972:376, Ex.5). By “locative adverbials” Labov is indicating the supplementation of the verb with spatial details. In terms of local and textual structure under Labov’s framework, broadly, the appearance of spatial information on a syntactic basis is possible in any clause contributing to any rhetorical function. However, Labov never talks about the type of spatial information that may occur relative to other elements. This is the central exploration of this dissertation.

Labov and Waletzky’s original definition of narrative went through one last reformulation with Labov (1997:3) – “a report of a sequence of events that have entered into the biography of the speaker by a sequence of clauses that correspond to the order of the original events.” For this definition of narrative, the inclusion of “entered into the biography of the speaker” is further clarified as necessary to “distinguish narrative from simple recounting of observations like the events of a parade by a witness leaning out a window.” Concomitantly, narratives of personal experience center on at least one reportable event – defined as an event “which justifies the automatic reassignment of speaker role to the narrator” (Labov 1997:9). The “most reportable
event is the event that is less common than any other in the narrative and has the greatest effect upon the needs and desires of the participants in the narrative” (Labov 1997:9). A number of related concepts (theorems) stem from this perspective. In particular, Labov considers correlations to the credibility of the reportable events and the narrator’s theory of causality as important for determining the narrative events leading up to the most reportable event. Returning to (1), the most reportable event would arguably be (1e) and I started yelling “Help!” with the previous clause (1f) and, going down the third time, I caught cramps, being, from the narrators perspective, a causal link to (1e).

A narrator’s personal theory of causality may or may not match how the actual events transpired. The reason for this, under Labov’s framework, is because the evaluative function of narrative dictates the personal viewpoint of the narrator relative to the point of the story that the narrator is attempting to convey. This is not to say that the events are false, just that a particular viewpoint is provided by the narrator for a particular purpose, which may or may not reflect every critical element of the actual event sequence. Consequently, viewpoint is broken down into both objective events (the Complicating Actions in 1(f-e)) – “one[s] that became known to the narrator through sense experience” – and subjective events (the Evaluations in 1l-n) – “one[s] that the narrator became aware of through memory, emotional reaction or internal sensation” (Labov 1997:14).

Labov (2001) discusses how narrative structure can be exploited to resolve the complete narrated (i.e. actual) events relayed from the narrator’s perspective. Labov (2001:22) explores the event structure of narrative with the particular focus of “stand[ing] behind the narrators, from the moment of their first motivation to project a story that has entered into their biography, and
follow the logic of narrative construction.” Labov relies on two analytical tools to uncover the event structure of narrative – participant analysis and verb semantics. Further, Labov applies his analysis to the *Complicating Actions* (i.e., the narrative chain of events). For example, given the following sequence of *Complicating Actions* in (2) from a narrative about a Judge’s son and the death of a Chauffeur, a participant analysis table is constructed (Table 1):

(2) a. And this son – I guess he must’ve got drunk because he drove through town with a chauffeur with one of those old touring cars without, you know – open tops and everything, big cars, first ones–
b. and they- they come thr- through town in a-late in the night.
c. And they went pretty fast, I guess,
d. and they come out here to the end of a– where-uh-Pontiac Trail turn right or left in the road
e. and they couldn’t make the turn
f. and they turned left
g. and they tipped over in the ditch,
h. steerin’ wheel hit this fellow in the heart, this chauffeur,
i. killed him.

(2) = Labov (2001:4)

In Table 1, y is an “active causal agent,” z is the patient “directly affected,” and x represents “other participants” (Labov 2001:7). Note that the event analysis that Labov is concerned with only focuses on the *Complicating Actions*, narrative sequence, and not other elements of the discussed narrative framework – e.g., evaluations. Further, the primary unit of analysis is the independent clause and, in particular, the semantics of the verb and related syntactic elements and thematic roles for which the verb is lexically subcategorized. For example, the resolution in (e) that the *chauffeur* is the “active causal agent” is determined because of the semantics of *chauffeur* (one who drives another) and the related sense of *drove* (driving both the *car* and the *judge’s son*). In reality, there are many more events that take place in (2) between the *judge’s son*
(and possibly the chauffeur) getting drunk and the crashing of the car resulting in the chauffeur’s death. However, under Labov’s framework, it is the narrator’s theory of causality that is conveyed for purposes of making a point (Evaluation). Even though events are deleted and some constructions are ambiguous – which can be exploited by the narrator to make his or her point – the events that are included are still grounded in a logical verb semantics relative to general narrative discursive constraints (i.e., the necessity of temporal progression and events).

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
<th>g</th>
<th>h</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gets drunk</td>
<td>Drove</td>
<td>Came</td>
<td>Went</td>
<td>Came</td>
<td>Turned</td>
<td>Tipped</td>
<td>Hit</td>
</tr>
<tr>
<td>Judge</td>
<td>(y)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>y</td>
<td>y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Judge’s Son</td>
<td>(y)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>y</td>
<td>y</td>
<td>z</td>
<td>z</td>
</tr>
<tr>
<td>Chauffeur</td>
<td>y</td>
<td>y</td>
<td>y</td>
<td>y</td>
<td>y</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car</td>
<td>z</td>
<td>z</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steering Wheel</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>y</td>
<td>y</td>
</tr>
</tbody>
</table>

**Table 1.** Participant analysis table for (2) (Labov 2001:7, Ex. 5).

In sum, for Labov, narratives are collections of local discourse structures (events and temporal constraints) that pattern into larger textual discourse structures (Orientations, Evaluations, etc.). Labov provides additional insights that will prove useful for the analyses presented in subsequent chapters (e.g., narratives are from the narrator’s biography, point of view and perspective on causality, and that there is some evaluation of the narrative actions). Section 3 further develops the elements of local discourse structure that will recast and model the Labovian perspective in terms of formal semantics and pragmatics. As developed in Chapter II, spatial information will be plugged into this framework.

3. **The Semantics and Pragmatics of Local Discourse Structure.** Broadly, semantics is the linguistic field of study concerned with the meaning of words and utterances. There are a myriad
of different approaches in semantics designed to solve different problems. For example, truth-
conditional semantics is focused on determining the truth conditions of a given utterance.

Another focus is on compositional semantics or how meaning is built up in words and sentences.
These approaches often consider the syntactic structure of the utterance and facilitate the use of
logical operations and computations to derive meanings. For example, from a generative
standpoint, given the sentence *Grimsby lives in Northfield*, each word in this sentence has a
lexical entry denoting the semantics of the word (e.g., following Heim and Kratzer (1998)):

(3) \[
\begin{align*}
[[\text{Grimsby}]] &= \text{Grimsby} \\
[[\text{lives}]] &= \lambda x \in D_e. x \text{ lives} \\
[[\text{in}]] &= \lambda y \in D_e. [\lambda f \in D_{e,<t}>. [\lambda x \in D_e. f(x)=1 \text{ and } x \text{ is in } y]] \\
[[\text{Northfield}]] &= \text{Northfield}
\end{align*}
\]

In (3), *Grimsby* and *Northfield* are expressions whose referents exist in the world which are
Grimsby and Northfield. The verb *lives* has a lexical entry that is a function requiring the input of
variables. The verb is a function ($\lambda$) from individuals in the domain of elements ($D_e$) to a truth
value. The spatial preposition *in* functions similarly. The function denoted by *in* indicates a
relation between two individuals and a property, such that the expression is true when the
individual having the property (Grimsby) is spatially located within the other individual
(Northfield). These functions allow for the complete composition of the sentence to be
represented and the veracity of the sentence evaluated. In short, the utterance *Grimsby lives in
Northfield* is true if and only if there is a Grimsby that lives and is in Northfield. Compositional
and truth-conditional semantics reduce a given utterance down to a formal representation that is
generalizable to other utterances independent of the linguistic surface forms. Further, it is clear
that there is a dependency on the morpho-syntactic structure of a given utterance. This is important as spatial information is morpho-syntactically encoded and, therefore, implementable into those semantic frameworks that consider syntactic structure (developed in Chapter II).

Based on the discussion of narrative structure in Section 2, the following sections focus on the clause level semantics of event and temporal information (Section 3.1). I am assuming for purposes of this dissertation, and consistent with insights from Labov, that the unit of analysis will be the independent clause. From this clause level perspective, it will then be possible to discuss the representation of semantic and pragmatic information in a discourse (multi-clause) model (Section 3.2). In particular, SDRT provides a robust model that facilitates the implementation of event and temporal information and includes pragmatic rhetorical relations (Asher & Lascarides 2003). Section 3.3 will present, through a discussion of TimeML (Pustejovsky et al. 2003) and SDRT, how event and temporal information will be encoded into the analyzed data.

3.1 EVENT AND TEMPORAL STRUCTURE. Event semantics seeks to formally describe, represent and, to a certain degree, typologize a number of different happenings, occurrences and actions that people can talk about. “Events” typically refer to described actions or things that undergo some change. Events are in contrast to “states” which describe things in the world as they are and do not undergo any type of described changes. Further differentiation (and different approaches to classification) have been observed by, for example, Bach (1986) – states, processes and events where states are either dynamic or static and events are protracted or momentaneous and momentaneous events are either happenings or culminations; Dowty (1979) – the decomposition
of action events into *cause, do* or *become* predicates; and Vendler (1967) – exploiting the
temporal aspect of events and categorization into *activities* and *processes* which have indefinite
time periods; *accomplishments* which have definite time periods; *states* which have indefinite
time instants; and *achievements* which have definite time instants. Following Vendler (1967), (4)
provides illustrations:

(4) **activities/ processes**

a. Grimsby scratched his back.
b. Grimsby played in the creek.

**accomplishments**

c. Grimsby completed obedience school.
d. Grimsby slept through the night.

**states**

e. Grimsby has food allergies.
f. Grimsby is 8 years old.

**achievements**

g. Grimsby finished the rawhide
h. Grimsby entered the house.

As indicated in (4), there is a range of information within the clause that facilitates the
determination of what is being described in the clause (“event type”). For example, adverbial
(4h) and prepositional modifiers can be used to determine the duration of events (4d) and
“diagnose” whether the event being described is an activity, processes or states (atelic – lacking a
specific goal or endpoint) or an accomplishments or achievements (telic – having a specific goal
or endpoint) (see Verkuyl (1993)). However, verb tense and aspect are contributing a great deal
to the determination of event type as well.

Tense refers broadly to *when* the event types occur. At the time of a given utterance, the tense
indicates something that has happened at a point in the past, present or in the future. Reichenbach
(1947) formalizes past, preset and future in terms of speech time (S), event time (E) and
reference time (R) (reformulated as topic time (T) by Klein (1994)). Further, E can be E_s indicating an event state and E_e as an event action. Different tenses can be represented in set theoretic notation. For example, the past can be represented as T < S (where ‘<’ is an indicator of temporal precedence) and E_e \subseteq T, E_s \subseteq T or T \subseteq E_s and present tense can be represented as T=S and T \subseteq E_s or T \subseteq E_s. There is not necessarily an explicit link between event types and a given tense – i.e., the different event types indicated in (4) can happen in the past, present or future time. However, aspect in English can, and does, vary relative to event type. Aspect in English varies the time frames within the past, present and future distinction. Consequently, aspect alters the relationship between E and T. In Reichenbach’s terms, T < S for past and T=S for present remain the same, but instead of T being in a subset relationship with either E_e or E_s, the relationship between the two is E < T (non-progressive aspect). Similarly, for progressive aspect, T is in a subset relationship with E generally (T \subseteq E). (5) illustrates some correspondences between tense, aspect and event types:

(5) present

a. Grimsby is at the park
b. Grimsby runs to the park

c. Grimsby was at the park
d. Grimsby ran to the park

e. Grimsby will be at the park

f. Grimsby is running to the park
g. Grimsby has run to the park

h. Grimsby has been running to the park

i. Grimsby was running to the park
In (5), simple past, present and future can indicate a state (5a, c, e) with indefinite time instants, but also accomplishments (5b, d) with definite time periods. The present and past and past progressive denote indefinite time periods and indicate activities and processes (5f, i). The present and past perfect denote definite time periods and indicate accomplishments (5g, j). The present and past perfect progressive shift back to indefinite time periods and indicate activities and processes. Overall, there is some systematic variance between tense, aspect and event type.

The total picture of the event semantic formalism (similar to the compositional representation in (3)) is as follows. The semantics of an utterance such as I drove to the city, could be represented as in (6):

(6)  a. I drove to the city
    b. ∃x (x consists in fact that I drove to the city).
    c. ∃(x,y) [drive (x), to (y): I (x), city (y)]
    d. I drove to the city in September
    e. ∃x (x consists in fact that I drove to the city and x took place in September)
    f. ∃(x,y) [drive (x), to (y), in (z): I (x), city (y), September(z)]

In terms of truth-conditional/ compositional semantics, if, in a given contextual environment, I actually drove to the city (6a-c), then the utterance would be evaluated as true. This formulation, which follows Reichenbach (1947), is supplemented by Davidson (1967 [1980]) with the example I drove to the city in September as in (6d-f). “x” is considered an event argument, which exists in tandem with any event type utterances (Davidson 1967[1980]:174-180) – other
elements of participants, thematic roles and sub-events can be included as well (Parsons 1990). Note that these formalisms do not tell us much about the types of events being describe, but simply what conditions are necessary (independent of surface forms) to evaluate the overall truth conditions (6b,e) (cf. (3)). However, the lexical semantics of the verbs and prepositions can be plugged into the formal event representation for a more nuanced picture (6c, f). As discussed in Section 3.3, I will be following TimeML’s annotation scheme for marking up event and temporal information. However, it is first necessary to extend observations in clause level semantics to the formal semantic and pragmatic representation of multi-clause discourses.

3.2 SEGMENTED DISCOURSE REPRESENTATION THEORY. SDRT is a revision of Discourse Representation Theory (henceforth “DRT”) (Kamp & Reyle 1993). DRT is a model of discourse representation designed to address several phenomenon that clause level semantics is inadequate to handle (e.g. coreference, scope, presupposition) when they exist in multiple clauses. To illustrate, consider the following:

(7) a. Grimsby chased the car
    b. He caught it

The issue in (7) is how to make the determination that he and it in (7b) refers to Grimsby and the car in (7a) respectively. DRT first builds a participant and event representation of (7a) in (8):

(8) [x, y: Grimsby(x), the car(y), chased(x,y)]
And then a participant and event representation of (7b) is constructed independently – i.e., with the realization that he and it refer to different entities than those given in (7a). The variables \( v \) and \( w \) do not have any referents assigned to them (9):

\[
(9) \quad [v, w: \text{caught}(v, w)]
\]

As (7a) and (7b) occur in series (i.e., considered a minimal discourse), the participant and event representations in (8) and (9) can be merged together in (10):

\[
(10) \quad [x, y, v, w: \text{Grimsby}(x), \text{the car}(y), \text{chased}(x,y), \text{caught}(v,w)]
\]

Now, \( v \) and \( w \) can be assigned references Grimsby and the car respectively and, based on embedding and accessibility rules (not covered here), the correct representation of the discourse properly resolves all of the anaphors:

\[
(11) \quad [x, y, v=x, w=y: \text{Grimsby}(x), \text{the car}(y), \text{chased}(x,y), \text{caught}(x,y)]
\]

The examples in (7-11) are a very simple illustration of how DRT works. More complex examples involve, for example, negation and scope and a full host of rules for how elements are subordinated and related and how the truth-conditional and compositional semantics are constructed. The process is not far removed from making these determinations on a per-clause basis. However, because discourses can be long and complex, sometimes more information is needed to resolve these issues. In these instances, DRT tends to break down. Consider (12) which is an example given by Lascarides and Asher (2007: 8, Ex.5):
(12)  a. John had a great evening last night.
    b. He had a great meal.
    c. He ate salmon.
    d. He devoured lots of cheese.
    e. He won a dancing competition.
    f. It was a beautiful pink.

(12) = Lascarides and Asher (2007:8, Ex.5)

In DRT, an evaluation of the semantics is performed with the last clause. DRT is a representational model of discourse such that, with the inclusion of each new utterance, the semantics is updated (e.g., in terms of participants and events). However, in (12f), *it* most likely refers to *salmon* in (12c), because of the semantic intuition and pragmatic inference that salmon is generally pink – and not (12b) or (12d) depending on the context (e.g. a pink meal or a pink cheese) – but not anything in (12e). In DRT, *salmon, meal or cheese*, are all equally accessible for proper reference resolution. However, DRT has no way to indicate that *salmon* is the “preferred” interpretation. SDRT’s answer to this problem is that rhetorical relations must also be included in the representation of the discourse semantics to properly resolve *it* in (12f) with *salmon* in (12c).

Like DRT, SDRT is a theory of discourse representation. However, it extensively exploits how discourses are *interpreted* to formalize a number of rhetorical relations. A key motivation

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b A number of different discourse models exist that focus on global discourse features and structures – for example, Temporal Discourse Model (Mani & Pustejovsky 2004), Rhetorical Structure Theory (Mann & Thompson 1988), and coherence-based (Hobbs 1985a) – and those, like (DRT), that focus on smaller scale issues – e.g. anaphora resolution (e.g. Byron 2000) or tense (e.g. Webber 1987), just to name a very few.
for the inclusion of rhetorical relations is the notion of discourse coherence (e.g. Hobbs 1985a). The more coherent a discourse, the easier it is to process and interpret. Elements that contribute to a discourse’s coherence are references, presuppositions, tenses and other elements, which can cause problems (via ambiguity and scope) with interpretation. Often, a number of possible resolutions for an ambiguous phenomenon in discourse are available, but how do we choose? For SDRT, the choice which best maximizes discourse coherence (i.e., ranking possible interpretations) is the best choice – embodied in the Maximize Discourse Coherence (MDC) Principle (Lascarides & Asher 2007:13):

The Maximize Discourse Coherence (MDC) Principle:

1. All else being equal, the more rhetorical connections there are between two items in a discourse, the more coherent the interpretation.
2. All else being equal, the more anaphoric expressions whose antecedents are resolved, the higher the quality of coherence of the interpretation.
3. Some rhetorical relations are inherently scalar.

It is important to note that coherence is a scalar notion; some discourses are more or less coherent. Further, the MDC principle relies on the information content of individual utterances. Pursuant to SDRT (and consistent with the MDC principle), discourses have a structure that is relative to rhetorical connections. For example, Figure 1 provides the rhetorical (tree) structure of (12):
As Figure 1 indicates, *it* in (12f) is part of an utterance which is rhetorically connected, via ELABORATION to *He ate salmon* in (12c). Between these two utterances, *it* can really only refer to salmon as they are structurally connected through a subordinating ELABORATION relation even though they are not adjacent in the unfolding of the discourse. The existence of a defined rhetorical relation between these two clauses facilitates accessibility of variables to resolve anaphora just as in DRT (7-11). Formally, (12) would be represented as follows in (13):
(13) \[ A=\{\pi_0, \pi_1, \pi_2, \pi_3, \pi_4, \pi_5, \pi_6, \pi_7, \pi_8\} \]

\[
F(\pi_1)=K\pi_1, F(\pi_2)=K\pi_2, F(\pi_3)=K\pi_3, F(\pi_4)=K\pi_4,
F(\pi_5)=K\pi_5,
F(\pi_6)=K\pi_6
\]

\[
F(\pi_0)=\text{Elaboration (\pi_1, \pi_7)}
\]

\[
F(\pi_7)=\text{Narration (\pi_2, \pi_5) \wedge Elaboration (\pi_2, \pi_8)}
\]

\[
F(\pi_8)=\text{Narration (\pi_3, \pi_4) \wedge Elaboration (\pi_3, \pi_6)}
\]

LAST=\pi_6

In (13), the set of speech act discourse referents include the overall context of the discourse (\(\pi_0\)), each segment of the discourse (\(\pi_1 - \pi_6\) (corresponding to 12a-12f) and synonymous with the independent clause), and the rhetorical relations (\(\pi_7 - \pi_8\)). (\(K\pi_n\) is a labeling convention and \(F\) is a function that maps the speech act discourse referents to the discourse structure). It is not necessary to go into further detail at this point about all of the nuances of SDRT. What is most relevant for the immediate purposes of this proposal is that SDRT provides useable definitions of rhetorical structures that can be included in the proposed analysis.

Asher and Lascarides (2003:459-463) provide the definitions of several rhetorical relations. \(\text{BACKGROUND, CONSEQUENCE, CONTINUATION, ELABORATION, EXPLANATION, RESULT and NARRATION}\) are defined, by example, in (14a-p):

\[
(14) \quad \text{BACKGROUND} \quad a. \text{I ordered the Americano}
\]
\[
\quad b. \text{It was pipping hot}
\]

\[
\text{CONSEQUENCE} \quad c. \text{If I order the Americano}
\]
\[
\quad d. \text{then I’m at the Blue Monday}
\]

\[
\text{CONTINUATION} \quad e. \text{I couldn’t find my wallet}
\]
\[
\quad f. \text{I looked under the table (NARRATION between e and f)}
\]
\[
\quad g. \text{Cati looked in her purse}
\]
\[
\quad h. \text{Pascale looked in the stroller}
\]
ELABORATION
i. I had a great time at the cafe
j. The Americano was fantastic

EXPLANATION
k. I burned my tongue
l. The Americano was piping hot

RESULT
m. The Americano was piping hot
n. It burned my tongue

NARRATION
o. I ordered the Americano
p. Then I read the paper

There are different levels of definition for these relations. Given the nature of narrative discourses, and what is observed in the analyzed data, the three SDRT relations of NARRATION, BACKGROUND and ELABORATION are most central. NARRATION, as mentioned throughout, holds if the sequence of events depicted in the clauses matches the actual sequence of events. Asher and Lascarides (2003:462) also indicate that there is a topic constraint on the two clauses – i.e., the clauses are depicting events in the same and not different sequences – and that there is a spatiotemporal consequence of narration – “where things are in space and time at the end of [event 1] is where they are at the beginning of [event 2].” BACKGROUND and ELABORATION are closely related relations. BACKGROUND relations provide “information about the surrounding state of affairs” which applies to the previous clause and the clauses temporally overlap (Asher and Lascarides 2003:460). While not explicit, ELABORATION (which will serve an evaluation function consistent with Labov (1972) – e.g. (14i-j)) also provides information about the surrounding state of affairs, but the second clause is temporally subordinate (part-of) to the previous clause (Asher and Lascarides 2003:461). This subtle distinction is best illustrated with an example:
(15) BACKGROUND a. I slept on the couch last night.
b. The couch smells like dog.

ELABORATION c. I slept on the couch last night.
d. The couch makes my back hurt

In (15a-b), (15b) indicates a property of the couch that exists independent of whether or not I slept on the couch. My sleeping on the couch and the fact that it smells like dog temporally overlap. In (15c-d), (15d) also indicates a property of the couch that potentially exists independent of whether or not I slept on the couch, but this property is invoked only as part of the preceding event of sleeping. The fact that the couch makes my back hurt is temporally a part of the fact that I slept on the couch last night. Note that there is no evaluative component to (15c-d) – the ELABORATION relation is not synonymous with evaluation in the Labovian sense – evaluation is merely a type of ELABORATION. Overall, SDRT simply provides a useful framework to describe the local structure of discourse that subsumes event and time semantics with rhetorical pragmatics.

Contrary to temporal information, SDRT – which is a type of temporal relation – does not make any obvious predictions about the types of spatial information that may occur in a discourse. However, SDRT does not explicitly forestall the possibility of spatial information appearing in any clause that contributes to a rhetorical relation either. Again, space is explicitly mentioned only in the NARRATION relation. However, this does not, a priori, indicate that spatial information is more likely to appear in clauses contributing to this relation as compared to other relations. From the Labovian framework, spatial information is likely to occur in Orientations
(BACKGROUND) as clauses contributing to this relation are providing setting information – the overarching who, what, when and where of the narrative actions (This is somewhat supported by Smith’s (2003) observation that the Descriptive Mode focuses on spatial details). However, Labov (1972: 376) also points out that the inclusion of spatial information is a general feature of basic narrative syntax. Overall, Labov – despite, perhaps, a tendency towards Orientation clauses – does not really indicate a preference for the appearance of spatial information in any given clause or rhetorical relation that holds between clauses. This lack of preference similarly extends to the type of space that may occur. Falling from the distinction between narrative events and descriptive background, it is reasonable to assume that descriptions may include more static spatial relationships whereas events may include more motion spatial relationships. However, beyond this, I am reluctant to make any specific predictions; especially ones that are not explicitly accommodated by the theories relied upon here.

3.3. EVENT, TEMPORAL REFERENCE, TENSE AND ASPECT ANNOTATION. As I am concerned with the variance of spatial information relative to structural elements of narrative discourse, the clausal elements of event, temporal reference, tense and aspect should also be included in the coding for sake of completeness (following from observations of event semantics in Section 3.1). Note however, that temporal reference, tense and aspect ultimately do not play much of a role in the machine learning experiments. This is largely because only a few types (or the absence of any type) occur in the vast majority of the data (cf. Chapter IV, Section 2.1). For time and event coding, I rely on the TimeML annotation scheme (Pustejovsky et al. 2003).
TimeML annotates event information relative to temporal information in texts; events and time are not treated as distinct, but rather dependent, phenomena. As a reflected in the annotation, events are located in time, the type of time is indicated (e.g. durations, points in time), and the events can be sequenced throughout a given discourse. TimeML consolidates a broad range of events and temporal information that is consistent with the observations made in Section 3.1 and Section 3.2 and will serve as an appropriate complement to spatial information. While I will not be leveraging all that TimeML has to offer – it is a very robust coding scheme – several of the event and time annotation types are useful.

In terms of events, TimeML focuses on six verb-based categories (Sauri et al. 2006:10-14):

- **REPORTING** – said, exclaimed, referenced, reported
- **PERCEPTION** – saw, heard, felt, sensed
- **ASPECTUAL**
  - INITIATION – start, begin, commence, set off
  - REINITIATION – restart, reignite, rerun
  - TERMINATION – stop, arrest, hit, end
  - CULMINATION – arrive, reach, complete
  - CONTINUATION – proceed, continue, keep going
- **INTENSIONAL ACTION** (I_ACTION)
  - attempt, try, scramble
  - investigate, investigation, look at, delve
  - delay, postpone, defer, hinder, set back
  - avoid, prevent, cancel
  - ask, order, persuade, request, beg, command, urge, authorities
  - swear, vow
  - name, nominate, appoint, declare, proclaim
  - claim, allege, suggest
• ALTERNATE WORLDS (I_STATE)
  o believe, think, suspect, imagine, doubt, feel
  o want, love, like, desire, crave, lust
  o hope, expect, aspire, plane
  o fear, hate, dread, worry, be afraid
  o need, require, demand
  o be ready, be eager, be prepared
  o be able, be unable

• STATE
  o Temporal states
  o States of changing
  o States introduced by I_ACTION, I_STATE or REPORTING

• OCCURRENCE
  o Indicates all other non-state events that do not fit into the above categories

REPORTING and PERCEPTION events are fairly straightforward in terms of what they encode. ASPECTUAL events focus on different temporal pieces of a larger event. INTENSIONAL ACTIONS introduce event arguments. INTENSIONAL STATES introduce references to alternate or possible worlds. General STATES can be introduced by I_ACTION, I_STATE or REPORTING events. General states are also, consistent with the nature of TimeML, anchored to some temporal frame and can change throughout a given document. As indicated, OCCURRENCE is a “catch all” for events that do not fit into any particular type.

Temporal expressions in TimeML are based on work by Setzer (2001) and Ferro et al. (2001). There are four primary types of temporal expressions:

• DATES – September 24, 2010, Christmas Eve

• TIMES – 12:00 GMT, 10 past 2
• DURATIONS – 3 hours, 4 days

• SETS – every month, several times a year

There are several other attributes of temporal expressions that I am not be concerned with (e.g., function of time in document), rather I simply focus on the type and occurrence of temporal expression. The reason for this is the bulk of expressiveness in TimeML is in relation to linking events in a given discourse. I rely on text sequence relative and the temporal implications of rhetorical relations to provide event relationships.

Text sequence, or *progression* in Smith’s (2003) terms, is based, especially in narrative texts, on the dynamics of event sequences. If the central sequence of events are distilled from a given narrative discourse, in the absence of explicit temporal reference, event 1 will occur before event 2, will occur before event 3, … will occur before event n, etc. This progression is largely determined by the sequence of text rather than reliance on the event/ tense/ aspect representation in a given clause. Nonetheless, it is not the case that there is *no* relationship either. Consequently, consistent with the discussion of time and event in Section 3.1, each clause will be marked for tense (PRESENT, PAST, FUTURE, NONE, INFINITIVE, PRESENT PARTICIPLE, PAST PARTICIPLE) and aspect (PROGRESSIVE, PERFECTIVE, PERFECTIVE PROGRESSIVE, NONE), rounding out the full temporal picture of discourse.

4. CONCLUSION TO CHAPTER I. Before drawing this chapter to a close, I think it relevant to summarize the material covered in the previous sections with a discourse example complete with the type of information anticipated to be accounted for; consider (16):
In (16), each clause is marked with tense information, event type information, rhetorical
relations (START (16b) refers to the first clause in a discourse as rhetorical relations are based on
clause pairs), explicit temporal information and text progression information (“0” indicates either
no explicit temporal information (16b, h, n, q, t, w) or no temporal progression (16b, e, q, t). For
now, I simply want to illustrate what the formal semantic representation of the clauses looks like
From a perspective of the larger narrative text, (16a) and (16d) provide Orientation information. (16g, j, m, p) are Complicating Actions providing a narrative chain of events from the narrator’s perspective. An Evaluation is given in (16s) and then the narrative chain continues in (16v). From a rudimentary spatial perspective, clauses including spatial information involve Orientation (16a) and Complicating Actions (16g, m, p, v). Further, while this will be further developed in Chapter II, there are shifts in the types of information. For example, there is movement from larger spaces (Minneapolis, Minnesota (16a)) to smaller spaces (the dealership (16m), my desk (16p), the chair (16v)). Other spatial relationships in (16) also include static descriptions (16a, p, v) and dynamic (16g, m), the inclusion of distance information (16g) and the inclusion of geocoordination (16m). I will revisit this example in the next chapter after a discussion of theoretical considerations in spatial language.

This chapter has provided the semantic and pragmatic frameworks of discourse structure that spatial information will be incorporated into. These frameworks, SDRT and TimeML, formalize the semantic and pragmatic relationships within and between the events and times morpho-syntactically encoded in clauses. The inclusion of spatial information into these frameworks is non-problematic and has been accounted for in some way already. Event and time elements of the local discourse structure, and their progression, then group into larger narrative text structures. Insights from Labov and Smith, which are not inconsistent with fundamentals of SDRT and TimeML, reveal the components of the narrative text structure (Narrative Mode). The spatial perspective on narrative discourse structure has been limited by the absence of surface linguistic forms. Nonetheless, spatial information is assumed to be present and contributing to local discourse structure. Chapter II will fully discuss the linguistic realization of spatial
information and consolidation of insights in research on spatial language into a robust coding scheme. This coding scheme, consistent with SDRT and TimeML, will allow for the representation of semantic spatial relationships and how these relationships vary, relative to other spatial relationships, temporal information, event information and rhetorical relations, as the discourse unfolds.
CHAPTER II - SPACE

1. INTRODUCTION TO CHAPTER II. In order to argue for the structural nature of space, it is useful to account for as many different types of spatial information as possible. Further, variation in the types of spatial information relative to temporal, event and rhetorical relation information must be tracked throughout a given discourse. Being able to demonstrate patterns (and the strengths of those patterns) in spatial information independently, and relative to other structural elements of narrative discourse, is essential to answering the posed research question and associated hypotheses. The goal of this chapter is to determine (1) what types of spatial information to keep track of and (2) how types of spatial information can qualitatively vary across discourse. Again, the ultimate goal is to determine a generalized model of representing structural spatial information that is applicable to narrative discourses in English.

This chapter is structured as follows. Section 2 focuses on the role of spatial information in narrative discourse research, which has traditionally been of somewhat limited scope (i.e., relegated to background and setting information if structurally contributing at all), culminating in a discussion of Herman (2001) who, based on analyses of spatially rich ghost stories, argues for a reevaluation of spatial information in narrative discourse. This discussion will serve to constrain the types of spatial information and discourses that will be coded in this dissertation. Section 3 develops relevant perspectives in spatial language research to set a template of spatial language (to evaluate types and variation of types), which is a balance of considerations in research on spatial cognition and cognitive semantic models of linguistic categorization (Section 3.1) and morpho-syntactic research on spatial prepositional phrases (Section 3.2). Additional spatial linguistic elements are explored: verbs (Section 3.3), deixis (Section 3.4), frames of reference
(Section 3.5), and granularity of spatial description (Section 3.6). Section 4 develops relevant perspectives on linguistic semantic models of spatial language (Section 4.1) and formal (mathematical) models of space; in particular, mereotopology (Section 4.2). Sections 4.3 and 4.4 discuss the mereotopological representations of spatial verbs, prepositions, figures, frames of reference and granularity of spatial description. Section 5 concludes Chapter II.

2. THE ROLE OF SPATIAL INFORMATION IN NARRATIVES OF PERSONAL EXPERIENCE. Looking at local and text level discourse structure in the previous chapter illustrates the importance of event, states and time, but little mention is made of space (see Tenbrink (2007)). Albeit true that space is referenced in the definition of the NARRATION SDRT relation and other semantic and pragmatic phenomena in discourse, the fact that surface realizations of spatial information are not a necessity calls into question the status of spatial information as a structural primitive in narrative discourses. The role of spatial information has been observed in non-narrative discourses. For example Smith’s (2003:19) Description Mode, where the progression is “spatial advancement through the scene or object.” However, the Descriptive Mode is typically a particular type of discourse specifically requesting spatial information (e.g. descriptions of apartment layouts (Linde & Labov 1975); the HCRC Map Task (Anderson et al. 1991); and wayfinding tasks (Tenbrink & Winter 2009), just to name a very few).

Spatial information in narrative, as Herman (2001:518) observes, has been of minimal concern – typically focused on Orientation information or other descriptive elements (Labov 1972:360). Further, deixis (person, temporal, or spatial) can be instrumental in returning to the present time and space in the Coda (Labov & Waletzky 1967[1997]:36). Spatial information is
also included in Labov’s (2001) event resolution based on participants and verbs of narrative clauses. It is possible that the verb of clauses participating in the NARRATION relation could be a spatial verb (motion) or subcategorized for an adjunct or complement prepositional phrase (PP) or determiner phrase (DP) indicating spatial location (cf. Chapter I, Ex. (1) and Table 1). However, this possibility follows from general lexical semantics rather than from a spatial structural phenomenon. Research focusing on spatial information in textual discourse structure has been sparse: for example, space has been a focus for different perspectives of narrative analysis; for example, pseudo-narratives (Wald 1973); deictic theories (Duchan et al. 1995; Zubin & Hewitt 1995); identity (Baynham 2003); cognitive theories (Talmy 1995); and cross-disciplinary (literary and cognitive) approaches (Zoran 1984; Ryan 1991, 2003; Buchholz & Jahn 2005; Bridgeman 2007).

Herman (2001), consistent with Asher and Lascarides (2003), argues that the minimal temporal juncture between two past-time events should be re-evaluated as a spatiotemporal juncture. However, Herman bases this argument on observations on both the local and textual structure. In particular, narrative is not just “temporally structured communicative acts, but also… sets of verbal or visual cues anchored in mental models having a particular spatial structures” (Herman 2001:519). These narrative domains are part of “a mental construct that encompasses the history of spatial relationships between storyworld objects [i.e., the world being told about]” and do more than just convey the spatial information in narrative for purposes of describing the spatial backdrop of the narrative. Narrators are, therefore, able to provide discursive linguistic cues which allow interlocutors to construct a (cognitive) map of the narrative which is “fundamental and obligatory for narrative understanding, not a derivative or
optional aspect of telling and comprehending stories” (Herman 2001:518). Hence, the inclusion of space, whether implicit or explicit, conscious or subconscious, is part of what minimally constitutes a narrative, at least at the cognitive level (whether or not that spatial information is linguistically expressed is another issue that is explored in this dissertation). To illustrate Herman’s approach, consider (1):

(1) a. When my grandmother died it sounded like somebody was standing in the window
b. I was sitting on the bed.
c. And … a door goes through to the other room
d. And then there was a window that high
e. I could look, sit on my bed and look straight out that window
f. And I was sitting in there [on the bed] sewing a baby’s dress.
g. And sound like somebody jumped down out from out of that window on the floor.
h. And I stopped and looked.
i. I said “What in the world was that”
j. And I got up and went to the window and looked out
k. I didn’t see nobody.
l. And a little while after that my mother done come and told me my grandmother had died.

(1) = Herman (2001:524-525, Ex.3)

(1) is a structurally well-formed narrative discourse. Following Labov, there are a number of Orientations (1c-e), Complicating Actions (1b, f-l), and Abstract/ Evaluations (1a, i) (Labov 1972: 363-373). In terms of space, under a Labovian framework, only a few things can be said – i.e., that it occurs in certain types of textual clauses and, for the Complicating Actions, is additional information for resolving the event and participant structure of the narrative actions. Labov’s framework does not tell us anything about the type of spatial information if it is included. Alternatively, following Herman, spatial discourse cues create narrative domains in (1)
which group narrative events into spatial locations of the bed (1b, e, f, h, i); the window (1d, e, g, j, k); and the area in between (1c, j). The spatial discourse cues include:

- The notion of deictic shift, whereby a storyteller prompts his or her interlocutors to relocate from the here and now of the current interaction to the alternative space-time coordinates of the storyworld (e.g. Bühler 1982) (like Coda in Labov’s framework);

- The distinction between figure, ground, and manner alternatively described as located object versus reference object (also trajectory, path and landmark), which is a versions of What and Where systems (Landau & Jackendoff 1993) (e.g. Langacre 1987; Talmy 2000);

- The distinction between topological (or inherent) and projective (or viewer-relative locations (e.g. frame of references (Levinson 1996));

- The deictic functions of motion verbs located on a semantic continuum whose poles, in English, are come and go (e.g. Fillmore 1971);

Examples of these discourse cues from (1) include deictic verbs (1j, 1l), figure and ground relationships (1b, 1f), and projective relations (1c, 1g). Under Herman’s framework, there is the ability to not only account for where spatial information occurs in narrative discourses, but the type of spatial information and all associated theoretical considerations can be accounted for as well. Herman provides numerous examples of the occurrence of these discourse cues and suggests that text level patterning into narrative domains originates from the use of spatial language in clauses to construct shared cognitive maps. These discourse cues will be further developed below in Section 3. However, there are two additional insights from Herman’s work that bear immediate relevance. First of all, the type of spatial information being considered is based on the narrator’s actual perceptions of the remembered environment. Therefore, spatial
information that does not refer to elements in the physical environment will not be a consideration in this dissertation and will be put aside for future research. Examples include:

- Reference to space in an idiom or metaphor – *The DJIA rose above 10,000 points, I went in under the pretense of bowling, Atticus Finch put the dog down*;

- Reference to space in reported speech – *She told me to drive to Disney Land, I said that I wanted to sit in the chair*;

- Reference to space in alternate worlds – *We could go to Maine, I need to go to the bathroom, I plan on going to church*;

- Reference to space within the scope of negation – *She didn’t go to school, Larry wasn’t in his car*

Second, Herman relies on the notion of the “cognitive map” to motivate the structure of narrative domains. Cognitive maps, originally termed by Tolman (1948) who experimented on a rat’s ability to navigate mazes relative to memory for food sources, are an individual’s internal mental representation of the physical environment. Cognitive maps have been the focus of a number of different disciplines including cognitive and environmental psychology, municipal planning, sociolinguistics and, to be discussed in Chapter V, environmental criminology. However, despite treatment by these different disciplines testing diverse hypotheses (*see generally* Golledge (1987:147-49) for an extensive list) there is remarkable stability in terms of how cognitive maps are compositionally defined. I will follow Lynch’s (1960:47-48) formulation of urban cognitive maps, which are comprised of:

- *Paths* – Paths are the channels of movement: roads, walkways, and railroads. For many people, paths dominate the image of a city;
• **Edges** – Edges are linear elements not used as paths. They may be railroads, edges of developments, or shorelines, for example. Although edges are not as important as paths in forming images, they still help to organize cognitive maps;

• **Districts** – Districts are fairly large subareas of cities that are recognizable by unifying characteristics. People can move in and out of districts. Districts often have well established cores but fuzzy borders. Financial and industrial districts exist in many large cities. Housing areas may also be districts if they have a unifying element or elements;

• **Nodes** – Nodes are intense foci of activity in cities. One can enter and leave nodes. Nodes are junctions of major paths, such as intersections or railway terminals, where people leave one type of path and move to another. Nodes may also be just concentrations of activity or interest. The cores of districts are nodes; the corner store may be a node;

• **Landmarks** – Landmarks are point references that the traveler does not enter, for example, signs, buildings, or mountains. Landmarks are used for orientation and path finding. Distant landmarks help maintain local orientation as paths bend and twist. Local landmarks can be signs, specific trees, and other small-scale objects used in local pathfinding (*I turn by the Donut Shop*) or in generally triggering of familiarity.

These common elements (which can be both physical and symbolic in nature (e.g. Appleyard 1979), by definition, exhibit spatial relationships and are categorical in nature – e.g. specific elements identified will fall into one of these categories. However, which of these elements is included in an individual’s cognitive map is relative to the individual’s physical environment from the individual’s perspective. *A priori* the individual, relative to what exists and is perceived by the individual in the individual’s physical environment, has complete choice over what to include, what not to include, what is relevant to the individual and what is not relevant to the individual. This observation holds whether or not the medium of experimentation is map drawings, responses to testing or verbal (written or spoken) descriptions in laboratory testing or sociolinguistic interviews.
Returning to Herman’s perspective and reasoning, exploiting the characteristics of the cognitive map, and how spatial language constructs elements of the cognitive map, is crucial to understanding the spatial characteristics of narrative. Further, theoretical perspectives on narrative already discussed – narratives based on the narrator’s theory of causality from objective and subjective viewpoints – are not inconsistent with being able to linguistically determine how the narrator’s cognitive map is constructed in narrative. However, note that there is nothing inherently linguistic about cognitive maps. They are, on one hand, a shorthand for consolidating not only verbal cues, but drawings, and physical behavior into a cohesive cognitively informed spatial representation and, on the other hand, linking these cohesive spatial representations to spatial cognitive abilities. The innovation in Herman’s perspective that is of most use in this dissertation (in addition to the motivation of questioning the role of space in narrative in the first place) is that there is, arguably, a spatial architecture to narratives based on the fact that the narrator experienced the events and states being narrated. This spatial architecture should be resolvable via the traditional structural primitives of narrative discourse – i.e., spatial information should systematically vary relative to time and event. However, how this actually happens or is expressed is not linguistically straightforward, but it is an empirical question.

While Herman’s (2001) insights are premised on spatial richness, Labov (1972:376) indicates that spatial information is somewhat common. To clarify Herman (2001), an assumption is made that the ghost story narratives are spatial rich because: (1) there is an unquantified intuition that there is a lot of spatial information despite the status of spatial information as “unnecessary” for structural diagnostics; and (2) patterns are recoverable from the spatial information that vary in relation to other spatial information and some structural elements. Spatial richness is a cover
term for spatial density. That is to say, how often does spatial information, however it is defined, occur in a given narrative discourse. As indicated throughout, whether or not spatial information is included appears to be an optional feature on the linguistic surface. Consequently, an a priori assumption is that spatial information could be in every clause (100% density) or no clauses (0% density) in a given narrative discourse. So, spatial density is an empirical question that is investigated in this dissertation. Further, whether or not spatial density is related in anyway to the ability to predict spatial, temporal, event and rhetorical information is also investigated.

3. THE LINGUISTICS OF SPACE. Again, use of the term “spatial information” in this dissertation is shorthand for reference to physical space. Specifically, this dissertation investigates the types of spatial information that are linguistically encoded in references to physical space through attention to spatial language – the surface realization of this linguistic encoding of spatial information. However, before this investigation moves forward, there are two different levels of insight that must be engaged to understand the relationships between physical space, how humans perceive physical space (Section 3.1), and how linguistic structures encode the perception of physical space in English (Section 3.2). In particular, the linguistic encoding of spatial verbs (Section 3.3), deixis (Section 3.4), frames of reference (Section 3.5) and granularity (Section 3.6).

3.1. SPATIAL COGNITION AND COGNITIVE SEMANTIC MODELS. The physical environment exists independent of human existence. What we come to know about the physical environment, how we navigate the physical environment and how we relay information about the physical environment, is based on the cognitive and perceptual processes of humans generally. For
example, given a scene of a cup of coffee on a table (disregarding the linguistic bias for how this scene is described for the moment), we are keeping track of two entities in space, a cup of coffee and a table, and the relationship that exists between these two entities, the cup of coffee being on the table. There is a wealth of research from cognitive psychologists that indicate, based on task-based performances, the types of spatial information that humans keep track of and store in and retrieve from memory.

Very generally, the spatial cognitive and (largely visual) perceptual abilities of humans center on:


- the physical make-up of objects (e.g. sides, tops, bottoms and axes) (e.g., based on acquisition research, pre-verbal infants can categorize scenes based on left/ right (Behl-Chadha & Eimas 1995) and above/ below (Antell & Caron 1985) distinctions; and pre-verbal infants “know” the shapes of containers (Baillargeon 1995)); and

- tracking of an object’s movement through space (again, in acquisition research, pre-verbal infants “know” that objects fall (Needham & Baillargeon 1993); and that moving objects have a defined trajectory that can be interrupted by other moving objects (Spelke et al. 1992).

(see also Piaget and Inhelder (1967), Gibson and Spelke (1983), Landau (2000), Clark (2001), Landau and Hoffman (2005), and Lakusta and Landau (2005)). Consequently, insights from spatial cognition provide a “model” that potentially helps explain spatial phenomena in other disciplines, such as the focus of this dissertation, morpho-syntax and semantics within linguistics.
Illustrations of the influence of visual spatial cognition on linguistic research is found in Jackendoff (1996:5) who assumes a Conceptual Structure - responsible for the “encoding of linguistic meaning that is independent of the particular language whose meaning it encodes” that is independent from Spatial Representations – responsible for encoding uniquely spatial information. Spatial information for Jackendoff includes the shape of seen and unseen objects, parts of object, object change and movement, object categorization, and full spatial layouts including alternative perspectives, summarized as follows (14-19): (1) axial part vocabulary – top, bottom, front, back, sides – indexing regions of objects based on axial information which is independent of what the actual shape of the described object is; (2) dimensional adjectives – high, wide, long, thick – indexing degrees of an object’s axes; (3) spatial prepositions – above, below, in front of, right of – indexing locations relative to a reference object’s axes; and (4) “frames of reference” – larger viewpoints of object locations relative to other objects relies on viewer, reference object or geo-coordinate axes.

These insights are consolidated in Landau and Jackendoff (1993:227) into “what” and “where” systems. “What” systems are defined relative to a simple locational paradigm of figure objects located relative to a reference object. Reference objects can be described with: (1) volume, surface and line information (in, near, at); (2) horizontal or vertical axes (on top of, in front of); and (3) quantity (between, among). Figure objects are typically described by single

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\( ^c \) Space, like time, color, and number, is part of the basic human experience. This potential universality of spatial cognition may or may not emerge in linguistically consistent ways across the world’s languages. Consequently, research into typological linguistic descriptions of space has been used to argue for and against Sapir-Whorfian effects (e.g. Haviland 1993; Pederson et al. 1998; Bowerman & Choi 2001) and semantic conceptual structures (e.g. physical and metaphorical (Tyler & Evans 2003); Connectionist models (Regier 1996); and Mental Spaces (Fauconnier 2003). While I will not be concerned with these avenues within spatial language research, there are numerous shared concepts that will be implicated in this dissertation.
axial structures only (*along, across, above*) (228). “Where” systems are similarly focused on reference and figure object relationships. The describable regions where reference and figure object relationships exist include: (1) relative distance – interior (*in, inside*), contact (*on*), proximal (*near*), and distal (*far*); (2) direction – vertical (*over*) and horizontal (*front, back, side*); (3) axis choice/ “frame of reference” – intrinsic, relative or absolute; and (4) paths/ trajectories – via (*through*), to (*into*), toward (*toward*), from (*from*) and away (*away*).

A distinction which emerges in this linguistic research is between descriptions of static vs. dynamic spatial relationships. Further, some linguistic paradigms tend to highlight one versus the other. For example, drawing parallels between the right brain hippocampus, which is neurologically responsible for key aspects of spatial cognition (Kosslyn 1987, 1994; Kemmerer 2006; Postma & Laeng 2006), and the left brain hippocampus, where language may or may not have been mapped onto similar cognitive structures, O’Keefe (1996: 278) developed a cognitively informed “vector grammar.” O’Keefe suggests that a “semantic map,” consisting of names of objects and their spatial features, is created in similar ways to cognitive maps consisting of objects located in the physical environment and “would incorporate linear temporal information…providing the basis for narrative comprehension and narrative memory.” Relevant elements of O’Keefe’s semantic map include *places, distances* and *directions* between places and distances that can be represented in terms of vectors.

Cognitive maps, as previously mentioned, are larger representations of physical environments. By larger, based on research in cognitive psychology, I mean two things: (1) cognitive maps are series of spatial relationships experienced and encoded over time; and (2) summative internal pictures of the spatial make-up of a given area. However, before a larger cognitive map-like
picture can be distilled from linguistic discourse, it must be acknowledged that spatial relationships are constructed one at a time. The research described in this section seeks to fully understand the underlying cognitive semantic structure of surface linguistic forms on a morpho-syntactic level. Therefore, it is first necessary to evaluate, in the next section, morpho-syntactic representations space. Formal semantic modeling that accompanies the morpho-syntactic representations of space, which are more or less informed by some spatial cognitive insights, will also be discussed.

3.2. THE MORPHO-SYNTAX OF SPATIAL EXPRESSIONS IN ENGLISH. The relationship between spatial cognitive insights and the analysis linguistic surface forms, while focusing on ultimately different theoretical goals, is not completely unrelated. In English, the depiction of objects located in space is realized primarily by spatial prepositions. This is true of both static and dynamic spatial relationships. However, as will be discussed, the verb plays a role in the construction of static and dynamic relationships as well. Because semantic spatial relationships are ultimately being modeled, and given that the cognitive semantic models discussed in Section 3.1 consider syntactic structure as a key part of compositionality, it is necessary to explore the syntax of spatial expressions in English.

Syntactically, prepositions (P) are assumed to be a lexical category (e.g. Jackendoff (1973), van Riemsdijk (1978), and Chomsky (1995)). For example, following Corver and van Riemsdijk (2001), P exhibits specific semantic content, is a free-standing word, theta-marks its complement, and has variable c-selection. Lexical categories contrast with functional categories. While prepositions in English are considered to be a closed class of words, this is one of the few
ways that P falls into a functional category. In languages other than English, the inventory of words in P is much larger and is more open-class. These observations hold for all prepositions and associated senses. For example, The Preposition Project (Litkowski 2002) contains a comprehensive list of prepositions in English which are classified with senses relative a given preposition’s dictionary definition (http://www.clres.com/prepositions.html). To illustrate, The Preposition Project entry for at includes nine different senses:

- Spatial – They live at Conway House
- Temporal – The children go to bed at nine o’clock
- Activity – It was at university that he first began to perform
- Scalar – Prices start at £18,500
- Quantity – At fourteen he began to work as a postman
- Backdrop – They were at a disadvantage
- Tandem – She was getting much better at hiding her reactions
- Target – I looked at my watch
- Means (Medium) – He held the prison officer at knifepoint

Of the 334 prepositions (which include several redundancies [e.g. versus and vs. and v.] and phrasal prepositions (e.g. on a level with, under the banner of, with respect to)), 95 have a spatial sense attributed to them. An additional 19 prepositions have Barrier, Tandem, Quantity, Activity and Backdrop senses which are spatial and can be found in descriptions of the physical environment (see also Quirk et al. (1985), Lexical Conceptual Structure (Dorr 1997), VerbNet (Kipper et al. 2000), and PrepNet (Saint-Dizier 2008) for alternative, but similar, semantic classifications).

Independent of the semantic sense of a given spatial preposition, the tree structure in Figure 2 of spatial prepositional phrases (PP) is assumed (based on Svenonious (2004, 2006, 2008) see also denDikken (2006), Kracht (2008)). In Figure 2, representing the PP back up to six feet in
front of the tree, several phrase levels within the PP are represented: Direction, Degree, Path, Place, Axial Part and a KP in X’ structure. Of course, not each element is present in every case. There are several assumptions that this model makes and will be incorporated into the larger methodology and analysis presented in Chapter III. First, PathP and PlaceP are the dominant types of PPs. Direction (DirP), Degree (DegP) and Axial Part (AxPartP) Phrases are optional spatial modifiers. KP stands for “Case Phrase.” P, either in Spec of PathP or PlaceP (synonymous with Directional or Locative P), assigns case to the Determiner Phrase (DP) object in KP. In Spec of KP is the eigenplace which serves, in semantic models, as the contextually given region occupied by the DP (Wunderlich 1991). The eigenplace is either of (from an Axial Part Phrase construction) or null. Second, particle constructions, such as drove up, ran back, biked off, will be treated as part of the PP rather than the verb phrase (VP). Sag et al. (2002) and Cappelle (2008) discuss the problematic nature of particle verbs and particle prepositions; in particular, particles can occur in the Spec position of Dir’ and of Path’ (e.g. back up to six feet down in front of the tree).
Figure 2. The syntactic structure of spatial P.

Third, the DP object in KP (which is the complement to P), indicates the “ground” of the semantic figure and ground relationship created by P. Talmy (2000) provides cross linguistic support for the basic spatial relationship of object 1 (= figure) being located and the reference object/ region 2 (= ground) that object one is being located relative to. This basic relationship is also implicated in the cognitive semantic models discussed above and is known in other terms (e.g. trajectory and landmark (Langacre 1987)). The use of P with a spatial sense always minimally references a figure and ground relationship. This is true whether the PP is
syntactically a **predicate** – *the coffee is on the table*; **argument** – *the coffee sits on the table*; or **adjunct** – *I drank the coffee on the table*.

Note that the syntactic representation of P does not, necessarily tell us anything about the nature of the semantic spatial relationship. The syntactic representation tells us that there is a figure and ground relationship. The syntactic representation can also tell us, superficially, how complex the relationship is (e.g., does it include directions, paths and axial parts), but, at best, this is semantically categorical. While the existence or not of space in a given utterance in discourse is the focus of analysis for one level of variation, the specific semantic nature of the spatial relationship being created is a second level of variation both of which are explored in this dissertation. However, before moving to this, and in order to get the full linguistic picture of spatial relationships, it is necessary to first discuss other morpho-syntactic sources of spatial information; in particular, verbs, frames of reference, granularity of description and deixis.

### 3.3. Spatial Verbs
As indicated by Figure 2, P is either Place (locative) or Path (directional). Path P indicates some motion between the figure and ground while Place P indicates some static relationships between the figure and ground. The verb that accompanies both types of prepositions typically indicates the same – motion (*run, drive*) or stasis (*is, stay*). For motion verbs, there is an additional consideration *manner*, or how the figure undergoes motion. For example, Levin (1993) provides numerous classifications for over 3000 verbs including nine classes of motion verbs:
• Inherently directed motion – arrive, go
• Leave verbs – leave, depart
• Manner of motion:
  o Roll verbs – bounce, move
  o Run verbs – float, jump
• Manner of motion using a vehicle:
  o Vehicle name verbs – bike, roller-skated
  o Verbs not associated with vehicle names – fly, drive
• Waltz verbs – boogie, polka
• Chase verbs – follow, pursue
• Accompany verbs – accompany, escort

No matter how complex or simple spatial prepositional phrases are, the figure and ground relationship remains primary. This is true whether or not the indexed figure and ground relationship is further qualified as being a motion-based or non-motion-based relationship (e.g., I ran to the store vs. I am at the store). However, for those relationships that are motion-based, an additional level of information emerges; namely, there are a number of motion (manner) types that can qualify a figure and ground relations (e.g., I biked to the store vs. I waltzed to the store). In this regard, Levin’s classifications are principled, but do not originate from the perspective of space as discussed in Section 3.1 – there are numerous static and motion verbs that are not spatially defined by Levine (stay, sit, stand, attach, remove, hit); specific classes are discussed below. Overall, prepositions, verbs and verbs with prepositions (particle constructions) create figure and ground relationships. For those relationships created by motion verbs, additional information is present that qualifies the motion of the figure relative to the ground.

3.4. Deixis. Deixis is the linguistic phenomenon that requires contextual information for the interpretation of an utterance’s meaning. Grammaticalized deixis create phenomena and are categorized into three types: **Personal** (I, you); **Spatial** (locative adverbs (here, there), verbs
(come, go), and demonstratives (this, that); and Temporal (then, now). Use of deictic words create contextual anchorings based in person, time and space. In interaction, who is speaking at the immediate time and immediate place, absent information to the contrary, is treated as the origo or deictic center – denoted by the deictic words here, now and I (Lyons 1977, Bühler 1982, Levinson 1983, and see Fillmore (1971[1997], 1982) and Barwise and Perry (1983) for analysis of individual utterances)). For example, in the utterance I am going to meet John at the library, I is the speaker, speaking at the present time and at the present place of the interaction. Both John and the Library are “away” from the speaker at the time of the utterance. The “away” from the speaker is denoted by the lexically antonymic (distal to the speaker) deictic words of there, then and you (these distinctions are binary in English).

This deictic center information (which is beyond the semantic and pragmatic information of the utterance – i.e. that I, John, and libraries exist and that there is motion from I to John via a “going” motion) is necessary to interpret the person, place and temporal meaning of the utterance (Hanks (2005:192)). However, the deictic center does not always stay with the speaker who produces the utterance, but instead can be shifted to an addressee, onto a present or non-present third-person, or onto some other present or non-present reference point. For example, in the utterance John is waiting for me to come to the library, the deictic center is transposed to John at the library in a future time. The ability to interpret the person, place and temporal information is done so relative to John and the library as the deictic center which is not in the immediate context of the utterance.

Bühler (1982:13) describes the deictic center as the zero point for a coordinate system, which is required to resolve the personal, spatial, and temporal aspects of utterances (as mentioned,
denoted by the deictic words *here, now, and I*). Deictic center transposition preserves the ability to resolve the personal, spatial, and temporal aspects of utterance, but, as viewed by Bühler, serves two associated function: (a) to refer to something not in the immediate physical context (called *deixis at phantasma* (12)); and (b) to demonstrate something visually (called *ad oculos* (12)). Bühler’s view of the deictic center and subsequent utterance interpretation relative thereto, is integrally linked to the speaker that is, as indicated by Hanks (2005:193), “understood in terms of speakers’ perception, attention focus, bodily orientation, and gestures.” By extension, the functions of deictic center transpositions are crucially linked to the speaker as well.d Deixis, therefore, folds in the notion of speaker and contextual perspective. By extension, this speaker and contextual perspective is analyzable by person, time and space.

In terms of figure and ground relationships, deixis is important in several ways. First, deixis introduces the notion of physical perspective. Second, the deictic adverbs *here* and *there* are grounds that are not complement DPs to P, but rather predicates to V. Third, the deictic verbs *come* and *go* are inherently spatial and perspectival. Hence the verbs are precategorized consistent with the motion versus stasis dichotomy mentioned above. The notion of perspective will be more fully explored in the following two sections (frames of reference and granularity).

Lastly, personal deixis is somewhat related to spatial deixis in that the figure is potentially the speaker (*I*), another individual (*you, she*) or some object (*it*). Shifting of the deictic center is a shifting of space and a shifting of the speakers keeping track of objects in space. In sum, in addition to keeping track of deictic elements as part of a comprehensive spatial perspective,

---

d For example, Miller and Johnson-Laird (1976) indicate that non-speaker *origos* are possible only where an intrinsic coordinate system is in place – a given language’s ability to generally locate objects relative to a reference object (*see also* Klein (1978), Sennholz (1985), Hermann & Schweizer (1998), Fricke (2002).
deixis will primarily characterize the figure types in the proposed annotation scheme. In particular, and based in part on the types of figures observed in the data to be analyzed, first (self) and third (other) persons in singular and plural. Other figures types are based on objects – still “other” in deictic terms – and is a reflection of insights from Landau and Jackendoff (1993) and Jackendoff (1996) discussed above in Section 3.1. Figure types will be further explicated in Section 4.4 and Chapter III.

3.5. Frames of Reference. Spatial (and personal) deixis is particularly about physical orientation. However, as just indicated in Section 3.4, the primary distinction in orientation is based on the person speaking and is binary – i.e. you vs. me, there vs. here, then vs. now. However, additional perspective information can be resolved. For example, given a static scene of Pascale sitting on the couch, each of the utterances in (2) would be an accurate description of the spatial relationships:

(2) DEICTIC
    CONTIGUITY       a. Pascale is here
    NAMED LOCATION   b. Pascale is on the couch.
    RELATIVE         c. Pascale is at the house.
    INTRINSIC        d. Pascale is in front of me.
    ABSOLUTE         e. Pascale is behind the pillow.

(2) follows Levinson’s (1996) classification which is a consolidation of several research perspectives (an in depth discussion can be found in Levinson 1996:126-134). (2a-c) are Non-coordinated frames of reference and represent the simple cases of spatial description – prepositions and DP types, the semantics thereof, and deictic elements are used to locate the figure and ground. (2d-f) are Coordinated frames of reference and represent complex cases of
spatial description as angular or coordinate information is required to resolve the locations.

While the examples in (2) describe static relationships, the classifications apply to dynamic relationships and vertical and horizontal relationships as well (Levinson 1996:360). These classifications are due largely to the type of preposition (on, at), the ground (here), and whether or not the preposition is complex (in front of, North of), or naturally denotes a coordinated relationship (behind). This characterization is consistent with Figure 2 (actually, Svenonious (2008) uses frames of reference to motivate the inclusion of the AxPart Phrase). So, taking into consideration, geocoordination, object characteristics and implicated spatial semantics, variation in types of perspective above the here and there distinction is garnered.

3.6. Granularity of Spatial Description. A broader notion of perspective – beyond relating self to environment – is the notion of granularity, or what level of detail is present in a given spatial description. Granularity is a generalizable term and has been applied to time, events and other phenomenon (Hobbs 1985b, Bittner & Smith 2001, Keet 2008). In spatial terms, Montello (1993) indicates four levels of spatial granularities (the cartographic analogue being scale) based on organization of spatial knowledge (and linked to observation in linguistics). Consider (3):

(3) a. [Pascale]Figure is in [my arms]Ground.
b. [Pascale]Figure is on [the couch]Ground.
c. [Pascale]Figure is crawling around [the floor]Ground.
d. [Pascale]Figure is in [Northfield]Ground.

(3a) is a Figural granularity which describes space smaller than the body. (3b) is a Vista granularity which describes space from a single point of view. (3c) is an Environmental granularity which describes space much larger than the body with multiple (scanning) point(s) of
view. (3d) is a *Geographic* granularity which describes space even larger than the body and “learned via symbolic representations” (Montello 1993:315).

Montello’s classification draws on several perspectives, most relevant is by Zubin (reported in Mark et al. 1989:13-17). Zubin breaks up the notion of scale, in linguistic terms into types of objects (A-D) that parallel the four classes of Montello (Figural – Geographic). Examples of Zubin’s object types include (14-15):

- **Type A Objects:**
  - A pen, plants, animals, hand-sized artifacts, parts of larger objects
- **Type B Objects:**
  - The outside of a house, an elephant, trees, large machines, a fence, a mountain, a pond in the woods
- **Type C Objects:**
  - This room [large], a yard, a field, a lake, a small valley, a theater (inside), a cave,…the horizon
- **Type D Objects:**
  - A forest, a desert, a town or city, a farm, a state, a country, an island, a sea, ocean, the inside of a house or an apartment, the shoreline of a river.

These object types can be dynamic in that an object can be a one type at one point and then another type at a second point (16). For example, *a bench* can be a Type B Object and the arm of that bench can be a Type A Object. The ontology of these classifications is perceptually based. The narrator has seemingly free choice in what perspective to use. The change in the perspective over time, either in relation to specific objects, different objects, or both, is the type of qualitative variation that can be tracked across a given narrative discourse.

**3.7. INTERIM SUMMARY.** Let us take stock of the previous sections by applying the discussed concepts to our sample discourse:
(4) a. [I] FIGURE was living in [Minneapolis, Minnesota] GROUND
b. It was a cold day as usual
c. [I] FIGURE drove 5 miles from [my house] GROUND to [the grocery store] GROUND
d. [I made a call] FIGURE at [the pay phone] GROUND
e. Then [I] FIGURE drove east to [the dealership] GROUND
f. I had to follow [a salt truck] FIGURE [the entire way] GROUND
g. [A Brainerd police officer] FIGURE was waiting in front of [my desk] GROUND
h. She looked very serious
i. I put [my briefcase] FIGURE in [the chair] GROUND
j. And asked her what she was doing here

Focusing just on the spatial clauses (4a) (4c-g) and (4i), figure and ground relationships are indeed created by spatial prepositions (in, from, to, at) in conjunction with verbs (living, drove, follow, waiting, put). The spatial prepositions can exhibit complexity in the form of degree (east), measure (5 miles), and axial part (in front of) information. Figures can be the narrator (I) or shifted to some other entity (a salt truck, brief case), person (a Brainerd police officer) or event (I made a phone call). In terms of perspective, the frames of reference vary – Named Locations (in Minneapolis, Minnesota, at the pay phone); Contiguity (in the chair); Absolute (east to the dealership); and Intrinsic (in front of my desk). Also, ground varies by granularity – Figural (in the chair); Vista (at the pay phone, in front of my desk); Environmental (5 miles from my house to the grocery store, the entire way) and Geographic (in Minneapolis, Minnesota).

It would seem, therefore, that a number of linguistic spatial phenomena can be captured in discourse. Further, if we track each type of spatial information, we indeed see that there is variance. However, not all of the linguistic spatial information types are systematic enough to be useful in terms of developing a coding scheme. In particular, while granularity, which captures ground information, frames of reference, which capture perspectival information, and figure, which captures deictic information, are set-up to be useful, the verb, preposition categories are
not. Under the cognitive semantic and syntactic accounts, it would be necessary to either have a
different category for each preposition and verb encountered or to group them based on some
ontological principle. Having an individual category for each preposition and verb is untenable
and explanatorily inadequate. The reason for this is that the type of verb and preposition used in
narrative discourse is largely going to follow from the types of activities being narrated. While
some empirically supported insights may be garnered (e.g., what types of prepositions and verbs
are preferred (in English)), the generalizability of the insights from the variance of space in
narrative discourse is diminished.

In order to adequately address this issue, it is necessary to engage the semantics (not just the
syntax) of spatial prepositions and verbs. It is the categorization of semantic spatial relationships
that will prove to be most useful for capturing qualitative variations in spatial expressions in
narrative discourse. It is also necessary to look beyond purely linguistic models of space, which
may fall prey to the same problem of having numerous nuanced definitions. As discussed next,
the model relied on in this dissertation – *mereotopology* – comes from formal ontology,
mathematics and artificial intelligence.

**4. SEMANTIC MODELS OF SPACE.** Before discussing mereotopology (Section 4.2), it is useful to
discuss research on the semantics of spatial language (Section 4.1). I will then move to a
preliminary discussion of the translation of spatial prepositions and verbs (Section 4.3) and
figure, granularity, and frames of reference (Section 4.4) into mereotopological terms. A full
discussion of the developed coding scheme will be presented in Chapter III.
4.1. **LINGUISTIC APPROACHES TO THE SEMANTICS OF SPACE.** In terms of linguistic spatial semantics, basic elements of compositional and truth-conditional semantics are the same for spatial expressions as any other expression. Rather, research in this domain has focused on capturing spatial meaning that is consistent with existing compositional and truth-conditional approaches, but also provide the basic mechanisms and elements of *spatial* meaning (assuming this is a distinct type of meaning). The mechanisms and elements of spatial meaning includes not only the representation of different physical figure and ground relationships, but more nuanced spatial information as well (e.g. path, degree, measure, frame of reference, etc.). Focusing primarily on spatial P, approaches to the semantics of spatial P draw a central distinction between locative and directional PPs. However, directional PPs (especially in terms of Path) are treated as a sub-case of locative PPs. Consequently, directional PPs are derived from locative PPs. There are two general approaches to the semantics of locative PPs – conceptualization in terms of *regions* or *vectors*.

A region-based analysis of the semantics of space, following, Wunderlich (1991), seeks to determine the location of the figure relative to the ground. Figure and ground, in particular, the areas that each occupies, are treated as a regions. There is then a function (p), assumed to originate from the *eigenplace*, which assigns a relationship to the figure and ground. For example, for the spatial prepositions *in* and *over*, relating the figure (u) and ground (v), the following functions are defined in (5):

\[
\begin{align*}
\text{(5) } & \quad a. \ (u,v) \in [[\text{in}]] \iff p[u] \subseteq \text{INT}[v] \\
& \quad b. \ (u,v) \in [[\text{over}]] \iff p[u] \subseteq \text{EXT}[v, +\text{VERT}] 
\end{align*}
\]
In (5) the semantics of *in* and *under* are represented in set-theoretic notation. In (5a), the figure and ground relationship \((u,v)\) is an element of *in* if and only if the *eigenplace* function assignment of the figure \((u)\) is a subset or equal to the things which are internal to the ground \((v)\). In (5b), the figure and ground relationship \((u,v)\) is an element of *over* if and only if the *eigenplace* function assignment of the figure \((u)\) is a subset or equal to the things which are external to, and is vertical to, the ground \((v)\). (5b) includes axial as well as regional information.

Wunderlich’s formulations are broad stroke, but intuitively complete – a wide range of spatial prepositions can ostensibly be reduced under such a framework to general relationships. However, it is not clear under an *ad hoc* region-based framework how to capture more complex spatial relationships (e.g. degree and measure phrases, frames of references). Vector-based analyses address this issue in part.

A vector-based analysis of the semantics of space, following Zwarts (1997), represents spatial relationships as sets of vectors – lines between points in space. For example, the PP *under the sink* is semantically comprised of vectors from the sink to points under the sink. If we make the PP more complex, *in front of the sink*, this frame of reference is simply captured by a different set of vectors – those running from the sink to points in front. Further, if we add degree and measure modification, e.g. *6.5 inches above the sink*, we have a space that is the intersection of the set of 6.5 inch length vectors and the set of lines from the sink to points above vectors. The advantage of this type of approach, in addition to facilitating compositionality of complex spatial phrases, is that it also makes predictions about the predictability of modifying certain
prepositional phrases. For example, not all propositions can take a modifying measure phrase
(6.5 inches above the sink vs. *6.5 inches between the sinks).

Regional and vector approaches to spatial semantics treat paths as atemporal. For example,
Wunderlich (1991) considers paths to be extended regions that connect locations. However,
paths do invoke motion of some kind which, strictly speaking requires attention to the temporal
domain. In vector semantics, Verkuyl and Zwarts (1992) assume that paths are atemporal, but,
semantically, allow for mappings between the atemporal path and points in time needed to
traverse the path. Further, Zwarts (2005) draws a parallel between spatial verb categorization and
prepositions in that locative PPs compare with static spatial verbs and directional PPs compare
with dynamic spatial verbs. This viewpoint allows for the categorization of prepositions based on
bounded or unbounded properties of the space being described. Bounded and unbounded
compare with telic (goal oriented) and atelic (non-goal oriented) in the verbal domain. For
example, prepositions such as to, from, into and onto are bounded/ telic as they are used to
indicate movement to specific areas or objects. However, prepositions such as towards and along
are unbounded/ atelic as they are used to indicate general (potentially directed) motion. Similar
to locative PPs, the vector semantic approach to directional PPs also lends itself well to
compositional approaches to semantics generally.

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c Zwarts and Winter (2000) cast this phenomenon in terms of upward and downward monotonicity. Prepositions that
are upward monotone, more complex phrases in English, can take a measure phrase (in front of, above, under). Prepositions that are downward monotone, more simple prepositions in English, cannot take a measure phrase (in, at, near).
f Zwarts (2005) also explains this distinction in terms of cumulative reference. Unbounded/ atelic prepositions have
a cumulative reference (e.g. breathing oxygen) and bounded/ telic prepositions are non-cumulative (e.g. breathing a
bottle of oxygen).
There are additional semantic approaches to spatial PPs that are highly specific and less generalizable (e.g. Fong’s (1997) approach to paths as phase quantifiers). Other approaches are highly specific, but offer some generalizations (e.g. Kracht’s (2002) approach to paths as spatiotemporal event modifiers). Generalizability is important for the present task as the version of spatial meaning that I am ultimately concerned with in this dissertation is the representation of spatial relationships. However, to capture the representation of spatial relationships in terms qualitative variations as the discourse unfolds, a coding scheme that is both robust and manageable is necessary. Further, the coding scheme needs to be nuanced enough to capture and categorize multiple linguistic phenomena, but not having so many categories as to be explanatorily inadequate. Also, while not strictly necessary for the present dissertation, a generalized coding scheme should allow for more complexity and nuance even if it is not the primary focus – i.e., the coding scheme should be consistent with, and not contradictory to, relevant semantic insights into spatial relationships. Similar to the cognitive approaches discussed in Section 2, using one of the existing linguistic semantic frameworks just discussed would ultimately prove problematic for this reason. Little would be added to the discourse in (3) in terms of qualitative variation, only additional information within the nuances of particular prepositions and verbs. Consequently, I will rely on a fundamentally non-linguistic categorization of spatial relationships known as mereotopology to organize different linguistic phenomena.

4.2. MEREOTOPOLOGY. Mereotopology facilitates comprehensive modeling of the semantics of the spatial prepositions and spatial verbs that create figure and ground relationships where other
insights from linguistics are either too general or too specific (at least for the proposed goals of the present dissertation). Ultimately, I adopt the mereotopological classification of spatial prepositions proposed by Asher and Sablayrolles (1995) and the mereotopological classification of spatial verbs proposed by Muller (1998, 2002) as modified by Pustejovsky and Moszkowicz (2008). The verb classifications rely on a form mereotopology known as Region Connection Calculus (henceforth “RCC”) (Randell et al. 1992) whereas the preposition classifications rely on a closely related form of RCC. However, before discussing these classifications, it is necessary to address several underlying concepts in mereotopology.

Mereotopology is a combination of mereology and topology. Putting topology aside for the moment, mereology, the study of part–whole relationships, originated in metaphysical philosophy and formal ontology as early as Plato (the *Parmenides* and the *Thaetetus*) and Aristotle (*Metaphysics*) and later in Leibniz (*Monadology*) and Kant (*Monadologia physica*). The central idea of the theory is that entities in the world can be categorized by their respective part–whole relationships – fingers are parts of hands; handles are parts of cups; books are part of a library. However, these works, and many others, do not posit a formal theory of relationships, but rather only insights into explaining the world in terms of part–whole relationships. The discussion is restricted to physical rather than metaphorical entities – e.g., eggs are part of a healthy breakfast. Although, note that events can be mereological – e.g., the seventh-inning stretch is part of the baseball game.

Formal theorizing in mereological terms does not appear in earnest until Husserl (*Third Logical Investigation*) and Leśniewski (*Foundations of a General Theory of Manifolds*) – it is actually Leśniewski who coined the term mereology – and (following Leśniewski) Tarski (1935)
and Leonard and Goodman (1940) (*see generally* Simons 1987). As they are relevant for discussions of mereotopology and classifications of spatial prepositions and spatial verbs, I will now provide the basic axioms of mereology (as summarized in Casati and Varzi (1999:29-49)).

Mereological systems are axiomatic and first order logics (logical operators and quantifiers ranging over a domain of discourse). All mereological systems consist of three primary axioms based on “parthood” (the variables $x$, $y$, and $z$ range over some entitles in the world):

(P.1) $\forall x \, P_{xx}$
(P.2) $\forall xy \, (P_{xy} \land P_{yx}) \rightarrow x=y$
(P.3) $\forall xyz \, (P_{xy} \land P_{yz}) \rightarrow P_{xz}$

(P.1), read as “$x$ is a part of $x$,” is a reflexivity condition such that each entity is a part of itself. (P.2) is an antisymmetry condition such that if $x$ is a part of $y$ and $y$ is a part of $x$, then $x$ is equal to $y$. (P.3) is a transitivity condition such that if $x$ is a part of $y$ and $y$ is a part of $z$, then $x$ is a part of $z$. Systems that adhere only to (P.1) – (P.3) are known as *Ground Merological* systems. Using the primitive parthood predicate $P$, number of additional relations can be defined ($=_{df}$); for example:

- **Overlap**  $O_{xy} =_{df} \exists z \, (P_{zx} \land P_{zy})$
- **Underlap**  $U_{xy} =_{df} \exists z \, (P_{xz} \land P_{yz})$
- **Proper Part**  $PP_{xy} =_{df} P_{xy} \land \neg P_{yx}$
- **Over Crossing** $OX_{xy} =_{df} O_{xy} \land \neg P_{xy}$
- **Under Crossing** $UX_{xy} =_{df} U_{xy} \land \neg P_{xy}$
- **Proper Overlap** $PO_{xy} =_{df} OX_{xy} \land OX_{yx}$
- **Proper Underlap** $PU_{xy} =_{df} UX_{xy} \land UX_{yx}$

(P.1)-(P.3) and various definitions explicate the relationship between entities with two parts. However, to ensure that entities with multiple parts are accounted for, two additional axioms –
weak supplementation (P.4) and strong supplementation (P.5) (which implies (P.4)) – are necessary:

\[
\begin{align*}
(P.4) & \quad PP_{xy} \rightarrow \exists z (P_{zy} \land \neg O_{zx}) \\
(P.5) & \quad \neg P_{yx} \rightarrow \exists z (P_{zy} \land \neg O_{zx})
\end{align*}
\]

Mereological systems that include (P.4) are Minimal Mereological systems and those that include (P.5) are Extensional Mereological systems.

Two additional extensions to Ground Mereology ((P.1)-(P.3)) allow for more robust reasoning about entities and their parts: closure and atomism. First, closure allows for defining the sum (underlap) (P.6) and product (overlap) (P.7) of parts:

\[
\begin{align*}
(P.6) & \quad U_{xy} \rightarrow \exists z \forall w (O_{wz} \leftrightarrow (O_{wx} \lor O_{wy})) \\
(P.7) & \quad O_{xy} \rightarrow \exists z \forall w (P_{wz} \leftrightarrow (P_{wx} \land P_{wy}))
\end{align*}
\]

Mereological systems including (P.6) and (P.7) become, for example, Closure Minimal Mereology or Closure Extensional Mereology. Further, while (P.6) and (P.7) are restrictions on a given entity, these can be extended to arbitrary entities as well via fusion (P.8) (\(\Phi\) is any formula within a given mereological system):

\[
(P.8) \quad \exists x \Phi \rightarrow \exists z \forall y (O_{yz} \leftrightarrow \exists x (\Phi \land O_{yx}))
\]

(P.8) is a first order axiom schema (not a second order formula). Mereological systems including (P.8) ((P.6) and (P.7) follow from (P.8)) are general mereologies (e.g. General Extensional Mereology). Second, mereological systems can facilitate atomlessness (P.9) – there can only be
entities with parts – or atomicity (P.10) – there are entities of which there are no parts.

Mereological systems can only facilitate atomicity or atomlessness, not both.

\[(P.9) \ \forall x \exists y PP_{yx}\]
\[(P.10) \ \forall x \exists y (P_{yx} \land \neg \exists z PP_{zy})\]

(P.1) – (P.10) comprise the central axioms of most every mereological system. Of course, there are nuanced differences in mereological systems designed to address deficits in the theory that are far beyond the scope of the immediate discussion. However, one issue and proposed resolution in mereology bears relevance for the immediate discussion. The issue centers on what assumptions are made when utilizing products and sums; in particular, what do we need to know about wholes, not just parts of wholes. The problem with focusing on just parts is that combining parts into wholes does not always ensure that that the resulting whole is realistic. Consequently, Whitehead (1929) originally proposed to include the topological notion of connection.

Topology, drawing heavily on geometry and set theory, is a branch of mathematics focused on properties of continuous physical space. The combination of topology and mereology via connection comprises mereotopology. While Whitehead was the first to posit this idea, several aspects of Whitehead’s approach were problematic. Clarke (1981, 1985) ultimately revised Whitehead’s approach and, as summarized in Casati and Varzi (1999:51-69), three connection-based axioms now minimally accompany the mereological axioms (P.1) – (P.3) in any mereotopological system (E indicates enclosure):

---

\(^9\) Mathematicians have been interested in mereology as an alternative to set theory as, under certain algebraic formulations of mereology – in particular, General Extensional Mereology – the “infinite zeros” problem of set theory is avoided (Tarski 1935). Whitehead himself had planned a fourth volume to Principia Mathematica which was purported to be a mereological approach to geometry.
(C.1)  \( \forall x \ Cxx \)
(C.2)  \( \forall xy \ Cxy \rightarrow Cyx \)
(C.3)  \( \forall xy \ Pxy \rightarrow Exy \)

(C.1) is a reflexivity condition such that an entity is connected to itself. (C.2) is a symmetry condition such that if \( x \) is connected to \( y \), then \( y \) is connected to \( x \). (C.3) is a monotonicity condition such that if \( x \) is a part of \( y \), then \( x \) is encosed by \( y \).

Similar to the mereological systems, there can be different types of mereotopological systems depending on what connection-based axioms are included. However, these connection-based axioms consider the same mereological issues – i.e., extensionality vs. minimalist; sum, product and fusion; and atomicity vs. atomlessness (called boundary and boundary-free, respectively) (an additional strong version is possible only in mereotopological systems if (C.3) and its converse (\( Exy \rightarrow Pxy \)) hold). Further, similar to (1-7), a number additional definitions of mereotopological relations are definable in a given mereotopological system. The mereotopological system relied upon in this dissertation is primarily RCC-8 (Randell et al. 1992) (classified by Casati and Varzi (1999:67) as a strong boundary free closure extensional mereotopology). However, while RCC-8 is invoked in research on spatial verb classification, a closely related variant of RCC-8 (strong boundary free closure minimal mereotopology – i.e., weak supplementation (P.4) is used and not strong supplementation (P.5)) is implicated in research on spatial preposition classifications.

RCC, which draws on the mereotopological perspectives of Clarke (1981, 1985), was developed by the Artificial Intelligence Group at Leeds University. It treats entities as regions
and allows for abstract spatial representations. RCC-8, in addition to (C.1) and (C.2), consists primarily of the following eight relations:

- Disconnection \( DC_{xy} = df \neg C_{xy} \)
- External Connection \( EC_{xy} = df C_{xy} \land \neg O_{xy} \)
- Partial Overlap \( PO_{xy} = df O_{xy} \land \neg P_{xy} \land \neg P_{yx} \)
- Equality \( EQ_{xy} = df P_{xy} \land P_{yx} \)
- Tangential Proper Part \( TPP_{xy} = df PP_{xy} \land \exists z [EC_{zx} \land EC_{zy}] \)
- Non-Tangential Proper Part \( NTPP_{xy} = df PP_{xy} \land \neg \exists z [EC_{zx} \land EC_{zy}] \)
- Tangential Proper Part\(^1\) \( TPP_{1,xy} = df TPP_{yx} \)
- Non-Tangential Proper Part\(^1\) \( NTPP_{1,xy} = df NTPP_{yx} \)

These eight relations can be visually related as a “conceptual neighborhood”:

\[ \text{Figure 3. RCC-8 conceptual neighborhood (from Randell et al. (1992:172)).} \]

The motivation for using RCC-8 stems from several points of view. First, RCC-8 has been used in a number of spatial reasoning tasks in artificial intelligence and lends itself well to computationally-based tasks such as the one ultimately presented in this dissertation. Second, RCC-8 provides for comprehensive modeling in models of space implicated in semantic research.

\(^h\) Six additional relations are necessary to define the eight relations in RCC-8: Part \(-\ P_{xy} = df \forall z [C_{zx} \rightarrow C_{zy}]\); Proper Part \(-\ PP_{xy} = df P_{xy} \land \neg P_{yx}\); Overlap \(-\ O_{xy} = df \exists z [P_{zx} \land P_{zy}]\); Discrete \(-\ DR_{xy} = df \neg O_{xy};\ Part^{1}\ -\ P^{1,xy} = df P_{yx}\); Proper Part\(^1\) \(-\ PP^{1,xy} = df PP_{yx}.\)
(e.g. Euclidean space). Third, research has already been performed in natural language processing, artificial intelligence and semantics, all of which have applied RCC-8 principles to categorizing spatial language. In particular, the categorization of spatial verbs and spatial prepositions. Before moving to this discussion, it should be noted that the application of RCC-8 to natural language semantics is not without controversy. However, the controversies do not pose an impediment to the use of RCC-8 and related mereotopological variants in the present task.¹

4.3. MEREOTOPOLOGICAL REPRESENTATIONS OF SPATIAL VERBS AND SPATIAL PREPOSITIONS.

Linguistic research, which leverages mereotopology for categorization of the spatial semantics of spatial prepositions and spatial verbs, focuses on a primary distinction between static and dynamic representation. The previous discussion lends itself easily to static representations of space. However, the dimension of time is required for dynamic representations of space.

Taking spatial verbs first, Muller (1998, 2002) provides an RCC-8 based categorization of motion. Muller posits a number of mereotopologically based temporal operations, drawing on insights from Allen (1984), Galton (1993) and Kamp (1979), which integrate temporal precedence – e.g., spatial event 1 happens before spatial event 2; temporal inclusion – e.g., Event 1 happens during Event 2; temporal overlap – e.g., Event 1 starts, then Event 2 starts, then Event

¹ An issue of concern with using RCC frameworks for natural language tasks centers on whether or not the mereotopology should be boundary free or bounded. This is articulated in Asher and Vieu (1995:852):

it is…cognitively important to be able to view material objects as closed individuals and their complements as open ones, so that their interpretations don’t share any point. Indeed, we don’t want the air around the glass to have a ‘glass boundary’ belonging to it,…[in RCC] an object and its complement are externally connected, and so in that theory the unintuitive consequence about glass boundaries seems to follow unless one does a lot of fiddling with the way we refer to objects in NL.

To address this issue, Asher and Vieu propose a distinction between strong and weak contact so that the differences between individuals, closures and interiors, which are cognitively salient, can be made stronger.
ends; temporal contact – e.g., Event 2 starts instantaneously at the end of Event 1; and temporal equality – Event 1 happens simultaneously with Event 2. Indeed these temporal concepts are the same as those integrated into SDRT. Muller’s innovation is showing that the spatial properties of the eight relations of RCC-8 parallel these temporal properties. In particular, two regions (or spatial events) in motion at a given point in time exhibited a spatiotemporal relation that is a composite of a RCC-8 relation and corresponding temporal relation.

Muller’s abstract representation, which holds in Euclidean and topological space, becomes clearer as it serves as a categorization scheme for spatial verbs. Based on the RCC-8 conceptual neighborhood and temporal considerations, Muller categorizes motion verbs into six classes: Leave, Hit, Reach, External, Internal and Cross. These six classes are depicted in Figure 3, which is a reproduction of Muller (2002:438, Figure 10). In Figure 4, x and y are regions during some slice (y/u and x/u) of time u. The spatial relationship between x and y unfolds over the course of u and terminating at the point when u expires. For Leave motions, region x is within region y at the beginning of u and, at some point during u, leaves region y and is completely disconnected from region y at the termination of u. For Hit motions, regions x and y are disconnected from each other at the beginning of u and regions x and y are externally connected at the instant u terminates. For Reach motions, regions x and y are disconnected from each other at the beginning of u and region x becomes enclosed in region y at some point during u, remaining so at the termination of u. For External motion, regions x and y are disconnected for the entire duration of u. For Internal motion, region x is within region y for the entire duration of u. Lastly, for Cross motions, region x is disconnected from region y at the beginning of u, passes
through region $y$ at some point during $u$ and is again disconnected from region $y$ at the termination of $u$.

Muller’s formulation is not explicitly a categorization of spatial verbs of motion, but rather general qualitative spatial reasoning. Pustejovsky and Moszkowicz (2008) mapped Muller’s classes (as well as Asher and Sablayrolles (1995)) to FrameNet (Baker et al. 1998) and found that linguistic semantic categorizations of motion verbs is largely similar with several additions. As a result, Pustejovsky and Moszkowicz (2008:96) pose the following ten categories of motion (and stative) verbs: Move – run, fly, drive; Move.getExternal – pass, drive around; Move_Internal – walk around the room; Leave – leave, desert; Reach – arrive, enter, reach; Detach – take off, disconnect, pull away; Hit – land, hit; Follow – follow, chase; Deviate – flee, run from; and Stay – remain, stay.
Asher and Sablayrolles (1995) provide a classification of motions verbs and prepositions in French. The classification is not explicitly based in a RCC framework, but rather a non-extensional strong boundary free closure minimal mereotopology (following Aurnague and Vieu (1993), which is based on Clarke (1981, 1985)). Asher and Sablayrolles (1995:183) create a four by four matrix based on the inner-halo, contact, outer-halo, and outer-most (halo) aspects of one region, and the positional, initial directional, medial positional, and final positional characteristics of a second region moving through the first. French prepositions which fall into one of the sixteen categories are summarized in Table 2. This classification is applicable to English spatial prepositions as well.

<table>
<thead>
<tr>
<th>Preposition</th>
<th>Inner-Halo</th>
<th>Contact</th>
<th>Outer-Halo</th>
<th>Outer-Most</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Positional</strong></td>
<td>chez; dans (at; in)</td>
<td>sur; contre (on; against)</td>
<td>Sous; derrière; à (below; behind; at)</td>
<td>loin de (far away from)</td>
</tr>
<tr>
<td><strong>Initial Directional</strong></td>
<td>de chez (from)</td>
<td>de sur (from on to)</td>
<td>de derrière (from behind)</td>
<td>de dehors (from the outside)</td>
</tr>
<tr>
<td><strong>Medial Positional</strong></td>
<td>par (through)</td>
<td>au fil de (-)</td>
<td>le long de (along)</td>
<td>au-delà de (beyond)</td>
</tr>
<tr>
<td><strong>Final Positional</strong></td>
<td>jusque dans (up to the inside of)</td>
<td>jusque sur (up on to)</td>
<td>vers (towards)</td>
<td>pour (for)</td>
</tr>
</tbody>
</table>

**Table 2.** Asher and Sablayrolles (1995:183) spatial preposition classification.
Asher and Sablayrolles’ (1995) classification pairs well with that of Pustejovsky and Moszkowicz (2008) and, consequently, provides a robust classification of spatial verbs and spatial prepositions which are central to creating figure and ground relationships. Under this mereotopological perspective, figure and ground are treated as independent regions which can be described with a unified representational semantics. This representation holds at the clause level and multi-clause level discourse. Before concluding this chapter, and for sake of completeness, it is useful to comment on the mereotopological nature of figure, ground and frame of reference.

4.4. MEREOTOPOLOGICAL REPRESENTATIONS OF FIGURES, FRAMES OF REFERENCE AND GRANULARITY OF SPATIAL DESCRIPTION. As mentioned in Section 2, figures, frames of reference and granularities are already set up to provide meaningful qualitative variations for purposes of this dissertation. However, these three elements of spatial expressions are not explicitly in mereotopological terms. Figure is ultimately going to be a measure of personal deictic shifts – e.g., the narrator is going to locate him or herself, someone else, some object or some area. These designations indicate the quality of the figure region and are the types of things that are allowed under mereological and mereotopological philosophy.

Granularity indicates the quality of the ground in terms of scale – organized here relative to cognitive insights. Scale or size is not an inconsistent notion with mereological and mereotopological philosophy. As the discourse unfolds, and the quality of the granularity changes, the relative sizes of the grounds can be represented mereotopologically as well. For example, if I locate my self in New York City and then I locate myself in the Empire State
Building, the Empire State Building stands in a non-tangential proper part relationship to the larger New York City. So, the fact that grounds are treated as regions allows for attention to the size of those regions for additional qualitative determinations.

Lastly, non-coordinated frames of reference, following Levinson 1996, are indicated by prepositions (at – Named Location, in – Contiguity) and deictics (here – Deictic), which would be set up by a mereotopologically classified spatial verb. Coordinated frames of reference are created by prepositional phrases (behind – Relative), complex prepositional phrases (in front of – Intrinsic), and geocoordinated modifiers (east – Absolute). Because these are driving by the spatial preposition, mereotopological extensions are available. The coordinated frames are more complex because they denote a region within a region. However, for purposes of this dissertation, I am simply going to focus on whether or not there is a complex frame of reference and not on the relationships between the embedded regions.

4.5. Interim Summary. The overarching purpose of this chapter is to garner the most comprehensive perspective on the linguistics of spatial information possible. The rationale for doing so is premised on the fact that, in terms of demonstrating relationships between spatial information and structural elements of discourse, really any type of spatial information could be relevant to this dissertation’s empirical examination. As indicated in Chapter I, no concrete expectation about how much space or the type of space emerges from narrative research. As indicated throughout this chapter, the literature is fairly consistent in terms of what basic components of spatial relationships emerge in linguistic surface forms – i.e., figure and ground relationships indexed by verbs and prepositions. Further, the literature is consistent in terms of
indicating that additional spatial information, qualifying the semantics of the figure and ground relationship, is present. However, how best to represent the semantics of spatial relationships is a key point of differentiation. Consequently, I rely primarily on a mereotopological interpretation of the figure and ground relationship (two regions) that qualifies the verb and preposition creating the relationship. Further, I rely on frame of reference (Levinson 1996) to further qualify the linguistically portrayed point of view on the figure and ground relationship. Lastly, types of figures are based on insights from personal and spatial deixis (Buhler 1982) and types of grounds are based on insights from the granularity of spatial description (Montello 1993). All of these elements adequately represent the collective knowledge of linguistic spatial information and are consolidated into a novel XML-based annotation scheme to address the specific research questions and hypotheses posed in this dissertation.

The use of XML (Extensible Markup Language – a particular type of data structure that converts any information you want in a given document into a machine readable form) is a common choice in NLP research where the underlying semantics of relationships are not obvious from surface forms. Content in the document is tagged – e.g. <date>March 13, 1976</date> – where <date> is the start tag and </date> is the end tag and March 13, 1976 is the content of the “date” element. Any number and types of elements can be defined. Additionally, XML is hierarchical in that each element can also have a number of embedded (child) elements and a number of attributes. For example, <date type = calendar> <month>March</month> <day>13</day> <year>1976</year></date>, contains the element “date” with an attribute called “type” that has a value “calendar.” Then there is a series of three embedded elements “month”, “day”, and “year” – each of which could have additional embedded elements or attributes.
There have been several coding schemes of spatial information developed by other researchers. For example, Mani (2010) presents a multifaceted model of narrative analysis that consolidates, temporal, event and spatial perspectives into a larger annotation scheme. The spatial component of Mani’s analysis is SpatialML (MITRE 2010). SpatialML is an XML markup of spatial language with a central focus on proper name locations. The proper name locations and subsequent relationships are then linked to an atlas for an actual geographic representation. Other practical systems deal with giving and receiving route directions or other map information. SpatialML builds off of prior work in temporal (e.g. TimeML) and toponym resolution (e.g. Garbin & Mani 2005, Leidner 2006) and focuses on resolving the spatial aspects, primarily the where, of events in (narrative) text. SpatialML is an annotation scheme with specific guidelines in terms of what is coded and how ambiguities are resolved and is used to annotate a corpora of text by hand (or (semi) automatically), the information contained therein can then be subsequently used for any number of descriptive or reasoning based tasks.¹

SpatialML consists of four tags, PLACE, LINK, RLINK (“relative link”) and SIGNAL. The PLACE tag does the lion’s share of work in SpatialML, the reason for this is that, where possible, the PLACE tag is linked to an atlas, gazetteer or geo-coordinate database which allow for fast and accurate determinations, especially for toponyms such as *Washington, DC, Indiana,* and the *Nile*. The LINK and RLINK tags are used to express relationships between places and indicate relational mappings where possible as a means to providing greater specificity and disambiguation. However, because of SpatialML’s purpose, it is not explicitly designed to

¹ Other coding schemes include Sinha and Thorseng (1995), and Bateman et al. (1995) (Generalized Upper Model), which do consider all types of space, not just geographic references, but are very fine grained with a multitude of categories.
incorporate nontoponym based places. Therefore, to annotate narratives, DP objects of prepositions such as *the house, a park, the bowling alley, the second table, her ankle*, would not receive a PLACE tag under SpatialML guidelines. Further, while SpatialML share some of the characteristics of the theories discussed in this chapter, it is not specifically designed to explore the theoretical level of discourse structure as I am attempting in this dissertation. Chapter III will provide an in depth explanation of the developed coding scheme.

5. **Conclusion to Chapter II.** This chapter provides a broad introduction to the nature of spatial expressions in language with particular emphasis on English. The linguistic analysis of spatial expressions is based on morpho-syntactic surface forms and their underlying semantics, which is describable from a number of cognitive, truth-conditional, compositional and formal insights. Ultimately, attention to surface forms alone is inadequate for measuring the representation and variation in spatial expressions in discourse. Attention to the semantics is also necessary. In particular, it is the organization of spatial semantics into mereotopological categories that provides the most useable and flexible framework for analyzing variation in discourse. Moving forward, three levels of insights will be relevant in terms of spatial information: (1) the morpho-syntactic – how spatial relationships are created on the linguistic surface; (2) the formal semantic meaning of these clause level relationships; and (3) the cognitive semantic meaning and function (e.g. deictic shifts and perspective taking). These three levels will be accounted for and tracked across narrative discourses, their distributions analyzed and determinations made as to the structural nature and organization of spatial information.
CHAPTER III – METHODOLOGY

1. INTRODUCTION TO CHAPTER III. This chapter consolidates the discourse and spatial information discussed in Chapters I and II into an annotation scheme for narrative discourses. The annotated information will then be extracted for use in a series of statistical machine learning experiments designed to demonstrate patterns between spatial, temporal, event and rhetorical information. There are multiple methodological approaches considered in this dissertation. First, the collection of data and the annotation of linguistic features is based in corpus linguistics (e.g. Biber et al. 1998, McEnery et al. 1998, Facchinetti 2007). In order to argue for generalized linguistic phenomena, it is necessary to empirically demonstrate their occurrence and distribution in natural language data. The more data collected, relative to certain parameters, the stronger an empirical demonstration can be made. Second, empirical demonstrations are not purely based on a robust data set, but also choice of features, the process of annotating those features and the choice of tools used to quantify features. As indicated, statistical machine learning is the tool used to quantify features. Lastly, the features are the spatial, temporal, event and rhetorical information discussed in the previous two chapters. Annotation of these features by hand is necessary for this (and other tasks) as the language indicating these features is complex and ambiguous; extracting or recognizing this information automatically is problematic. Each of these pieces is influenced by NLP research and is computationally implemented.

This chapter is structured as follows. Section 2 introduces the three narrative corpora analyzed in this dissertation. The source of the data, criterion for selection and context of collection are
discussed as well the presentation of relevant analytical details – including, for example, the length of text and the amount of spatial information. Section 3 presents the structure of the annotation scheme and its computational implementation via an XML coding scheme (including the Document Type Definition (DTD)). Additionally, the guidelines governing the application of the coding scheme to the data and the results of inter-rater reliability statistics between myself and an additional coder for the structural features to be analyzed, are discussed. Lastly, the distribution of the coding elements is presented. Section 4 details the use of the coding elements in a number of machine learning experiments, the results of which are presented in Chapter IV.

2. SUMMARY OF DATA. I am choosing to evaluate multiple types of data to present conclusions that are as well-rounded and as generalizable to other sources of narrative discourse as possible. This choice is motivated by the analytical tenor of the dissertation – i.e., uncovering a generalized structure that should, in theory, be applicable to all narratives of personal experience. To this end, three different corpora will be analyzed: (1) The Charlotte Narrative and Conversation Collection from American National Corpus (henceforth “CNCC”) (Ide & Suderman 2007); (2) narratives from the Degree Confluence Project (henceforth “DCP”) (http://confluence.org); and (3) criminal narratives collected from legal institutionalized settings (e.g., guilty pleas, confession statements) (henceforth “CRI”).

The CRI narratives were collected from public legal records from the United States and United Kingdom. The two specific contexts represented are guilty pleas and confession statements. While these contexts are highly constrained - for example, there are thematic elements, strict sequence of the thematic elements, particular participant roles, and specific terms
and phrases representative of the context and of the legal system generally (for guilty pleas, see Philips (1998), and for confession statements, see Shuy (1998)). However, despite these constrained contexts, the narratives provided by the serial offenders are akin to an elicitation task. Often the offender is asked, “What did you do that makes you believe that you are guilty?” The offender then continues at length and is uninterrupted. Finding criminal narratives is a difficult task as there simply is not that much data to begin with and, what data does exist is typically in a strict “yes – no” interview of format – i.e., the offender is not provided the opportunity to narrate the details of the crime at length.

Two additional corpora were selected: narratives from the Degree Confluence Project – which narrate spatial activities by design – and narratives from the Charlotte Narrative and Conversation Collection (Ide & Suderman 2007) – which are akin to the types of narratives analyzed in Labov’s work. By this I mean that the narratives were primarily the result of elicitations. The Degree Confluence Project was started in February of 1996 by Alex Jarret (http://confluence.org/infodcp.php#goals) because “[he] liked the idea of visiting a location represented by a round number such as 43°00'00"N 72°00'00"W. What would be there? Would other people have recognized this as a unique spot?” The goal of the DCP (http://confluence.org/infodcp.php#goals) “is to visit each of the latitude and longitude integer degree intersections in the world, and to take pictures at each location. The pictures, along with a narrative, are then posted on [the DCP] website. This creates an organized sampling of the world.” As of September 1, 2010, there have been 24,640 successful visits to 183 countries. In order to be a “successful” visit, individuals must submit pictures (including a picture of a GPS
When you submit your visit, you must supply a narrative. The narrative's content is up to you, however, there are some minimum requirements.

PREFERRED
A description of the confluence and the surrounding area. This can include information that supplements the confluence photos, such as details of the flora and fauna, your impressions of the area, etc.

Some information about your journey to the confluence. This will depend on the nature of your trip to the confluence. It may include information about preparations before you left home, experiences during your travels to the confluence, interesting people you met along the way, etc.

MINIMUM
A brief description of the confluence and the surrounding area and/or information about how to get to the confluence.

NOTE: The minimum requirements should not be used as a guideline for writing your narrative. We would prefer that you provide more than “the minimum”.

You are welcome to submit your narrative in your native language. If possible, please also provide an English translation of your narrative. If you cannot provide an English translation, we may be able to translate the narrative for you. Your visit will not be posted on our site until we have an English version of your narrative.

The narrative may contain links to off-site web pages related to your visit, however, that is not a substitute for submitting a proper narrative to our website.

The DCP narratives are written and often accompany pictures of the confluence points. By design, these narratives are about spatial activities and the elicitations of the narratives specifically ask about those spatial activities. The DCP narratives are, therefore a counterpoint to the CRI and CNCC narratives as the subject matter is explicitly spatial in nature.
The CNCC narratives are closest to Labov in that they are based somewhat on a sociolinguistic interview format. However, it is not clear from the data what the structure of that format actually is. By and large, the interview simply asked the interviewee to tell some stories; specifically, ones that they remembered from childhood. Narratives either emerged as a direct result of this question or spontaneously in subsequent conversation. The CNCC narratives are from the American National Corpus and include interviews with 95 residents of North Carolina. The CNCC began in 1995 when students from the Department of English at the University of North Carolina, Charlotte, at the direction of Boyd H. Davis, recorded oral narratives. The CNCC is now part of the New South Voices digital sound project (http://newsouthvoices.uncc.edu/cncc.php). The interviewees are largely from Mecklenburg County and are different genders and ages. The interviews are exclusively conversational, as opposed to a strict question-and-answer format, and narratives do emerge. Based on the recordings, the interview format is free form, and while the questions are different in each interview, the focus is largely on memories from childhood, where the interviewee and his or her family lived, the types of activities they engaged in, where and what he or she thought of school, etc. Again, the narratives that emerge in the CNCC corpus are reminiscent of the Labovian type narratives that emerged from sociolinguistic interviews. While there was no specific “danger of death” question posed in the observed data, the narratives in the CNCC are, nonetheless, the result of an elicitation. Transcripts and recordings of the spoken narratives in the CNCC corpus are available as part of the corpus.

Despite the title of the CNCC corpus, not all interviews contained narratives in the Labovian sense. Some interviewees were unable to provide a narrative while others provided descriptions
of past habitual actions – i.e., no specific reportable event necessary for the narrative text type. I did not perform an exhaustive analysis of how many Labovian narratives actually exist in the CNCC corpus. Knowing that the CRI corpus set the upper limit at 25, I simply worked through the CNCC corpus and identified 40 narratives from 15 of the 95 speakers. 25 narratives from each corpus were selected for analysis.\(^k\) Each narrative from all three corpora conforms to the Labovian perspective discussed in Chapter I. The narratives, with some potential key differences (e.g. number of speakers) are summarized in Table 3 (samples are found in Appendix I).

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Mode</th>
<th>Speakers</th>
<th>Narratives</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNCC</td>
<td>Spoken Conversation</td>
<td>8</td>
<td>25</td>
</tr>
<tr>
<td>DCP</td>
<td>Written</td>
<td>22</td>
<td>25</td>
</tr>
<tr>
<td>CRI</td>
<td>Spoken Institutional</td>
<td>6</td>
<td>25</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>36</td>
<td>75</td>
</tr>
</tbody>
</table>

**Table 3.** Mode, number of speakers and narratives for analyzed corpora.

The narratives were assigned unique identifiers and segmented by me into independent clauses. There are a number of different perspectives on the segmentation of discourse. Use of the independent clause was a syntactic choice based on previous narrative research.\(^1\) The independent clause is syntactically defined as containing a subject and matrix verb whereas dependent clauses (especially with an overt complementizer), while containing a subject and

\(^k\) 40 narratives were extracted from the CNCC conversations and a random number generator created 25 unique values (17, 29, 31, 20, 3, 25, 32, 15, 10, 11, 37, 34, 9, 18, 6, 8, 4, 1, 16, 26, 12, 7, 5, 36, 40). For the DCP narratives, there have been 10,261 successful visits, a random number generator retrieved 40 narratives (89, 1755, 8119, 10002, 6413, 6621, 3124, 714, 2258, 5900, 4785, 5266, 1955, 4859, 1488, 8151, 153, 5913, 6381, 3765, 8985, 2726, 2252, 2873, 142, 1982, 6227, 138, 8847, 7970, 3586, 2627, 7948, 1574, 1253, 9901, 3543, 7490, 7768, 8345) and then the random number generator created 25 additional unique values (36, 8, 39, 2, 28, 7, 4, 35, 38, 23, 32, 27, 21, 16, 22, 37, 15, 13, 34, 17, 30, 5, 25, 31, 3).

\(^1\) Other choices include intonation units (Chafe 1994); turns (e.g. Sacks et al. 1974); or segments chosen with an eye toward relationships between segments: (1) intentional – relationship between the discourse segment, the speaker and participant’s intentions, and an additional segment (e.g. Mann & Thompson 1988); (2) attentional – what is the focus at a given point in the discourse (e.g. Grosz & Sidner 1986); or (3) informational – how does the meaning of one segment relate to the meaning of another segment (e.g Hobbs 1985a).
verb as well, are subordinated to a matrix verb clause. For example, an independent clause would be *Pascale was eating her cereal*, but a dependent clause would be *While Pascale was eating her cereal* (dependent clause), *we were watching television* (independent clause). In the segmentation of the narratives, independent clauses with any modifying dependent clauses constituted a single unit of analysis “Clause” where any information in the dependent clause (spatial or otherwise) was considered, but was not the primary locus of evaluation. For example, in a clause such as *While we were eating breakfast at the hotel, a car drove through the lobby*, the primary figure and ground relationship is *a car drove through the lobby*, not *we were eating breakfast at the hotel*, despite the existence of two spatial prepositional phrases. Albeit true that some useful information is potentially being disregarded by focusing on the matrix clause, this approach captures the core analysis sought in this dissertation – while information in a dependent clause may provide additional information, it is not expected to disrupt the primary figure and ground information.

Those clauses with explicit spatial information, consistent with the syntactic insights discussed in Chapter II (“Spatial Clauses”) were coded following the annotation guidelines discussed in Section 3.1 and found in Appendix II (issues with identifying spatial information are discussed as part of inter-rater reliability statistics in Section 3.3). These distributions are reported in Table 4.

There are 8 authors in the analyzed CNCC corpus (DC, EA, EB, JC, RHB and TF). The CNCC narratives average 34.80 clauses in length (ranging from 18-109), 40.00% of which contain explicit spatial information (Standard Deviation ($\sigma$) = 14.13). There are 22 authors in the analyzed DCP corpus – 53N_2W and 53N_3W are the same authors and 35S_58W, 35S_59W
and 35S_60W are the same authors. The DCP narratives are shorter, averaging 24.32 clauses in length (ranging from 8-43), 55.92% of which contain explicit spatial information (σ = 13.28).

There are 6 authors – 2 are single offenders (KO and GD) and 4 are serial criminals (DR, CS, PS, UC) – in the analyzed CRI corpus. The CRI narratives are longer, averaging 77.52 clauses in length (ranging from 20-172), 42.72% of which contain explicit spatial information (σ = 10.85).

<table>
<thead>
<tr>
<th>CNCC</th>
<th>Total Clauses</th>
<th>Spatial Clauses (n / %)</th>
<th>DCP</th>
<th>Total Clauses</th>
<th>Spatial Clauses (n / %)</th>
<th>CRI</th>
<th>Total Clauses</th>
<th>Spatial Clauses (n / %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BA_1</td>
<td>18</td>
<td>7 / 38.89</td>
<td>8N_1E</td>
<td>30</td>
<td>21 / 70.00</td>
<td>DR_2</td>
<td>99</td>
<td>36 / 36.36</td>
</tr>
<tr>
<td>BA_2</td>
<td>42</td>
<td>17 / 36.17</td>
<td>13S_72W</td>
<td>43</td>
<td>16 / 37.21</td>
<td>DR_3</td>
<td>79</td>
<td>27 / 34.17</td>
</tr>
<tr>
<td>BA_3</td>
<td>24</td>
<td>15 / 62.50</td>
<td>17N_63W</td>
<td>22</td>
<td>13 / 59.09</td>
<td>DR_4</td>
<td>64</td>
<td>17 / 26.56</td>
</tr>
<tr>
<td>BD_1</td>
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<td>13 / 65.00</td>
<td>17S_12E</td>
<td>23</td>
<td>11 / 47.83</td>
<td>DR_5</td>
<td>59</td>
<td>28 / 47.45</td>
</tr>
<tr>
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<td>5 / 25.00</td>
<td>17S_177E</td>
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<td>17 / 48.57</td>
<td>DR_7</td>
<td>69</td>
<td>33 / 47.82</td>
</tr>
<tr>
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<td>18N_99E</td>
<td>25</td>
<td>15 / 60.00</td>
<td>PS_1</td>
<td>127</td>
<td>49 / 38.58</td>
</tr>
<tr>
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<td>23 / 40.35</td>
<td>19S_29E</td>
<td>32</td>
<td>19 / 59.38</td>
<td>PS_2</td>
<td>79</td>
<td>37 / 46.83</td>
</tr>
<tr>
<td>DC_4</td>
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<td>18 / 43.90</td>
<td>21N_104E</td>
<td>8</td>
<td>6 / 75.00</td>
<td>PS_3</td>
<td>62</td>
<td>28 / 45.16</td>
</tr>
<tr>
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<td>24N_121E</td>
<td>42</td>
<td>25 / 59.52</td>
<td>PS_4</td>
<td>77</td>
<td>47 / 61.03</td>
</tr>
<tr>
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<td>34N_74E</td>
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<td>15 / 68.18</td>
<td>PS_5</td>
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<td>28 / 45.16</td>
</tr>
<tr>
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<td>10 / 40.00</td>
<td>35S_58W</td>
<td>38</td>
<td>17 / 44.74</td>
<td>PS_6</td>
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</tr>
<tr>
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<td>35S_59W</td>
<td>16</td>
<td>13 / 81.25</td>
<td>PS_8</td>
<td>65</td>
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<tr>
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<td>45 / 47.47</td>
<td>35S_60W</td>
<td>24</td>
<td>17 / 70.83</td>
<td>PS_9</td>
<td>78</td>
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<td>11 / 64.71</td>
<td>37S_113W</td>
<td>23</td>
<td>11 / 47.83</td>
<td>PS_11</td>
<td>41</td>
<td>21 / 51.21</td>
</tr>
<tr>
<td>RHB_2</td>
<td>12</td>
<td>4 / 33.33</td>
<td>38S_144E</td>
<td>17</td>
<td>7 / 41.18</td>
<td>PS_12</td>
<td>78</td>
<td>34 / 43.58</td>
</tr>
<tr>
<td>RHB_3</td>
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<td>10 / 43.48</td>
<td>51N_46E</td>
<td>28</td>
<td>7 / 25.00</td>
<td>PS_13</td>
<td>42</td>
<td>24 / 57.14</td>
</tr>
<tr>
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<td>28 / 54.90</td>
<td>52N_18E</td>
<td>33</td>
<td>23 / 69.70</td>
<td>PS_14</td>
<td>69</td>
<td>45 / 65.21</td>
</tr>
<tr>
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<td>53N_2W</td>
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<td>19 / 73.08</td>
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<td>118</td>
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</tr>
<tr>
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<td>15 / 55.56</td>
<td>53N_3W</td>
<td>17</td>
<td>13 / 76.47</td>
<td>CS_2</td>
<td>158</td>
<td>76 / 48.10</td>
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<tr>
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<td>3 / 30.00</td>
<td>54N_92E</td>
<td>23</td>
<td>12 / 52.17</td>
<td>CS_3</td>
<td>172</td>
<td>44 / 25.58</td>
</tr>
<tr>
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<td>30</td>
<td>13 / 43.33</td>
<td>63S_61W</td>
<td>11</td>
<td>6 / 54.55</td>
<td>KO_1</td>
<td>39</td>
<td>11 / 28.20</td>
</tr>
<tr>
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<td>71S_8W</td>
<td>18</td>
<td>9 / 50.00</td>
<td>UC_1</td>
<td>44</td>
<td>29 / 65.90</td>
</tr>
<tr>
<td>TF_3</td>
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<td>4 / 15.38</td>
<td>74N_12W</td>
<td>22</td>
<td>11 / 50.00</td>
<td>UC_2</td>
<td>54</td>
<td>24 / 44.44</td>
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<tr>
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<td>10 / 58.82</td>
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<td>103</td>
<td>40 / 38.83</td>
</tr>
<tr>
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<td>8 / 17.78</td>
<td>82S_120W</td>
<td>13</td>
<td>7 / 53.85</td>
<td>GD_1</td>
<td>20</td>
<td>6 / 30.00</td>
</tr>
</tbody>
</table>

**Total**: 870/348 / 40.00 608/24.32 340/55.92 1938/77.52 828/42.72

**Table 4.** Narrative identifiers, total and average non-spatial and spatial clauses.
In terms of spatial density, the three corpora are similar in terms of the percentage of clauses that include spatial information. These values are not significantly different from each other nor from any *a priori* assumptions (except if we assume that the spatial density should be 100%). This is a very interesting result in two ways. First, because the literature in narrative and morpho-syntax and semantic research betrays no explicit assumptions about the occurrence of spatial information, just that it occurs, that there is a consistent percentage distribution between the three corpora is possibly reflecting not only some fact about spatial information in narrative discourses, but some structural fact – i.e., Would narratives with significantly more or less spatial information be well-formed under Labovian and Herman narrative frameworks? Does the fact that the percentage distribution is not lower cast doubt on the optionality of space at the local and textual level? These questions will be explored throughout.

Second, and related to the consistency across all three corpora, there is a suggestion that contextual factors may not play a significant role as to whether or not spatial information occurs: the CRI narratives are institutional and as such are susceptible to being well-formed, but programmatic, the CNCC narratives originate from sociolinguistic interview and conversational settings, and the DCP narratives are written with explicit instructions to make the narratives about space. I find it surprising that the DCP narratives do not have a higher density of spatial information. It is reasonable to assume that if someone is tasked with writing a narrative exclusively about interactions with space that there simply would be a large amount of space (not just slightly over 50%). The suggestion with this observation is that narrative structure is constrained in certain ways that has the effect of limiting the amount of spatial information. A logical rational is that narrative discourses are about conveying an evaluated chain of events for
some personal purpose and that this somehow constrains the overarching form. Again, these insights will be explored further in the following chapters. But before this exploration moves forward, it is first necessary to discuss the annotation process and garner a sense for what the distribution of the types of spatial, temporal, event and rhetorical information in the three corpora actually is.

3. Annotation and Computational Processing of Spatial Information. Specific NLP focus on spatial language has been largely subsumed under syntactic/semantic research (cognitive perspectives can be found in Herskovitz (1986)), i.e., prepositions as a syntactic category; for example, part of speech tagging – the Penn Treebank contains transitive (IN) and syntactically selected (RP) and unselected (RB) intransitive prepositions tags (Marcus et al. 1993). Specifically, methods to improve tagging, parsing and analysis have focused on the attachment of PP and multiword expressions (particle constructions). This research has been applied to languages other than English (e.g., Finnish (Lestrade 2006), Polish (Tseng 2004) and French (Abeillé et al. 2003)). In terms of automaticity – i.e., detecting prepositional phrases and different senses – there has not been much research. What research has been performed indicates that differentiating common prepositions (in, on, to) is straightforward if syntactic and semantic information is relied upon (O’Hara & Wiebe 2003, Ye & Baldwin 2006). For the present research, the state of the art is simply not able to handle annotation and analysis on an automatic basis for spatial prepositions, let alone spatial verbs, figures, frames of reference and granularity (see generally Baldwin et al. (2009) for an in depth introduction).
Nonetheless, numerous computational systems have been developed that focus on spatial information (e.g., modeling the acquisition of spatial semantics (Regier 1996), XML coding of wayfinding semantics in the HRCR Map Task (Anderson et al. 1991)). In terms of computational, narrative specific, research, there are comparatively larger; e.g., deictic-center theory of narrative (Zubin & Hewitt 1995, Rapaport et al. 1989 (applied to fictional narratives)), point of view (Wiebe 1994), cognitive structures (Talmy 1995) and semantic based knowledge representation (the SNePS (Semantic Network Processing System) (Shapiro & Rapaport 1987, 1992)) and smaller (e.g., reference resolution (Wiebe & Rapaport 1988) and inferencing (Shapiro & Rapaport 1995, Niehaus & Young 2009)) foci. There have been very few direct computational approaches concerned with space and narrative. Most notable is Yuhan and Shapiro’s (1995:206) discussion of the Cassie System (Cognitive Agent of the SNePs (Semantic Network Processing System) System – an Intelligent Entity). Basically, “Cassie reads a simple narrative, understands the story, paying particular attention to spatial information, resolves the spatial reference problems based on a coherent model of the story kept in her “mind,” and maintains and tracks the deictic center.” The “spatial reference problem” deals primarily with disambiguating the narrator’s perspective between shifted and non-shifted deictic centers. For example, is it possible for a computational system to differentiate the location of an object or individual referenced in a narrative when given competing spatial information? Yuhan and Shapiro rely on the semantics of “spatial” events in terms of the prepositions, spatial verbs and the extended constructions based thereon – including proximity and directionality relationships as well as the perspectival nature of frames of reference. A number of rules (building off of Yuhan (1991)) are posited which the system relies on to maintain the spatial information relative to the syntactic, semantic and
discursive structure. The spatial information is either maintained or updated based on the last piece of spatial information.

As mentioned briefly in Chapter II, Section 4.5, marking up complex information that is not readily apparent (for extraction or computation) from surface forms is a common methodology in NLP research. Because I am primarily concerned with the representation of multiple complex structural relationships, relying on an annotation scheme is an appropriate methodology. The following sections provide the details of this annotation scheme (Section 3.1). The performance of a human inter-rater in detecting and coding spatial, temporal, event and rhetorical information in narrative will be analyzed (Section 3.2). The distribution of the spatial, temporal, events and rhetorical elements annotated in the data will be presented (Section 3.3). Lastly, the use of the extracted information in machine learning tasks will be presented in Section 4.

3.1. SPATIAL, TEMPORAL, EVENT AND RHETORICAL ANNOTATION SCHEME. The insights into spatial language from Chapter II, and temporal, event and rhetorical considerations from Chapter I, are consolidated into an annotation scheme and translated into XML. XML schemes are consolidated into a Document Type Definition (DTD), which serves as a guideline for the XML annotation. The DTD used in this dissertation is in Table 5 (I used <oXygen/> XML Editor, v.12.1, to code the data).
| a. | <!ELEMENT DISCOURSE (#PCDATA | CLAUSE)*> |
| b. | <!ATTLIST DISCOURSE id ID #REQUIRED> |
| c. | <!ELEMENT CLAUSE (#PCDATA | FIGURE | VERB | FRAME | TIME)*> |
| d. | <!ATTLIST CLAUSE id ID #REQUIRED> |
| e. | <!ATTLIST CLAUSE RHETtype1 (NAR | ELAB | BACK | RES | CON | EXP | ALT | 0) #REQUIRED> |
| f. | <!ATTLIST CLAUSE RHETtype2 (NAR | ELAB | BACK | RES | CON | EXP | ALT | 0) #REQUIRED> |
| g. | <!ATTLIST CLAUSE RHETlocPAIR CDATA #REQUIRED> |
| h. | <!ATTLIST CLAUSE s_status (S | NS ) #REQUIRED> |
| i. | <!ELEMENT FIGURE (#PCDATA)> |
| j. | <!ATTLIST FIGURE id ID #REQUIRED> |
| k. | <!ATTLIST FIGURE type (1 | 3 | 4 | 6 | NP | EVENT | AREA) #REQUIRED> |
| l. | <!ELEMENT VERB (#PCDATA)> |
| m. | <!ATTLIST VERB id ID #REQUIRED> |
| n. | <!ATTLIST VERB tense (P | T | I | F) #REQUIRED> |
| o. | <!ATTLIST VERB aspect (O | P | PP | N) #REQUIRED> |
| p. | <!ATTLIST VERB event (S | O | IA | IS | AI | AR | AC | AT | AU | R | P) #REQUIRED> |
| q. | <!ATTLIST VERB type (STATE | MOTION | OUTSIDE | HIT | NS) #REQUIRED> |
| r. | <!ELEMENT FRAME (#PCDATA | PREP | GROUND)*> |
| s. | <!ATTLIST FRAME id ID #REQUIRED> |
| t. | <!ATTLIST FRAME type (NL | CT | DX | INT | REL | ABS ) #REQUIRED> |
| u. | <!ELEMENT PREP (#PCDATA)> |
| v. | <!ATTLIST PREP id ID #REQUIRED> |
| w. | <!ATTLIST PREP type (PI | PC | PO | PM | II | IC | IO | IM | MI | MC | MO | MM | FI | FC | FO | FM | 0) #REQUIRED> |
| x. | <!ELEMENT GROUND (#PCDATA)> |
| y. | <!ATTLIST GROUND id ID #REQUIRED> |
| z. | <!ATTLIST GROUND type (GEOGRAPHIC | ENVIRONMENTAL | VISTA | FIGURAL ) #REQUIRED> |
| aa. | <!ELEMENT TIME (#PCDATA)> |
| bb. | <!ATTLIST TIME id ID #REQUIRED> |
| cc. | <!ATTLIST TIME type (DATE | SET | TIME | DURATION) #REQUIRED> |

**Table 5. Annotation scheme Document Type Definition.**

The top element in the DTD is DISCOURSE. DISCOURSE has a unique identifier (b) and it can have any number of the embedded elements called CLAUSE (a). Within each CLAUSE, the embedded elements of FIGURE, VERB, FRAME and TIME can occur (c). In addition to having
a unique identifier (d), the type of rhetorical relation for the first clause pair (e), the second clause pair (f), and the clause pair creating the rhetorical relation (g), and whether or not the clause is spatial (i.e., is there an explicit physical figure and ground relationship) (h) are required attributes of the CLAUSE element. The rhetorical relations are those in the SDRT inventory.

The FIGURE element (i) has a required identifier (j) and type (k). The types of figures include first and third person singular (1, 3) and plural (4, 6), objects (NP), events (EVENT) and areas (AREA). These values are based largely on observations in the data as to what types of things are figures (second person singular and plural (2, 5) were possible codes as well, but did not emerge in the data).

The VERB element (l) has a required identifier (m) and tense (n), aspect (o), event (p), and type (q) attributes. The values for the tense, aspect and event attributes come from TimeML: tense – present (P), past (T), infinitive (I) and future (F); aspect – progressive (O), perfect (P), perfective progressive (PP), none (N); event – state (S), occurrence (O), intensional action (IA), intensional state (IS), aspectual initiation (AI), aspectual reinitiation (AR), aspectual continuation (AC), aspectual termination (AT), aspectual culmination (AU), reporting (R) and perception (P). The values for the verb type attribute are one of four categories of mereotopologically classified verbs (a consolidation of Pustejovsky and Moszkowicz (2008)): STATE, MOTION, OUTSIDE, HIT. An additional NS value is used for those clauses where the verb is marked for temporal codings, but not spatial.

The FRAME element (r) contains the PREP and GROUND elements. An identifier is required (s) and the type values are one of six frames of reference following Levinson (1996) (t). Frames of reference under Levinson’s classification are largely based on the semantics of the preposition
and ground denoting DP. The PREP element (u) has a unique identifier (v) and the type values are those from Asher and Sablayrolles (1995) (cf. Table 2) (w). An additional “0” value is used for those clauses where the figure and ground relationship is created by the verb only. The GROUND element (x) has a unique identifier (y) and the type values are those from Montello (1993) (z).

Lastly, the TIME element (aa) has a required identifier (bb) and is one of four types from the TimeML annotation scheme: DATE, SET, TIME and DURATION (cc).

In terms of applying the annotation scheme, which is based on explicit figure and ground relationships as discussed in Chapter II, not every clause with explicit spatial information was straightforward. Again, reference to space in an idiom or metaphor, reported speech, alternate worlds and within the scope of negation were excluded from coding. There were 219 total clauses that fell into these categories: idiom/ metaphor = 14; reported speech = 110; alternate worlds = 75; and negation = 20. This indicates that there were 1735 total clauses with a linguistic spatial construction and 1516 (87.37%) of these were “physical” spatial constructions.

First, clauses that involved particle constructions with no explicit ground (e.g. I ran up; The car drove down) were coded with a granularity resolved from the context. A similar approach was taken to any missing information (e.g., implicit figures, verbs, etc.). However, implicit space is discussed in Chapter IV presents an approach to filling in this information from previous clauses. Second, for those clauses with dependent clauses (e.g. After we went to park, we sat down on a bench; When I ran around the corner, I saw her in the car), only the matrix clause was coded with spatial information. Third, for those clauses with multiple grounds (as part of a dependent clause or a chain of prepositional phrases) (e.g. We sailed from Egypt around South
Africa to Portugal) only the highest DP of P was considered for the ground. This avoided issues of trying to determine the granularity of the entire PP with variable DPs. However, all of the information in the PP could be used for whatever determinations were relevant; in particular, frames of reference. The full annotation guidelines are in Appendix II.

To illustrate the conversion from text to markup, consider DCP narrative 21N_104E in (1) and subsequent markup in (2). Because of the visual complexity of the XML markup, a shorter narrative was chosen. (2a) is a standard declaration that identifies what follows as having an XML data structure. Further, (2b) is the DTD declaration that applies the DTD to the document to determine whether or not the data conforms to the DTD. This serves as a check that the document is encoded consistent with the parameters set forth in the DTD.

(1) a. Oct-2009 --To reach the CP we have created a combined unit, consisting of a pointman (ex military guy), a como specialist and a interpreter-MRE bearer.
   b. We started our advance in Hanoi at 13-42.
   c. And hit our RON site in SonLa at 19-06.
   d. 31/10/2009 we left our vehicle on the road at a distance of 1.2 km to the C point.
   e. Our unit began to climb on the crest of the mountain.
   f. Our pointman quickly cut down the trail.
   g. And after 2,5 hours we reached the CP.
   h. The C point is located on the hillside, thickly overgrown with jungle.

(2) a.  

b. <![CDATA[<?xml version="1.0" encoding="UTF-8"?>]]>

b. <![CDATA[<!DOCTYPE DISCOURSE SYSTEM "file:/Users/blakestephen/Desktop/Marked_Up Dissertation Data/Dissertation_Spatial_Mark_Up(v1.0).dtd">]]>

c.  <DISCOURSE id="DCP_21N_104E">
To reach the CP we have created a combined unit, consisting of a pointman (ex military guy), a como specialist and a interpreter-MRE bearer.

We started our advance. Our RON site began to the road at a distance of 1.2 km to the C point. We started our RON 2,5 MRE. SonLa reached the CP at 13-42.

Our pointman quickly cut down the trail. And after 2,5 hours we reached the CP.
The entire narrative is enclosed by the DISCOURSE tag (1c) and (1l) where the identification attribute is the name of the corpus (DCP) and narrative (21N_104E). Each clause in the narrative is then surrounded by a CLAUSE tag (1d) through (1k) which contain the clause identifiers, whether or not the clause contains spatial information, the rhetorical relation and the pair of clauses creating the relation. The first clause receives a “0” for the rhetorical relation and “START” for the pair as it is the first clause. Then each clause minimally receives a VERB tag, indicating tense, aspect and event information. If the clause is spatial, then the additional elements of FIGURE, FRAME, GROUND, PREP and all associated attributes are tagged. All of this information was then extracted and used in subsequent analyses.

3.2. INTER-RATER RELIABILITY. To ensure that an annotation scheme is feasible in terms of its understandability by individuals other than the developer of the scheme, reproducibility for subsequent testing and experimentation, and for consistency with native speaker judgments, individuals will code a subset of the data to determine these factors for the annotation scheme. The differences between two coders is then statistically analyzed to determine the percentage

---

m The rhetorical structure of the narratives was largely flat – i.e., rhetorical relations were identified between clause 1 and 2, clause 2 and 3, clause 3 and 4, etc. Following SDRT, it is possible to have relations not just between adjacent clauses, but any clause previous to the current clause (cf. Figure 1). The more rhetorical connections, the more coherent the discourse is in accordance with the Maximise Discourse Coherence (MDC) Principle. However, determining the rhetorical structure based on adjacent clauses, while not the best-case scenario for the MDC, is not incorrect, just an under specification. Thank you to Laure Vieu for pointing this out.
agreement between them and the likelihood of the agreement occurring purely by chance – i.e., did the coders really agree, or is it coincidence due to the distribution of the data.

For two coders, Cohen’s Kappa provides the relevant statistical measure (Cohen 1960) – the equation is given in (3):

\[
\kappa = \frac{(Pr(a) - Pr(e))}{(1 - Pr(e))}
\]

Pr(a) is the average agreement between two coders and Pr(e) is the probability of chance agreement between the two coders (based on observations in a given data set). To illustrate, consider a hypothetical task where two coders are asked to categorize 50 red apples into three different types: Fuji, Pink Lady and Red Delicious. Coder 1 classified the 50 red apples accordingly: Fuji = 20, Pink Lady = 10, Red Delicious = 20 and Coder 2 classified the 50 red apples accordingly: Fuji = 15, Pink Lady = 13, Red Delicious = 22. To evaluate the agreement between Coder 1 and Coder 2, a confusion matrix is constructed to tease apart the types of errors made between the coders; consider Table 6:

<table>
<thead>
<tr>
<th>Coder</th>
<th>Coder 1</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Code</td>
<td>Fuji</td>
<td>Pink Lady</td>
</tr>
<tr>
<td>Coder 2</td>
<td>Fuji</td>
<td>30</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Pink Lady</td>
<td>2</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Red Delicious</td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 6. Cohen’s Kappa hypothetical confusion matrix.

The average agreement between Coder 1 and Coder 2 is 81.00% – both coders classified the red apples into Fuji (30), Pink Lady (20) and Red Delicious (31). As both coders categorized 50
apples each, the total instances equals 100. So, both coders agreed on coding for 81 out of 100 of the apples. Therefore, \( Pr(a) \) is .8100.

\( Pr(e) \) is equal to the sum of the probability of chance agreement between the two coders. For example, *Coder 1* categorized the 50 red apples as Fuji 40% of the time, Pink Lady 20% of the time and Red Delicious 40% of the time. *Coder 2* categorized the 50 red apples as Fuji 30% of the time, Pink Lady 26% of the time and Red Delicious 44% of the time. The probability of chance agreement between the two coders for Fuji is .1200 (.4000 x .3000), Pink Lady is .1120 (.2000 x .2600) and Red Delicious is .1760 (.4000 x .4400). Therefore, \( Pr(e) \) is the sum .4080 (.1200 + .1120 + .1760). Plugging these values into Cohen’s Kappa equation in (3) where \( \kappa = (\frac{.8100 - .4080}{1 - .4080}) = .6790. \)

Performance based on average agreement is an intuitive measure – the closer to 100% agreement the better. Kappa statistics are somewhat less intuitive. Pursuant to Landis and Koch (1977), \( \kappa < 0 \) indicates no agreement, 0-.2000 indicates slight agreement, .2100-.4000 indicates fair agreement, .4100-.6000 indicates moderate agreement, .6100-8000 indicates substantial agreement and .8100 to 1.000 indicates near perfect agreement. Pursuant to Fleiss (1981), 0 -.4000 indicates poor agreement, .4100-.7500 indicates fair to good agreement, and .7510-1.000 indicates excellent agreement. These guidelines have been subject to a good amount of debate as these distinctions are largely arbitrary. However, following Carletta (1996), who discusses the use of Kappa statistics in NLP research, the types of tasks found in NLP research can be difficult – not unlike the coding task presented in this dissertation. Consequently, the use of existing guidelines should be considered informative, but by no means the final word. Rather, the comparison of similar types of NLP research tasks should be considered as well.
An additional aspect of inter-rater reliability methodologies is to cast the coding elements into a collapsible hierarchy. The idea is that despite best intentions of having a robust and nuanced annotation scheme, how easily individuals are able to reproduce the annotation scheme can vary quite a bit. It could be that individuals are very good at capturing general categorizations rather than more subtle distinctions. The hierarchical structure of the annotation elements is typically informed by the theoretical underpinnings of the task. A key idea in having a collapsible hierarchy is to have a built-in method to achieve acceptable Kappa statistics. For example, Hovy et al. (2006) discuss a “90%” solution for inter-annotator agreement for annotating multiple features in a large corpus; in particular, for a word sense disambiguation task. Basically, annotators use a full annotation scheme and the Kappa is computed. If the Kappa is below .9000, then the annotation scheme is revised and annotation occurs as many times as necessary to have a coding scheme with a demonstrated .9000 Kappa.

The approach taken in the present methodology is somewhat similar in construction to Hovy et al. (2006). As mentioned, the annotation scheme is hierarchical, which facilitates collapsing for purposes of improved Kappa statistics. In particular, based on the insights presented in Chapter II, Figure is collapsed into self (1, 4) and other (3, 6, NP, Area, Event); Verb is collapsed into State and Motion (Hit and Follow); Preposition is collapsed into Position (PI, PC, PO, PM) and Motion (II, IC, IO, IM, MI, MC, MO, MM, FI, FC, FO, FM) (similar to verb; Ground is collapsed into Figural, Vista (including Environmental) and Geographic; and Frame is collapsed into Coordinated and Non-Coordinated; all aspectual events are collapsed as well. However, the presented methodology is different from the 90% solution in that there was no back-and-forth between coders in multiple iterations of coding.
I (Coder A) coded all of the narratives consistent with the coding scheme presented in Section 3.1. A subset of the data (20% - 15 narratives, 5 from each corpus), already segmented into clauses, was coded by an additional individual (Coder B). The recognition of spatial information between the two coders was high. Coder A coded 325 clauses with explicit spatial information whereas Coder B coded 320 clauses with explicit spatial information. The 320 mutually coded clauses were the same. The 5 clauses not coded by Coder B were due to simple error – i.e., missing that the clause had explicit spatial information. For this level of variation – i.e., whether or not explicit spatial information occurs in a given clause – the average agreement between Coder A and Coder B is near perfect (99.59% with a .9917 Kappa) (while a slightly different task, Hois (2010) indicates similarly that an individual’s recognition of spatial role (i.e., arguments that participate in spatial relationships) falls within acceptable ranges (e.g., Agreement = 82.21% / $\kappa = .78$ for English and Agreement = 79.58% / $\kappa = .74$ for German)). The ability to recognize this information is a critical, and, of course, a logical necessity for the effectiveness of this methodology.

Coder B was provided with a set of guidelines – consisting only of the names of the elements to be coded and two linguistic examples of each – and as much time as needed to complete the task. There were a total of 610 clauses – 320 of which (52.45%) included explicit spatial information. Taking the spatial elements first, Table 7 summarizes the average agreement and Kappa statistics for the five coding categories.
<table>
<thead>
<tr>
<th>Spatial Coding</th>
<th>Average Agreement (%)</th>
<th>Cohen’s Kappa (κ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIGURE</td>
<td>90.51</td>
<td>.8105</td>
</tr>
<tr>
<td>VERB</td>
<td>75.00</td>
<td>.5126</td>
</tr>
<tr>
<td>PREPOSITION</td>
<td>76.29</td>
<td>.5262</td>
</tr>
<tr>
<td>GROUND</td>
<td>74.56</td>
<td>.5126</td>
</tr>
<tr>
<td>FRAME OF REFERENCE</td>
<td>76.29</td>
<td>.5262</td>
</tr>
</tbody>
</table>

**Table 7.** Average agreement and Cohen’s Kappa for spatial codings.

With the exception of Figure, the average agreement and Kappa statistics for the spatial codings are low no matter what metric of evaluation is used. Essentially, being able to recognize all of the elements in the spatial coding scheme is a difficult task – the selection of which, between Coder A and Coder B is not far from chance. A possible explanation is that the coding scheme is too nuanced and that individuals do not necessarily have intuitive judgments about language based on, for example, mereotopological categories or the full range of granularity and frame of reference possibilities. Consequently, this is an opportunity to collapse the codings to improve performance.

For verbs, most disagreements between Coder A and Coder B were based on the classification of Hit and Outside verbs as Motion. Both Hit and Outside verbs are subtypes of motion verbs generally, just with a mereotopological nuance. Collapsing Hit and Outside verbs into Motion creates a binary spatial verb category of Motion and State. The preposition category can be similarly collapsed based on motion and state – Positional (Positional) and Motion (Initial, Medial, Final) (there is also a third category for no preposition). For frame of reference, disagreements between Coder A and Coder B were largely within the complex (Intrinsic, Relative, Absolute) and non-complex (Named Location, Contiguity, Deixis) distinction and can be collapsed accordingly. Lastly, for granularity, disagreements between Coder A and Coder B
were largely between the Vista and Environmental elements. Despite the distinction given by Montello (1993), both elements are essentially from a singular points of view, Environmental is simply a larger space (requiring scanning points of view). Consequently, Vista and Environmental can be collapsed into one category. It is important to note that the collapsing of certain elements within these spatial categories does not call into question the underlying theories, just in what is salient for the linguistic encoding thereof. For example, the distinction between Vista and Environmental is cognitively real. However, it is drawing this distinction in a linguistic medium that is shown to be difficult in the present data. The same issue is apparent in mereotopological categorizations and frame of reference distinctions. Collapsing the spatial coding elements thusly improves the average agreement and Kappa statistics; summarized in Table 8.

<table>
<thead>
<tr>
<th>Spatial Coding</th>
<th>Average Agreement (%)</th>
<th>Cohen’s Kappa (κ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIGURE</td>
<td>90.51</td>
<td>.8105</td>
</tr>
<tr>
<td>VERB</td>
<td>87.50</td>
<td>.7292</td>
</tr>
<tr>
<td>PREPOSITION</td>
<td>83.62</td>
<td>.6875</td>
</tr>
<tr>
<td>GROUND</td>
<td>83.62</td>
<td>.6875</td>
</tr>
<tr>
<td>FRAME OF REFERENCE</td>
<td>84.05</td>
<td>.6093</td>
</tr>
</tbody>
</table>

TABLE 8. Average agreement and Cohen’s Kappa for collapsed spatial codings.

The performance on the collapsed codings (not including Figure) is improved. While average agreement is over 80% in all cases, Cohen’s Kappa is still ostensibly low. Coder B did report that the task was difficult. However, in comparing these numbers to other research is problematic as the spatial codings are novel.

In terms of the temporal elements, Table 9 summarizes the average agreement and Kappa statistics for the four coding categories.
<table>
<thead>
<tr>
<th>Temporal Coding</th>
<th>Average Agreement (%)</th>
<th>Cohen’s Kappa (ĸ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TENSE</td>
<td>99.65</td>
<td>.9945</td>
</tr>
<tr>
<td>ASPECT</td>
<td>99.30</td>
<td>.9937</td>
</tr>
<tr>
<td>EVENT</td>
<td>73.62</td>
<td>.5004</td>
</tr>
<tr>
<td>RHETORICAL</td>
<td>69.38</td>
<td>.5670</td>
</tr>
</tbody>
</table>

Table 9. Average agreement and Cohen’s Kappa for temporal codings.

Both tense and aspect are shown to be straightforward categories for coding, but event and rhetorical relations appear more difficult. For event, the largest confusions were between different aspectual events and between different aspectual events and Intensional Actions. Collapsing all aspectual events into one class improved accuracy by 13% and Cohen’s Kappa by 14%. However, there is no clear way to collapse Intensional Actions with aspectual events. So, I leave this discrepancy to be resolved in the future. For rhetorical relations, the largest confusions were between BACKGROUND and ELABORATION. BACKGROUND and ELABORATION, which exhibit a subtle distinction between temporal overlap and temporal inclusion respectively, were collapsed into one category. This improved accuracy by 12% and Cohen’s Kappa by 7%. The average agreement and collapsed codings are summarized in Table 10.

<table>
<thead>
<tr>
<th>Temporal Coding</th>
<th>Average Agreement (%)</th>
<th>Cohen’s Kappa (ĸ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TENSE</td>
<td>99.65</td>
<td>.9945</td>
</tr>
<tr>
<td>ASPECT</td>
<td>99.30</td>
<td>.9937</td>
</tr>
<tr>
<td>EVENT</td>
<td>86.15</td>
<td>.6445</td>
</tr>
<tr>
<td>RHETORICAL</td>
<td>81.02</td>
<td>.6361</td>
</tr>
</tbody>
</table>

Table 10. Average agreement and Cohen’s Kappa for collapsed temporal codings.

There are no specific comparisons of human performance on TimeML event classifications. There is associated research where humans have been asked to classify the underlying verbs (Puscasu & Mititelu 2008) or relative durations of events (Pan et al. 2006), which are typically
high, but not the events themselves. Tense and aspect are typically high as well (e.g. Wiebe et al. 1997). Coder B did not feel that the event codings were particularly difficult. However, Coder B did indicate that the examples given for Intensional Actions were narrow – i.e., there were many more different types of verbs that fell into the category that were not readily apparent from the examples. Consequently, it cannot be determined without further research if this task is complex or difficult to justify the low performance. The rhetorical relation agreement is consistent with previously reported performances (e.g. Agreement = 71.25% / $\kappa = .6100$ (Sporleder & Lascarides 2005)).

Moving forward, both uncollapsed and collapsed codings are considered in the analysis; although, results based on collapsed codings will be considered stronger because of the results of the inter-rater reliability statistics.

3.3. The Distribution of Spatial and Temporal Annotations. Algorithms were developed to extract and account for the tags and attributes from the coded data. This facilitated a survey of the type, frequency and distribution of the spatial and temporal codings. This survey works toward answering the posed research question in terms of determining how often does spatial information occur, and is there a particular character (distribution) to the variation. However, before evaluating the distribution of spatial information, let’s first consider the distribution of the temporal codings (Table 11) – considering rhetorical relations a temporal relation under SDRT. The spatial codings are summarized in Table 12.
<table>
<thead>
<tr>
<th>Coding</th>
<th>CNCC</th>
<th>DCP</th>
<th>CRI</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>RHETORICAL</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Narration</td>
<td>358</td>
<td>263</td>
<td>1032</td>
<td>1653</td>
</tr>
<tr>
<td>Background</td>
<td>233</td>
<td>155</td>
<td>486</td>
<td>874</td>
</tr>
<tr>
<td>Elaboration</td>
<td>197</td>
<td>107</td>
<td>229</td>
<td>533</td>
</tr>
<tr>
<td>Continuation</td>
<td>17</td>
<td>30</td>
<td>115</td>
<td>162</td>
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<tr>
<td>Explanation</td>
<td>25</td>
<td>15</td>
<td>31</td>
<td>71</td>
</tr>
<tr>
<td>Result</td>
<td>19</td>
<td>13</td>
<td>20</td>
<td>52</td>
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<tr>
<td>Alternation</td>
<td>1</td>
<td>0</td>
<td>19</td>
<td>20</td>
</tr>
<tr>
<td>TIME</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>824</td>
<td>532</td>
<td>1802</td>
<td>3158</td>
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<tr>
<td>Date</td>
<td>21</td>
<td>28</td>
<td>35</td>
<td>84</td>
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<tr>
<td>Time</td>
<td>19</td>
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<tr>
<td>Duration</td>
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<td>21</td>
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<td>37</td>
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<tr>
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<td>3</td>
<td>6</td>
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<tr>
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<td></td>
<td></td>
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<tr>
<td>Past</td>
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<td>1813</td>
<td>2898</td>
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<tr>
<td>Present</td>
<td>214</td>
<td>110</td>
<td>111</td>
<td>435</td>
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<tr>
<td>Future</td>
<td>5</td>
<td>7</td>
<td>5</td>
<td>17</td>
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<tr>
<td>Infinitive</td>
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<td>5</td>
<td>4</td>
<td>15</td>
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<tr>
<td>ASPECT</td>
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<tr>
<td>None</td>
<td>767</td>
<td>550</td>
<td>1774</td>
<td>3091</td>
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<td>Progressive</td>
<td>106</td>
<td>51</td>
<td>106</td>
<td>263</td>
</tr>
<tr>
<td>Perfect</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Perfective</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>5</td>
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<tr>
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<td></td>
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<td></td>
</tr>
<tr>
<td>EVENT</td>
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<tr>
<td>Aspectual</td>
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<td>246</td>
<td>628</td>
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<tr>
<td>State</td>
<td>267</td>
<td>164</td>
<td>398</td>
<td>829</td>
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<tr>
<td>Intensional</td>
<td>127</td>
<td>62</td>
<td>287</td>
<td>476</td>
</tr>
<tr>
<td>Intensional</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>52</td>
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<tr>
<td>Perception</td>
<td>64</td>
<td>24</td>
<td>84</td>
<td>172</td>
</tr>
<tr>
<td>Intensional</td>
<td>24</td>
<td>50</td>
<td>74</td>
<td>148</td>
</tr>
</tbody>
</table>

Table 11. Distribution of temporal and rhetorical coding elements per corpora.
In terms of the rhetorical structure, based on all three corpora, the narrative discourses under analysis are predominately **Narration**, **Background** and **Elaboration** relations: 49.12% of relations are **Narration**, 25.97% are **Background**, and 15.83% are **Elaborations**. The remaining 9.08% of clauses are split between **Continuation** (4.81%), **Explanation** (2.10%), **Result** (1.54%) and **Alternation** (0.59%). The tense profile of narratives indicates that narratives discourses are predominately in simple past time (86.12%) with some present tense

**Table 12. Distribution of spatial coding elements per corpora.**
(12.92%) and no aspect (91.85%) except for some progressives (7.81%). There is very little explicit temporal reference (93.84%). Date (2.49%) and Time (2.37%) occur slightly more often as compared to Duration (1.09%) and Sets (0.17%). Events are predominately Aspectual (33.34%) and States (25.63%). Alternate worlds (14.14%) and non-temporal Occurrences (12.57%) round out the top 85.68% with Reporting (8.73%), Perception (5.11%), and Intensional Actions (4.39%) comprising the remainder.

Figures are largely split between “self” (both singular (1) and plural (4)) (46.10%) and “other” person (21.76%) or object (23.61%). Areas and Events comprise the remaining 8.4%. For verbs, both Motion (34.23%) and State (35.68%) predominate. Hit is also high (27.77%), but over 70% of these verbs are found in the CRI corpus and not the CNCC nor DCP. Outside verbs occur 2.30% of the time. Prepositions based on position, rather than contact, are distributed by Positional (40.36%), Final (27.04%), Medial (9.82%), Initial (8.90%) with the remainder having no preposition (13.85%). Granularities are predominately Vista (39.05%) and Environmental (30.40%) with Figural (16.55) and Geographic (13.98%) occurring less often. However, 76.09% of the Figural granularities occur in the CRI corpus and 50% of the Geographic granularities occur in the DCP corpus. There does seem to be some genre or subject matter effects being exhibited in the distribution of verbs and grounds. 43.93% of frames of reference are simple Named Locations followed by Contiguity (20.58%) and Intrinsic (16.09%). Deictic (12.53%), Absolute (3.62%) and Relative (3.23%) comprise the remainder.

The distribution of the spatial elements reflect the cognitive and formal theoretical insights, based on English, discussed in Chapter II. Figures are deictic in that they are balanced between self and other. Verbs are spatially static or motion (with nuanced subtypes of motion – Hit and
Outside). Prepositions follow verbs in being split between positional and motion, where motion are largely telic (Final). Granularity is from singular (either single or scanning) points of view. Geographic and Figural granularities, while existing in all three corpora, are largely indicative of the subject matter. Frames of reference are mostly non-coordinated with the Intrinsic coordinated frame (locating areas and objects) being preferred. Before fully considering the impact of this distribution, and the distribution of the temporal elements, on the ensuing analysis, it is necessary to determine how an individual other than myself performs on the coding task.

The distribution of certain coding elements are consistent with Labov’s framework. In particular, rhetorical relations are predominately NARRATION, BACKGROUND and ELABORATION (which, for purposes of this dissertation is serving a evaluation). Further, the coded narratives are largely in the past tense with no aspect. Beyond these observations, there are no explicit predictions made by the Labovian model in regard to the coded elements. In terms of space, Labov observes space in orientation clauses, but, in more complex syntax, potentially anywhere. No insight is necessarily given about what type of space, especially as it is coded here, should occur (with the exception of a deictic shift in the coda). Machine learning methodologies will garner a better understanding of where spatial information occurs relative to other temporal, event and rhetorical information. Machine learning results and analysis are presented in Chapters IV and V – Labov’s model will be revisited in these chapters.

4. MACHINE LEARNING. As a reminder, the reliance on machine learning in this dissertation is to uncover patterns in the spatial, temporal, event and rhetorical information. Specifically, do these different information types, which represent structural information in narrative discourse, relate
to each other? Machine learning is a branch of artificial intelligence focused on how computational systems learn. “Learning” in this capacity refers to evaluating a computational system’s performance on some task and, whether or not the performance, if positive, results in subsequently improved performance (experience) by the computational system (see e.g. Mitchell 1997, Bishop 2006, Clarke et al. 2009). Typically, algorithms developed for the purpose of learning seek to determine patterns in data and to express those patterns as generalizable functions or sets of rules that should hold for unseen data – depending on the theoretical and methodological parameters of the task. This process can take the form of supervised learning, where a series of data values are mapped to a particular class; and unsupervised learning, where the algorithms cluster data into categories. Supervised learning will be the focus of this dissertation.

To illustrate, let’s return to classifying the 50 red apples – a supervised learning task. Each of the apples is given a series of attributes: color, circumference, stem length, seed shape. For each attribute, there can be a range of values: color – red, dark red, pink; circumference – measurement in centimeters; stem length – measurement in centimeters; and seed shape – oval, oblong, circular. Lastly, there are three classes: fuji, pink lady, red delicious. So, an example of an instance of data (also known as a vector), based on one apple, would be: dark red, 12.5, 2.2, oval, red delicious. A supervised learning algorithm would then seek to determine if the class red delicious has a particular pattern of data based on the values of the remaining attributes in the instance. Similarly, fuji and pink lady would seek to be classified on patterns in the instance. In an unsupervised learning task, a clustering algorithm would just be given the vector without the classification (red delicious, fuji, pink lady) and, if the data contained in the vector has a close
relationship with the classifications, then it would be expected that the clusters would correspond with the classifications.

The majority of supervised machine learning classifiers used in NLP research are based on statistical theories – the most common of which include support vector machines, logistic regression, Bayesian networks, and decision trees. Typically, once a task is constructed, a range of classifiers will be run to determine the best performance. Different classifiers have different strengths when it comes to data. Some are better with numerical data (measurement in centimeters), some with nominal or categorical data (oval, oblong, circular), some require large amounts of data, and some do well on small amounts. The specific classifiers used in this dissertation are the Naïve Bayes, C4.5 decision tree and K-Star classifiers, will be discussed in Section 4.1. However, before this, there are several useful concepts worth discussing – in particular, how classifiers generally train and test the data sample, and how performance is measured.

As mentioned, a central goal to machine learning tasks is to make predictions about data that is unseen. We may be able to build a classifier for our 50 red apples, but that classifier will be of little use if it performs poorly with 50 different red apples. Of course, some of this is in the experimental design – i.e., were theoretically sound variables chosen, are they realistic measures of the things being sought to be classified, etc. For the classifier itself, there are a number of validation measures that work to ensure the generalizability of results. For example, the classifier could be trained first on a subset of the data (25%, 30%, 50%, etc.) and then classify the remainder or, what is used in this dissertation, all of the data is used, but portioned out into equal parts which are then used as both training and classification data. This is known as k-fold cross-
validation. The data is separated into \( k \) number of folds. The classifier trains on \( k-1 \) folds and then classifies the remaining fold. The classifier then takes the set of \( k-1 \) folds and then classifies the remaining fold. Typically, \( k = 10 \) – 10-fold cross-validation. So, in our set of apples, the classifier would first break the apples down into ten five-apple folds, train on 45 apples (folds 2-10) and test the first five apples (fold 1). Then the classifier would train on the next 45 apples (fold 1 and folds 3-10) and test the next 5 apples (fold 2). The performance on each of the ten iterations is averaged and that number indicates how well a classifier is doing.

The results provide insight into what attributes are contributing to the classification of certain item. After all apple data is run, for example, we might find by analyzing the results that, statistically, fuji apples are red, with a 15 cm circumference and 2.7 cm stem length; red delicious apples are dark red, with a 14.5 cm circumference and a 2.6 cm stem length; all pink ladies are pink, with a 16 cm circumference and a 2.6 cm stem length. The classifiers indicate which combination of features leads to the best classifications. An analysis is then performed to determine how close of a link there is between the features of classification and what is observed in the real world. What is not captured by the classifications and why? However, in order to get the strongest and most complete sense of how well the classifier is doing, it is necessary to calculate several performance measures.

Performance is measured in terms of how accurately a classifier performs. For example, if, in the actual data, there are 20 pink lady out of 50 apples, and if the classifier accurately predicts all 20 pink lady apples and only those 20, then the accuracy for that class is 100% for pink ladies. To evaluate the performance of a classifier’s accuracy, there are two basic measures. First is the majority class baseline. Say that of the remaining 30 apples, 15 are fuji apples and 15 are red
delicious. The statistical distribution of the classes is, therefore fuji apples at 30%, red delicious at 30% and pink ladies at 40%. The majority class baseline is 40% (pink ladies). This is to say, if the classifier chooses pink lady for each of the 50 instances, the classifier will be accurate 40% of the time. So, interpretation of the accuracy numbers should be viewed relative to the majority class to determine how strong the accuracies actually are. \( \chi^2 = \sum (\text{Observed Values} - \text{Expected Values})^2 / \text{Expected Values} \) is used to determine if the difference between the accuracy and the majority class baseline is significant or not.

The second measure of performance is what is known as the f-measure, which determines the precision and recall of the classifier. Precision refers to how well the classifier picks out from the data all of the fuji apples that are actually fuji apples. Said another way, if the classifier picks out 10 vectors and calls them fuji apples, what percent of those 10 vectors are actually fuji apples. Poor precision numbers involve calling things that are not fuji apples, fuji apples (over classification). Recall refers to how well the classifier picks from the data all of the fuji apples and calls them fuji apples. Said another way, the classifier picks out 18 vectors and calls them fuji apples, but there are actually 20 vectors that are fuji apples. Poor recall numbers involve missing fuji apples. Precision and recall are combined into an f-score \( 2 \times \frac{(\text{precision} \times \text{recall})}{(\text{precision} + \text{recall})} \) and is a more accurate picture of percentage accuracy. These basic ideas in machine learning, and evaluation of performance, will be utilized throughout the remainder of the dissertation.

Lastly, the Kappa statistic tells us something about the machine learning results as well beyond inter-annotator agreement. The difference between percentage accuracy of a classification algorithm and Kappa indicates the difficulty indistinguishing between a set of
features – e.g., the different types of figures. This measure gives some sense of the relative performance between humans and computers.

4.1. DATA PREPARATION AND MACHINE LEARNING ALGORITHMS. I used the Waikato Environment for Knowledge Analysis (version 3.6.1) (“WEKA”), which is an open source suite of machine learning algorithms. It was developed at the University of Waikato in New Zealand and is thoroughly explained in Witten and Frank (2002). WEKA requires a particular type of data format called the attribute-relation file format (.arff). The algorithms developed to extract the relevant coding information from the XML markup also output the codings into .arff files. For example, taking our sample narrative from (1), and the XML markup in (2), the .arff output would be as follows:

(4)  a. Oct-2009 --To reach the CP we have created a combined unit, consisting of a pointman (ex military guy), a como specialist and a interpreter-MRE bearer.
    b. 0, 0, DATE, NS, T, P, S, ?, ?, ?, ?, ?, ?, .125
    c. We started our advance in Hanoi at 13-42.
    d. NAR, 0, TIME, STATE, T, N, AI, 4, NL, PI, GEOGRAPHIC, 0, .250
    e. And hit our RON site in SonLa at 19-06.
    f. NAR, NAR, TIME, HIT, T, N, AT, AREA, NL, PI, GEOGRAPHIC, DC, .375
    g. 31/10/2009 we left our vehicle on the road at a distance of 1.2 km to the C point.
    h. NAR, NAR, DATE, MOTION, T, N, AI, NP, INT, PC, VISTA, DC, .500

---

n An alternative and, admittedly, more robust measure is the ceiling measure. The ceiling measure requires a task where humans are asked to classify based on the same information that the machine leaning algorithms rely on. For example, if the vector is 4, M, P, INT, ENV and we are seeking classification of figure, both the human and the algorithm are asked to make the determination that “4” is associated with “M, P, INT, ENV” etc.
Our unit began to climb on the crest of the mountain.

Our pointman quickly cut down the trail.

And after 2.5 hours we reached the CP.

The C point is located on the hillside, thickly overgrown with jungle.

In (4), each clause is reduced to a string of data. These strings constitute the instances (or vectors) used in machine learning tasks. The attribute template for these strings is: rhetorical relation (argument 2), rhetorical relation (argument 1), time, verb, tense, aspect, event, figure, frame, preposition, ground, previous ground, sequence. The values that go into this attribute template are the “types” of these attributes. The sequence is simply the proportional value of a given clause’s position in the discourse. Where \( n \) is the total number of clauses, \( 1/n = 1^{\text{st}} \) clause position, \( 2/n = 2^{\text{nd}} \) clause position, … \( n/n \) is the last clause position. In a machine learning experiment, any one of these attributes can serve as a class and the remaining eleven attributes would be used to classify that class. Further, the vectors in (4) represent the information in single clauses. Clause pairs were also extracted for the particular purpose of classifying rhetorical relations.

As a precursor to the results presented in the next chapter, there were three classifiers that performed particularly well on a series of machine learning experiments designed to answer the posed research question; the C4.5, K-Star and Naïve Bayes classifiers. The C4.5 classifier (J48 in WEKA) is a decision tree developed by Quinlan (1993). C4.5 relies on information (Shannon)
entropy of attributes to compute information gain. For example, let’s say that there are 16 values for stem length in our apple data. One assumption is that each of the 16 values is equally likely to occur (i.e., the values are in free variation). The Shannon entropy reduces the possible values in a given event as an expression of bits (0 or 1) (Shannon 1948). For eight values, only 3 bits would be necessary to describe each value. Said another way, 3 bits is exactly the amount of information needed to convey 8 values:

\[
\begin{array}{cccccccc}
\text{a.} & \text{Value 1} & \text{Value 2} & \text{Value 3} & \text{Value 4} & \text{Value 5} & \text{Value 6} & \text{Value 7} & \text{Value 8} \\
\text{b.} & 001 & 010 & 011 & 100 & 101 & 110 & 111 & 000 \\
\end{array}
\]

The computation of the Shannon Entropy \(H(X)\) for values in uniform distribution is simply the negative log (base 2) of the probability of the number of values (more succinctly, the log of the number of values). For values that are not in uniform distribution, the Shannon Entropy is the probability of a value \(p(i)\) times the log of that probability, summed for all values \(x\) in a given group of values \(X\):

\[
H(X) = - \sum_{x \in X} p(i) \log_2 p(i)
\]

In these circumstances, where values are not in uniform distribution, the relative contributions of each value can change the overall entropy of the event.

For example, if we have two values, and they are in uniform distribution, \(H(X)\) is 1 bit (\text{Value 1}=0, \text{Value 2}=1). If the values are not in uniform distribution, then they are in some type of complementary distribution. So, if one value occurs 66% of the time, the other value occurs 33% of the time. \(H(X) = .92\) with this distribution. The lower the entropy, the smarter we
are about the distribution of the data (which requires fewer bits). The differences in entropy between distributional models are either information gain or loss (actually a ratio of gain or loss to avoid those attributes with the largest number of values dominating the tree). In our two-value example, the information gain is 1 - .92 or .08.

For C4.5, the algorithm takes a training set, computes the information entropy of the values of a given attribute in free variation and then based on their actual distribution in the training set. Those values with the largest gain of information, are highest nodes in the decision tree. Then those values with the next largest gain of information are next highest in the decision tree. This iterates until items sought to be classified are on the bottom of the tree. You can then trace back the nodes to determine which values (and associated attributes) led to, or classified, the item.

The K-Star classifier (“K*”) is an instance based classifier. The K* classifier expresses the differences between two instances as a distance based on a transformation of one instance into another. The more complex the transformation, the greater the distance between the two instances. The complexity of the transformation is an information theoretic (Shannon) entropy measure of the Kolmogorov complexity (the amount of computational resources necessary to specify some object (text, numbers, etc.) (Kolmogorov 1968)). First, all possible transforms, or paths, from one instance to another are calculated:

\[
P^*(b|a) = \sum_{t \in P: t(a) = b} p(t)
\]
In (7), the probability \( P \) of all possible paths \( t \) between instances \( a \) and \( b \) is the summation of all probabilities of \( t \). Then the \( K^* \) function expresses \( P^* \) in terms of the Shannon Entropy:

\[
(8) \quad K^*(b|a) = -\log_2 P^*(b|a)
\]

To determine if an instance falls into some category, the probabilities between an instance to other instances within a given category are summed \( (P^*) \), and the converted values to \( K^* \) are used to define the category. So, *pink lady*, *fuji*, and *red delicious* would have an associated \( K^* \) value range and the idea is that all of the instances in a given category have a \( K^* \) which falls into the category range (and distinct categories will have distinct \( K^* \)s *(see Cleary & Trigg (1995)* for the full technical specification). Once the categories are determined, they are compared to the actual data and performance is measured.

The Naïve Bayes classifier utilizes Bayes Theorem which gives the conditional probability of some event \( a \) given the occurrence of event \( b \):

\[
(9) \quad P(a|b) = \frac{P(b|a) P(a)}{P(b)}
\]

For example, let’s restrict our hypothetical apple data to fuji (60%) and pink lady apples (40%). All of the fuji apples in our data have round seeds and half of the pink lady apples have round seed and the other half are oblong. If we have a round seed, what is the probability that the apple is a pink lady? Event \( a \) is the observation that the apple is a pink lady and event \( b \) is the observation that the seeds are round. So, to determine the probability of a pink lady, given that a round seed has been observed \( (P(a|b)) \), we need to know the probability that the apple is a pink
lady \(P(a)\), which is 40\%. We also need to know the probability that the seeds are round \(P(b)\), which is 80\% (all fuji plus half pink lady). Lastly, we need to know the probability of the seeds being round given that it is a pink lady \(P(b|a)\), which is 50\%. So, the probability of a pink lady, given that a round seed has been observed is equal to \(\frac{.50 \times .40}{.80}\), or .25.

The Naïve Bayes classifier computes the probabilities of all of the different attributes in an instance of data relative to a given class. For our apples, probabilities would be computed, using Bayes Theorem, between stem length given fuji, stem length given red delicious and stem length give pink lady and then the process repeated for color, seed shape and circumference (Note that, as part of the equation, the reverse probability of fuji given stem length, red delicious given stem length, and pink lady given stem length will also be computed). What makes the Naïve Bayes classifier “naïve” is that it does not compute any conditional or joint probabilities between attributes. Each attribute is assumed to be independent of one another an only having a statistical relationship with the class. Once these probabilities are computed, which creates a model of the data, a decision rule is used to determine how the classes are defined by the attributes relative to how the actual data is distributed:

\[
\text{class}(v_1, \ldots, v_n) = \arg \max_p(C = c) \prod_{i = 1}^{n} p(V_i = v_i | C = c) \tag{10}
\]

(10) indicates that the classification of some series of attribute values \((v)\) is equal to the maximum result of the probability of the actual class of that series of attributes \((C)\) equaling the class modeled by the classifier \((c)\) yielded by the product \((\Pi)\) of the probabilities of actual attribute values given actual classes \((p(V_i = v_i | C = c))\). So if there is a high probability between
round seed shape and fuji apples, round seed length becomes a part of the fuji apple class (for a full technical explanation, see Zhang (2004)).

It is important to understand the underlying function of any algorithm being used in an analysis. The underlying assumptions made in the classifiers can prove useful for later analyses. Concepts covered in this section will be revisited throughout the remainder of the dissertation.

5. Conclusion to Chapter III. This chapter presented all critical elements of the employed methodology. This chapter also partly answered the posed research question of How does the spatial information of events relate to narrative discourse? In particular, the baseline distribution of spatial and temporal elements for narrative discourses provides insight into how often explicit spatial information occurs and what type of spatial information occurs. Remember, one assumption is that each type of spatial information is in free discourse variation - the spatial template is set with five attributes and all values within that attribute are, a priori, equally likely. However, an equal distribution of all coding elements is not seen.

How these distributions play a role in classification, and a more in depth analysis of the total relationships between the spatial and temporal elements, will be demonstrated in Chapters IV and V. The ability to demonstrate that there are patterned relationships between spatial information and the temporal elements – which consolidate what is considered to be theoretically structural and non-optional for narrative discourse structure – facilitates a concrete answer to the posed research question. Uncovering the patterns and determining if the relationships have statistical significance is well placed in machine learning methodologies. Further, the qualitative
variations in the distributions per corpus, despite being largely similar along the lines of the collapsed inter-rater reliability codings, will be explored.
CHAPTER IV – RESULTS (GENERALIZATIONS)

1. INTRODUCTION TO CHAPTER IV. This chapter presents the results of several machine learning experiments that leverage different combinations of the spatial, temporal, event and rhetorical relation information coded in the three corpora of narratives. The different combinations of coded elements are designed to garner a better understanding of the types spatial information that occur in narrative discourses and how types of spatial information vary relative to structural temporal, event and rhetorical information (and vice versa). Being able to demonstrate relationships between these elements provides answers to the posed research question – *How does the spatial information of events relate to narrative discourse?* Demonstrating relationships, and their relative strength, in machine learning tasks requires a primary presentation of the factors discussed in Chapter III; specifically, whether or not the accuracy of prediction and F-measures over majority class and human performance (Kappa) baselines is statistically significant. Additional insights about the demonstrated relationships can be determined depending on the types of classifiers that perform best and the relative contributions of different features. This chapter focuses on all corpora combined for the purposes of uncovering general trends in narrative discourse.

This chapter is organized as follows. Section 2 focuses only on relationships in those clauses with explicit spatial information. The experiments explore the predictability of spatial information given other spatial information and then the inclusion of event and rhetorical relations as well as tense, aspect, and explicit reference to time. Section 3 runs similar experiments as Section 2, but with the inclusion of implicit spatial information and textual sequence. Predictions based on collapsed codings (following the Kappa results in Chapter III) are
also explored. Section 4 discusses in some detail how the spatial information of events relates to narrative discourse. This presentation includes a discussion of the distribution of the data in terms of information theory, which is a direct reflection of the best performing classifiers. Further, statistical correlations between features are examined relative to text sequence and a consistent template of spatial, temporal, event and rhetorical information types emerges. This template is argued to hold for all narrative discourses.

2. EXPLICIT SPATIAL INFORMATION. This section describes two groups of machine learning experiments. The first group seeks to determine the predictability of types of spatial information relative to other types of spatial information. For example, each clause that contains explicit spatial information is coded with a five-part vector: Figure, Verb, Preposition, Ground, Frame. The experiments seek to predict, for example Figure, given Verb, Preposition, Ground, and Frame; and then Verb, given Figure, Preposition, Ground, and Frame, etc. The second group runs the same experiments, but includes rhetorical relations, events into the vector, as well as tense, aspect, and explicit reference to time.

2.1. CLASSIFICATION RESULTS ON EXPLICIT SPATIAL INFORMATION. Focusing only on those clauses in the three corpora that contained explicit spatial information, I ran multiple classification algorithms at 10-fold cross-validation and focus here on the best performing algorithms: the Naïve Bayes (NB), C4.5 (J48), and K-Star (K*) classifiers at 10-fold cross-validation. I ran five experiments. Each experiment treated a different spatial feature as a “class” to be predicted based on the vector consisting of the remaining four spatial features:
Figure is a 7-way classifier (1, 3, 4, 6, NP, AREA, EVENT)

Verb is a 4-way classifier (MOTION, STATE, OUTSIDE, HIT)

Preposition is a 17-way classifier (PI, PC, PO, PM, II, IC, IO, IM, MI, MC, MO, MM, FI, FC, FO, FM, 0)

Ground is a 4-way classifier (FIGURAL, VISTA, ENVIRONMENTAL, GEOGRAPHIC)

Frame is a 6-way classifier (NAMED LOCATION, CONTIGUITY, DEIXIS, INTRINSIC, RELATIVE, ABSOLUTE)

The results are summarized in Table 13.

<table>
<thead>
<tr>
<th></th>
<th>NB</th>
<th>F-Score</th>
<th>J48</th>
<th>F-Score</th>
<th>K*</th>
<th>F-Score</th>
<th>MC</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure</td>
<td>40.56</td>
<td>.377</td>
<td>39.70</td>
<td>.369</td>
<td>41.55</td>
<td>.381</td>
<td>29</td>
<td>90</td>
</tr>
<tr>
<td>Verb</td>
<td>62.73</td>
<td>.616</td>
<td>60.42</td>
<td>.594</td>
<td>62.13</td>
<td>.611</td>
<td>35</td>
<td>75</td>
</tr>
<tr>
<td>Preposition</td>
<td>33.90</td>
<td>.307</td>
<td>30.01</td>
<td>.266</td>
<td>33.90</td>
<td>.303</td>
<td>16</td>
<td>76</td>
</tr>
<tr>
<td>Ground</td>
<td>55.21</td>
<td>.541</td>
<td>51.12</td>
<td>.486</td>
<td>55.80</td>
<td>.533</td>
<td>39</td>
<td>74</td>
</tr>
<tr>
<td>Frame</td>
<td>51.51</td>
<td>.472</td>
<td>54.48</td>
<td>.485</td>
<td>54.61</td>
<td>.483</td>
<td>43</td>
<td>76</td>
</tr>
</tbody>
</table>

TABLE 13. Spatial feature prediction based on explicit space for all corpora combined (n=1516).

For Figure, the best classifier performs 12 points above majority class (MC) (K*). For Verb, the best classifier performs 27 points above MC (NB). For Preposition, the best classifier performs 18 points above MC (K* and NB). For Ground, the best classifier performs 16 points above MC (K*). For Frame, the best classifier performs 11 points above MC (K*). Determining statistical significance with $\chi^2$, taking the best performance as “observed” values, and treating the MC as an “expected” values, these results are statistically significant ($\chi^2 = 53.23$, d.f. = 4, $p \leq .001$). F-scores are largely similar to the accuracies, which strengthens the impact of the numbers. However, accuracies are low overall. In regard to comparing accuracies to human performance via Kappa, prediction of Verb (13), Ground (19) and Frame (22) by the
classification algorithms are closest to, but below, Kappa. Comparatively, Figure (49) and Preposition (43) are better predicted by humans than by classification algorithms. Overall, for explicit spatial information, there is a 29 point average difference between classification algorithms and Kappa for explicit spatial information. Consider Table 14, which includes prediction based on spatial information and event and rhetorical relations and includes the following additional classifiers:

- Rhetorical (including Argument 1 and Argument 2) is a 7-way classifier (Narration, Background, Elaboration, Continuation, Alternate, Result, Explanation)

- Event is a 11-way classifier (State, Occurrence, Intensional Action, Alternate Worlds, Reporting, Perception, Initiation, Reinitiation, Culmination, Continuation, Termination)

In the following tables, “Rhetorical” indicates prediction based on two clauses – e.g., the information in clause 1 and clause 2 is used to predict the rhetorical relation of clause 2. “Rhet Arg1” and “Rhet Arg2” indicates prediction based on single clauses – e.g., with the exception of the first clause of a discourse, each clause is both the first argument of the next clause’s rhetorical relation and the second argument of the current clause’s rhetorical relation (based on the previous clause’s rhetorical relation).
Overall, there is a slight bump in performance for the spatial features, but the classifiers perform largely similarly as compared to Table 13. For Figure, the best classifier performs 13 points above MC (K*). For Verb, the best classifier performs 38 points above MC (K*). For Preposition, the best classifier performs 20 points above MC (K*). For Ground, the best classifier performs 18 points above MC (K*). For Frame, the best classifier performs 11 points above MC (J48). The best Event classifier (J48) performed 30 points above MC and the Rhetorical classifier performs 13 points above MC. For the argument components of the rhetorical relations, the best Arg1 classifier (NB) performed 7 points above MC, the best Arg2 classifier (J48) performed 3 points above MC. These results are statistically significant ($\chi^2 = 123.47$, d.f. = 8, $p \leq .001$).

Against Kappa, Figure (48) and Preposition (41) are still difficult for the classification algorithms, while Verb (2) and Rhetorical Relations (2) perform as well as humans. Ground (17), Frame (22), Events (17), Rhet Arg1 (11) and Rhet Arg2 (16) fall between Figure and Preposition on one end and Verb and Rhetorical Relations on the other. Overall, for explicit spatial, event

<table>
<thead>
<tr>
<th>Feature</th>
<th>NB</th>
<th>F-Score</th>
<th>J48</th>
<th>F-Score</th>
<th>K*</th>
<th>F-Score</th>
<th>MC</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure</td>
<td>41.02</td>
<td>.377</td>
<td>41.49</td>
<td>.384</td>
<td>42.54</td>
<td>.401</td>
<td>29</td>
<td>90</td>
</tr>
<tr>
<td>Verb</td>
<td>70.71</td>
<td>.699</td>
<td>72.62</td>
<td>.716</td>
<td>73.35</td>
<td>.724</td>
<td>35</td>
<td>75</td>
</tr>
<tr>
<td>Preposition</td>
<td>33.24</td>
<td>.311</td>
<td>32.38</td>
<td>.304</td>
<td>35.68</td>
<td>.332</td>
<td>16</td>
<td>76</td>
</tr>
<tr>
<td>Ground</td>
<td>56.00</td>
<td>.551</td>
<td>54.08</td>
<td>.521</td>
<td>57.71</td>
<td>.564</td>
<td>39</td>
<td>74</td>
</tr>
<tr>
<td>Frame</td>
<td>51.51</td>
<td>.469</td>
<td>54.61</td>
<td>.486</td>
<td>52.44</td>
<td>.483</td>
<td>43</td>
<td>76</td>
</tr>
<tr>
<td>Events</td>
<td>53.95</td>
<td>.512</td>
<td>55.21</td>
<td>.513</td>
<td>56.33</td>
<td>.536</td>
<td>25</td>
<td>73</td>
</tr>
<tr>
<td>Rhet Arg1</td>
<td>58.10</td>
<td>.542</td>
<td>57.96</td>
<td>.553</td>
<td>55.98</td>
<td>.521</td>
<td>51</td>
<td>69</td>
</tr>
<tr>
<td>Rhet Arg2</td>
<td>52.50</td>
<td>.502</td>
<td>53.75</td>
<td>.511</td>
<td>50.06</td>
<td>.488</td>
<td>50</td>
<td>69</td>
</tr>
<tr>
<td>Rhetorical</td>
<td>59.12</td>
<td>.585</td>
<td>67.36</td>
<td>.635</td>
<td>59.86</td>
<td>.571</td>
<td>54</td>
<td>69</td>
</tr>
</tbody>
</table>

Table 14. Spatial, event and rhetorical feature prediction, including tense, aspect and explicit temporal reference, based on explicit spatial information for all corpora combined (n=1516).
and rhetorical information, there is a 19 point average difference between classification algorithms and human performance, which is a ten point improvement over explicit spatial information alone.

Based on Tables 13 and 14, and despite results being statistically significant based on spatial information alone, the results are better if event and rhetorical information are included. Further, the NB, J48 and K* classifiers perform roughly similarly. Tense, aspect and explicit reference to time where included in the prediction, but not classified themselves because they are heavily skewed in the data. For example, for explicit time, a classifier would be 93.95% accurate in predicting the majority class that no explicit time is presents (e.g., the J48 tree for aspect has only one node – NONE). The inclusion of this information does not affect the results all that much.

2.2. DISCUSSION: EXPLICIT SPATIAL INFORMATION. To reiterate, the stronger the prediction of spatial, temporal, event and rhetorical information the stronger the argument, and answer to the posed research question, that spatial information is of a structural nature. Stronger predictions are equivalent to uncovering particular groups of relationships between the coded elements. If it is the case that the strength of prediction is not strong – i.e., performing at the majority class baseline or worse – this indicates that the elements are relatively independent of each other. Poor prediction for temporal, event and rhetorical elements does not equate with these elements not being structural as this is confirmed by other means discussed in the previous three chapters (e.g., participation in diagnostics). However, because spatial information is optional on the linguistic surface, the only way space can be demonstrated to be structural is via patterned relationships with other structural elements. If prediction accuracy is low for spatial information,
then its potential status as a structural element of discourse is called into question and the optional character of spatial information would appear to be an accurate point of view.

To start, Table 13 provides insight as to whether or not spatial information, in and of itself, demonstrates patterns. In particular, prediction of the verb based on other spatial information performs well in relation to other spatial information types. This is followed by preposition and ground and then by figure and frame. It may see somewhat surprising that verb is so predictable as research into spatial language in English places so much emphasis on the preposition in the creation of figure and ground relationships. However, remember that the verb in English has to allow for a prepositional phrase. The verb really drives the syntax and semantics of a given clause. The results here indicate that the inclusion of spatial information in the form of spatial prepositional phrases creating figure and ground relationships is subordinate to verbal information. Preposition is the second best performing classifier based on explicit spatial information so it is not the case that prepositions are completely unrelated to co-occurring spatial information. Ground performs similarly to preposition and this falls from the fact that spatial prepositional phrases are a constituent (Preposition + Ground denoting DP). Interestingly, frame of reference appears to be independent from the prepositions and grounds comprising it. Frame is a perspectival classification that is resolved from the surface linguistic information, not specifically encoded (with the exception of there for the deictic frame of reference). The most syntactic distance is between figure, which is typically the subject, and the verb complex (including the verb and spatial prepositional phrases). Figure’s comparatively weaker performance is arguably a reflection the type of subject being somewhat independent of the spatial relationship it is in. So, based on explicit information, the distribution of the prediction
patterns appear to reflect the syntactic and semantic insights discussed in Chapter II and indicate that the types of spatial information emerging in narrative discourses are relative to largely syntactic considerations. This is consistent with Labov’s framework as well.

This perspective is strengthened with the inclusion of temporal, event and rhetorical information (“temporal information”) in Table 14, as the same distributional pattern of predicting spatial information is maintained. The temporal information increases the prediction accuracy, the groupings of prediction performance become more solidified. It appears that the temporal information is participating in the prediction of spatial information, otherwise we would not see a jump in prediction accuracy. However, it is not immediately clear if spatial information is participating in the prediction of temporal information, which interferes with the ability to link spatial information to established structural elements of narrative discourse – this will be explored further in Section 4.2. However, Table 14 does indicate that temporal information is predictable within those clauses containing explicit spatial information. Event performs the best and indicates that there is some relationship between spatial and temporal elements in spatial clauses. The relationships contributing to event predictions are ostensibly stronger than those contributing to rhetorical relations; although rhetorical relation prediction performs well.

Remember, the prediction of rhetorical relations is based on pairs of arguments. The prediction of individual arguments does not perform comparatively well and is possibly a reflection of the fact that rhetorical relations are constructed locally. This is to say, knowing the rhetorical relation that a previous clause contributed to, does not help predict the rhetorical relation that a current clause is contributing to. Only both pieces of information together, possibly in addition to other spatial and temporal elements contribute to successful prediction.
In sum, spatial information appears to exhibit patterns relative to other spatial elements and relative to formal syntactic insights. Further, the inclusion of temporal information contributes to understanding spatial information by increasing prediction accuracy. Event information also appears to be predictable for clauses with explicit spatial information. Rhetorical relation information performs well and exhibits patterns consistent with theoretical insights into rhetorical structure. Thus, the machine learning algorithms can be said to be performing in ways consistent with theoretical linguist insights and indicating, at the very least, relationships between all of the coded elements. However, as mentioned, before we can strengthen the argument for spatial information as a structural component of narrative discourses, specific relationships must be explored. But first, I seek to improve performance of prediction by including implicit spatial information.

3. IMPLICIT AND EXPLICIT SPATIAL INFORMATION AND TEXT SEQUENCE. Let’s revisit SDRT relations briefly:

(1)  a. NARRATION: Pascale got up. She walked to the kitchen.
    b. ELABORATION: Pascale got her aardvark. It was under the crib.
    c. BACKGROUND: Pascale got her aardvark. It was dirty.
    d. EXPLANATION: The aardvark was dirty. Pascale had dropped it in a puddle.
    e. RESULT: Pascale dropped the aardvark in a puddle. It got really dirty.
    f. CONSEQUENCE: If Pascale dropped the aardvark in the puddle, then it got dirty.
    g. ALTERNATION: Pascale got her aardvark or her stuffed bunny.
    h. CONTINUATION: Pascale got her aardvark. Grimsby got his rawhide.
When spatial information is explicit, it is possible to maintain that information throughout additional clauses that do not contain explicit space; for example, consider (1).

(2)  
   a. Grimsby entered the kitchen. 
   b. He drank some water. 
   c. Then he begged for a biscuit.

In (2), it is arguably the case that (2b) and (2c) occur in the same location indicated in (2a) \textit{(the kitchen)}. It could be the case that (2b) and (2c) occur in locations other than the kitchen, but the lack of explicit spatial information creates the expectation that the kitchen is the location for the entirety of (2). The extension of spatial information across clauses is feasible in (2) as the \textit{narration} relation has a defined spatiotemporal consequence (Asher & Lascarides 2003).

Other rhetorical relations are not as transparent in terms of their spatial implications. However, there appears to be a restricted space in narrative discourses, which facilitates the extension of spatial information to other rhetorical relations. For example, implicit spatial information can be extended to \textit{elaboration} (1b) and \textit{background} (1c) clauses - the fact that the aardvark was under the crib and that the aardvark was dirty exists in the same location as where Pascale got the aardvark. \textit{Result} (1e) and \textit{consequence} (1f) can be considered this way as well. The events of the second clause in consequence and result occur in the same location as the first clause. The reverse is true for \textit{explanation} (1d), \textit{alternation} (1g), and \textit{continuation} (1h) are less straightforward because these relations tend to obtain between clauses that contrast some information. However, the extension of implicit spatial information is possible in the example clauses. Although, for \textit{continuation}, the event described in the second clause (assuming it is temporally simultaneous with the first) suggests the possibility that the
location is different.

In the absence of explicit updating of the spatial information, however, extension of spatial information is acceptable. The implicit spatial information will be underspecified in terms of actual location; for example, in (2), the drinking of water and the begging for biscuits arguably occur in different, separate locations within the kitchen. Essentially, if you ask “where” the events occur, the answer is recoverable from previously given information. The idea behind considering implicit space comes from the temporal inertia that is pragmatically resolved from text progression – as the text moves forward, the progression gives the impression of time moving forward (inertially) relative to the content of a given utterance (see generally, Smith (2003) and Rapaport et al. (1994)). I suggest here that similar principles apply to spatial information. To illustrate, consider (3):

(3)  a.  Grimsby brought his Kong into the kitchen.
    b.  NP, MOTION, FI, VIS, NL, .33, 0, 0, ASP
    c.  He barked.
    d.  ?, ?, ?, ?, .66, NAR, OCC
    e.  NP, MOTION, FI, VIS, NL, .66, NAR, 0, OCC
    f.  Then he ran to the window
    g.  3, MOTION, FC, ENV, NL, 1, NAR, NAR, ASP

(3a) is coded with figure, verb, preposition, ground and frame (3b) NP, MOTION, FI, VIS, NL) consistent with the guidelines discussed in Chapter III. (3f) is coded similarly ((3g) 3, MOTION, FC, ENV, NL). In addition to the spatial information, the clause's proportional position is included, the rhetorical relation, and event. (3a-b) and (3f-g) contain explicit information whereas (3c) does not. In the first group of machine learning experiments, which focused on explicit spatial information, (3c) would simply not be included despite non-spatial information
existing - .66, NAR, 0, OCC (3d). In the next group of machine learning experiments, which focus on implicit spatial information, this clause would receive the same spatial coding as the previous clause (3b), with the sequence, rhetorical relation and event being updated (3e).

Again, it should be noted that the NARRATION relation, and narrative discourses in general, are unique in that the extension of implicit space is germane to the underlying theory, extension to non-narration relations and discourses is not, necessarily. While the present examples are constructed in such a way as to facilitate the extension of implicit spatial information, and assuming an analysis within experiential narrative discourses, this may not always be the case. Sensitivity to this issue was considered in coding the data. In particular, if the content of the utterance was such that implicit space could not be extended, then it was not.

3.1. CLASSIFICATION RESULTS ON IMPLICIT AND EXPLICIT SPATIAL INFORMATION AND TEXT SEQUENCE. The same experiments found in Section 2 were run here, but with the inclusion of implicit spatial information consistent with the parameters discussed in Section 3. As compared to explicit space, the total number of vectors is increased from 1516 to 3421. The classification results are summarized in Table 15.
The inclusion of implicit space does increase performance, but only for the J48 and K* classifiers. For Figure, the best classifier performs 25 points above MC (J48). For Verb, the best classifier performs 37 points above MC (K*). For Preposition, the best classifier performs 28 points above MC (J48). For Ground, the best classifier performs 27 points above MC (K*). For Frame, the best classifier performs 21 points above MC (J48). The performance of the best Event classifier (K*) performed 12 points above MC, which is a drop from classification based only on explicit spatial information. The Rhetorical classifier performs 18 points above MC, an improvement over explicit spatial information. For the argument components of the rhetorical relations, the best Arg1 classifier (J48) performed 21 points above MC, the best Arg2 classifier (J48) performed 5 points above MC. These results are statistically significant ($\chi^2 = 142.64$, d.f. = 8, $p \leq .001$).

Against Kappa, Figure (33) and Preposition (27) are still difficult for the classification algorithms, while Verb (0) and Rhetorical Relations (3) perform as well as humans. Ground (5), Frame (10), Events (27), Rhet Arg1 (0) and Rhet Arg2 (17) fall between Figure and Preposition.
on one end and Verb and Rhetorical Relations on the other. Overall, for explicit and implicit spatial, temporal, event and rhetorical information, there is a 13 point average difference between classification algorithms and Kappa, which is a 6 point reduction based on classifiers that focus only on explicit information.

The divergence between the Naïve Bayes classifier and the J48 and K* classifiers is even more pronounced when including sequential information. Like the extension of implicit spatial information, the motivation for including sequential information is based on text progression and the inertial movement of time (again, Smith (2003) and Rapaport et al. (1994)). As the text moves forward, speech time and, depending on the nature of the clause, narrative time moves forward. This phenomenon occurs whether or not there is explicit reference to temporal elements in the discourse. Consider Table 16:

<table>
<thead>
<tr>
<th>Feature</th>
<th>NB</th>
<th>F-Score</th>
<th>J48</th>
<th>F-Score</th>
<th>K*</th>
<th>F-Score</th>
<th>MC</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure</td>
<td>43.56</td>
<td>.427</td>
<td>68.09</td>
<td>.678</td>
<td><strong>71.25</strong></td>
<td>.708</td>
<td>32</td>
<td>90</td>
</tr>
<tr>
<td>Verb</td>
<td>65.00</td>
<td>.647</td>
<td>78.09</td>
<td>.778</td>
<td><strong>84.03</strong></td>
<td>.840</td>
<td>38</td>
<td>75</td>
</tr>
<tr>
<td>Preposition</td>
<td>37.89</td>
<td>.366</td>
<td>62.80</td>
<td>.625</td>
<td><strong>63.91</strong></td>
<td>.635</td>
<td>21</td>
<td>76</td>
</tr>
<tr>
<td>Ground</td>
<td>57.69</td>
<td>.574</td>
<td>76.87</td>
<td>.767</td>
<td><strong>78.12</strong></td>
<td>.779</td>
<td>42</td>
<td>74</td>
</tr>
<tr>
<td>Frame</td>
<td>55.26</td>
<td>.525</td>
<td>75.05</td>
<td>.742</td>
<td><strong>75.73</strong></td>
<td>.752</td>
<td>45</td>
<td>76</td>
</tr>
<tr>
<td>Events</td>
<td>42.35</td>
<td>.397</td>
<td>45.10</td>
<td>.426</td>
<td>41.62</td>
<td>.407</td>
<td>32</td>
<td>73</td>
</tr>
<tr>
<td>Rhet Arg1</td>
<td>67.14</td>
<td>.632</td>
<td><strong>68.60</strong></td>
<td>.665</td>
<td>62.23</td>
<td>.603</td>
<td>48</td>
<td>69</td>
</tr>
<tr>
<td>Rhet Arg2</td>
<td>52.14</td>
<td>.489</td>
<td><strong>53.08</strong></td>
<td>.511</td>
<td>49.40</td>
<td>.465</td>
<td>47</td>
<td>69</td>
</tr>
<tr>
<td>Rhetorical</td>
<td>64.49</td>
<td>.593</td>
<td><strong>66.76</strong></td>
<td>.621</td>
<td>55.02</td>
<td>.528</td>
<td>48</td>
<td>69</td>
</tr>
</tbody>
</table>

**Table 16.** Spatial, event and rhetorical feature prediction including tense, aspect, explicit temporal reference and textual sequence, based on explicit and implicit spatial information for all corpora combined (n=3421).

The J48 and K* classifiers enjoy a significant boost in performance from the sequence information. For Figure, the best classifier performs 38 points above MC (K*). For Verb, the best classifier performs 46 points above MC (K*). For Preposition, the best classifier performs
28 points above MC (K*). For Ground, the best classifier performs 36 points above MC (K*).
For Frame, the best classifier performs 30 points above MC (J48). The performance of the best Event classifier (J48) performed 13 points above MC (J48). The Rhetorical classifier performs 18 points above MC. For the argument components of the rhetorical relations, the best Arg1 classifier (J48) performed 20 points above MC, the best Arg2 classifier (J48) performed 6 points above MC. These results are statistically significant ($\chi^2=259.20$, d.f. = 8, $p \leq .001$).

Against Kappa, Verb (+9) and Ground (+4) actually outperform human judgments. Figure (19), Preposition (13), Event (28) and Arg2 (16) perform less well compared to Frame (1), Arg1 (1) and Rhetorical Relations (3). Overall, for implicit spatial, temporal, event and rhetorical information with textual sequence, there is only a 7 point average difference between classification algorithms and Kappa, which is a 6 point reduction compared to implicit spatial information classifiers without textual sequence.

To provide results that are truly consistent with the underlying methodology, it is important to recast the results based on the inter-rater reliability statistics discussed in Chapter III. Based on the agreement between two coders, correcting for chance agreement, the coding elements were collapsed along theoretical and methodological grounds to ensure adequate reproducible performance of the proposed guidelines. Consistent with this collapsing of elements, the following classifiers were created: Figure – 5-way classifier (1, 3, 4, 6, NP); Verb – 2-way classifier (Motion, State); Preposition – 3-way classifier (0, Positional, Motion); Ground – 3-way classifier (Figural, Vista, Geographic); Frame – 2-way classifier (Non-Coordinated, Coordinated); and Rhetorical – 6-way classifier (NARRATION, BACKGROUND/ELABORATION, CONTINUATION, ALTERNATE, RESULT, EXPLANATION). The results of implicit and explicit space
with temporal elements and text sequence are presented in Table 17.

<table>
<thead>
<tr>
<th></th>
<th>NB</th>
<th>F-Score</th>
<th>J48 F-Score</th>
<th>K* F-Score</th>
<th>K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure</td>
<td>46.84</td>
<td>.442</td>
<td>56.60</td>
<td>.555</td>
<td>62.66</td>
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<td>Verb</td>
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<td>.763</td>
<td>79.32</td>
<td>.792</td>
<td>84.38</td>
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<tr>
<td>Preposition</td>
<td>62.89</td>
<td>.596</td>
<td>68.85</td>
<td>.680</td>
<td>72.92</td>
</tr>
<tr>
<td>Ground</td>
<td>71.90</td>
<td>.692</td>
<td>77.07</td>
<td>.757</td>
<td>79.47</td>
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<tr>
<td>Frame</td>
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<td>.767</td>
<td>83.39</td>
<td>.786</td>
<td>85.26</td>
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<tr>
<td>Events</td>
<td>53.23</td>
<td>.489</td>
<td>54.39</td>
<td>.514</td>
<td>54.51</td>
</tr>
<tr>
<td>Rhet Arg1</td>
<td>78.63</td>
<td>.772</td>
<td>79.94</td>
<td>.773</td>
<td>75.67</td>
</tr>
<tr>
<td>Rhet Arg2</td>
<td>59.80</td>
<td>.572</td>
<td>61.53</td>
<td>.594</td>
<td>58.93</td>
</tr>
<tr>
<td>Rhetorical</td>
<td>76.56</td>
<td>.737</td>
<td>77.70</td>
<td>.470</td>
<td>64.65</td>
</tr>
</tbody>
</table>

**Table 17.** Spatial, event and rhetorical feature prediction including tense, aspect, explicit temporal reference and textual sequence, based on explicit and implicit spatial information for all corpora combined, with collapsed codings (n=3421).

Using the collapsed codings, more normalized results are obtained. For Figure, the best classifier performs 30 points above MC (K*). For Verb, the best classifier performs 23 points above MC (K*). For Preposition, the best classifier performs 28 points above MC (K*). For Ground, the best classifier performs 36 points above MC (K*). For Frame, the best classifier performs 30 points above MC (J48). The performance of the best Event classifier (J48) performed 22 points above MC (J48). The Rhetorical classifier performs 29 points above MC. For the argument components of the rhetorical relations, the best Arg1 classifier (J48) performed 31 points above MC, the best Arg2 classifier (J48) performed 14 points above MC. These results are statistically significant ($\chi^2 = 332.65$, d.f. = 8, $p \leq .001$). The results for the Event and Rhetorical classifiers are improved with the reduction.

Against Kappa, only Frame (+1) outperforms human judgments. Similar to the uncollapsed codings, Verb (3), Ground (4), Arg 1 (2), Rhetorical Relation (4) perform close to human judgments whereas Figure (28), Preposition (11), Event (32) and Arg 2 (20). Overall, for implicit
spatial, temporal, event and rhetorical information with textual sequence, there is only a 11 point average difference between classification algorithms and Kappa, which is a 4 point increase compared to implicit sequence classifiers based on non-collapsed codings.

3.2. DISCUSSION: IMPLICIT SPATIAL INFORMATION AND TEXT SEQUENCE. The purpose of considering implicit spatial and sequence information is primarily to boost the accuracies of the classifiers. Based on Section 2, despite the fact that all prediction accuracies were above majority class baselines to a high degree of statistical significance is independent of what the prediction accuracy actually was – low in the majority of cases (30-50%). Including implicit spatial information does indeed boost performance. For example, Table 15 ranges from 46% to 75% in terms of prediction accuracy. Further, the ranking of distributions of prediction performance for spatial information are preserved – i.e., verb classifies best, followed by preposition and ground, with figure and frame having the lowest prediction accuracies. However, the ranking of distributions of prediction performance for temporal information are not preserved with the inclusion of implicit spatial information. In particular, the ability to predict events drops considerably (31 to 12 points above MC), the ability to predict rhetorical relations increases slightly (12 to 18 points above MC), the ability to predict the first argument of a rhetorical relation increases dramatically (7 to 21 points above MC), and the ability to predict the second argument of a rhetorical relation remains roughly the same (3 to 5 points above MC). In terms of the temporal information, Table 15 represents a more accurate distribution as all clauses are taken into consideration, not just those clauses with explicit spatial information (Table 14). Based on this more complete distribution, it appears that the ability to predict events in general,
based on spatial and temporal information, is difficult—suggesting the independence of event types from spatiotemporal information. In terms of rhetorical relations, there is a stronger expression of the relationships between the information contained in clauses contributing to a particular relation. In particular, the previous clause’s rhetorical relation—which is the first argument to the current clause’s rhetorical relation—is highly predictable. Said another way, knowing a current clause’s spatial and temporal information, including that clause’s rhetorical relation, tells you with some accuracy what rhetorical relation came immediately before it.

Further, because the prediction accuracy of the second argument from this same information is much lower, the suggestion becomes that the first argument in determining the rhetorical relation between two clauses is comparatively strong.

The inclusion of implicit spatial information does muddy the water a bit in terms of teasing apart the relative contributions of spatial and temporal information. There is a discernible boost in performance from Table 14 to Table 15; however, it is difficult to tell if this is representative of an increase in the participation of temporal information (through a more accurate distribution) or an increase in the number of instances of spatial information. I believe that it is more likely to be from an increase in the number of instances of spatial information. The reason for this is that the contribution of temporal information should, minimally, stay the same for those clauses with explicit spatial information despite a fuller picture of the temporal distributions. So, we would expect that the prediction accuracies would at least stay the same from Table 14 to 15. The fact that it increases while preserving the rank of distributions indicates that the central relationships exhibited in Tables 13 and 14 are being preserved in Table 15, there are just more instances to confirm the relationships, which then lead to higher accuracies. However, we cannot be sure of
this until we further explore specific relationships between elements. The prediction accuracies could have gone way down if it was the case that the temporal information for the implicit clauses was markedly different from the explicit clauses.

An interesting thing happens with the inclusion of text sequence. First, in terms of spatial information, there is a dramatic increase in prediction accuracies (45 – 84%). While it is possible, that sequence information is behaving as simply an additional form of temporal information with an additional boost to the spatial information. However, the ranking of the distributions of the spatial information changes quite a bit. Verb continues to have the highest prediction accuracy, but figure jumps to second, followed by ground at third, then frame and preposition last. With the exception of verb being highest, there are no local level syntactic insights that can be mapped onto, or otherwise help explain, this ranking distribution. Because the sequence is a continuous ranking within a given text – i.e., clause 1 through clause n (at the end of the text) – the opportunity to discuss text level structure a little more in depth presents itself. Further, the sequence effects seem to apply to the spatial information only as the ranking distribution of the temporal elements did not change with the inclusion of sequence information (Table 15 to Table 16).

The marked increase in figure information suggests that certain locations in a text correspond to whether or not the narrator is referring to him or herself or to some other entity. Figure indicates information that is part syntactic subject, personal deixis and spatial deixis in addition to being a key part of the syntactically constructed figure and ground relationship. Focusing on the textual level betrays a potential salience to the spatial and personal deictic feature of figure. Ground is in the same ranking position as in previous results, but with preposition falling lowest
overall with the inclusion of sequence information, the preposition and ground relationships based on spatial prepositional phrases appears to be minimized on the discourse level as well. Semantically, ground is a measure of scale and perspective via granularity. Frame is also, semantically, a measure of perspective and increases similarly as compared to prior results. The preposition, primarily responsible for the creation of the figure and ground relationship ultimately falls lowest. Overall, it seems that focus on the text-level via sequence information, reorganizes the ranking distribution of spatial information based on semantic features rather than syntactic features.

It interesting that the inclusion of sequence information “tips” the balance so to speak in terms of transitioning from syntactic relationships to semantic discourse relationships. This shift is also a shift from form-based relationships (syntax) and function-based relationships (semantics). However, before this insight can be explored further, a further investigation of relationships between elements, as opposed to just the bare distributions of the coded elements and comparative prediction accuracies is necessary. This is explored in Section 4.

4. SPATIOTEMPORAL PATTERNS IN NARRATIVE DISCOURSES. To summarize the results in the previous sections, consider Figure 5.
The overall trend in the classification results are as follows. Simply classifying explicit spatial, event and rhetorical information (ES + E, R) produces statistically significant performance above the majority baselines, but the accuracy is low for all classifiers. Adding temporal information – tense, aspect and explicit temporal information (ES + E, R, T) – does not improve (or worsen) performance. When implicit spatial information is included along with temporal information (IS + E, R, T), accuracy performance increases for the J48 and K* classifiers and not the Naïve Bayes. Performance for these classifiers increases even further when sequence information is included (IS + E, R, T, S). Further, the performance of the classification algorithms also approach human performance moving toward implicit space and sequence information. The normalized results increase average accuracy even further (Collapsed). However, the majority class baselines are increased as well.

Overall, the machine learning experiments are detecting trends in the distribution of spatial
information that is generalizable to narrative discourses and indicate that spatial information is related to narrative discourse. In particular, the temporal, event and rhetorical relation elements of narrative discourse structure. The specifics of these relationships are spelled out further in Section 4. Specifically, as the J48 and K* classifiers performed the best, and these classifiers are entropy based, Section 4.1 discusses the distribution of the coding elements in information theoretic terms. Section 4.2 discusses the role of text sequence, which appears to provide a uniform backdrop by which to evaluate the distribution of the coded elements.

To recap, the occurrence of spatial information in a given clause in a narrative discourse can be assumed, *a priori*, to be based on a uniform distribution. This means that whether or not explicit spatial information occurs is optional – i.e., non-critical for structure. Further, for purposes of this dissertation, when spatial information does occur, the type of spatial information can be of any kind. Of course, the caveat is, for narrative discourses, there is going to be *some* relationship between the type of spatial language used to describe narrative actions and the actual experienced actions – i.e., narrative actions are either going to involve movement or not, other people than the narrator or not, etc. Some of the spatial information accounted for here, in particular, the perspectival elements, can be assumed independent of the actual actions. However, these are just assumptions that are empirically testable.

**4.1 The Entropy of Spatiotemporality in Narrative Discourses.** Based on the discussions in Sections 2.2 and 3.2, the distributions of the coded spatial and temporal elements relative to explicit, implicit and sequential information indicate that machine learning algorithms are able to predict different types of spatial and temporal information in ways that reflect syntactic insights
and, in the case of sequence information, discourse semantic insights. As indicated, to better understand these distributions, and which elements contribute and relate to other elements, it is necessary to focus more in depth on the distributions and relationships of the spatial and temporal information.

In terms of the overarching distribution of the coding elements, because the entropy-based classifiers (J48 and K*) ultimately perform the best in terms of predicting spatial, event, rhetorical and temporal information (especially with implicit and sequence information), characterizing the distribution of these elements in information theoretic terms is apt. Let’s revisit the equation for the Shannon Entropy in (4).

\[
H(X) = - \sum_{x \in X} p(i) \log_2 p(i)
\]

On the first level of variation, I am assuming that it is equally likely for a clause in narrative discourse to include explicit spatial information or not – a 50/50 chance. The entropy \(H(X)\) of two variables equally likely to occur is 1 – i.e., 1 bit is equal to 0 and 1, therefore, to communicate the results of two values equally likely to occur, you need 0 and 1, or 1 bit. If the distribution of two values is not equally likely, then the entropy of information will be less than 1 and, if one value occurs to the exclusion of the other, only one-half of a bit is necessary (1 value). Entropy can be used to compare the efficiency of a given model. In this section, models of the free variation of the coding elements and will be compared to models based on the distribution of the coding elements.

Back to the first level of variation, \(H(X)\) of the uniform distribution model of spatial
occurrence is 1. Based on Table 4, \( H(X) \) of the CNCC corpus (40.00% explicit space) is .97; \( H(X) \) of the DCP corpus (55.92% explicit space) is .99; \( H(X) \) of the CRI corpus (42.72% explicit space) is .98; and the average \( H(X) \) of all corpora (44.37% explicit space) is .98. So, empirically, the occurrence or non-occurrence of explicit spatial information in the narrative discourse analyzed here is very close to being 50/50. What is interesting about this observation is not so much that the occurrence or non-occurrence of spatial information is equally likely to occur, it is that between 40.00 and 55.92% of clauses contain explicit spatial information. Given the optional nature of spatial information in terms of discourse structure, it is striking to see this average as high and as consistent as it is. While the DCP and CRI narratives concern spatial activities, which makes the averages less striking – i.e., narratives about spatial activities containing spatial information. However, there is no expectation, other than a uniform distribution, that the CNCC narratives would contain as much spatial information as they do. More discussion about corpus specific variation will be addressed in Chapter V.

Moving onto the next level of variation, which I will consider for not only spatial information, but event, rhetorical and temporal information as well, the uniform distribution (UD), actual distribution of the explicit spatial information (ED), and the actual distribution of the implicit spatial information (ID) entropy of all of the coding elements is shown in Table 18:
Starting with the event, rhetorical and temporal information, there is not necessarily an expectation that these elements should occur in a uniform distribution. Nonetheless, there is a significant drop in entropy for this information that corresponds to “knowing” more about the information in the model; “knowing more” should increase predictability. However, as mentioned above, the accuracy of predicting explicit temporal information, tense and aspect is very high because the majority classes are high – in particular, no explicit temporal reference occurs 96.40% of the time; past tense occurs 86% of the time; and no aspect occurs 88.37% of the time. These distributions are highly informative because they are skewed. The skew is reflected in the reduction of entropy in these elements (68% reduction for tense, 72% reduction for aspect, and 81% reduction for time). By comparison, events and rhetorical relations are less informative. Rhetorical relations are more so stemming from the majority relations being NARRATIONS, BACKGROUNDS and ELABORATIONS. The spatial information is less informative than the temporal information. The most informative is verb, figure and frame with ground and preposition (*based on the collapsing shown in Table 12) falling comparatively lower.

What is taken away from this discussion, in information theoretic terms, is that the uniform

<table>
<thead>
<tr>
<th>Spatial Information</th>
<th>$H(X)_{UD}$</th>
<th>$H(X)_{ED}$</th>
<th>$H(X)_{ID}$</th>
<th>Event, Rhetorical and Temporal Information</th>
<th>$H(X)_{UD}$</th>
<th>$H(X)_{ID}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure</td>
<td>2.80</td>
<td>2.43</td>
<td>2.40</td>
<td>Rhetorical</td>
<td>2.80</td>
<td>1.89</td>
</tr>
<tr>
<td>Verb</td>
<td>2</td>
<td>1.69</td>
<td>1.68</td>
<td>Time</td>
<td>2.32</td>
<td>0.42</td>
</tr>
<tr>
<td>Preposition*</td>
<td>2.32</td>
<td>2.07</td>
<td>1.97</td>
<td>Tense</td>
<td>2</td>
<td>0.64</td>
</tr>
<tr>
<td>Ground</td>
<td>2</td>
<td>1.87</td>
<td>1.84</td>
<td>Aspect</td>
<td>2</td>
<td>0.55</td>
</tr>
<tr>
<td>Frame</td>
<td>2.58</td>
<td>2.12</td>
<td>1.99</td>
<td>Event</td>
<td>2.80</td>
<td>2.44</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>11.70</strong></td>
<td><strong>10.18</strong></td>
<td><strong>9.88</strong></td>
<td><strong>Total</strong></td>
<td><strong>11.92</strong></td>
<td><strong>5.94</strong></td>
</tr>
</tbody>
</table>

TABLE 18. The entropy ($H(X)$) of spatial, event, rhetorical and temporal elements in uniform distribution (UD), explicit spatial distribution (ED), implicit distribution (ID) (the event, rhetorical and temporal distributions (D) are the same for both explicit and implicit distributions).
distribution entropy of the spatiotemporal architecture of narrative discourses is captured here, based on how the spatiotemporal architecture of narrative discourses, is 23.62. Based on the actual distributions of the coding elements, the model is more informative at 16.12, a 31% reduction. However, 80% of this reduction is due to the temporal elements and 20% is due to the spatial elements. When implicit space is considered, there is a slight improvement to 15.82, but this, more or less, indicates that the extension of the spatial information to clauses without explicit space did not drastically alter the underlying distribution. For completeness, Table 19 indicates the spatiotemporal entropy of the collapsed codings. The new uniform distribution total entropy is 19.18 and the coded entropy is 11.80. This model is more informative by nature because there are less categories. Similarly, there is no change in the contributions of spatial and temporal information – temporal elements are more informative than spatial elements.

<table>
<thead>
<tr>
<th>Spatial Information</th>
<th>$H(X)_{UDCC}$</th>
<th>$H(X)_{IDCC}$</th>
<th>Event, Rhetorical and Temporal Information</th>
<th>$H(X)_{UDCC}$</th>
<th>$H(X)_{IDCC}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure</td>
<td>2.32</td>
<td>2.09</td>
<td>Rhetorical</td>
<td>2.58</td>
<td>1.49</td>
</tr>
<tr>
<td>Verb</td>
<td>1.00</td>
<td>.96</td>
<td>Time</td>
<td>2.32</td>
<td>0.42</td>
</tr>
<tr>
<td>Preposition*</td>
<td>1.58</td>
<td>1.39</td>
<td>Tense</td>
<td>2.00</td>
<td>0.64</td>
</tr>
<tr>
<td>Ground</td>
<td>1.58</td>
<td>1.16</td>
<td>Aspect</td>
<td>2.00</td>
<td>0.55</td>
</tr>
<tr>
<td>Frame</td>
<td>1.00</td>
<td>.66</td>
<td>Event</td>
<td>2.80</td>
<td>2.44</td>
</tr>
<tr>
<td>Total</td>
<td>7.48</td>
<td>6.26</td>
<td>Total</td>
<td>11.70</td>
<td>5.54</td>
</tr>
</tbody>
</table>

Table 19. Based on collapsed codings, the entropy ($H(X)$) of spatial, event, rhetorical and temporal elements in uniform distribution (UDCC) and the implicit distribution of spatial information (IDCC).

These entropy numbers simply tell us about the distribution of the elements, but not the distribution of the elements relative to other elements. This distribution is important as it tells us relationships between figures and grounds, verbs and prepositions, events and rhetorical relations etc. These distributions are computed by the machine learning algorithms discussed in Chapter
III, the results of which are presented here. Further, as indicated in Sections 2 and 3 of this chapter, the K* and J48 classifiers out perform the Naïve Bayes classifier. A key difference between the K* and J48 classifiers and the Naïve Bayes classifier, is that the K* and J48 recast the distribution of relationships in information theoretic terms, rather than some other statistical distribution and consider the entropy of the relationships between the different attributes. Naïve Bayes considers the Bayesian distribution of attributes relative only to the class. While the Naïve Bayes classifier performs well, the increased performance of the K* and J48 indicate that the relationships between the attributes is important.

4.2. RELATIONSHIPS BETWEEN SPATIAL, TEMPORAL, EVENT AND RHETORICAL INFORMATION AND TEXT SEQUENCE. The discussed distributions in Section 4.1 tell us about the spatial, temporal, event and rhetorical make-up of narrative discourses generally (the distributions of these linguistic elements may vary for other types of discourses). However, as noted, theses distributions do not tell us about the relationships, if any, between the elements – i.e., Do certain figures associate with certain verbs? Events with prepositions? Tenses with frames? etc. The results of the classifiers indicate that there are relationships, otherwise the prediction accuracies would not be as good as they are. Focusing on text sequence, which, in addition to implicit space, perform the best of any combination, allows for a simplified presentation of what elements relate to other elements. To demonstrate this, I will rely on the Spearman’s rank correlation coefficient (Spearman’s rho ($\rho$)).

Spearman’s rho measures the statistical dependence between two variables by expressing one variable as a monotonic function of the other. This is accomplished by ranking each of the values
in a given variable and comparing the differences in those ranked values. Values of Spearman’s rho vary from +1 to -1. Positive values indicate that as one variable increases or decreases in rank, the other variable does the same. Negative values indicate that as one variable increases or decreases in rank, the other variable does the opposite (decreases or increases in rank respectively). The higher the value (towards +1 or -1), the stronger the correlation between the two variables – i.e., the goodness of fit of the two variables to a monotonic function. \( \rho \) is calculated with the equation in (5) where \( n \) is the total number of values per variable and \( d \) is the numerical difference between the individual ranks of each variable.

\[
(5) \quad \rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}
\]

For example, back to the apples, we can look at 5 instances of two variables, stem length and circumference, summarized in Table 20:

<table>
<thead>
<tr>
<th>Stem Length</th>
<th>Circumference</th>
<th>Stem Length Rank</th>
<th>Circumference Rank</th>
<th>Rank Difference (d)</th>
<th>(Rank Difference)² (d²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.8</td>
<td>8.6</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2.0</td>
<td>9.7</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2.8</td>
<td>9.9</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>2.7</td>
<td>10.0</td>
<td>4</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2.6</td>
<td>10.1</td>
<td>3</td>
<td>5</td>
<td>-2</td>
<td>4</td>
</tr>
</tbody>
</table>


Plugging these values into (5): \( \rho = 1 - (6(8)) / (5(25-1)) = 1 - (48 / 120) = 1 - .4 = .6. \) Because the value is positive, both variables increase or decrease together. The strength of the correlations between stem length and circumference is determined by evaluating the statistical significance of the \( \rho \) value of .6. Several scales are useful in determining the significance of \( \rho \) values. A
common distinction is that values between .9 and 1 show very strong correlations, .7 and .9 show strong correlations, and .5 and .7 show moderate correlations. Distribution tables (based on \(t\)-values) indicate that \(\rho \geq .794\) is significant to a \(p\)-value \(\leq .01\); \(\rho \geq .648\) is significant to a \(p\)-value \(\leq .05\); \(\rho \geq .564\) is significant to a \(p\)-value \(\leq .10\).

Breaking up text sequence into 10\% segments, each segment serves as a rank. Within each rank (representing a percentage section of the discourse), the raw numerical values of the most prominent features within each spatial, temporal, event and rhetorical category coded was accounted for. In particular, 1 and 3 Figures (1,3), Motion and State Verbs (MV, SV), Motion and State Prepositions (MP, SP), Figural and Geographic Grounds (F, G) (Vista was uniformly high), Coordinated and Non-Coordinated Frames (C, NC), Aspectual and State Events (AE, SE), Narration and Background/Elaboration Rhetorical Relations (N, B), Past and Present Tense (P, R), Progressive and No Aspect (PA, NA) and Explicit Temporal Reference and No Explicit Temporal Reference (T, NT). Spearman’s \(\rho\) was then computed for all possible pairs of series of values. The results are presented in Tables 22 and 23. Using .650 as an arbitrary threshold for purposes of discussion (slightly above a \(p\)-value of .05), the shaded boxes in Tables 21 and 22 indicate those pairs of coded elements demonstrating the highest correlations. Note that the correlations go in both directions, e.g., if Rhetorical Relations are correlated with Events, Events are similarly correlated with Rhetorical Relations.
<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>B</th>
<th>AE</th>
<th>SE</th>
<th>1</th>
<th>3</th>
<th>MV</th>
<th>SV</th>
<th>MP</th>
<th>SP</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>X</td>
<td>-0.92</td>
<td>0.72</td>
<td>-0.57</td>
<td>-0.45</td>
<td>0.47</td>
<td>0.32</td>
<td>-0.68</td>
<td>0.29</td>
<td>-0.40</td>
</tr>
<tr>
<td>B</td>
<td>X</td>
<td></td>
<td>-0.83</td>
<td>0.52</td>
<td>0.45</td>
<td>-0.36</td>
<td>-0.12</td>
<td>0.67</td>
<td>-0.16</td>
<td>0.39</td>
</tr>
<tr>
<td>AE</td>
<td>X</td>
<td></td>
<td></td>
<td>-0.75</td>
<td>-0.52</td>
<td>0.05</td>
<td>0.26</td>
<td>-0.66</td>
<td>0.21</td>
<td>-0.45</td>
</tr>
<tr>
<td>SE</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>0.53</td>
<td>0.06</td>
<td>-0.71</td>
<td>0.78</td>
<td>-0.35</td>
<td>0.31</td>
</tr>
<tr>
<td>1</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.15</td>
<td>-0.30</td>
<td>0.61</td>
<td>-0.20</td>
<td>0.17</td>
</tr>
<tr>
<td>3</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.10</td>
<td>-0.39</td>
<td>0.33</td>
<td>-0.32</td>
</tr>
<tr>
<td>MV</td>
<td>X</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.58</td>
<td>0.78</td>
<td>-0.55</td>
</tr>
<tr>
<td>SV</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>-0.35</td>
<td>0.34</td>
</tr>
<tr>
<td>MP</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.86</td>
</tr>
<tr>
<td>SP</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 21.** Spearman’s Rho calculation for all pairs of majority class codings (Part 1).

Starting with Rhetorical Relations, correlations are linked to Events, Verbs, Coordinated Frames and other Rhetorical Relations. In particular: Narration is in a very strong negative correlation Background/Elaboration; Narration is in a strong positive correlation with Aspectual Events; Narration is in a moderate negative correlation with Stative Verbs; Narration is in a strong positive correlation with Coordinated Frames; Background/Elaboration is in a strong negative correlation with Aspectual Events; and Background/Elaboration is in a moderate positive correlation with Stative Verbs.

Event correlates to Rhetorical Relations, Events, Verbs and Explicit Temporal Reference. In particular: Aspectual Events are in strong negative correlation with State Events; Aspectual Events are in moderate negative correlation with Stative Verbs; State Events are in strong negative correlation with Motion Verbs; State Events are in strong positive correlation with Stative Verbs; and State Events are in a strong positive correlation with Explicit Temporal Reference.
Table 22. Spearman’s Rho calculation for all pairs of majority class codings (Part 2).

<table>
<thead>
<tr>
<th></th>
<th>F</th>
<th>G</th>
<th>NC</th>
<th>C</th>
<th>R</th>
<th>P</th>
<th>PA</th>
<th>NA</th>
<th>T</th>
<th>NT</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>0.13</td>
<td>-0.58</td>
<td>-0.45</td>
<td>0.74</td>
<td>-0.55</td>
<td>0.46</td>
<td>0.34</td>
<td>0.22</td>
<td>-0.53</td>
<td>0.01</td>
</tr>
<tr>
<td>B</td>
<td>-0.11</td>
<td>0.46</td>
<td>0.64</td>
<td>-0.57</td>
<td>0.54</td>
<td>-0.22</td>
<td>-0.14</td>
<td>0.03</td>
<td>0.60</td>
<td>0.28</td>
</tr>
<tr>
<td>AE</td>
<td>0.27</td>
<td>-0.41</td>
<td>-0.35</td>
<td>0.53</td>
<td>-0.57</td>
<td>0.26</td>
<td>0.12</td>
<td>-0.03</td>
<td>-0.44</td>
<td>-0.19</td>
</tr>
<tr>
<td>SE</td>
<td>-0.39</td>
<td>0.59</td>
<td>0.05</td>
<td>-0.61</td>
<td>0.53</td>
<td>-0.39</td>
<td>-0.37</td>
<td>-0.14</td>
<td>0.75</td>
<td>-0.29</td>
</tr>
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<td>1</td>
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<td>0.87</td>
<td>-0.02</td>
<td>-0.11</td>
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<td>0.01</td>
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</tr>
<tr>
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<td>-0.01</td>
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<td>-0.07</td>
<td>0.27</td>
<td>-0.36</td>
<td>0.36</td>
<td>-0.19</td>
<td>0.47</td>
<td>-0.11</td>
<td>0.16</td>
</tr>
<tr>
<td>MV</td>
<td>0.38</td>
<td>-0.51</td>
<td>0.23</td>
<td>0.69</td>
<td>-0.34</td>
<td>0.72</td>
<td>0.29</td>
<td>0.57</td>
<td>-0.48</td>
<td>0.14</td>
</tr>
<tr>
<td>SV</td>
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<td>-0.09</td>
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</tr>
<tr>
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<td>-0.39</td>
<td>0.26</td>
<td>0.57</td>
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<td>0.04</td>
<td>0.67</td>
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<td>0.59</td>
</tr>
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<td>0.01</td>
<td>-0.56</td>
<td>0.15</td>
<td>-0.59</td>
<td>0.16</td>
<td>-0.55</td>
<td>0.35</td>
<td>-0.20</td>
</tr>
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<td>F</td>
<td>X</td>
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<td>-0.05</td>
<td>-0.10</td>
<td>0.56</td>
<td>-0.18</td>
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<td>G</td>
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<td>-0.25</td>
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<td>0.64</td>
<td>-0.49</td>
<td>0.49</td>
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<td>0.25</td>
<td>0.74</td>
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<td>0.22</td>
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<td>0.22</td>
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<td>-0.06</td>
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<td>0.12</td>
<td>0.22</td>
<td>0.22</td>
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<td>0.22</td>
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<td>P</td>
<td>X</td>
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<td>-0.20</td>
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<td>0.53</td>
<td>0.53</td>
<td>0.53</td>
<td>0.53</td>
<td>0.53</td>
</tr>
<tr>
<td>PA</td>
<td>X</td>
<td>0.16</td>
<td>0.54</td>
<td>0.54</td>
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<tr>
<td>NA</td>
<td>X</td>
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<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
</tr>
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<td>X</td>
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<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Figure correlates to Grounds and Explicit Temporal Reference. In particular: 1 Figures are in strong negative correlation with Figural Grounds; 1 Figures are in strong positive correlation with Geographic Grounds; and 1 Figures are in strong positive correlation with Explicit Temporal Reference. Verb correlates to Rhetorical Relations, Events, Prepositions, Tense, Frames, Ground and Explicit Temporal Reference – in particular: Motion Verbs are in strong positive correlation with Motion Prepositions; Motion Verbs are in moderate positive correlation with Coordinated Frames; Motion Verbs are in strong positive correlation with Past Tense; State Verbs are in strong positive correlation with Geographic Grounds; State Verbs are in strong positive correlation with Present Tense; and State Verbs are in strong positive correlation with Explicit Temporal Reference. Preposition correlates to other Prepositions, Verbs, Tense and Aspect – in particular: Motion Prepositions are in strong negative correlation with State
Prepositions; Motion Prepositions are in moderate positive correlation with Past Tense; and Motion Prepositions are in moderate positive correlation with No Progressive Aspect. Ground correlates to Figure, Verb, other Grounds and Explicit Temporal Reference – in particular, Figural Ground is in moderate negative correlation with Geographic Ground; and Geographic Ground is in moderate positive correlation with Explicit Temporal Reference. Frame correlates to Rhetorical Relation, Verb, Explicit Temporal Reference and Past Tense – in particular: Non-Coordinated Frames are in strong positive correlation with No Explicit Temporal Reference; and Coordinated Frames are in strong positive correlation with Past Tense. Tense correlates to Verb, Preposition, Frame, Aspect and Explicit Temporal Reference – in particular: Present Tense is in strong positive correlation with Explicit Temporal Reference; and Past Tense is in strong positive correlation with No Aspect.

Focusing on the strongest relationships between spatial and temporal information, the top twenty relationships (between .794 and 1) indicate that while there are strong relationships within temporal and spatial information there is some overlap: Narration and Background (-0.92); Background and Aspectual Events (-0.83); Positional and Motion Prepositions (-0.86); 1 Figures and Figural Granularities (-0.84); 1 Figures and Geographic Granularities (+0.87); Stative Verbs and Present Tense (+0.80); Stative Verbs and Temporal Reference (+0.83); and Coordinated Frames of Reference and Present Tense (+0.89). Further, these relationships explain the change in distribution ranks when considering sequence and spatial information. In particular, the relationships between figure and ground (deixis and perspective) are prominent.

In summarizing all of these correspondences, many conform to previous observations in narrative research (e.g., Labov’s insights that narratives are largely in the simple past tense, with
no aspect (except for some progressive aspect)). Further, the correspondences mirror research into tense, aspect and event (e.g., stative events based on stative verbs). As the positive and negative aspects of the correlations indicate relative movement between distributions of elements as the text unfolds from beginning to end. The following series of graphs illustrate the specific spatial, event, rhetorical and temporal correlations which, I argue, provide a template of information that is generalizable to all narrative discourses. Each graph indicates the percentage distribution of certain elements.

Figures 6 and 7 focus on rhetorical and event information respectively. Both figures demonstrate shifts from BACKGROUND/ELABORATION relations and State events in the first 20% of the text to narration and Aspectual events, peaking between 30 and 50% of the text, and then attenuating in percentage distribution to the end of the text (possibly crossing back over – rhetorical relations).

![Graph](image)

**Figure 6.** Rhetorical architecture.
Figures 8 and 9 represent the percentage distributions of Motion (M) and State (S) spatial verbs and Motion (M) and Positional (P) spatial prepositions. In particular, State spatial verbs and Positional spatial prepositions are highest in the first 20% of the discourse and transition to Motion spatial verbs and prepositions, again peaking between 30 and 50% of the text, and then attenuating in the last third of the text.

Figure 7. Event architecture.

Figure 8. Verb architecture.
This same pattern is seen for figures - self (1) vs. other (3) (Figure 10) (1st person figures include both singular and plural and 3rd person figures include singular, plural and NP. 2nd person singular and plural would have been included under “other” had they occurred in the data) and granularity - Figural (F) vs. Geographic (G) (Figure 11). Figures delay the crossing over until 30-40% but then conform to the demonstrated pattern. The pattern in granularity indicates that described space moves from larger to smaller to larger scales.
In sum, based on Tables 21-22, Figures 6-11 present the spatiotemporal structural profile of narrative discourses (based on those elements that demonstrate a statistical correlation). In taking some proportional slice of the discourse, the suggestion emerges that attention to where we are in a given narrative text correlates to the type of spatial, temporal, event and rhetorical information that is statistically more likely to emerge. It appears that text sequence is revealing something about the overall text structure of narrative discourses. It could be that the relationships created on the local level, despite variation, are underlyingly and theoretically very similar and so consistent as to demonstrate these spatiotemporal patterns across all narratives. From a top-down perspective, it could be that narrative discourses simply have an abstract information based architecture that linguistic forms conform to.

The Ground information is potentially illustrative of this. Measures of granularity, as they are accounted for here based on spatial scale and perspective, are also a measure of specificity. Based on Figure 11, as the text unfolds there is movement away from larger geographic spaces towards smaller more detailed spaces. This trend of providing information of some kind and then
building off of the information toward some rhetorical point (BACKGROUND/ ELABORATION), aspectual events, complex frames, progressive tenses, etc. is also being exhibited by these patterns. However, while interesting food for thought, this gets us quickly beyond the scope of the dissertation. What is clear is that perspectival and textual information can be leveraged for making predictions about linguistic theories. These predictions are based both in and outside of observed theory. It is arguably necessary to extend our view of linguistic theory to capture phenomena such as spatial information that would not otherwise be readily captured.

Tables 23 and 24, provide sample narratives from the CRI corpus that embody the sequential representation of spatial information in Figures 6-11. There are two narratives displayed which represent two text-level surface realizations of the occurrence of spatial information. Table 23 (CRI_GD_1) demonstrates that spatial information occurs, if at all, toward the beginnings of narratives and then tapers off. Table 24 (CRI_UC_1) demonstrates that spatial information occurs homogenously. In both narratives, the spatial information largely conforms to what is represented in unfolding of sequence in Figures 6-11: (1) Movement from 1st Person (singular or plural) figures to 3rd Person or “other” entities; (2) stative verbs to motion verbs; (3) positional to motion prepositions; (3) larger to smaller granularities; (4) stative to aspectual events; and (5) background/ elaboration to narrative rhetorical relations. Variation relative to other factors such as spatial density, authorship and implicit space will be discussed further in Chapter V.
It was Friday about around I think seven.

Seven in the evening.

And I bought her pop Snyder’s Market,

and from there we went walking

and I walked her down to the woods.

I just told her I was gonna walk around and I was gonna go to my grandmother’s house if she wanted to walk with me.

She said it was okay.

So I took her, I took her from there and from there we went walking and I walked her down to the woods.

nd that’s when I went and took advantage of her.

I started beatin her

and knockin her around

and I killed her

and I, I got scared

and I panicked

and I ran from the woods.

I’ve been through so much distress

and I couldn’t take it no more

so I took my advantage out on this little girl.

<table>
<thead>
<tr>
<th>CRI_GD_1 (30.00% spatial density)</th>
<th>Corresponding spatial annotation</th>
</tr>
</thead>
<tbody>
<tr>
<td>It was Friday about around I think seven.</td>
<td>?, ?, ?, ?, ?, 0.050, 0</td>
</tr>
<tr>
<td>Seven in the evening.</td>
<td>?, ?, ?, ?, ?, 0.100, BACK</td>
</tr>
<tr>
<td>And I bought her pop Snyder’s Market,</td>
<td>4, STATE, PI, GEO, 0, NL, 0.150, NAR</td>
</tr>
<tr>
<td>and from there we went walking</td>
<td>4, STATE, II, VIS, DX, 0.200, NAR</td>
</tr>
<tr>
<td>and I walked her down to the woods.</td>
<td>4, MOTION, FC, ENV, NL, 0.250, CON</td>
</tr>
<tr>
<td>I just told her I was gonna walk around and I was gonna go to my grandmother’s house if she wanted to walk with me.</td>
<td>?, ?, ?, ?, ?, 0.300, BACK</td>
</tr>
<tr>
<td>She said it was okay.</td>
<td>?, ?, ?, ?, ?, 0.350, BACK</td>
</tr>
<tr>
<td>So I took her, I took her from there</td>
<td>3, HIT, II, ENV, DX, 0.400, RES</td>
</tr>
<tr>
<td>and I took her to the woods</td>
<td>3, HIT, FC, ENV, NL, 0.450, NAR</td>
</tr>
<tr>
<td>nd that’s when I went and took advantage of her.</td>
<td>?, ?, ?, ?, ?, 0.500, BACK</td>
</tr>
<tr>
<td>I started beatin her</td>
<td>?, ?, ?, ?, ?, 0.550, NAR</td>
</tr>
<tr>
<td>and knockin her around</td>
<td>?, ?, ?, ?, ?, 0.600, CON</td>
</tr>
<tr>
<td>and I killed her</td>
<td>?, ?, ?, ?, ?, 0.650, NAR</td>
</tr>
<tr>
<td>and I, I got scared</td>
<td>?, ?, ?, ?, ?, 0.700, NAR</td>
</tr>
<tr>
<td>and I panicked</td>
<td>?, ?, ?, ?, ?, 0.750, NAR</td>
</tr>
<tr>
<td>and I buried her.</td>
<td>?, ?, ?, ?, ?, 0.800, NAR</td>
</tr>
<tr>
<td>and I ran from the woods.</td>
<td>1, MOTION, II, ENV, NL, 0.850, NAR</td>
</tr>
<tr>
<td>I’ve been through so much distress</td>
<td>?, ?, ?, ?, ?, 0.900, EXP</td>
</tr>
<tr>
<td>and I couldn’t take it no more</td>
<td>?, ?, ?, ?, ?, 0.950, EXP</td>
</tr>
<tr>
<td>so I took my advantage out on this little girl.</td>
<td>?, ?, ?, ?, ?, 1.000, ELAB</td>
</tr>
</tbody>
</table>

Table 23. Narrative CRI_GD_1 with corresponding annotation.

5. CONCLUSION TO CHAPTER IV. Summing up all of the information in this chapter, the broad answer to the posed research question of How does the spatial information of events relate to narrative discourse? is structurally. And by structurally, I mean relative to linguistically defined elements of temporal information (tense, aspect, explicit reference) and temporally defined events and rhetorical relations. This structural relativity is revealed via the machine learning tasks presented here and based on the accuracy of prediction of a given spatiotemporal structural elements based on a pool of other spatiotemporal structural elements. While structural patterns emerge based on explicit spatial information, these patterns are refined with implicit spatial information and reducing the information along the lines of inter-rater reliability statistics.

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A few days later. I was leaving Utah about six in the morning.

A sign saying gas and diesel at the truck stop ahead,

and went in.

There was an older elderly woman at the counter.

bought me a soda, some potato chips

and … uhh, cased out the place.

And “Yeah, uhh, this is what I want I’m gonna have this woman,”

and walked out.

Get in the car

and waited.

Uh, there was a car pulled up

and left.

And uhh, these two buses with no passengers I guess came in,

turned around

and she says uh, you want … She asked if there was anything else I needed or wanted.

And I said, “no,”

I turned

and walked around the store a little bit.

Then I reached in my shirt,

shot her in the body some where.

She goes, “ahhh.”

I shot her in the head

She fell to the floor.

I walked around,

opened up the cash register

and took all the bills out.

Looked underneath to see if there was any extra money.

Ripped open her blouse,

pulled her bra up over her big, gorgeous, big breasts.

Fondled and sun … fondled ‘em.

Her eyes were rolling,

it was still blinking like she was looking around.

So I shot her through the temple,

and the blood oozed out the side of her nose.

Yeah, ole girl I got your life.
Further insight is garnered about the nature of the relationships – delving deeper into the *how* answer to the posed research question – when taking a closer inspection of the mechanics of machine learning classifiers. In particular, those classifiers that view the data in information theoretic terms and consider relationships between attributes perform very well. These classifiers, for example, via the visual representation of the J48 trees, indicate that spatial information patterns somewhat independently, but also relative to temporal elements. When the information is collapsed, this relationship is more blended with the dominance of temporal information appearing much more critical for spatial information prediction than spatial information being more critical for temporal information prediction. Overall the patterns in information are consistent with linguistic theories.

Additionally, the choice of coding, which includes perspectival (granularity) and text (sequence) information, appears to play a role in demonstrating spatiotemporality in narrative discourses in general. This observation takes us beyond morpho-syntactic, semantic and pragmatic perspectives and conclusions are more guarded. While it could be that text level patterns demonstrated in Section 4.2 are plausibly the result of clause level patterning, which is suggested by the theory and methodology of this dissertation, there seems to be something beyond the clause level that is influencing the patterns.

The results presented in this chapter are a generalization of all of the data. The next chapter addresses the issue of variance per corpora, per narrative, and the influence of implicit spatial information. The question of “spatial richness” will be revisited as well. Based on previous research, there is an expectation that the CRI narratives exhibit more predictable patterns above the general templates just discussed in Figures 6-11, because of the nature of the activities.
narrated. Ultimately, the prediction accuracy of each corpus is roughly similar. However, because of the cognitive theoretical underpinnings of spatial language discussed in Chapter II, it is relevant to engage in this literature deeper to account for differences, no matter how subtle, in individual corpora. Specifically, the theories discussed in Chapter II are shared by environmental criminology, which views crime as a spatial activity. Exploration of the CRI corpus sheds interdisciplinary light on the relationship between cognition, behavior and language as it pertains to narratives of personal experience.
CHAPTER V – RESULTS (VARIANCE)

1. INTRODUCTION TO CHAPTER V. Thus far, it appears that in answering the posed research question of *How does the spatial information of events relate to narrative discourse?* – there are two answers based on level of investigation. First, at the local clause level, spatial information is predictable relative to other spatial information in a distribution that reflects the underlying syntactic form of spatial information in the clause. If temporal information participates in the prediction of spatial information, it is minimal (and vice versa). Second, at the textual level (via sequence), spatial information is predictable relative to other spatial information in a distribution that reflects the underlying semantic function of the discourse. In particular, focus on the deictic and perspectival semantic content of the spatial information. The results presented in Chapter IV indicated, for all corpora combined, that predicting spatial information in narrative discourse relative to other structural elements is possible (based on prediction accuracies and statistically significant performance above baseline) – indicating spatial information’s structural nature – and is best when considering entropy-based distributions of spatiotemporal information.

Statistical correlations were demonstrated between certain elements, which patterned consistently across all discourses relative to text sequence and assumptions about implicit space. This patterning was based on majority-class elements and, while accurate, is somewhat underspecified. By underspecified I mean that of all of the elements originally annotated it is only a relative few, albeit important ones, that participate in general spatiotemporal narrative structure. While these results are for all corpora combined, which normalizes subject matter, length of text and densities of information, this chapter takes a closer look at variation in individual corpora. This chapter also addresses what interdisciplinary insights from
environmental criminology, in addition to those discussed in Chapter II in relation to spatial cognition, may be relevant for deeper questions about the spatial temporal structure of narrative discourses.

This chapter is structured as follows. Section 2 focuses on elements of variation in all corpora as a way to make the general structural insights about space, time, event and rhetorical relations garnered in this dissertation, as solid as possible. Section 3 evaluates the CRI corpora in relative to insights from environmental criminology, which views crime as a spatial activity. In particular, I present the basic concepts in the spatial analysis of crime and apply these concepts to the distribution of spatial information in the CRI corpus.

2. MACHINE LEARNING RESULTS FOR INDIVIDUAL CORPORA. As mentioned in Chapter IV, each corpus individually exhibited similar overall classification trends as compared to all data combined. Tables 25-27 (CNCC, DCP, CRI, respectively) illustrate based on implicit spatial information and text sequence.

<table>
<thead>
<tr>
<th></th>
<th>NB</th>
<th>F-Score</th>
<th>J48</th>
<th>F-Score</th>
<th>K*</th>
<th>F-Score</th>
<th>MC</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure</td>
<td>49.31</td>
<td>.488</td>
<td>72.76</td>
<td>.727</td>
<td>76.08</td>
<td>.760</td>
<td>27</td>
<td>90</td>
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<tr>
<td>Verb</td>
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<td>75</td>
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<td>Preposition</td>
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<td>.469</td>
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<td>74.84</td>
<td>.742</td>
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<td>76</td>
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<tr>
<td>Ground</td>
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<td>.854</td>
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<td>73</td>
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<td>Rhet Arg1</td>
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<td>.582</td>
<td>66.33</td>
<td>.642</td>
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<td>.497</td>
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<tr>
<td>Rhet Arg2</td>
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<td>58.24</td>
<td>.564</td>
<td>45.35</td>
<td>.422</td>
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<td>Rhetorical</td>
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<td>61.29</td>
<td>.573</td>
<td>48.47</td>
<td>.480</td>
<td>42</td>
<td>69</td>
</tr>
</tbody>
</table>

Table 25. Spatial, event and rhetorical feature prediction including tense, aspect, explicit temporal reference and textual sequence, based on explicit and implicit spatial information for the CNCC corpus (n = 875).
In the CNCC corpus, the best Figure classifier performs 49 points above MC (K*). For Verb, the best classifier performs 38 points above MC (K*). For Preposition, the best classifier performs 22 points above MC (K*). For Ground, the best classifier performs 42 points above MC (K*). For Frame, the best classifier performs 36 points above MC (K*). The performance of the best Event classifier performed 17 points above MC (NB). The Rhetorical classifier performs 19 points above MC (J48). For the argument components of the rhetorical relations, the best Arg1 classifier (J48) performed 24 points above MC, the best Arg2 classifier (J48) performed 17 points above MC. These results are statistically significant ($\chi^2 = 233.01$, d.f. = 8, $p \leq .001$). Against Kappa, Verb (+11), Ground (+11) Frame (+9) outperform human judgments. Figure (14), Event (26) and Arg2 (11) perform less well compared to Arg 1 (3), Preposition (2), and Rhetorical Relations (8). Overall, for implicit spatial, temporal, event and rhetorical information with textual sequence, there is a 4 point average difference between classification algorithms and Kappa.

<table>
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<tr>
<th></th>
<th>NB</th>
<th>F-Score</th>
<th>J48</th>
<th>F-Score</th>
<th>K*</th>
<th>F-Score</th>
<th>MC</th>
<th>Kappa</th>
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<tr>
<td>Figure</td>
<td>54.44</td>
<td>.505</td>
<td>61.01</td>
<td>.607</td>
<td>69.73</td>
<td>.695</td>
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<td>90</td>
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<td>.762</td>
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<td>76</td>
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<td>.539</td>
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<td>.468</td>
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<td>69</td>
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</table>

Table 26. Spatial, event and rhetorical feature prediction including tense, aspect, explicit temporal reference and textual sequence, based on explicit and implicit spatial information for the DCP corpus (n = 608).
In the DCP corpus, the best Figure classifier performs 29 points above MC (K*). For Verb, the best classifier performs 26 points above MC (K*). For Preposition, the best classifier performs 10 points above MC (K*). For Ground, the best classifier performs 39 points above MC (K*). For Frame, the best classifier performs 13 points above MC (J48). The performance of the best Event classifier performed 7 points above MC (NB). The Rhetorical classifier performs 14 points above MC (J48). For the argument components of the rhetorical relations, the best Arg1 classifier (J48) performed 21 points above MC, the best Arg2 classifier (J48) performed 10 points above MC. These results are statistically significant ($\chi^2 = 101.41$, d.f. = 8, $p \leq .001$).

Against Kappa, Verb (+1) and Ground (0) perform as well as human judgments. Figure (21), Preposition (19), Event (26) and Arg2 (15) perform less well compared to Frame (8), Arg 1 (5), and Rhetorical Relations (11). Overall, for implicit spatial, temporal, event and rhetorical information with textual sequence, there is only an 11 point average difference between classification algorithms and Kappa, a 7 point increase over the CNCC narratives.

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<th>K*</th>
<th>F-Score</th>
<th>MC</th>
<th>Kappa</th>
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<td>.560</td>
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<td>.864</td>
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<td>76</td>
</tr>
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<td>Ground</td>
<td>60.11</td>
<td>.601</td>
<td>79.05</td>
<td>.790</td>
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<td>.803</td>
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<td>74</td>
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<tr>
<td>Frame</td>
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<td>Rhet Arg1</td>
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<td>70.15</td>
<td>.659</td>
<td>58.80</td>
<td>.565</td>
<td>53</td>
<td>69</td>
</tr>
</tbody>
</table>

**Table 27.** Spatial, event and rhetorical feature prediction including tense, aspect, explicit temporal reference and textual sequence, based on explicit and implicit spatial information for the CRI corpus (n = 1938).
In the CRI corpus, the best Figure classifier performs 37 points above MC (K*). For Verb, the best classifier performs 51 points above MC (K*). For Preposition, the best classifier performs 25 points above MC (K*). For Ground, the best classifier performs 36 points above MC (K*). For Frame, the best classifier performs 37 points above MC (K*). The performance of the best Event classifier performed 14 points above MC (J48). The Rhetorical classifier performs 16 points above MC (J48). For the argument components of the rhetorical relations, the best Arg1 classifier (J48) performed 21 points above MC, the best Arg2 classifier (NB) performed 14 points above MC. These results are statistically significant ($\chi^2 = 207.63$, d.f. = 8, $p \leq .001$).

Against Kappa, Verb (+11), Ground (+6), Frame (+2), Arg 1 (+4) and Rhetorical Relations (+1) outperform human judgments. Figure (10), Preposition (10), Event (27) and Arg2 (2) perform less well. Overall, for implicit spatial, temporal, event and rhetorical information with textual sequence, there is only an 2 point average difference between classification algorithms and human performance, a 2 point decrease over the CNCC narratives and a 9 point decrease over the DCP narratives.

The ranking distributions of prediction accuracies for all three corpora are the same as the general insights from Chapter IV – based on text sequence results, verb, figure, ground, frame and preposition from highest to lowest. Overall, while the DCP narratives perform less well as compared the CRI and CNCC narratives, all of the corpora perform similarly. Further, while the CRI narratives have the best human performance (Kappa), and some of the highest overall accuracies, the CNCC performs similarly, undercutting the markedness, on a linguistic theoretical level, of the CRI narratives.
As summarized in Figure 12, the patterns under discussion are more readily classifiable in the CNCC and CRI narratives, rather than the DCP narratives. There could be several reasons for this; namely that the DCP corpus has more authors, are in a written medium, are spatially more dense, and exhibits less contextual control. Let’s take each one of these reasons in turn. First of all, the CNCC corpus has 8 speakers, the CRI corpus has 6 speakers (cf. Table 3), but the DCP corpus has 22 speakers. The increased individual variation in the DCP narratives could have a normalizing effect on the results and suggests, based on the expanded codings, that there is room for individual author or event variation. However, when looking at the average performance above baseline based on the collapsed codings in Figure 13, the DCP actually outperforms the CNCC and CRI corpus (on spatial information alone): DCP = 16.40; CRI = 14.40; and the CNCC = 13.80. Despite the expanded coding potentially exhibiting author variation, when reduced along inter-rater reliability results, individual author variation becomes normalized.
based on the density of spatial information: DCP = 55.92; CRI = 42.72; and the CNCC = 40.00. The fact that individual corpora perform similarly when considering the collapsed codings indicates the soundness of the theoretical underpinnings in this research. This fact also argues against the written mode of narrative contributing to differences in the underlying patterns.

![Figure 13. Individual corpus performance above baseline based on implicit space and text sequence of the collapsed codings.](image)

Considering again for the moment the expanded codings, the spatial density in the DCP is arguably contributing to its lower performance as well. The suggestions becomes whether or not more explicit space in a given narrative, as a base case, is harder to predict than those narratives with less. Creating the subsequent suggestion that patterns being revealed are more about the implicit, rather than the explicit space. This is a very realistic possibility. Remember, spatial information, despite exhibiting structural patterns as demonstrated here throughout, is optional. This optionality applies not only to whether or not spatial information is included, but also the
type of spatial information (relative to the types of events being described). From an explicit/implicit point of view, explicit information updates the spatial information and implicit information maintains the spatial information. It makes sense that those narratives with a high density of explicit space—i.e., multiple updates of spatial information—are going to be harder to predict based on expanded codings. There is simply a lot of variation that can be exhibited. This is exactly what is seen as depicted in Figure 14.

![Figure 14](image)

**Figure 14.** Individual corpus performance above baseline based on implicit space and text sequence of the expanded codings based on narratives with over and under 44% explicit spatial information.

For narratives with less than 44% explicit spatial information (chosen based on the average density), the average performance is 30% higher (42.20) than for narratives with more than 44%

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[^1]: BA_1, BA_2, DC_1, DC_2, DC_3, DC_4, DC_5, EB_1, JC_1, RHB_2, RHB_3, RHB_5, RHB_7, TF_1, TF_2, TF_3, TF_4, TF_5, 13S_72W, 38S_144E, 51N_46E, DR_2, DR_3, DR_4, PS_1, PS_6, PS_9, PS_12, CS_1, CS_3, KO_1, UC_3, GD_1 (n=33 (narratives)/ 1907 clauses).
explicit spatial information^ (32.60). This indicates that patterns in narratives that exhibit less variation in the spatial information are easier to detect than those narratives that exhibit more variation in the spatial information. Remember, these performances all converge when considering the collapsed codings. What is ultimately being demonstrated is that the extension of explicit spatial information to implicit clauses may provide an “artificial” boost to the accuracies, but the patterns are similar. This insight may help to explain why event information performs so poorly. Event (and Rhetorical Information) is always explicit, compared to spatial information, and very informative. Consequently, patterns are more difficult to detect because event information is constantly being updated. This is simply a fact of English discourse and is similarly found in tense and aspect information as well.

So, as the CNCC narrative may be performing with a high accuracy based on a higher density of implicit spatial information, it is the CRI narratives that have the highest accuracy to spatial density ratio. The CRI does have the smallest number of authors, which could be contributing to the increased numbers, but the number of contexts is different compared to the CNCC and DCP corpora. The CRI narratives are based on guilty pleas (DR_2, DR_3, DR_4, DR_5, DR_7), confession statements (PS_1, PS_2, PS_3, PS_4, PS_5, PS_6, PS_8, PS_9, PS_11, PS_12, PS_13, PS_14, KO_1, GD_1, UC_1, UC_2, UC_3), and interrogation interviews (CS_1, CS_2, CS_3) whereas the CNCC narratives are based on a sociolinguistic interview format and the DCP narratives are based on uniform guidelines. I believe that there is sufficient contextual and author variability to avoid the argument that the good performance of the CRI narratives is based on.

^ BA_3, BD_1, EA_1, RHB_1, RHB_4, RHB_6, 8N_1E, 17N_63W, 17S_12E, 17S_177E, 18N_99E, 19S_29E, 21N_104E, 24N_121E, 34N_74E, 35S_58W, 35S_59W, 35S_60W, 37S_113W, 52N_18E, 53N_2W, 53N_3W, 54N_92E, 63S_61W, 71S_8W, 74N_12W, 74S_12W, 82S_120W, DR_5, DR_&, PS_2, PS_3, PS_4, PS_%, PS_8, PS_11, PS_13, PS_14, CS_2, UC_1, UC_2. (n=42 (narratives)/ 1719 clauses).
on such factors. Further, the CRI narratives are only 2.72% more dense than the CNCC narratives. Therefore, the effect of implicit spatial information is felt in the CRI narratives. What is “marked” about the CRI narratives is that it is not necessarily intuitive that crime is a spatial activity. 12 of the 25 CRI narratives have less than 44% explicit spatial information, but 18 of the CNCC narratives have less than 44% explicit spatial information. The CRI narratives are more constrained in terms of topic, which may be contributing to the slightly increased numbers; an interdisciplinary rationale explored in Section 3.

Focusing more closely on example narratives in the plus or minus 44% density groups, two types of distributions emerge. The low-density narratives conform to what traditional theory has observed – i.e., spatial information occurs closer to the beginning of the narrative (“setting the stage”). Also, spatial information appears to occur towards the end of the narrative chain of events and at the very end of the narrative (c.f. Table 23). Albeit it is true that some clauses were excluded from coding because they were reported speech or an expression of a negative or alternate world, etc., and these led to a decrease in spatial density, this is part of natural variation in discourse. For narratives with high spatial density, the distribution is more homogeneous and does not necessarily conform to insights from previous research – i.e., there is not a strict adherence to providing background information. Rather, there is more focus on the spatial aspects of the narrated activities (c.f. Table 24). Again, as part of the natural variation in discourse, even though the DCP narratives depict activities that are spatial, how these translate into narrative discourses is, not surprisingly, still restricted by linguistic parameters. Further, despite degrees of sparseness, the general patterns observed in Chapter IV, relative to text sequence (as well as the per corpora variance indicated in Tables 5 and 6), are still largely intact.
Remember, the patterns relative to text sequence where based on majority distributions, there can be divergences, for example, a narrative starting with narrative rather than background clauses; it is a probabilistic measure.

Again, for purposes of detecting patterns in spatial information relative to discourse structure, the more naturally high density narratives are harder to predict than lower density narrative. This is due to constantly shifting updates in spatial information. While spatial richness has never been truly operationalized, it seems fair to associate those narratives with a certain threshold percentage of spatial information fall into the “spatially rich” category. This runs parallel to the methodological considerations of implicit space – i.e., the full spatial picture for low and high density narratives, will be different despite both groups exhibiting similar predictable patterns.

From a linguistic standpoint, the type of spatial information that can be included in a narrative potentially varies relative to a number of factors – context, author preference, topics, types of experiences, etc. But what clearly emerges from these results is the following: (1) English narratives of personal experience exhibit a pattern distribution of spatial information that is more informative than uniform distributions; (2) while the expansiveness of the coding allows for more variability in the type of spatial information included, there is ultimately a convergence of information based on Kappa statistics for all corpora; and (3) the idea of a “spatially rich” narrative, as it relates to density of spatial information, patterns no differently than those narratives with lower spatial density – provided the boost from implicit spatial information is corrected for. These observations apply largely to the Labovian model and distributions relative to syntactic insights. These observations apply also to the Herman model, but it is necessary to
engage with the larger spatial cognitive and cognitive semantic insights, if possible, to obtain the full implication of the present research on Herman’s model.

3. INTERDISCIPLINARY INSIGHTS FROM ENVIRONMENTAL CRIMINOLOGY. The theoretical link between general cognitive processes and spatial language – beyond the categorical insights indicated in Chapter II – has not been fully explored in this dissertation up to now. This is largely because it is simply beyond my expertise. However, issues about memory, the ability to recall details and what individual variation along these lines may look like in individual narratives and over time are relevant concerns. As a way to explore these issues more deeply, and in conjunction with observations about the nature of criminal activity and the CRI narratives, interdisciplinary insights from environmental criminology are not only helpful but are akin to the types of questions we might ask about the interface between cognition and linguistic structure.

Environmental criminology seeks to explain criminal behavior relative to an individual criminal’s environment. In this context, space includes not only the physical environment, but how individuals navigate and make decisions based on the environment. For example, one of the earliest environmental criminological studies by Shaw and MacKay (1942) (as cited in Bottoms & Wiles 2002:621-622) drew a correspondence between residences of juvenile offenders and spatially defined municipal zones of Chicago. In particular, cities can be conceptualized as concentric zones: (1) the city central zone contained the business district; (2) the next zone outward is transition zone which were industrial and poorer areas; and then (3) three residential zones which increased in wealth and social status the further away from the city one went. Shaw and MacKay demonstrated that the residences of juvenile delinquents were highest in the
transition zone and decreased the further away from the city center one went. This observation held for other cities and the zones were additionally representative of other social problems.

Environmental criminology has developed and differentiated since the early 1940s and typically focuses on the spatial distribution of either offenders or offences and considers multiple factors (housing markets, economic shifts) and multiple offenses (car theft, juvenile delinquency, vandalism). While individual offences and offenders are a necessary consideration, the end result of environmental criminological studies is often higher-level policy considerations. For example: where are car thefts in a given city; why might they be occurring from a standpoint of environmental criminology; and what can be done, environmentally, to correct the problem (i.e., these are known as meso- and macro-spatial analyses). Some recent approaches have focused more on the generalization about the individual offender (i.e. micro-spatial).

An innovation in micro-spatial environmental criminology came with the development and application of routine activities theory (Cohen & Felson 1979). Routine activities theory addresses deficits in the application of opportunity theory to environmental criminological issues. Opportunity theory views crime as a confluence of target attractiveness, which varies depending on the crime and offender, and accessibility of a given target. While opportunity theory is able to explain criminal behavior to some degree, it does not account for the distribution of victimization (Bottoms & Wiles 2002: 629). As an alternative to opportunity theory, routine activities theory, which focuses on the everyday activities of offenders and includes a defined spatial element, seeks to explain crime as “events which occur at specific locations in space and time, involving specific persons and/or objects” (Cohen & Felson 1979: 589-90). Specifically, whether or not a crime will occur at a given time and space is dependent
on likely offenders, suitable targets, and the absence of capable guardians.

Exploiting the link of the offender and the offense space on the individual level even further is research focused on the space of an offender’s habitual routine activities. Brantingham and Brantingham (1984) argue that all offenders (like all individuals) possess cognitive maps of the environments in which they live, work and interact. There are foci within the environments of the offender, which spatially anchor the routine activities of the offender (e.g., home, work, recreation, shopping). The cognitive map of the offender’s routine activity, which includes just those activity nodes and the pathways between them, is termed an activity space (Brantingham & Brantingham 1984: 349-352). The offender’s activity space is situated within a larger environment. The offender may know extensions of the activity space well and possibly not. The offender may have taken a detour one day to work, or had to travel to a doctor’s appointment in a different or less well known part of the city. However, the offender is certainly aware of other environments, which are extensions of the activity space. The sum of the activity space and these extensions constitute the offender’s awareness space, which is additionally part of the offender’s cognitive map (Brantingham & Brantingham 1984: 352-355).

Opportunities exist across the boundaries of an offender’s awareness space and the intersection of the two increases the likelihood of criminal activity by the offender. Brantingham and Brantingham’s perspective is couched within a larger Crime Pattern Theory which integrates observations in routine activity theory, cognitive maps, activity and awareness spaces into a cohesive framework (Brantingham & Brantingham 1981; 1993a; 1993b). A critical aspect of this framework is an additional theoretical construct termed the crime template defined as “a holistic image with a complex interaction of past and present relationships seen from varying
perspectives …[used in] selecting targets or victims and in deciding to commit the crime at a particular place and time” (Brantingham & Brantingham 1993a: 2). The idea is that, for (serial) criminals, numerous perceptual mechanisms encode environmental properties relative to habit and experience in criminal offending. Over time these patterns cycle and become individually tailored and solidified. As demonstrated above, the cognitive map which emerges through the spatial language in the linguistic narrative, arguably contains evidence for the existence of this criminal template as indicated by the regularity of spatial structure across all offenders and narratives. In as much as we can say that the spatial aspects of narrative depict elements of the offender’s cognitive map, activity and awareness spaces, the victim becomes seamlessly integrated as if the victim is simply an additional feature of the physical environment. For example, based on the general spatiotemporal event profile of narratives, criminal narratives exhibit the following patterns:

- Geographic scale moves from larger to smaller spaces
  - Utah => the truck stop ahead => the counter => my pants
  - => her nose

- Movement of described physical relationships from disconnection to connection
  - A sign saying gas and diesel at the truck stop ahead, There was an older elderly woman at the counter => Got in the car, Then I reached in my shirt

- Shifting of the offender’s physical orientation from simple to complex
  - I shot her in the head => And the blood oozed out the side of her nose.

- Shifting of spatial events from states to general motions to following motions to attachment, detachment or hitting motions
  - there was an older elderly woman at the counter => I walked back in the store => shot her in the body somewhere

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This linguistic observation of the spatial aspects of crime is very different from the visual medium of cognitive maps where victimological characteristics usually appear as points on a map (Canter & Hodge 2000). Linguistic victimological characteristics in crime narratives are indicated by smaller granularities, “following” and “attachment” type verbs, complex frames of reference and general spatial connection to things. In visual media of the cognitive map, the bodies of the victims are not included, the locations of wounds are not included. It is important to note that while the emergence of victimological characteristics may be an artifact of the medium of analysis, which includes temporal and event information in a dynamic framework, the crime template is still cognitively informed on a similar level to spatial cognition: “[t]he process of template construction and the search process may be consciously conducted, or these processes may occur in an unconscious cybernetic fashion so that the individual cannot articulate how they are done” (Brantingham & Brantingham 1981: 29).

Several other aspects of these linguistic observations are additionally supportive and stem from the fact that these narratives are from a point in the offender’s career where the offender has reached some level of experience and proficiency in offending. As Brantingham and Brantingham (1981: 29) indicate, “[o]nce the template is established, it becomes relatively fixed and influences future search behavior, thereby becoming self-reinforcing.” Further, each offender narrative, which are successful crimes, exhibited victim integration and seemingly indicate the aggregate sum of victim selection experience. Again, as indicated by Brantingham and Brantingham (1981:29):
As experiential knowledge grows, an individual who is motivated to commit a crime learns which individual cues, clusters of cues, and sequences of cues are associated with “good” victims or targets. These cues, cue clusters, and cue sequences can be considered a template which is used in victim or target selection. Potential victims or targets are compared to the template and either rejected or accepted depending on the congruences.

What the linguistic elements show in the CRI narratives, as well as general trends discussed in Chapter IV, is that an engagement with the more nuanced elements of spatial information facilitate a broader interdisciplinary engagement where possible. These interdisciplinary insights can be useful for several theoretical and practical purposes. As an example, recognizing that there is a general spatiotemporal template to narrative discourses, which can exhibit degrees of nuance depending on the type of activity being narrated, and coming to an understanding of cognitively informed patterns, can be useful for geographic profiling.

Geographic profiling is a predictive model of serial-crime investigation designed to locate the home of the offender based on the linkage of a number of victims (e.g. Canter and Youngs (2008a, 2008b); and Rossmo (2000). As influenced by Zipf’s Least Effort Principle (1949), the key theoretical construct that underlies geographic profiling is environmental criminology as discussed above – again, based on routine activities theory which assumes that crime is the result of opportunities which are defined as the intersection in time and space of three elements: (1) a motivated offender; (2) a suitable and vulnerable target; and (3) the absence of a capable guardian against crime. Geographic profiling draws a distinction between geographically stable and non-stable offenders (e.g., marauders vs. commuters (Canter & Larkin 1993).

Cognitive mapping research seems to account for the successful implementation of geographic profiling for particularly stable offenders, “[t]he goodness of fit between cognitive
configuration and objective reality increased with length of residence and level of interaction with the areas” (Golledge 1987:132). This suggests that stable offenders have a degree of environmental consistency which may emerge in narrative. Computationally, geographic profiling works well for geographically stable offenders as opposed to non-stable offenders. In theory, there is no reason to assume that the theoretical bases of geographic profiling are inadequate to capture cases of both commuter- and marauder-type serial offenders. Nonetheless, to this end, it has been suggested, by van der Kemp and van Koppen (2007:354), that computational geographic profiling models based on these theories (the most well known of which are CrimeStat (Levine 2000), Rigel (Rossmo 2000) and Dragnet (Canter & Youngs 2008a)), is one potential reason for the low accuracy for commuter offenders. Therefore, it is possibly an issue of theoretical power being lost in application, i.e., by embracing minimal aspects of the underlying theory, computational models of geographic profiling are only capturing the best fit models and ignoring other important theoretical considerations such as the decision processes that underlie criminal routine activity.

Consistent with van der Kemp and van Koppen’s observations, in order to improve geographic profiling, it will be necessary to find a way to build more abstract information about the environmental and decision-making constraints into geographic profiling models – possibly at the expense of minimizing computational assistance (van der Kemp & van Koppen 2007:354-55). The proposed research, while agreed that inclusion of more abstract information will make the process of geographic profiling more difficult, works to provide a specific base of knowledge that can be drawn upon to possibly increase the effectiveness of geographic profiling. That knowledge base is victimology – the focus on victim characteristics as it pertains to the decisions...
of the offender (e.g. Douglas, et. al 1992). As presented here, the linguistic realization of the
spatial characteristics of crime narratives indicates a spatial preoccupation with victim
characteristics in the narrative for all offenders analyzed thus far. Further, victimological data is
already available and considered in geographic profiling when victims are being linked.
Inclusion of this data, as revealed in serial-offender narratives, makes important those victims
that could have been selected but were not (van der Kemp & van Koppen 2007:353). Again,
while this may exponentially increase the geographic area where the offender may reside, it is
only after acknowledging where improvements can be made that we can begin to implement the
changes. The results that emerge from this dissertation will seek to assist in this endeavor.

In terms of the linguistic goals, engaging in an interdisciplinary discussion such as this begins
to shed light on the deeper questions implicated by the results presented in Chapter IV. In
particular, because there is an analytical perspective that seems to privilege the cognitive
semantic structure of narrative discourse. Understanding the cognitive semantic structure, while
be organic to spatial language and Herman’s perspective, ultimately will require robust
engagement with issues such as memory, recall, and the linguistic interface. These issues are
touched on in this dissertation, but much, much more research is required. Again, this
presentation is meant to be an illustration of the types of theoretical and practical
interdisciplinary questions that can be addressed with the research and results presented here.
However, these types of explorations must remain guarded at this point. The reason for this is
that a stronger understanding of the linguistic structure of narrative, and potential forms and
sources of variation, is necessary before getting too far a field.
4. Conclusion to Chapter V. This chapter illustrated that on an individual corpus and narrative level, general patterns demonstrated in Chapter IV are consistent. Further, while each corpus exhibits variability in the expanded codings, arguably relative to the subject matter being narrated, all corpora perform similarly along collapsed inter-rater performances. The variation in predictability among the three corpora is not based on number of authors, context or spatial density – although, those narratives that are less dense, with prediction based on more comparative implicit space, do perform marginally better than higher density narratives, but in similar proportions. On an individual narrative level, whatever distributional patterns characterize a given corpus, those patterns emerge independent of the density of spatial information. However, those narratives with a lower density typically provide spatial details consistent with narrative theory – i.e., setting the stage at the outset of the narrative actions – and wrapping of the narrative actions for the close of the narrative.

Relying on interdisciplinary insights, it is possible to bridge the gap between spatial cognition and the linguistic depiction of space. While there is an observed link between the two based on previous research (cf. Chapter II), it is beyond the scope of this dissertation, and my expertise, to explore this link with any great detail. That said, this chapter presented an interdisciplinary application of this research, which touches on spatial cognition beyond the linguistic realization thereof. In particular, environmental criminology views crime as a spatial activity. Analyzing the distribution of the types of spaces narrated by both serial and non-serial criminals, we can draw parallels between the patterns demonstrated in the linguistic elements and models of criminal behavior. To this end, it was demonstrated that the nature of space involved during the narration of criminal activity is very small, centered on victims, which are integrated into background
space. This helps to make suggestions about practical implementations of environmental criminological theory, and also suggests that there may be some degree in top-down processing when it comes to the experience-based depictions of the physical environment. This is left to future research. The next section will conclude the dissertation.
CONCLUSION

1. RESEARCH QUESTIONS. The goal of this dissertation is to provide a quantified empirical demonstration of the structural nature of spatial information in narrative discourses – standing in answer to the posed research question:

   (1) How does the spatial information of events relate to narrative discourse?

As demonstrated in Chapter IV, based on statistically significant prediction accuracies, spatial information varies relative to multiple linguistics features deemed structural by semantic and pragmatic research in (narrative) discourse structure. Classifiers that exploit the information theoretic distribution of the information perform the best. These results hold for explicitly provided spatial information, and extensions of that information to clauses without spatial information. This extension addresses the issue of spatial information being optional on the linguistic surface – other structural elements of time, event and rhetorical relations are pervasive. These results confirm one of the hypothesis stated in the Introduction:

   (2) Based on the strength of prediction in statistical machine learning classification tasks, spatial information is a structural element of the narrative discourse of personal experience

Further, these insights are generalizable to all analyzed narratives. Specifically, NARRATION and BACKGROUND/ELABORATION rhetorical relations, Aspectual and Stative events, First person figures, Motion and State verbs, Figural and Geographic Granularities, Coordinated frames of reference, Past and Present Tense, Progressive and No Aspect, and Explicit References to Time, are all shown to have correlations in and among themselves relative to the sequential unfolding
of a given narrative discourse. These results confirm the other hypothesis stated in the

Introduction:

(3) Certain types of spatial, temporal, rhetorical and event information conform to a consistent structural profile based on text sequence that is generalizable to all narrative discourses of personal experience

The confirmation of (3) is an unexpected, but exciting result. As mentioned throughout, there was an expectation that there would be some amount of discernible variation between the CRI, DCP and CNCC corpora. As indicated in Chapter V, while there is some specified variation among the different corpora, the generalized results are shown to be not particular to a certain type of narrative discourse, i.e., despite subject matter, number of authors, contextual parameters of production, length of text or density of spatial information.

Chapter V also explored more closely some of the theoretical underpinnings of spatial language based in spatial cognition. In particular, through an exploration of environmental criminology, correspondences between the linguistic variation of the spatial information in criminal narrative discourse and observations in the generalized cognitive behavior of especially serial criminals (i.e., 23 out of the 25 CRI narratives were from serial rather than non-serial criminals). As discussed, from an interdisciplinary standpoint, linguistic insights are potentially useful for criminological research – e.g., revealing the salience of victimological considerations in the spatial aspects of criminal narratives. In sum, the contributions that the present linguistic research makes to the study of environmental criminology are: (a) insofar as the cognitive map is a shared theoretical construct between environmental criminology and the Herman model of narrative structure, the linguistic narrative provides an alternative format of the cognitive map for
analysis; (b) this “alternative format” indicates much of the same type of spatial information that drawn cognitive maps provide, but with more nuance – in particular, the focus on small spaces based on the victim as a narrated environment; (c) narration of smaller victim-based spaces betrays a preoccupation with victims that is accounted for in environmental criminology under victimological studies; and (d) armed with knowledge that victims play a detailed role in the linguistic cognitive map of offenders, a source of information emerges to refine current practical techniques, such as geographical profiling, that rely on environmental criminology as a central tenet.

Overall, the results answer the posed research question in (1) in two ways. First, on the local clause level, spatial information is shown to co-vary with structural elements of narrative discourse and to follow a ranking of prediction accuracies consistent with syntactic insights. However, as the co-variance with certain structural elements falls prey to similar forms of optionality, failing traditional diagnostics, this fuller presentation of space does not necessarily lead to a concrete conclusion as to its structural nature. Consequently, the second way in which the posed research question is answered is by expanding our notion of “structure” by focusing on the textual level, via discourse sequence, where the distributional ranking of spatial information prediction accuracies transforms into cognitive semantic considerations. Here, reliance on deictic shifts, perspectives and shifts between motion and stasis is shown to be consistent and generalizable to all analyzed narratives. Section 2 returns these results to the frameworks of Labov and Herman for a fuller explanation of these results, bringing the dissertation full circle. A discussion of limitations will be folded into the following discussion.
2. IMPACT OF RESULTS ON LABOV AND HERMAN NARRATIVE FRAMEWORKS. The results of the 
machine learning experiments and associated interpretation (Chapter IV) and the indication that 
these results are indeed generalizable to the data under analysis independent of authorship, 
context, or effects from explicit space (Chapter V) provide a fuller and more nuanced picture of 
the frameworks of both Labov and Herman. In terms of the Labovian framework, spatial 
information is predicted to occur in Orientation and Coda clauses, but, certainly in more 
complex narratives, it can occur virtually anywhere throughout the narrative. As mentioned in 
Chapter IV, two distributions of the occurrence of spatial information were observed in the data. 
One distribution has spatial information occurring toward the beginning in clauses where the 
BACKGROUND and NARRATION relation holds and again toward the end of the narrative chain of 
events – providing a reorientation (Coda) of sorts (although, very few RESULT relations were 
oberved for the Labovian Resolution. The other distribution has spatial information occurring 
homogenously throughout the narrative. Both distributions are consistent with observations from 
Labov and follow from the core syntactic character of English, spatial expressions in English, 
and narrative syntax. However, focus on simply the distributions of spatial information 
occurrence only speaks to the local and textual form of the narratives and not the function of 
narratives.

The occurrence of spatial information does not appear to follow any particular pattern in 
regard to the function of the Labovian narrative beyond providing basic spatial reference. The 
occurrence of spatial information was most often seen in clauses where NARRATION relation held, 
not in the BACKGROUND or ELABORATION clauses. Given that the type of spatial information 
contributed to the determination of a given relation (as indicated by prediction accuracies in the
machine learning experiments), but this is not *function* in the Labovian sense. Further, spatial information still does not appear to be critical for what is considered to be structural – i.e., surviving diagnostics based on surface forms. Spatial information, when available, does co-vary with other types of spatial information and information taken to be structural, which is telling and suggestive of spatial information being a structural element. However, Labov really only facilitates a syntactic investigation of spatial information and as such, the ability to argue for the structural nature of space is limited to demonstrating correspondences with other structural elements.

Ultimately, from a Labovian perspective, the framework is not explanatorily adequate to cast spatial information as a structural element of narrative discourses of personal experiences. This observation holds in regard to the semantic function of spatial information, as revealed in the sequence based results. While there is some link between contours of certain spatial information – in particular, granularity (contour of information specificity that unfolds as the discourse progresses) – that is akin to Labov and Waletzky (1997[1967]) and Labov (1972) in terms of “where” elements occur in a prototypical narrative based on displacement of clause types, interpretation of the semantic function relative to existing frameworks requires reliance on Herman’s insights. The reason for this is that the underlying theories in the categorization and function of spatial information, beyond the syntactically-based surface realizations, are irrevocably linked to cognitive insights – the same insights relied on by Herman (2001).

As indicated in the implicit space- and sequenced-based results, the ranking of the prediction accuracies for spatial information shift from syntactic interpretations (verb (V) => preposition, ground (PP to V) => figure (DP to V) => frame) to (cognitive) semantic interpretations (verb
(motion vs. stasis) => figure (deictic) => ground (granularity/ scale) => frame (perspective/ complexity) => preposition (motion vs. stasis)). Interpretation of narrative as a grouping of spatial shifts and categorization of events in location relative to a given physical perspective is a different notion of “structure” as compared to syntactically-based linguistic surface forms. Under an expanded notion of structure, linked here by Herman to general spatial cognitive and the organization of spatial knowledge, the distribution spatial information appears to participate in robust ways. While it may seem that this is somewhat of an empty statement – i.e., that there are structural patterns of spatial information in spatial information – remember, it could have been the case that no (statistically) meaningful correspondences would have emerged. Further, the patterns in the semantic function emerged as a generalizable pattern such that, it is not only that there are shifts in groupings of the location of events, narrators and motion and states, but that these shifts happen in particular ways relative to the location of the linguistic utterance in discourse (Figures 6-11).

Of course, the fact that from a cognitive perspective, space patterns in very particular ways, implicates several deeper questions. In particular, the results here indicate that depending on the analytical perspective taken on the encoding of surface linguistic forms, two different but compatible perspectives can emerge, which expands our perspective on experiential discourses. This analysis is certainly facilitated by the fact that spatial information has a close link with cognitive insights (cognitive maps, etc.) and it remains to be seen how cognitive insights would be measured in non-experiential discourses and in circumstances where spatial information is not available. This forces an engagement with an expanded notion of “structure” that is different from linguistic surface forms, but at least touch on the interface between experiential processing,
memory, recall and retelling in a linguistic product. Further, to understand these relationships more completely, it will be necessary to engage in more contextual and pragmatic parameters. The results here appear to be immune from certain external contextual influences, but the results do not indicate anything about internal contextual influences (e.g., general pragmatic settings in interaction or writing.)

Engagement with these interactions is superficially presented here in the discussion of environmental criminology. However, based on the present research, it is not possible to come anywhere near teasing apart all of the issues lurking in the interface between general cognition in discourse. Consequently, the tenuous contributions of the present research to environmental criminology outweigh anything more substantive to say about the relationships between multiple interfaces. However, it would have been beyond the scope of the dissertation to attempt a more in depth cognitive psychological investigation.

Despite these limitations, the results do appear to be generalizable. Of course, more data is always needed to confirm, deny or reformulate this moving forward. Note that the results should be generalizable beyond English as well. The original figure and ground research by Talmy was a cross-linguistic exploration indicating the cognitive primacy of this spatial construction. Cross-linguistic differences typically focus on this relationship being created either by the verb or the preposition, but the relationship is generally same semantically from language to language (Talmy 2000). Frame of reference research is largely cross-linguistic as evidenced by Levinson’s research (Levinson 1996). Cross-linguistic narrative research indicates that similar elements, e.g. events and temporal considerations, are present in languages other than English (e.g., Berman & Slobin 1994). Because of the underlying theories, it is expected that the insights presented in this
dissertation would hold for other languages as well. The only caveat being that the linguistic form of the elements may be different and different pragmatic settings may be employ, either of which would lead to an altered distribution of coded elements – potentially different from English. However, again, I would expect the prediction accuracies to be similar.

Future linguistic research will focus on the role of spatial information in different types of discourses; in particular, non-experience based (e.g., letters, summaries, news texts, etc.). While the results here suggest that spatial information is more pervasive and structurally relevant than previously accounted for, it is not known how this will manifest itself in other discourse structures and genres. Further, research will focus on leveraging assumptions about the overarching structure of discourse to resolve certain types of information at the clause level. For example, since the sequence-based template is shown to be consistent across different narrative discourses, it will be interesting to see if knowing this information up front when computationally processing new discourses improves the ability to analyze and reason with them. Lastly, the annotation scheme used in this dissertation, while being used primarily for representation in the presented analysis, can also be used for robust semantic reasoning and different types of discourse analysis (e.g., agency and event). This dissertation provides a deep representation of the spatial aspects of narratives which provide a more complete understanding of the theoretical primitives of experiential discourses and indicate that information theoretic approaches to discourse analysis and processing are a fruitful area of research expansion.
APPENDIX I – SAMPLE DATA

This appendix provides several sample texts. Two texts from each corpus were selected; one with a spatial density over 44% and one under 44%: TF_1 (under) and RHB_6 (over) from the ANC corpus; DR_4 (under) and PS_3 (over) from the CRI corpus; and 13S_72W (under) and 52N_18E (over) from the DCP corpus.

Sample Text 1: DCP_52N_18E

03-Jan-2009 -- Polski -- After snowless and rainy Christmas it started snowing on New Year’s Day and on Saturday, January 3rd we finally had true winter weather – snow, sunny and light frost. It would be a sin to waste such a beautiful day so I departed from Poznań at 9 AM and headed towards the sun (i.e. to the east) to open a new season of confluence “hunting”. Via Września I came to Borzykowo – a little village near Pyzdry, In Pyzdry I crossed the Warta River and I drove south to Gizalki and then headed east. In Królików I turned to the south again and on local roads via Łądek and Zaguźnica. I came to Stara Ciświca. I parked the car near the first buildings of the village and off I went. The confluence point was ca. 1.2 km away and the weather was still perfect – sunny, thin layer of snow and temperature about -6 °C. During my first visit I approached the point from the east so this time I went more to the west. Firstly I followed a forest road, then a path and finally I made my way directly through a dense thicket of trees. This route was much less comfortable that the one we went four years ago. I could see animal tracks in the snow and in shrubbery I came across a dead roe deer. At the confluence I managed to get a 5 m accuracy and localized the point a bit further to the east than the last time, among snow-covered pines. After taking pictures I retreated to a nearby glade where I had my déjeuner sur la neige (breakfast on the snow). I returned to the car by the other way, following
dirt roads between snowy fields. Nothing remained of the picturesque ruin of an old cottage (depicted on the photographs from previous visits) – it must have collapsed in the meantime. On the way home I stopped in Łódź on the Warta River to take pictures of the Cistercian monastery and ice floes floating down the river. The weather suddenly changed, it started snowing and the wind increased in strength. On A2 motorway to Poznań we had almost a blizzard.

Sample Text 2: DCP_13S_72W
25-Aug-2007 -- I left Cusco around 9h00 and grabbed the first taxi that passed by. He agreed to take me to Paucarpate for a reasonable price of 160 Soles (about 40 US$. But I think afterwards he really regretted meeting me that morning -. It took us about 1 hour to get to Calca and from there on, the route went bad and dusty for the next 3 hours. The little taxi just barely got over the pass of 14,764 ft. On the way you pass Indian communities who listen to the name of Huaytanchoque, Huancarcocha, Anparaes and some thermal baths close to Calca. But finely after a bumpy road and 1 kilo of dust in our lungs we arrived safe and sane in the little village of Paucarpate. I immediately asked if someone knew the mountains at the other side of the road and Federico kindly offered his service to guide me to whatever I was searching for. I left the taxi driver (without paying, otherwise he certainly would have taken off) and told him that I would be back in 2 hours. I had to be back around 15h00 to make sure we could arrive in Cusco again before nightfall. I knew the heading of the confluence-point but distances are very hard to estimate so we just went up the other side of the hill until around 10,827 ft to close in horizontally. On the way I explained to Freddy about the project of confluences and the more I told him about it the more he got involved and started asking me every 15 min. at what distance
we were. At 14h00, the hour to get back we were at 328 ft and I was devastated, tired and done. I was going to give up but then I realized I infected Freddy with the “confluence”-virus so badly that he started to convince me to get on going. I realized he was right, I got this far and 328 ft really would be nothing. So I finally got a confluence-point on my name that had never been visited before at all, thanks to Freddy. The way back was much easier, we found a small river and just kept on following it back to civilization and crossed a beautiful waterfall on the way down. Finally we arrived at 16h00 back in Pauccarpate. I paid Federico and said goodbye to his family promising to send their picture once back at home in Venezuela. On the way back the taxi driver told me everybody in the town was asking what I was searching for and they were convinced that I was on a quest for gold. I really enjoyed this discovery and got back in Cusco all enthusiastic about the trip. If you want to do this trip all over again I suggest you do it in 2 or 3 days and you can even pass by Lares on the way back. And do me a favor, ask for Federico Valdez Volker to be your guide, you might find the pot of gold.

Sample Text 3: ANC_RHB_6

That was when we first moved here to NC we uh, had a job across the street from where we build him a house uh, Truman house. And uh, we were borrowing a guy's saw, chop saw, miter saw and um, I upstairs nailing down trim and I hear the saw every once in a while so I know he's down there working and all of a sudden don't hear the saw and I run out of new trim. “Are you down there?” I look nobody is standing at the saw. I look around well he was right here. I see a few drops of blood on the floor. I look out the window and there he's booking across the yard heading for the house. I get over to the house. He said that saw drifted down and hit him right
across the back of his thumb. Yeah so he's kind of standing there at the kitchen sink and my mom's running around like a chicken with her head cut off. “Need a Band-Aid, need some gauze, need some tape.” Well she can't find any of it. My mom's not real organized when it comes to things like that. Band-Aids are at the kitchen sink, the peroxide is in the basement you know, the gauze is in the bathroom and the tape for that is upstairs. Oh lord, she's running around carrying on well, Dad makes the mistake of looking at his wound and his knees go out from under him. He buckles down onto the floor. I think uh-oh 200 pounds of mush going to be laying on the floor, I'll never get him up you know. So we quick think and I go, well grab a paper towel and wet it and throw a couple of ice cubes in and put it on his hand, get him up to his feet and haul him off to the emergency room. Well meantime my Mom is running around she doesn't hardly know that we left. She's still looking for Band-Aids. Take him to the First Med Place. They stitch him up good went back to work later that afternoon. He's a trooper that way he, that doesn't make any difference as far as him being hurt he'll work. He'll work it off.

**Sample Text 4: ANC_TF_1**

I remember, some of my friends, I remember one time when I went to lunch, and I always had this Pac Man lunchbox, pull out this Pac Man lunchbox, and I would, that I was so proud of, and, you know, do my thing, and I would be talking so much and laughing about the stupidest things that I wouldn't even, I wouldn't even eat my lunch. I would just laugh the whole time, and one time I did it so much that I never even opened my lunch out of the bag, and it was like a minute before, a minute before lunch was over and the teacher, the P.E. teacher came up to me, and he said, “Look, this is horrible, Thomas. This is just,” you know, “Look you're in trouble. You're
not eating your lunch,” come with him, so I went, he, I had to follow him and remember being really nervous and he sat me down a corner and he told me I had to sit there until I ate all my lunch, and I remember, um, crying for a long time and I think that basically what happened there was that was just an amazing mood swing because I went from being extremely happy, and I was extremely sad. It was an amazing mood swing. I think that's why I remember that.

Sample Text 5: CRI_PS_3

The next one I did was X X. I then owned a Red Corsair and also a White Corsair KWT 721D the reg No of the Red one was PHE 355G. I had both of these at the same time and I honestly cannot remember which one I was using that night. I drove to Leeds after the pubs shut. It was my intention to find a prostitute to make it one more less. I saw this girl walking in some cross streets in the middle of the vice estate near a big club. I stopped my car and she got in without me saying a word. I told her I might not have wanted her, she said “I'LL SHOW YOU A GOOD TIME. YOU ARE NOT GOING TO SEND ME AWAY ARE YOU.” She told me to drive to the park. At this time you knew where I was picking them up. She told me where to drive and we came to this big field which was on my left. I drove off the road onto the field and stopped near some toilets. She wanted to use the toilets so she got out and went over to them. She came back and said they were locked. Before she went to the toilet she took of her coat and placed it on the ground. When she came back she said she would have a wee on the ground. She took her boots off and placed them on the ground then she crouched down to have a pee. By this time I was out of the car and I had my hammer in my hand. As she was crouching down I hit her on the head from behind at least twice maybe three times she fell down. I then lifted up her cloths and
slashed her in the lower abdomen and also slashed her throat. I left her lying face down and I
covered her up with her coat I put her knee boots on top of her before I covered her up. I then got
into my car and drove off the field. I cannot remember whether I drove off or backed off. When
I got to the road I saw a couple sitting on a bench near the toilets. I did not see a car. I was living
with my wife at 6 Garden Lane, Heaton I drove straight home. I looked at my cloths before I
went in I did not see any blood stains I was wearing jeans and I believe I had some boots on. I
don't remember throwing any of my cloths away. I kept the Stanley knife but I haven't seen it for
a long time I think I may have lent it to someone. I'm still not sure which car I was in the Red or
White Corsair. I sold the white Corsair first to a lad called Y Y who lives at 46 Tanton Crescent,
Clayton. He only had it about a week and he seized it up. I kept the Red one for several months. I
bought the White Corsair back off Y after about two weeks and sold it at Canal Road Scrap Yard
at Bradford.

Sample Text 6: CRI_DR_4

X was another one of the projects. Uh when I was uh trolling the area I noticed her go in the
house one night. Sometimes I would and anyway, I put her down as potential victim uh. Uh at
first uh she was-uh spotted, and then I did a little homework. I dropped by once to check the
mailbox to see what her name was, uh found out where she worked, uh stopped by there once at
Helzberg, kind of sized her up, I had- the more I knew about a person the- the more I felt
comfortable with it, so I did that a couple of times, and then I just selected a night, which was
this particular night, to try it, and it worked out. About two or three blocks away I parked my car
and walked to that residence. I knocked at the knocked at the door first to make sure, see if
anybody was in there cause I knew she arrived home at a particular time from where she worked. Uh nobody answered the door, so I went around to the back of the house, cut the phone lines. I could tell that there wasn't anybody in the uh north apartment. Uh broke in and waited for her to come home in the kitchen. I confronted her, uh told her there I was a I had a problem, sexual problem, that I would have to tie her up and have sex with her. Uh she was a little upset. We talked for a while, uh she smoked a cigarette. Uh while the while we smoked a cigarette I went through her purse, uh identifying some stuff, and she finally said, “uh well, let's get this over with so I can go call the police.” I said, “Okay,” and she said, “Can I go to the bathroom?” I said, “Yes.” Uh she went to the bathroom and came and I told her when she came out to make sure that she was undressed. And uh when she came out I uh handcuffed her and uh don't really remember whether I Well, anyway, I had her I handcuffed her, had her lay on the bed, and then I tied her feet, and uh then I- I- I was also undressed to a certain degree, and then I got on top of her, and then I reached over, took either- either- either her feet were tied or not tied, but anyway, I took- I think I had a belt. I took the belt and then strangled her with the belt at that time. Okay, uh after I strangled her with the belt I took the belt off and retied that with pantyhose real tight, Uh removed the handcuffs and uh tied those with uh with pantyhose. Can't remember the colors right now. Uh I think I maybe retied her feet, if they hadn't already they were probably already tied, her feet were, uh and then at that time uh- uh- masturbated, sir. No, No, no. I told her I was, but I did not. Uh- dressed and then went through the house, and took some of her personal items, and kind of cleaned the house up, went through and made checked everything and then uh left.
APPENDIX II – ANNOTATION GUIDELINES

This appendix includes the guidelines that were developed and followed for this dissertation. Each of 75 narratives were annotated pursuant to these guidelines. The guidelines are presented in such a way as to mirror the annotation process (i.e., Step 1, do X; Step 2, do Y; etc.). These guidelines should be considered in tandem with the DTD presented in Table 5 (Chapter III) and the discussion of XML in general (Chapter II, Section 4.5; and Chapter III, Section 3.1). For purposes of illustration, I also provide the full XML annotation of DCP_52N_18E. In the interest of not adding several hundred pages to this dissertation, I only provide this one sample XML coding. Full data with annotation will be made available at a future date.

Annotation Guidelines

1. Once a narrative discourse is identified (see generally Chapter I for how this determination was made), it is surrounded by the <DISCOURSE> tag with an obligatory “id” attribute indicate the unique identifier for the text being analyzed.

2. The text within the <DISCOURSE> tag is then segmented into independent clauses (see Chapter III, Section 2). Each independent clause is surrounded by the <CLAUSE> tag with an obligatory “id” attribute – CLx, where x is the sequence number of the clause. The <CLAUSE> tag also includes the type of rhetorical relation (“RHETtype”) represented by the independent clause relative to the clause before. For the first independent clause in a text, the value of the rhetorical relation is “0”. Whether or not the <CLAUSE> tag contains coded spatial information is also indicated (“s_status”). The
<CLAUSE> tag either does ("S") or does not ("NS") contain spatial information – specifically, a physical figure and ground relationship.

3. Each <CLAUSE> tag also receives a <VERB> tag that surrounds linguistic verb information and includes an obligatory unique identifier Vx where "V" indicates that a verb is being identified and x indicates the sequence number of the verb. The <VERB> tag also includes a “type” attribute where the value of the verb is encoded; an “event” attribute where the type of event is encoded; a “tense” attribute where the type of tense is encoded; and an “aspect” attribute where the type of aspect is encoded. In the event that the clause is not a spatial clause, then the type is “NS”.

4. For those clauses that contain spatial information, the following four types of information are tagged in addition to the <VERB> tag:

   a. The <FIGURE> tag surrounds linguistic figure information and includes an obligatory unique identifier Fxy where “F” indicates that a figure is being identified, x indicates a particular entity that may reappear again in the text, and y indicates the sequence number of the entity. For example, if the narrator mentions himself in a spatial relationships – I was in front of the car – the identifier for I would be FA1. Subsequent mentions of I would be labeled FA2, FA3, etc. When a new entity is mentioned – She was sitting on the bench – the identifier for she would be FB1 (with subsequent mentions being FB2, FB3, etc.). In addition to
the unique identifier, the <FIGURE> tag includes a “type” attribute where the value of the figure is encoded.

b. The <FRAME> tag surrounds the <PREPOSITION> and <GROUND> tags and includes an obligatory unique identifier FRx where “FR” indicates that a frame of reference is being identified and x indicates the sequence number of the frame of reference. The <FRAME> tag also includes a “type” attribute where the value of the frame is encoded.

i. The <PREPOSITION> tag surrounds linguistic preposition information and includes an obligatory unique identifier Px where “P” indicates that a preposition is being identified and x indicates the sequence number of the preposition. The <PREPOSITION> tag also includes a “type” attribute where the value of the preposition is encoded.

ii. The <GROUND> tag surrounds linguistic ground information and includes an obligatory unique identifier Gxy where “G” indicates that a ground is being identified, x indicates a particular ground that may reappear again in the text, and y indicates the sequence number of the entity. The <GROUND> tag also includes a “type” attribute where the value of the ground is encoded.
5. Lastly, the <TIME> tag, if applicable, surrounds explicit reference to time and includes an obligatory unique identifier Tx where “T” indicates that explicit temporal reference is being identified and x indicates the sequence number of the explicit temporal reference. The <TIME> tag also includes a “type” attribute where the value of the preposition is encoded. There can be multiple <TIME> tags within a <CLAUSE> tag.

6. There are several additional considerations for annotation:

   a. For complex grounds (i.e., multiple prepositional phrases), only the top preposition in the tree is coded. For example, in a clause such as I arrived at highway 35 just north of the 44 interchange via Apple Valley, the entire ground is highway 35 just north of the 44 interchange via Apple Valley. However, only highway 35 is encoded. Similarly, as only the primary figure and ground relationship in a given spatial clause is coded, information in dependent clauses are either ignored (if they are not spatial) or added to the complex ground. Adding to the complex ground does not change the encoding of the top node.

   b. Particle constructions were broken up into respective verb and prepositions tags – e.g., I ran up the street = <FIGURE>I</FIGURE> <VERB>ran</VERB> <FRAME> <PREPOSITION>up</PREPOSITION><GROUND>the street</GROUND></FRAME> rather than up be a part of the <VERB> tag and the <PREPOSITION> being null.
c. For those clauses with missing information, a number of default heuristics and values are used

i. For missing event, tense, aspect, figure, verb and preposition information, the previous clause’s type is used or is otherwise resolved from the context;

1. For example, I drove on Highway 35, then County 43. Then County 43 is treated as a separate independent clause. The figure would be “I”, the verb would be “drove”, the preposition would be “on”.

ii. For missing ground information, the type is “VISTA”;

iii. For missing frame information, the type is “NL”;

iv. When extending spatial information to non-spatial clauses, if the first clause of a text is non-spatial, the default values “1, S, NL, P, VISTA” (for figure, verb, frame, preposition and ground, respectively) are used.

Annotation of DCP_52N_18E

<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE DISCOURSE SYSTEM "file:/Users/Marked_Up Dissertation Data/Dissertation_Spatial_Mark_Up(v1.0).dtd">

<DISCOURSE id="DCP_52N_18E">

<CLAUSE id="CL1" s_status="NS" RHEType="0">After snowless and rainy <TIME id="1" type="DATE">Christmas</TIME> it started snowing on <TIME id="2" type="DATE">New Year’s Day</TIME> and on <TIME id="3" type="DATE">Saturday, January 3rd</TIME> we finally <VERB id="V1" type="NS" event="S" tense="T" aspect="N">had</VERB> true winter weather – snow, sunny and light frost.</CLAUSE>

<CLAUSE id="CL2" s_status="NS" RHEType="ELAB">It <VERB ID="V2" type="NS" event="IA" tense="F" aspect="N">would be</VERB> a sin to waste such a beautiful day.</CLAUSE>

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and <FIGURE id="FA2" type="1">0</FIGURE><VERB id="FA2" type="1">headed</VERB> <FRAME id="FR2" type="ABS"><PREP id="P2" type="FO">towards</PREP> <GROUND id="GA1">the sun (i.e. to the east)</GROUND> <FRAME> to open a new season of confluence “hunting”.</FRAME>

<CLAUSE id="CL6" s_status="S" RHETtype="NAR"><FIGURE id="FA4" type="1">I</FIGURE> <VERB id="V4" type="MOTION" event="AC" tense="T" aspect="N">headed</VERB> <FRAME id="FR4" type="INT"><PREP id="P4" type="0">0</PREP> <GROUND id="GD1">the Warta River in Pyzdry</GROUND> <FRAME><CLAUSE>

<CLAUSE id="CL7" s_status="S" RHETtype="NAR"> and <FIGURE id="FA5" type="1">I</FIGURE> <VERB id="V5" type="MOTION" event="AT" tense="T" aspect="N">came</VERB> <FRAME id="FR5" type="ABS"><PREP id="P5" type="0">0</PREP> <GROUND id="GE1">south to Gizalki</GROUND> <FRAME><CLAUSE>

<CLAUSE id="CL8" s_status="S" RHETtype="NAR"> and then <FIGURE id="FA6" type="1">0</FIGURE><VERB id="V6" type="MOTION" event="AC" tense="T" aspect="N">headed</VERB> <FRAME id="FR6" type="ABS"><PREP id="P6" type="0">0</PREP> <GROUND id="GF1">east</GROUND> <FRAME><CLAUSE>

<CLAUSE id="CL9" s_status="S" RHETtype="NAR"> <FIGURE id="FA7" type="1">I</FIGURE> <VERB id="V7" type="MOTION" event="AC" tense="T" aspect="N">turned</VERB> <FRAME id="FR7" type="ABS"><PREP id="P7" type="FC">to</PREP> <GROUND id="GG1">the south again in Krolıkow</GROUND> <FRAME><CLAUSE>

<CLAUSE id="CL10" s_status="S" RHETtype="NAR"> and <FIGURE id="FA8" type="1">I</FIGURE> <VERB id="V8" type="MOTION" event="AT" tense="T" aspect="N">came</VERB> <FRAME id="FR8" type="INT"><PREP id="P8" type="FC">to</PREP> <GROUND id="GH1">Stara Ciswica on local roads via Ladek and Zaguznica</GROUND> <FRAME><CLAUSE>

<CLAUSE id="CL11" s_status="S" RHETtype="NAR"> I <VERB id="V11" type="MOTION" event="AT" tense="T" aspect="N">parked</VERB> <FRAME id="FR9" type="INT"><PREP id="P9" type="PO">near</PREP> <GROUND id="GI1">the first buildings of the village</GROUND> <FRAME><CLAUSE>
During my first visit a path was made along the western edge which was still perfect – sunny, thin layer of snow and temperature about -6 °C. The experience was of a dense thicket of trees. The weather was dry and warm but the path was rough.

My second visit was much more to my way. The path was much better, though still a dense thicket of trees. After a 1.2 km, the path began to reduce in width and become more rutted. The weather was sunny, thin layer of snow and temperature about -6 °C.

The path was much better, though still a dense thicket of trees. After a 1.2 km, the path began to reduce in width and become more rutted. The weather was sunny, thin layer of snow and temperature about -6 °C. A dead roe was seen in the road.

This route was much more comfortable than the one we went four years ago. It could be followed during the winter as the footpath was clearly visible through the snow and in shrubbery. A dead roe was seen in the road.

The path was much better, though still a dense thicket of trees. After a 1.2 km, the path began to reduce in width and become more rutted. The weather was sunny, thin layer of snow and temperature about -6 °C. A dead roe was seen in the road.
At the confluence I managed to get a 5 m accuracy.

A bit further to the east than the last time, snow-covered pines along the Warta River.

After taking pictures and retracted in the meantime.

Nothing remained of the picturesque ruin of an old cottage (depicted on the photographs from previous visits).

The car by the other way.

dirt roads between snowy fields.

Lad on the Warta River to take pictures of the Cistercian monastery and ice floes floating down the river.

The weather suddenly changed.

and the wind in strength.

A motorway to Poznan we a blizzard.
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