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Leveraging Pragmatic Features for Microblogged Information Extraction During Crises

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Leveraging Pragmatic Features for Microblogged
Information Extraction During Crises

by

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B.A., Rhodes College, 2006

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A thesis submitted to the
Faculty of the Graduate School of the
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of the requirements for the degree of
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Leveraging Pragmatic Features for Microblogged Information Extraction During Crises
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The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.
Corvey, William John (Ph.D., Linguistics and Cognitive Science)

Leveraging Pragmatic Features for Microblogged Information Extraction During Crises

Thesis directed by Dr. Martha Palmer

Previous research in natural language processing in support of information extraction for Crisis Informatics has exploited a variety of linguistic features for the semantic characterization of Twitter communications produced during hazard situations. Project EPIC (Empowering the Public with Information in Crisis)\(^1\) studies have pursued the annotation and extraction of named entities (Corvey et. al. 2012; Verma et. al. 2011), semantic roles (Corvey et. al. 2012), and the tweet-level attributes of linguistic register, subjectivity, and personal or impersonal style (Verma et. al. 2011; Corvey et. al. 2012). The latter, high-level linguistic features have been applied in the classification of a key behavioral attribute, Situational Awareness (Verma et. al. 2011; Corvey et al. 2012). However, pragmatic features pertaining to a user’s perceived confidence in and ownership of the hazard information presented on Twitter have yet to be explored. I propose an information extraction system targeting key pragmatic features, centered around the concepts of linguistic Evidentiality (Aikhenvald 2004; Fox 2001; Chafe 1986), Territory of Information (Kamio 1997), and Speech Act Theory (Austin 1962; Searle 1969, 1976, 1979). The system aims to improve information retrieval through refining the characterization of a tweet’s relevance to Situational Awareness. This thesis discusses theoretical motivations and background; presents the results of a series of experiments testing the utility of the pragmatic annotations proposed; and engages key theoretical questions motivated by these experimental results.

\(^1\) An interdisciplinary research effort funded by the National Science Foundation and housed in the Department of Computer Science, University of Colorado at Boulder (http://epic.cs.colorado.edu/)
Dedication

To my family, for more love, support, and encouragement than anyone could ask for.
Acknowledgements

I would first like to acknowledge the support that my advisor, Dr. Martha Palmer, has given throughout my graduate career. Martha is a wonderful mentor to her students and her guidance and expertise have been invaluable throughout my time at Colorado and in the preparation of this thesis. I am incredibly grateful to have had Martha as a supervisor during my Masters and PhD programs at Colorado and to have had the opportunity to collaborate on research. Her expertise, leadership, and the genuine concern she shows for all her students have been a blessing.

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Chapter 1

Introduction

1.1 Motivation

The field of crisis informatics (Hagar & Haythornthwaite, 2005; Palen, et al. 2009) is dedicated to the study of information exchange between formal and informal entities during times of disaster. Palen and colleagues associated with Project EPIC (Empowering the Public with Information in Crisis)\(^1\) conduct research at the intersection of crisis informatics and social media analysis, particularly for the Twitter platform. In a 2010 paper entitled “A vision for technology-mediated support for public participation and assistance in mass emergencies and disasters,” the authors motivate an information extraction task targeting social media during times of crisis with the following question:

“How can publicly-available, grassroots, peer-generated information be deemed to be trustworthy, secure and accurate, so that it can be leveraged and aligned with official information sources for optimal, local decision-making by members of the public?” (Palen et. al. 2010: 2)

Work towards answering this question has produced several natural language processing (NLP) components of the Project EPIC software infrastructure, which have exploited a variety of linguistic features for the semantic characterization of Twitter communications produced during hazard situations. EPIC studies have pursued the annotation and extraction of named entities (Corvey et. al. 2012, Verma et. al. 2011, Corvey et. al. 2009), and semantic roles (Corvey et. al. 2012), as well

\(^1\) An interdisciplinary research effort funded by the National Science Foundation and housed in the Department of Computer Science, University of Colorado at Boulder (http://epic.cs.colorado.edu/)
as linguistic register, subjectivity, and personal or impersonal style (Verma et. al. 2011; Corvey et. al. 2012). The latter, high-level linguistic features have been applied to the classification of a behavioral attribute, situational awareness (SA), defined as “an understanding of a situation as a whole” and “a complex process that requires the perception and comprehension of what is happening in one’s environment” (Corvey et. al. 2012; following Endsley, 1995, Endsley and Garland, 2000). Vieweg (2012) elaborates on the characteristics of situational awareness and its significance in crisis response. Foremost, situational awareness is a state that actors achieve through interfacing with the physical and social environments (1-3). Past research in crisis informatics demonstrates that members of the public utilize Twitter in times of crisis in order to author and propagate information that may contribute to situational awareness (Vieweg et. al. 2010, cited in Vieweg 2012: 4). Tweets that may be potentially relevant to situational awareness provide information contributing to a holistic understanding of the crisis scenario. By necessity, such information is disaster-specific and actionable.

For tweets that are potentially relevant to Situational Awareness, Vieweg (2012) has proposed a taxonomy of crisis-relevant information categories (ICs). Vieweg organizes these categories taxonomically under three high-level nodes: the Social, Built, and Physical environments. The complete taxonomy is included as Appendix A. Sample tweets for several of the information categories included in the taxonomy are shown in Table 1.1.²

² All examples taken from Vieweg (2012).
<table>
<thead>
<tr>
<th>Macro-category</th>
<th>Information Category</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social</td>
<td>Status - Personal</td>
<td>“I’m crashing early to be ready for more flood fighting. I am sleeping in the basement so I can hear any H2O invasion. #flood09 #fargoflood”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“Wow this little girl is stuck under cement. This is sad. #haiti on CNN”</td>
</tr>
<tr>
<td></td>
<td>Status - community</td>
<td>“close to home now: RT @cbcmanitoba: Residents on Kingston Crescent, off of Osborne Street, may be at risk for flooding. #flood09 #winnipeg”</td>
</tr>
<tr>
<td>Built</td>
<td>Status - Infrastructure</td>
<td>“Hwy 2 in GF is still open #flood09”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“CNN International Desk: landlines and local cell phones are still down in #Haiti but internet seems to be working (via @vhernandezcnn)”</td>
</tr>
<tr>
<td></td>
<td>Status - Personal Property</td>
<td>“Oakport development North of Moorhead, MN has lost 500 homes. #fargoflood”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“@thebroadbroad Thanks darling! My house is safe but my parents live by the river so we have been sandbagging it’s looking better”</td>
</tr>
<tr>
<td>Physical</td>
<td>Prediction</td>
<td>“Well this fire here in oklahoma it looks like its going to get bigger than the 12 miles it is now”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“River Projections Looking Positive: The river level is up, but so are spirits tonight. <a href="http://bit.ly/cZ80H6%E2%80%9D">http://bit.ly/cZ80H6”</a></td>
</tr>
<tr>
<td></td>
<td>Historical</td>
<td>“The World Series quake of ’89 (SF Bay area) was of a similar strength to the one in #Haiti, but killed only 63. Big diff: building codes!”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“Video: Catastrophe in Haiti. Strongest Earthquake in 200 Years <a href="http://ow.ly/16ksO1%E2%80%9D">http://ow.ly/16ksO1”</a></td>
</tr>
</tbody>
</table>

Table 1.1: Vieweg (2012) Information Categories

Each of the tweets included here is potentially relevant to Situational Awareness; however, the character of the information included in the tweets varies dramatically. For instance, while the
first *Status - Personal* example describes the activities of a user engaging in disaster response, the second example simply relates a story from national news; whereas the first *Prediction* example appears to offer a personal opinion, the second example functions as a pointer to a website. Due to this variation, IC annotations are not sufficient to answer questions such as the following:

- Is the information presented as if it originated with the user? If not, how distanced is the user from the source of the information? Is it possible to determine the source of information?

- Does the user consider this information to be reliable?

Intuitively, information ownership and reliability appear linked, perhaps acutely so in a crisis scenario. Information potentially relevant to Situational Awareness which is owned and tweeted by a user can be expected to have special significance because of the user’s necessary proximity to the disaster situation. Information ownership may be understood by two metaphors, both involving “distance” from a speaker. Evidentiality, as reviewed in Chapter 4, offers a mechanism for analyzing tweets in terms of discrete units of distance between a speaker and the information. For instance, if a user has gotten the information from a website, then the distance to the information is one unit; if in turn the information posted on a website comes from a named source, such as CNN, then the distance is two units. In contrast, Territory of Information describes ownership as a more continuous phenomenon, where information may be owned by a speaker, a hearer, or both in varying amounts along a continuous scale. Importantly, Territory of Information casts the marking of ownership as principally a pragmatic phenomenon, which is vulnerable to other pragmatic phenomena such as politeness practices.

A pragmatic annotation of crisis tweets seeks to establish ownership of the information contained in a tweet and to characterize the reliability of that information. While the EPIC data contains additional attributes that are not linguistic characteristics of the tweets themselves, such

---

3 The use of evidential marking as a politeness strategy is also well-studied (e.g. Hyland 2000). Evidential marking may be seen as a feature for establishing territory.
as the tweet author, which could provide useful features for derivation of information (e.g. is a tweet containing a news story authored by an affiliate of the news company), the focus in this study is on features of the tweet text only, on the assumption that these features will complement research exploiting user attributes and characteristics of the social network. Conceptual approaches to information ownership and reliability (as demonstrated by speaker certainty or text trustworthiness) are explored via the linguistic theories of Evidentiality (Aikhenvald 2004; Fox 2001; Chafe 1986), Territory of Information (Kamio 1997), and Speech Act Theory (Austin 1962; Searle 1969, 1976, 1979).

The identification of information ownership and reliability as applied to crisis tweets readily interfaces with a larger literature within computational linguistics addressing information attribution. While evidentiality has received some application in the task of information attribution, Territory of Information and speech act annotations have yet to be explored as features or frameworks for information attribution. While specific and therefore powerful in its application to information extraction in English tweets, the features included in the pragmatic annotation infrastructure presented here are largely domain and language-independent, and therefore applicable to other text genres explored in the information attribution literature, such as newswire. This thesis presents results for the classification of speech acts, evidentiality, and Territory of Information, as well as accuracies for two systems that rely on these classifications for information distance calculation and information attribution. These systems demonstrate that speech acts, evidentiality, and Territory of Information are both tractable for machine learning algorithms and useful to systems designed to aid information retrieval.

1.2 Overview of the Dissertation

The remainder of the dissertation is organized into seven chapters. Chapter 2 provides an introduction to Project EPIC’s data collection practices and selected elements of the previous natural language processing infrastructure to which the pragmatic features described here are added. Chapter 3 describes related efforts in the computational linguistics literature in order to context-
tualize and further motivate the approach taken in this study. Chapter 4 reviews the annotation categories and the annotation process. Chapter 5 proceeds by describing the results of a series of classification experiments which test the identifiability and utility of evidentiality, speech acts, and Territory of Information as annotation categories, but also the utility of other existing annotations, and provides a qualitative analysis of system output. Chapter 6 offers a theory of the interaction between Territory of Information, speech acts, and evidentiality, supported by empirical analysis of the annotated data. Chapter 7 provides a qualitative analysis of the linguistic and informational factors contributing to tweet utility, including the pragmatic features defined here. Finally, Chapter 8 presents conclusions and early extensions of the pragmatic framework to cross-domain and cross-linguistic tasks.
Chapter 2

Twitter for Crisis Informatics and Corpus Linguistics

This chapter details the distillation of a body of Twitter data collected during four natural hazards into a dataset of appropriate size and scope for the linguistic analysis presented here. The chapter begins by providing an introduction to approaches to Twitter and web data in corpus linguistics and crisis informatics; a discussion of the Project EPIC data collection infrastructure follows; finally, an introduction is provided to both the natural hazards motivating collection for the datasets utilized here, and the sampling methods applied to the tweets collected.

2.1 Corpus Linguistics and the Internet

Corpus linguistics is a subdiscipline of Linguistics focused on the study of patterns of language structure and use that emerge from careful observation of linguistic data. Datasets constructed in service of corpus-linguistic research have been gathered from newspapers and magazines (e.g. The TIME Magazine Corpus of American English (Davies 2007)), fiction (e.g. the Brown corpus (Francis and Kucera 1979), which also includes non-fiction genres), telephone conversation (e.g. the Switchboard corpus (Godfrey and Hollimon 1997)), and most recently, the internet. Web corpora include compilations of blogs and web pages (e.g. the Corpus of Global Web-Based English (Davies 2013)), which may be characterized as static, but also include corpora of various exchanges between users, such as email (The Enron Sent Corpus (Klimt and Yang 2004)) or Twitter communications (e.g. Roberts et. al. 2012, Corvey et. al. 2012). Linguists have noted that web text often exhibits different properties than newswire or fiction. In an outline of a corpus-linguistic approach to online
communications, *Language and the Internet*, linguist and lexicographer David Crystal coins the term *netspeak* (2006: 26) to refer to a set of behaviors that users may employ in adapting language use to an online platform. For linguists interested in web corpora, Crystal suggests a central research question “how do users respond to the new pressures [of online communication], and compensate linguistically?” (2006: 26). Unlike some other text corpora, such as fiction or newspaper text, *netspeak* is said to incorporate features of both writing and speech. Crystal suggests that dialogic forms of *netspeak* appropriate the following features from conversational speech (2006: 31-32):

1. Communications are “time-governed” and may elicit a response.
2. Communications are “transient,” and therefore potentially relevant for only a certain period of time.
3. Communications carry the “energetic force which is characteristic of face-to-face interaction” (32).

Crystal also notes that communications may approximate certain speech features orthographically, as in cases where repeated letters are used to demonstrate vowel elongation (e.g. “sooo”) or capital letters signal high volume (e.g. “I SAID NO”) (37-38).

While many aspects of *netspeak* are relevant to a study of tweets, the Twitter platform provides specific attributes and constraints that distinguish it from other social media systems that may serve a similarly dialogic function. The following section provides an introduction to Twitter and to key linguistic features of tweets.

### 2.2 Twitter and Tweets

In a recent monograph, Zappavigna (2012) describes Twitter as “an online platform for posting small messages to the internet in chronological sequence” (Zappavigna 2012: 1). This definition highlights two aspects of Twitter messages (“tweets”) that are important considerations for corpus study: (1) message brevity (140 characters maximum) and (2) tweet temporality. In addition to its function as a service for posting messages to the internet, Twitter functions as a social network. Connections are formed through “following” relationships. When a user becomes a
“follower” of another, the “followed” user’s tweets appear in the subscribing user’s feed. However, tweets are also visible to non-followers if they are retrieved via a keyword search through an interface provided on the Twitter website or through a number of Twitter clients. The ability to retrieve tweets after they have been posted makes tweets a type of “searchable talk” (Zappavigna 2011, cited in Zappavigna 2012:1), such that a user need not be a follower or monitoring postings on Twitter in order to access information that has been posted.

Twitter corpora differ from collections of other speech genres for both linguistic-pragmatic and structural reasons. Because many tweets are not composed using syntactic sentences, NLP systems trained on other genres such as newspaper text may not perform well on instances of microblogged data (Zappavigna 2012: 19). Laboreiro and colleagues (2010: 81-82, cited in Zappavigna 2012: 19) describe the following features as especially problematic:

1. “Condensed orthography,” including missing spaces, punctuation, and non-standard abbreviations
2. Informality, including the use of conversational (oral) interjections
3. Spelling errors

In addition, Twitter provides users with three interactional mechanisms that are explicitly marked in the tweet text and make tweet text unique: retweeting, directed communication, and hashtag marking. Each practice is briefly introduced below; an additional overview is provided in Chapter 5, with reference to tweet annotation.

### 2.2.0.1 Retweeting

Retweeting is one method of information propagation available in the Twitter platform, and allows a user to quote a tweet. Generally, retweets are marked with a special symbol, “RT,” and include the username of the user whose content is retweeted:

RT @ounwcm: Increasing wildfire potential behind the dry line...increasing severe potential across eastern OK. #okfire #okstorms
Here, content issued by the user @ounwcm has been quoted by the current user. While this tweet represents a prototypical retweeting convention, the form of retweets may vary significantly.

2.2.0.2 Directed Communication

Users may direct a tweet to another user by placing that user’s username, which is marked by the symbol “@” (“@username”), at the beginning of the tweet:

@disaster36144 testing twitter #redcross

This practice is distinct from mentioning a username elsewhere in the tweet, which simply causes the tweet to appear in the mentioned user’s feed.

2.2.0.3 Hashtag Marking

As previously mentioned, hashtags may serve as markers of tweet topic. Hashtags occur as pre- and post-positions to tweet content or may occur as syntactic arguments. As topic markers, hashtags are often placed at the end of the tweet text:

To help the people of Haiti donate to the Humanitarian Coalition:
http://www.thehumanitariancoalition.ca/ #Haiti #earthquake

Because of the unique linguistic qualities of Twitter data, specialized corpora have been constructed for Twitter-oriented research. The following section details efforts in crisis informatics that have been enabled by the creation of corpora of crisis-relevant tweets.

2.3 Twitter and Crisis Informatics

Twitter’s status and effectiveness as an increasingly popular platform for information dissemination during crisis situations has been examined in a number of recent studies (Palen et al., 2009; Starbird et al., 2010; Vieweg et al., 2010; Sarcevic et al., 2012). Milet (1999; cited in Vieweg 2012: 5) provides a theory of the steps taken by citizens as they respond to a crisis event:

(1) Assess hazard vulnerability
(2) Examine possible adjustments
(3) Determine the human perception and estimation of the hazard
(4) Analyze the decision-making process
(5) Identify the best adjustments, given social constraints, and evaluate their effectiveness

Vieweg and colleagues (2010) identify these “coping strategies” (Vieweg 2012: 5) in tweets issued during two disaster events that contribute to the corpus utilized here: the 2009 seasonal flood of the Red River across the north-central United States and the April 2009 Oklahoma wildfires. Natural language processing of crisis tweets seeks to automate the human information search, acquisition, and synthesis process by discovering key features of crisis-relevant information disseminated via Twitter.

2.4 Data Collection and Dataset Composition

The data utilized in this study have also been the subject of a number of studies within Project EPIC. In the context of these previous studies, the data has been screened and sampled and the sampling methodologies introduced affect both the size and composition on the datasets that are the objects of the present annotation efforts. The following sections detail key aspects of the Project EPIC data collection infrastructure as well as previous research efforts that constrain the composition of each dataset. Details of the disaster events studied are also included in order to contextualize the sampling methods implemented and to provide background information relevant to an analysis of potential correspondences between features of the natural hazard and the linguistic features of tweets reporting on the hazard situation.

Data collection begins when a target hazard has been identified. The type and specific conditions of the hazard potentially affect all aspects of data collection and analysis. Hazards may be distinguished by their point of origin in the solid earth (the lithosphere), the fluid earth (the atmosphere or hydrosphere), or in the biosphere (Chapman 1994), or by characteristics of impact, including hazard duration and warning (Alexander 1993). Following Dynes (1970), Vieweg (2012) categorizes disaster events instead as either focalized or diffused. Whereas focalized disasters are
local with respect to the disaster impact and relatively short-term in their affect on a community, diffused disasters have more geographically widespread effects that are longer-lasting and more disruptive (Dynes 1970: 54; cited in Vieweg 2012: 42). The disaster events included in this thesis differ in both origin and impact. While the data collection architecture is uniform across disasters, sampling methodologies differ according to the type, scale, and duration of the crisis, among other factors.

2.4.1 Data Collection

The Project EPIC infrastructure for data collection and storage is described by Anderson and Schram (2011). Search terms, which notably include hashtags specific to an event, are manually assigned by subject matter experts, who monitor activity on Twitter as the crisis situation develops. The search terms for the four disaster events included in this study are included below. Terms are not case-sensitive.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Search Terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>okfire, oklahoma, grass fire, grassfire</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>earthquake, quake, shaking, tsunami, ouest, port-au-prince, tremblement, tremblement de terre</td>
</tr>
<tr>
<td>Red River Flood (2009)</td>
<td>red river, redriver</td>
</tr>
<tr>
<td>Red River Flood (2010)</td>
<td>fmflood, flood10, red river, redriver, ccflood, fargoflood</td>
</tr>
</tbody>
</table>

Table 2.1: Search Terms by Dataset

Note that not all search terms chosen are English words; data is frequently screened to provide English-only data for linguistic annotation.

For users who issue a tweet containing a search term during the collection period, a contextual stream is also gathered, which contains all tweets from that user during the collection period. The infrastructure also affords the ability to look “back in time” for tweets containing a search term, using the Twitter search API (Anderson and Schram 2011). The combination of tweets containing
a search term and tweets from contextual streams can yield very large datasets, often numbering in the millions of tweets, necessitating sampling prior to human analysis.

2.4.2 Collection Context and Data Sampling

Data processing and analysis are each sensitive to the specifics of the crisis situation. The following sections provide context for the data collection relevant to each hazard included in this study and offer an overview of the sampling methods implemented.

2.4.2.1 The Oklahoma Wildfires of 2009

On April 9, 2009, a wildfire began outside in Midwest City, Oklahoma, which would spread throughout the majority of the state (National Oceanic 2009, cited in Vieweg 2012), burning upwards of 100,000 acres (McNutt 2009, cited in Vieweg 2012). Data was collected over a period of five days, from April 8 through April 13, 2009. The final dataset derived from tweets gathered over this collection period was confined to geographically local individuals only, where “geographically local” is defined by the following criteria (Vieweg 2012: 54-55):

- User lives in the disaster area, and
- User profile indicates that user is a resident of an area containing a fire, or
- User has issued one or more tweet containing information demonstrating that the user is affected or threatened by a fire.

Individual is defined as a user who issues Twitter communications as single persons, rather than on behalf of a group or formal organization (Starbird et. al. 2010; cited in Vieweg 2012). Aggregation of tweets from these 46 local individuals resulted in a dataset of 2,779 tweets (Vieweg 2012: 59).

2.4.2.2 The Red River Flood of 2009

The first announcements of a potential 2009 Red River flood were issued on February 9, 2009 by the National Oceanic and Atmospheric Administration (NOAA) (Vieweg 2012: 46). Flood warnings and response unit activations took place from March 6, 2009 to March 18, with FEMA

Data were collected over a 51 day period from March 8 to April 27, 2009. As in the Oklahoma Fires study, tweets were sampled to include only geographically local individuals. The final dataset contains a total of 19,152 contextual stream tweets gathered from 49 unique users (Vieweg 2012: 59).

2.4.2.3 The Red River Flood of 2010

Projections for spring flooding of the Red River Valley were issued by the National Weather Service (NWS) on February 23, 2010 (National Oceanic, 2010; cited in Vieweg 2012). Several weeks later, FEMA forecast that the flood would have a similar impact to flooding of the previous year (Federal Emergency, March 15, 2010; cited in Vieweg 2012). From the period of March 19 to March 21, floods threatened communities along the river from North Dakota to Minnesota; however, damages were less than those reported in 2009 (Vieweg 2012: 48-49).

Data were collected for the 20 day period spanning March 15 to April 3, 2010. Unlike in the 2009 Red River flood, 2010 data was not downsampled to local users. Rather, a total of 370 unique users were identified as having tweeted one or more search terms during the collection period. Contextual streams were then gathered for the 101 user subset who issued three or more tweets containing a search term during the collection period. The subset contained accounts linked to individuals but also to organizations and businesses. From the contextual streams of these 101 users, a dataset containing 11,879 tweets was constructed.

2.4.2.4 The Haiti Earthquake of 2010

A magnitude 7.0 earthquake impacted Haiti on January 12, 2010, causing casualties and injuries in the hundreds of thousands each. Over 1 million citizens were displaced and property damage affected hundreds of thousands of structures across the island (Pan American Health,
Because of the scope of the crisis, the earthquake elicited a massive international response (Vieweg 2012: 49).

A radically different sampling method was employed for the Haiti Earthquake data. Vieweg (2012) motivates this approach by observing that the Haiti Earthquake exhibits features of a diffused disaster, such as widespread damage and lasting impact. The quake impact, together with the publicity generated around this event, elicited a worldwide response, with many non-local users tweeting about the event (Vieweg 2012: 55-56). Because the vast majority of tweets collected for the event originated with non-local users, a strategy of searching for local users could not be implemented. Therefore, the resulting dataset to be sampled for natural language processing studies was not restricted to geographically local individuals, nor users who issued greater than a threshold number of tweets containing a search term.

### 2.4.2.5 Sampling for Natural Language Processing Purposes

Crisis informatics datasets are often sampled further in order to provide manageable datasets for human annotation. For NLP research, instances are selected in order to maximize the variety of linguistic phenomena seen in the training data while minimizing spam and non-English tweets. Greater manual curation of datasets prior to NLP downsampling (in particular Oklahoma Fires) tends to yield a higher proportion of SA-relevant tweets in the final dataset. This thesis utilizes a subset of the data described by Verma and colleagues (2011) for their study of situational awareness.¹

### 2.5 Prior Semantic and Pragmatic Annotation of Crisis Tweets

Through several separate efforts related to natural language processing and broader information extraction tasks, the EPIC data has been enriched with a number of annotations relevant

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¹ Instances are excluded where the character encoding did not allow for clear analysis, was in a foreign language and therefore not relevant to English analysis, or, for a very few instances, where the tweet was composed of multiple lines and therefore very difficult to parse from Knowtator output. This reduced the total number of instances from 1,965 as reported by Verma and colleagues (2011) to 1,943, excluding 22 instances.
to the identification and extraction of linguistic and behavioral features. Each annotation layer is described in turn.

### 2.5.1 Named Entity Annotation

Named entity (or nominal entity) tagging (Bikel et. al. 1999) is inspired by the Automatic Content Extraction (ACE; Doddington et. al. 2004) guidelines (LDC, 2004) and labels entities including Person, Location, Organization, Facility, and Artifact. A preliminary annotation task (detailed in Corvey et. al. 2010) consisted of identifying the syntactic span and entity class for the first four types of entities in 200 tweets from the 2009 Oklahoma grassfires dataset. Through iterative development of the annotation guidelines, this initial taxonomy of named entities was expanded to include Artifacts, defined as physical or digital resources involved in disaster response, such as supplies, vehicles, or software used to disseminate disaster-relevant information. The hazard itself (Event: Hazard) is also annotated as an entity span. Annotations are performed using Knowtator (Ogren, 2006), a tool built within the Prot´eg´e framework (http://protege.stanford.edu/).

#### 2.5.1.1 Semantic Role Labeling

Data are also annotated with PropBank style semantic role labels (Palmer et al., 2005), which provide a verb-specific annotation of tweet meaning. Where PropBank labels are applied to nodes in a tree structure, the annotation process (broadly) consists of two steps: (1) identifying the correct subcategorization frame of a verb, referred to as its role set, which is chosen from a finite set of verb senses, and (2) identifying the types of arguments to and modifiers of the verb and assigning these elements to appropriate elements of the text (Bonial et. al. 2012). The verb is marked as a relation (“REL”) and event participants are marked as either numbered arguments (ARG0-ARG5) or as modifiers (e.g. ARGM-LOC for ‘location’, ARGM-TMP for ‘temporal modifier’); adjuncts are not annotated. ARG0 is a prototypical Agent and ARG1 is a prototypical Patient; other numbered arguments apply to a broader range of participant roles. As an example, the tweet “Editor’s pick: New Orleans residents flee Hurricane Gustav http://tinyurl.com/6qthmq” is annotated in
the following way:

Editor’s pick: [New Orleans residents]ARG0 [flee]REL [Hurricane Gustav]ARG1
http://tinyurl.com/6qthmq

Because, unlike other PropBank annotation efforts, the EPIC data is not parsed, gold-standard semantic role labels and spans are generated through two-stage hand-correction of the output of an in-house automated semantic role labeling system (Choi and Palmer, 2011a; Choi and Palmer, 2011b). The data pipeline is shown in Figure 2.1.²

![Figure 2.1: EPIC Semantic Role Labeling Pipeline](image)

The pipeline contains three stages of manual correction for part of speech tags, for semantic role labels, and for the spans of semantic arguments. The annotation process yields gold-standard spans for the semantic roles associated with each predicate in a tweet.

### 2.5.2 Information Category Annotation

As introduced in Chapter 1, information categories are designed to describe the disaster-relevant information content of a tweet. In order to be annotated with an information category (IC), a tweet must demonstrate situational awareness (Vieweg 2012: 203), which entails that the tweet is on-topic. Therefore, each IC dataset is first annotated with a ternary coding scheme labeling the tweet as off-topic, on-topic but not relevant to situational awareness, or relevant to

² Extracted from slides prepared by the author for the Linguistic Resources and Annotation Conference, 2012 (LREC-2012).
situational awareness. A second coding pass then annotates the high-level information type (Built, Physical, or Social environment). Finally, the IC itself is annotated as a third pass (Vieweg 2012). Each coding pass may be treated as a separate annotation layer.

### 2.5.2.1 Situational Awareness

Tweets that are potentially relevant to situational awareness contain information that may be useful for decision making within the hazard situation (Verma et. al. 2011; Vieweg 2012: 1-4). The following examples are said to demonstrate potential relevance to situational awareness:

- Niece and her dad are being evac’d in MWC, fire is headed towards SIL and her boyfriend in Harrah
- Country residents outside of Fargo are surrounded by flood waters. Some R being rescued.
- The Red River at Fargo ND is at 33.15 ft which is 15.15 ft above flood stage #flood10 #fargoflood

Instances that comment on the event without providing actionable information do not demonstrate relevance to situational awareness, as in the following examples:

- Tweeps please pray for the families and firefighters battling these crazy fires in Oklahoma
- Nothing upsets me more than listening to my Dad’s voice. He was born in a drought, and now watches his hometown flood
- Got a flood photo of mine published in the local paper today. Time for a new career?

Tweets that are deemed potentially relevant to situational awareness receive annotations according to the type of disaster-specific information they contain, as described in the following section.

### 2.5.2.2 Information Category Assignment

Vieweg (2012) details IC annotation for several datasets. After receiving annotation for potential relevance to situational awareness and high-level information type as described above, each
tweet receives one or more IC annotations chosen from within the high-level information types previously annotated. The complete IC taxonomy is included as Appendix A. Because annotations are applied to tweets as a whole rather than to tweet subspans, the interpretation of the annotations is that a tweet contains information of a certain type. In some cases, the tweet as a whole corresponds to one or more information categories, as illustrated by the following example:

Flames are threatening Choctaw High School. #okfires — Status - hazard, Status - public property

In other cases, syntactically separable spans pertain to different ICs:

@BarnettLP [most of the houses here have propane heat.] GENERAL AREA INFORMATION [I have a tank that’s buried in front yard] STATUS - PERSONAL PROPERTY

Because of the potential to separate tweets into separate information components, IC annotations are also approached as a named entity labeling task identifying specific tweet spans that signal an IC. Span identification permits the association of an event with specific named entities included under the same span.

Subsets of data included in the IC annotation process were chosen for tweet-level pragmatic annotation, as described in the following section. The resultant dataset comprises the corpus considered in this thesis.

2.5.3 Prior Pragmatic Annotation

Verma and colleagues (2011) explore three tweet-level (TL) linguistic characteristics in a situational awareness classification task: linguistic register, subjectivity, and style (personal/impersonal). Gold-standard annotations (via double-annotation and adjudication) are produced for all annotation categories as well as the target annotation of situational awareness. A brief description of each annotation is included below; all examples, as well as the general format of the feature presentation,
2.5.3.1 Register

Following Halliday (1978: 23), register is defined as a linguistic feature “determined by what is taking place, who is taking part, and what part the language is playing.” Register is encoded as a binary distinction between formal and informal, and formal register is marked by grammaticality and perceived completeness. The following tweets serve as examples of formal register:

- Red River @ Fargo is 32.87’. 14.87’ above flood stage. -7.95’ record crest. -0.06’ from last read. #fargo #nd #fmflood
- RT @RonTerrell: @RAMhaiti RT @EmilySinovic: Just heard from Tulsa’s In His Image Drs group. Pulled survivor from rubble in #Haiti *this...

In contrast, informal register is conveyed by a greater lack of grammaticality and possibly the presence of slang, as in the following examples:

- @user6 yup homes in Tonua’s neighborhood are on fire
- landed in fargo today...locals say red river will crest at 43 feet...worse then 97 flood

Note that while formality generally indicates syntactic complexity, it does not guarantee syntactic completeness or grammaticality. For instance, flood stage updates, while labeled as formal, bear little resemblance to standard English sentences. While register annotations appear consistent, the category formal conflates sentences such as newspaper headlines with other structures that might be considered informal with respect to standard written English.

2.5.3.2 Subjectivity

Objective tweets contain information presented as fact rather than opinion. The following tweets are coded as objective:

- OHP is responding to Cater County to assist with RD closures and evacuations due to fires in and near Tutums. Approx 20 homes in danger

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3 For clarity, the datasets that are the basis this work are referred to collectively as “ICWSM-11”.
• Here is a list of the earthquake survivors. You may find update from Hotel Montana: http://bit.ly/7o7mUk

In contrast, subjective tweets explicitly mark an opinion or offer a sentiment:

• so proud to be from Oklahoma. The outpouring of support for those devastated by the fires is amazing
• I think they’re being a bit over dramatic about the flooding. Trying to make us fearful but like always it wouldn’t be close to bad at all

2.5.3.3 Style

Finally, the authors code for personal and impersonal style, where tweets exhibiting personal style give evidence of emotional or egoic proximity to the tweet content. The following examples are coded as personal:

• Our best hopes and wishes go out to the folks in Manitoba. As the Red River is about to crest.
• Thinking of my friends in Fargo, and my time spent there. I will keep you all in my prayers. #FMflood

In contrast, tweets coded as impersonal do not demonstrate such proximity:

• Canadian and Oklahoma Counties under RED FLAG FIRE WARNING until 10 p.m. This warning means conditions are ripe for wildfire outbreaks.
• The Red River at Fargo is 40.76 feet. 22.76 feet above flood stage. 0.66 feet above 1897 record. #flood09 #fargoflood

Note that although subjectivity and style appear to be associated (and indeed a statistical analysis bears this out, with chi-squared tests showing a significant correlation between all pairs of high-level linguistic features\(^4\)), it is possible for a tweet to be personal in nature and yet objective as in the following example:

• @User13 The fires are away from our area, but I know people who live in some of the areas where houses burned. One works with my SIL

\(^4\) Data is from the Oklahoma Fires dataset. Subjectivity/Style: chi-squared = 468.6725, df = 1, p-value < 2.2e-16; Register/Style: chi-squared = 635.9775, df = 1, p-value < 2.2e-16; Register/Subjectivity: chi-squared = 407.3702, df = 1, p-value < 2.2e-16
2.5.3.4 Discussion

The categories are implemented as binary annotations, and the authors achieve high inter-annotator agreement, as shown in Table 2.1 below. Values are expressed as both the inter-tagger agreements (one annotator compared to the other; ITA) and as Kappa (κ) statistics, which adjust ITA values to account for the probability of agreement by chance (Cohen 1960). Performance for systems trained on the ICWSM-11 data for the classification of each high-level linguistic feature is shown in Table 5.4.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Subjectivity</th>
<th>Register</th>
<th>Style</th>
<th>SA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ITA</td>
<td>x</td>
<td>ITA</td>
<td>x</td>
</tr>
<tr>
<td>Red River Flood (2009)</td>
<td>.93</td>
<td>.86</td>
<td>.79</td>
<td>.57</td>
</tr>
<tr>
<td></td>
<td>.92</td>
<td>.83</td>
<td>.90</td>
<td>.80</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.89</td>
<td>.78</td>
<td>.86</td>
<td>.72</td>
</tr>
<tr>
<td>Oklahoma Fires</td>
<td>.97</td>
<td>.94</td>
<td>.90</td>
<td>.80</td>
</tr>
</tbody>
</table>

Table 2.2: ICWSM Annotator Agreement (Verma et. al. 2011)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Register</th>
<th>Subjectivity</th>
<th>Style</th>
<th>SA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td>I</td>
<td>S</td>
<td>O</td>
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<tr>
<td>Oklahoma Fires</td>
<td>375</td>
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<td>69</td>
<td>451</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>216</td>
<td>266</td>
<td>210</td>
<td>272</td>
</tr>
<tr>
<td>Red River Flood (2009)</td>
<td>332</td>
<td>110</td>
<td>84</td>
<td>358</td>
</tr>
<tr>
<td>Red River Flood (2010)</td>
<td>407</td>
<td>83</td>
<td>73</td>
<td>417</td>
</tr>
</tbody>
</table>

Table 2.3: Pragmatic Feature Frequency by Dataset

With the exception of the Haiti Earthquake, many pragmatic features exhibit a skewed distribution. In general, tweets are more likely to be written in formal register rather than informal, more likely to be objective than subjective, and more likely to demonstrate potential relevance to situational awareness than fail to demonstrate such relevance. The Haiti Earthquake dataset differs dramatically from the other three datasets in that the vast majority of tweets do not demonstrate potential relevance to situational awareness. This difference may be attributed to the fact that tweets included in the dataset were not required to be issued by local users.

2.6 Summary: Data for Pragmatic Annotation

The work outlined here utilizes a subset of the data defined in Verma and colleagues (2011) work because of its existing annotations for register, subjectivity, and style and its overlap with datasets containing semantic annotations such as named entity labels, semantic role labeling, IC annotations, and event annotations. While interactions with semantic annotations are not the focus of the current study, their inclusion in the dataset serves as a resource for future efforts and are explored in a corpus study for a subset of the data.
Chapter 3

Ownership and Reliability: Related Approaches and Previous Work

Computational linguists have addressed aspects of the description of information ownership and reliability through several broadly-defined tasks: (1) information attribution and (2) information verifiability, also cast as information “trustworthiness,” which is related to speaker commitment. Research projects in each of these tasks frequently engage in specialized annotation efforts in support of supervised machine learning tailored to the task at hand, but may also leverage additional features. This chapter will review a selection of efforts from each of these tasks which serve to contextualize and motivate the pragmatic annotation infrastructure proposed in Chapter 4 and serve as guideposts for additional work in pragmatic analysis for information certainty. For each task, a number of resources are reviewed that serve to illustrate the current state of the art in manual annotation and a selection of systems that illustrate a variety of computational methods; neither of these listings are meant to be exhaustive. Because existing studies do not address Twitter communications, the problems addressed and the solutions proposed are often incongruent with the challenges faced in tweet analysis. Where this is the case, the shortcomings of existing frameworks are explored.

3.1 Information Attribution

Information attribution is the computational task of marking the source of a piece of information, opinion, or sentiment. This has been identified as a task of interest in biomedical informatics (citation) but also for a broader range of text genres, including news and educational resources.
For instance, Zhang and colleagues (2003; cited in O’Keefe et. al. 2012: 791) apply information attribution techniques in order to distinguish the speaking parts for the characters in children’s stories read automatically. Two efforts in this domain appear as attribution categories in Twitter data: source attribution, and as a special subset of this problem, quotation attribution.

The task of labeling patterns and relations of attribution has been applied to corpora parsed with tree structures and to flat text. Prasad and colleagues (2006) describe the application of annotations marking various types of attribution to the Penn Discourse Treebank, a corpus of Wall Street Journal text marked for discourse relations (Marcus et. al. 2005). The study annotates four aspects of the attribution: (1) the source the information is attributed to; (2) the type of relation between the source and the information attributed; (3) the polarity of the information attributed (positive or negative); and (4) the determinacy of the information attributed (Indeterminate vs. Null). Attribution types include propositions, facts, and eventualities. The distinction between propositions and facts is that the truth of facts is presupposed. Eventualities are separated from propositions and facts by their ascription of intentionality to the speaker. In this way, the attribution type correlates with speech act performance.

In contrast to work on corpora with gold-standard parses, studies utilizing flat text cannot rely on features of syntactic structure in order to determine spans of information attributed. Abu-Jbara and Radev (2012) describe span determination as a problem of “reference scope identification.” The authors propose a system for determining the information attributed to citations in scientific text; citation attribution can be problematic in scientific and academic writing as sentences may contain several citations. The authors test three approaches: word classification, sequence labeling, and segment classification, with segment classification giving the best results. While word classification and sequence labeling approaches train their models to recognize if a word is inside or outside the scope of an adjacent citation on a per-word basis (84-85), segmentation classification proposes word sequences as the objects of classification. The authors test two methods of segmentation: (1) segmentation into phrases at the granularity of clauses or listed items and (2) segmentation at the level of grammatical units, which is provides fine-grained syntactic chunking into noun phrases,
verb phrases, prepositions, adjectives, and adverbs (85-86). Segmentation of type (1) provides the best results, with support vector machines and logistic regression showing similar performance. To explore quotation attribution in flat text, the Columbia Quoted Speech Corpus (Elson and McKeown 2010) annotates sources of information over a corpus of English literature. The study is limited to the detection of the speakers of quotes contained within quotation marks. The authors find that proximity of the character name and the use of the specific reporting verbs provide powerful features for locating the speakers of utterances. The information attribution algorithm outlined in Chapter 5 applies findings from this literature; specifically, attributed segments are assumed to comprise the largest logical span and be relatively close to the phrase marking the source of information.

3.2 Verifiability and Verification

In addition to information attribution, recent computational work has addressed the task of information verification. There is a paucity of corpora dedicated solely to the annotation of factuality, a fact that Saurí and Pustejovsky (2009) cite as a motivation for the creation of FactBank. FactBank adds an extra layer of semantic description to the TimeBank corpus (Pustejovsky et. al. 2006), a corpus of temporal annotations in the TimeML formalism (Pustejovsky et. al. 2005). In creating FactBank, the authors discriminate between annotations of factuality information, which are included in TimeBank, and annotations of factuality interpretation, which are the result of an examination of the evidence concerning event factuality (229). Thus, while TimeBank includes a special annotation class (SLINK) that annotates modality, factivity, and evidentiality (Pustejovsky et. al. 2003), the corpus does not provide an overall factuality interpretation for events under the scope of multiple interacting TimeML annotations (2009: 243). Event factuality is annotated with four classes, each containing three possible values as defined in the following table (Sauri and Pustejovsky 2009: 246, 257):
Each event annotation in TimeBank is marked with one of the eight factuality labels included above, “Other,” where the annotation category is unclear, or “NA” where the expression cannot be evaluated. As an example, the following contains six event predications (2009: 250)

Newspaper reports have **said** Amir was **infatuated** with Har-Shefi and **may** have been **trying** to **impress** her by **killing** the prime minister.

Because **may** is a modal attribute of **trying**, it is not included for factuality annotation. The factuality of each event is considered relative to two sources: (1) the author of the sentence itself and (2) the author of the news reports. The predicates are annotated as follows:

1. **said**
   - author of sentence: fact
2. **infatuated**
   - author of sentence: unknown or uncommitted
   - author of report: fact
3. **trying**
   - author of sentence: unknown or uncommitted
   - author of report: possible
4. **impress**
   - author of sentence: unknown or uncommitted
   - author of report: unknown or uncommitted
5. **killing**
   - author of sentence: unknown or uncommitted
   - author of report: unknown or uncommitted
Annotators are instructed to code according to text features as opposed to world knowledge (253).

Rich contextual complexity has been shown to aid certainty identification, but the features relevant to certainty classification may not appear in Twitter data. For instance, Su and colleagues (2010) use evidentiality cues as a feature for detecting the trustworthiness of information, as characterized by the text’s perceived level of certainty (absolute, high, moderate, low). The authors take a corpus-based approach to discovering lexical evidentials, and these are then associated with certainty levels as shown in Table 3.1 below.

<table>
<thead>
<tr>
<th>Certainty Level</th>
<th>Evidential Terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute</td>
<td>certainly, sure, of course, definitely, absolutely, undoubtedly, report, certain, definite</td>
</tr>
<tr>
<td>High</td>
<td>clearly, obviously, apparently, really, always, believe, see, must</td>
</tr>
<tr>
<td>Moderate</td>
<td>seemingly, probably, seem, think, sound, ought, should, would, could, can, possibly, likely, unlikely, probable, positive, potential</td>
</tr>
<tr>
<td>Low</td>
<td>maybe, personally, perhaps, possibly, presumably, doubt, wish, wonder, infer, assume, forecast, fell, heard, may, might, not sure, doubtful</td>
</tr>
</tbody>
</table>

Table 3.1: Lexical Evidential Features for Certainty Level Identification (Su et. al. 2010)

While this approach is successful in the context of the collaborative question answering system the authors seek to optimize, using these terms as lexical features for trustworthiness detection in the EPIC Twitter data fails because epistemic modals are simply absent from the tweet text due to the extreme brevity of Twitter communications. Approximately 87% of the ICWSM-11 data is unlabelable using the lexical features Su and colleagues provide.

Because existing resources do not provide features that are extractable from tweet text, a new method of characterizing certainty is required. For Twitter, distance to information and pragmatic assertion of speaker information ownership are proposed as features serving to indicate speaker certainty. The following chapter details an annotation scheme that encodes features relevant to the detection of these two features.
Chapter 4

A Pragmatic Annotation Infrastructure for Twitter

This chapter introduces a pragmatic annotation framework tailored to the identification of information ownership, information attribution, and speaker certainty. Section 4.1 describes the overall annotation process. Subsequent sections give theoretical background for each layer of the annotation and detail the specific criteria that define each annotation type.

4.1 The Annotation Process

Tweets undergo a series of annotation passes encoding three layers of pragmatic description. The following sections introduce the pragmatic annotation infrastructure, describing annotator training, illustrating specific annotation guidelines, and providing inter-annotator agreement (IAA) for each category.

4.1.1 Overview

Pragmatic annotation was conducted by a total of four Linguistics Masters students, each in the Department at the University of Colorado, Boulder. As is common for linguistic annotation projects, each file is completed by a pair of annotators and adjudicated by a third annotator (here, the author) in order to produce gold-standard annotations for training data in machine learning applications. Following the practices for certainty annotation in FactBank, annotators considered only the tweet text.
Labeling is performed using the Knowtator interface (Ogren, 2006); a screenshot is provided below.

Annotators begin by marking Evidentiality annotation, marking both the span and category of each annotation. The evidential spans thus defined are then adjudicated to form gold-standard spans for two separate, subsequent annotation passes, which code for speech acts and Territory of Information.

### 4.1.2 Annotator Training

Annotators were provided with a set of guidelines, included as Appendix D, which were iteratively refined and clarified during the annotation process. Because annotators would code the ICWSM-11 datasets exhaustively, example tweets included in the guidelines were derived from a number of other datasets collected by Project EPIC; the examples provided in the following sections are taken from the annotation guidelines. Annotators were given a general guideline to code based on the tweet text only, and not based on world knowledge or on suppositions about characteristics.
of the speakers.

Short training files, derived from a separate dataset gathered during the Western Australia Fires of 2011, were provided for each annotation layer and sufficient inter-annotator agreement defined as approximately 80% or above was required to progress to actual annotation. While the training data provided was collected during a wildfire event, it did not appear that annotators had any remarkable difficulty generalizing the annotation conventions learned for one disaster type to others. Following training, annotators worked independently and in a self-paced manner. The annotation team met intermittently to discuss any conceptual issues in the annotation that gave rise to systematic disagreements.

Following training, annotators coded the ICWSM-11 data using the annotation categories defined below. Annotation times per file varied widely both within and across annotators and annotation types, with times per fifty-tweet files ranging from eight minutes to over an hour depending on the annotator and the type of annotation performed. TOI annotation had the potential to be the most time-consuming, particularly early in the annotation process, and therefore, one could theorize, may be either the most unnatural or the most cognitively intense of the pragmatic annotations.

4.2 Evidentiality

The term evidentiality covers the set of linguistic behaviors used to mark the source of information (e.g. Aikenvald 2004). Evidentiality may be encoded either grammatically or lexically depending on the properties of a given language.\footnote{Aikenvald (2004) argues that the term evidentiality should refer only to the grammatical category indicating source of information. However, Chafe (1986) and Fox (2001) also apply this term to lexical items and expressions performing the same function. This broader definition of evidentiality is utilized here.} As Aikenvald (2004:6) notes, languages with an evidential component to the grammar may also utilize lexical expressions to show the source of information. For clarity, evidentiality encoded as a grammatical category, and possibly also through lexical means, is referred to as grammatical evidentiality and evidentiality utilizing purely lexical items and expressions is referred to as lexical evidentiality. Evidentiality has received attention
in several areas of the linguistics literature, including linguistic typology, corpus linguistics, and interactional linguistics.

4.2.1 Theoretical Background

The following sections provide an introduction to the typological literature in Linguistics concerning Evidentiality and to theories and corpus studies of Evidentiality in English.

4.2.1.1 Evidentiality in Typological Perspective

Aikhenvald (2004) synthesizes a number of studies from the typological literature in order to provide a unified taxonomy of evidential categories. Although English does not demonstrate grammatical evidentiality, divisions in the typology of evidential systems prove useful in describing lexical and Twitter-specific resources available for English evidential marking. Aikhenvald describes evidential systems that divide information using up to five of six possible semantic parameters for source of information: visual evidence, (other) sensory evidence, inference, assumption, hearsay, and quotative (65). The full inventory of attested divisions along these parameters is included as Appendix B. Systems utilize these parameters to mark from two to five evidential categories. The variation in evidential marking observed in the typological literature motivates the following question:

Assuming that English potentially marks the same evidential categories as systems that include grammatical evidentiality, but through lexical means, how many evidential categories are needed to describe English evidential marking? What evidence can crisis tweets provide?

While previous studies of English evidentiality have primarily treated conversational data, rather than computer-mediated communication like Twitter, inventories and hierarchies of lexical evidentials may apply across domains, and conversational practices may be incorporated in Twitter communications in theoretically interesting ways.
4.2.1.2 Evidentiality versus Epistemic Modality

While evidentiality concerns the marking of a source of information, epistemic modality encodes a speaker’s expression of the certainty of some information. While epistemic modality is formally described in terms of logical possibility and necessity (e.g. Palmer 1979), it is equally possible to describe levels of speaker confidence in some piece of information or to describe a speaker’s relative commitment to the information. Because evidentiality and epistemic modality each describe aspects of a speaker’s relationship to the information, many studies combine these categories, using “evidentiality” as a blanket term for both the assignment of source of information and the identification of speaker stance, particularly for languages that lack grammatical evidentiality, such as English. For such studies, epistemic stance markers like “apparently” are said to have evidential significance. While both evidentiality and epistemic modality are relevant to the information retrieval task outlined here, they are of independent theoretical interest. Therefore, the distinction is maintained, reserving the term evidentiality for linguistic mechanisms marking source of information and epistemic modality for mechanisms marking speaker confidence, commitment, or certainty.

4.2.2 Theories of English Evidentiality

As previously stated, English relies on lexical rather than grammatical markers for the construction of evidential forms. Two foundational studies inform the analysis presented here. Chafe (1986) describes English evidential practices evident in conversation and academic writing. The author defines evidentiality through its relevance to “attitudes about knowledge” (262). Several information types are organized on a cline of reliability, with specific lexical items associated with each information type. The hierarchy is shown as Figure 4.2 below.

Belief > Induction > Sensory Evidence > Hearsay > Deduction

Figure 4.2: Chafe (1986) hierarchy of evidential types
Chafe proposes the additional categories of hedges (270) and expectations (270-271); while hedges always decrease the reliability expressed, expectations may increase or decrease reliability depending on the lexical items included. Zero-evidentials are also discussed as “bald assertions” (267), which do not contain any additional characterization of their reliability. The lexical items associated with each evidential type are included as Table 4.1.

<table>
<thead>
<tr>
<th>Evidential Category</th>
<th>Lexical Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belief</td>
<td>think, guess, suppose</td>
</tr>
<tr>
<td>Induction</td>
<td>must, obvious, seem to, evidently</td>
</tr>
<tr>
<td>Sensory Evidence</td>
<td>see, hear, feel, looks like, sounds like, feels like</td>
</tr>
<tr>
<td>Hearsay</td>
<td>apparently, seems, supposed to, have been said</td>
</tr>
<tr>
<td>Deduction</td>
<td>should, presumably, can, could, would</td>
</tr>
<tr>
<td>Hedges</td>
<td>sort of, about</td>
</tr>
<tr>
<td>Expectations</td>
<td>of course, oddly enough, actually, in fact, at least, even, only, but, however, nevertheless</td>
</tr>
</tbody>
</table>

Table 4.1: Chafe (1986) inventory of evidential categories and lexical cues

While the first five categories pertain to evidential marking as it is defined here, Hedges and Expectations instead mark epistemic modality. Chafe appears to treat this list of lexical items as exhaustive, as he is able to report frequency data for a corpora of conversational speech and academic writing; evidentials occur at a rate of 60 and 64 per 1000 words in conversation and writing respectively. Fox (2001) also provides an inventory of lexical evidential forms in conversation, included as Table 4.2.

| hear, see, look (like), sound (like), say, must, seem (like), apparently, evidently, according to |

Table 4.2: Fox (2001: 171-172) Lexical Evidential Markers

The inventories exhibit considerable overlap. As both lists are derived from empirical examination of separate corpora, each study helps to verify the inventory of the other. Like Chafe, Fox considers zero evidentiality as a category in its own right. However, while Fox utilizes evidential categories such as hearsay, the description of a taxonomy of evidential types is not the goal of the
study. Rather, Fox proposes that evidentiality “index[es] social meanings and, hence, is sensitive to the relationship between speaker and recipient(s) and/in a particular context of utterance” and that the primary meanings indexed are those of authority, responsibility, and entitlement (2001: 170). Thus, in contrast to Chafe, Fox focuses not on utterance reliability as it relates to the propositions expressed, but rather on the discourse practices that give rise to socially conditioned formulations of knowledge.2 Thus, the presence of lexical evidentials may signal characteristics of both speaker knowledge and of the relationships between speakers, as well as the speakers’ mutual relationship to the knowledge discussed. Because (following Fox) a speaker’s use of evidential marking is not necessarily correlated with the reliability of the propositions conveyed, where reliability is discussed, it is referred to as the expressed reliability of information. Like Chafe (1986), Fox (2001) considers epistemic modals like “apparently,” “evidently,” and “must” as evidential markers.

In addition to the lexical evidentials discussed, users may employ a variety of non-lexical evidential practices in order to convey source of information. One of these practices, retweeting, as already been introduced. However, users may also attribute information to websites, to other users, or to sources outside of Twitter. Evidential categories encompassing these behaviors, which are termed non-lexical evidentials, are discussed in Section 4.2.3

4.2.2.1 Discussion

Previous efforts, although informative for the work outlined here, have implemented only partial evidential frameworks. Such frameworks, while theoretically interesting and often computationally powerful, are often domain and language-specific. A more general solution to the problem of text reliability, and the related problem of verifiability, must incorporate a wider range of linguistic findings into a single framework.

2 Fox (2001: 169-170) positions this research among studies related to Territory of Information, described in Section 4.4.
4.2.3 Evidentiality Annotation

As previously discussed, evidentiality annotation provides the spans utilized for marking speech acts and Territory of Information. Tweets may have multiple spans relevant to the annotation of evidential categories and spans may have an embedded structure. For annotation, two classes of evidential categories are distinguished: those that contain an obligatory embedded span and those without an obligatory embedded span.

4.2.3.1 Determining Annotation Spans

Annotation types are defined as either obligatory-embedding or non-obligatory embedding. The set of non-obligatory embedding annotations (Zero-evidential, Visual, Non-Visual, Assumed, Inferred, and Hearsay) is examined first; obligatory-embedding annotations (Retweet, Source Attribution, Website Attribution, and Quotative) are then described.

4.2.3.2 Zero-evidential

In addition to coding for various types of evidential marking, the annotation scheme also marks spans containing a lack of evidential marking, defined as zero-evidentiality. Zero-evidentiality is a property of a span, rather than a tweet. As such, zero-evidential spans may appear as sub-spans of spans marked for an evidential category. Some examples of zero-evidential tweets are the following:

(1) what a day! thanks for all the sweet tweets about dallas storms :D
(2) Pray for the families who has lost there homes in this storm that crushed through Dallas/Ft. Worth today
(3) Bad storms in Dallas yesterday,none here in Austin,Call ZINDLER AND SONS ROOFING for your leaky roof !!!

As described in Fox (2001), English speakers need not provide a source for a piece of information. Therefore, zero-evidentiality cannot guarantee that the user is the source of the information, simply

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3 In the examples included in each section, where a tweet contains multiple spans, the relevant spans and annotation types appear in bold-face font. Examples are included from a variety of Project EPIC datasets, not simply the subset of Project EPIC data annotated here.
that the user did not feel pragmatically obligated to provide a source of information.

4.2.3.3 Visual

Spans marked for Visual evidentiality describe an event of visual perception whereby the speaker acquires knowledge of an event, state, or characteristic. Visual evidentials must be distinguished from zero-evidential spans that describe events of visual perception. The contrast is shown in the following tweets:

(1) today was a good day...helped donate to those in Haiti and then spent time with the girls and saw an old friend ; ) — Zero-evidential

(2) Just saw that @cnn is streaming @news9 live feed of the wildfires #OKFire — Visual

Whereas in (2) the event of seeing provides evidence for the assertion of another event (“@cnn is streaming @news9 live feed of the wildfires #OKFire”), in (1) the verb “saw” signals the visual acquisition of a percept (“an old friend”). The following examples serve to illustrate Visual evidential marking.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Just saw three pieces of sleet fall. Nemo is hitting Russellville! Buy bread! Start your fireplaces! Barricade your doors! #sarcasmfont</td>
<td>Visual</td>
</tr>
<tr>
<td>1</td>
<td>RT @RRFNWick: [On the way to Mankato, MN yesterday], I saw tillage has started in southern MN. Still way too wet in Red River Valley. #farm</td>
<td>Retweet</td>
</tr>
<tr>
<td>2</td>
<td>On the way to Mankato, MN yesterday, I saw tillage has started in southern MN. Still way too wet in Red River Valley. #farm</td>
<td>Visual</td>
</tr>
<tr>
<td>1</td>
<td>@themunfocused I saw the pictures of Christchurch today. Unbelievable destruction. Be safe over there.</td>
<td>Visual</td>
</tr>
</tbody>
</table>

---

4 Hashtags are included in contiguous spans as a matter of principle, even when not in a possible syntactic position. Hashtags serve to contextualize the information presented and their association with one particular span over another is often unclear.

5 Of course, the sense of “see” here is one of visual perception with social interaction.
4.2.3.4 Non-visual

Non-visual evidentials encompass all instances where a primary sensory event other than visual perception provides the source of information about the existence of another event. Non-visual evidentials are distinguished from Hearsay events, which may also contain the verb “hear,” by the fact that non-visuals encode direct perception. The following examples illustrate Non-visual evidentiality. This distinction is motivated by the typological literature; there is no special claim here about the status of visually-acquired information as opposed to information acquired via the other senses.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>did i hear hilary barry say the death toll could rise 200 more? jesus christ this is terrible, #christchurch</td>
<td>Non-visual</td>
</tr>
</tbody>
</table>

4.2.3.5 Inferred

Inferred information is usually marked by “appears (to be)” or “seems (to be).” Annotators were instructed that in order to mark inferred information, a verb such as “seem” or “appear” must be a matrix verb with an embedded predication (e.g. “She seems fine.” or “Christchurch appears to be recovered.”). Verbs referring to a speaker’s mental processing of information (e.g. “I gathered/understood/discovered that the weather was improving...”) were also said to signal an Inferred evidential.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>It seems that maybe as many as a third of the buildings in central Christchurch may have to be demolished, such... <a href="http://fb.me/Qss6lfWD">http://fb.me/Qss6lfWD</a></td>
<td>Inferred</td>
</tr>
<tr>
<td>1</td>
<td>got my family back from chch. Nice to be on solid ground seems to be the consensus</td>
<td>Inferred</td>
</tr>
</tbody>
</table>
### 4.2.3.6 Assumed

Assumed information is marked by a relatively small class of conventional linguistic formulations. Annotators were instructed that spans marked for Assumed evidentiality would likely contain one of the following expressions: “assumed (to be),” “likely (to be),” or “believed (to be).” However, corpus annotation may expand this list of lexical indicators.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Irish man ‘trapped’ in NZ quake building: It’s believed a man from the Republic of Ireland could be trapped in a ... <a href="http://bit.ly.fPyfSN">http://bit.ly.fPyfSN</a></td>
<td>Assumed</td>
</tr>
<tr>
<td>1</td>
<td>The tragedy of the Christchurch quake has hit home for me with the horrible realisation that someone I knew is among those believed dead.</td>
<td>Assumed</td>
</tr>
</tbody>
</table>

### 4.2.3.7 Hearsay

Hearsay evidence comes to a speaker by some means other than direct non-visual experience. Nonetheless, and often confusingly to annotators, hearsay segments generally contain the verb “hear.” Hearsay can also be marked by expressions such as “Caught wind of...” or “Reports that X has occurred...”. For annotators, the important distinction between Hearsay and Source Attribution is that Hearsay spans never mark the source of the information. Thus, even if the source of the information is known to the annotator, perhaps via inference from other tweets in the dataset or from world knowledge, if a span contains reported information and a source is not named, the span will be labeled Hearsay.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>@minimonos @Cade77MM I hope that everybody is safe over there a NZ. I heard there have been some deaths though. STAY SAFE NEW ZEALAND :D</td>
<td>Hearsay</td>
</tr>
</tbody>
</table>
4.2.3.8 Source Attribution

Information may be attributed to a source outside of Twitter, such as a person or news organization. Annotators were instructed never to use the Source Attribution label to attribute information to a username, which were instead coded as instances of User Attribution. The information attributed to a source, while frequently Zero-evidential, could theoretically pertain to any evidential category.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PM: Boosing efforts to locate backpackers missing in NZ quake: <a href="http://bit.ly/hHhmiC">http://bit.ly/hHhmiC</a> YNet</td>
<td>Website Attribution</td>
</tr>
<tr>
<td>2</td>
<td>PM: Boosing efforts to locate backpackers missing in NZ quake</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Boosing efforts to locate backpackers missing in NZ quake</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Two crew missing from movie ship in Sandy - CNN: CTV NewsTwo crew missing from movie ship in SandyCNNNE... <a href="http://t.co/VRTknxBw">http://t.co/VRTknxBw</a></td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>Two crew missing from movie ship in Sandy</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Officials reporting that the fire is spreading south</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>the fire is spreading south</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Fire department says it sees that everybody is safe.</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>it sees that everybody is safe</td>
<td>Visual</td>
</tr>
</tbody>
</table>

4.2.3.9 Quotative

In contrast to Hearsay or Source Attribution spans, Quotatives attribute specific words to a speaker, generally via the use of quotation marks, as in the following examples.
Both complete and partial quotations, where only a subset of a sentence or phrase appears in quotation marks, are included as Quotatives. Partial quotatives are marked as components of larger Source Attribution spans, as shown below.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Gov. confirms at least 34 injured. Some hot spots in south central OK. &quot;Amazing no lives were lost.&quot; Property loss could have been</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>Amazing no lives were lost.</td>
<td>Quotative</td>
</tr>
</tbody>
</table>

Where quotation marks were present but no source of information could be identified, annotators were instructed not to code the span as Quotative.

### 4.2.3.10 Website Attribution

Information in spans is typically attributed to websites by listing the website after the information given. However, other positions in the tweet may be utilized, and not every website listed in a tweet is the object of information attribution. For instance, in tweets where a span explicitly directs the reader to a website or merely mentions website content (e.g. “Friends from home took these pictures! – Storm Pictures from the Dallas-Fort Worth Metroplex http://t.co.LvMQZcnM” or “Stuff have photos here, including Press office http://www.stuff.co.nz/4688231/Deaths-destruction-in-Christchurch-quake OMG”), that span does not, on its own, demonstrate Website Attribution; only in cases where there is another statement before or after the span directing the user that is
attributed to the website is the full span marked as Website Attribution (e.g. “(Emma) Also: NZ Book Month voucher spending begins - with photos - correct link: http://bit.ly.gTyvXn”). Additionally, some tweets ending in a website may be cutoffs, where the website provides a link to a continuation of the tweet content and not to the information source (e.g. “Overheard from a #TTC operator: “On time is not happening!” So, business as usual then. #snowmageddon @... http://t.co/VqsRBCRN”); these spans are not marked as Website Attribution.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RT @wildfiretoday: Body of 3rd victim found in #LowerNorthForkFire in Colo. <a href="http://t.co/bq71BTfx">http://t.co/bq71BTfx</a> <a href="http://t.co/V917TWhh">http://t.co/V917TWhh</a></td>
<td>Retweet</td>
</tr>
<tr>
<td>2</td>
<td>Body of 3rd victim found in #LowerNorthForkFire in Colo. <a href="http://t.co/bq71BTfx">http://t.co/bq71BTfx</a> <a href="http://t.co/V917TWhh">http://t.co/V917TWhh</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Body of 3rd victim found in #LowerNorthForkFire in Colo.</td>
<td>Zero-evidential</td>
</tr>
</tbody>
</table>

In some cases, the website may contain media that provide supporting evidence for a statement, as in the following example:

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mike Francesa on Nemo: ’Don’t overreact.’ #video <a href="http://t.co/7QaTttvZ">http://t.co/7QaTttvZ</a> via @BobsBlitz</td>
<td>User Attribution</td>
</tr>
<tr>
<td>2</td>
<td>Mike Francesa on Nemo: ’Don’t overreact.’ #video <a href="http://t.co/7QaTttvZ">http://t.co/7QaTttvZ</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Mike Francesa on Nemo: ’Don’t overreact.’</td>
<td>Quotative</td>
</tr>
<tr>
<td>4</td>
<td>Don’t overreact.</td>
<td>Zero-evidential</td>
</tr>
</tbody>
</table>

4.2.3.11 User Attribution

Information may be attributed to a user by listing the username, typically after the word “via” or “from” or through other means of citation, such as putting a username in parentheses after the span containing the information. In order or to be marked as User Attribution, a span was required to exhibit explicit marking. The mere mention of a username near a potentially attributed proposition is not said to signal User Attribution, as mentioning a username is also a
mechanism for having that tweet appear in the mentioned user’s feed.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>'Nemo' storms Twitter - <a href="http://t.co.zL0Gt5v9">http://t.co.zL0Gt5v9</a> <a href="http://t.co.rGYm5gEU">http://t.co.rGYm5gEU</a> via @nypost (I'm sure BuzzFeed is on this too)</td>
<td>User Attribution</td>
</tr>
<tr>
<td>2</td>
<td>'Nemo' storms Twitter - <a href="http://t.co.zL0Gt5v9">http://t.co.zL0Gt5v9</a> <a href="http://t.co.rGYm5gEU">http://t.co.rGYm5gEU</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>'Nemo' storms Twitter</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Update: Power outages at 350,000 as winter storm batters New York, New England. (@AP) #Nemo</td>
<td>User Attribution</td>
</tr>
<tr>
<td>2</td>
<td>Update: Power outages at 350,000 as winter storm batters New York, New England.</td>
<td>Zero-evidential</td>
</tr>
</tbody>
</table>

4.2.3.12 Retweet

Retweeting is a method for the automatic quotation of tweet content. When a user retweets, the content appears in a text box in the Twitter client such that the user is able to manipulate or add to the text. Although Retweets may vary in their presentation, the prototypical form is made by placing “RT @username:” at the beginning of the tweet, as in the following example:

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RT @wildfiredotoday: Body of 3rd victim found in #LowerNorthForkFire in Colo. <a href="http://t.co/bq71BTfx">http://t.co/bq71BTfx</a> <a href="http://t.co/V917TWhh">http://t.co/V917TWhh</a></td>
<td>Retweet</td>
</tr>
<tr>
<td>2</td>
<td>Body of 3rd victim found in #LowerNorthForkFire in Colo. <a href="http://t.co/bq71BTfx">http://t.co/bq71BTfx</a> <a href="http://t.co/V917TWhh">http://t.co/V917TWhh</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Body of 3rd victim found in #LowerNorthForkFire in Colo.</td>
<td>Zero-evidential</td>
</tr>
</tbody>
</table>

As a first variation, Retweets may be multiply retweeted, as in the following examples:

- RT@mkokc@elmofromok @patrickallmond #OKFires #OKFire Updated fire map: http://www.srh.noaa.gov/oun...
- RT @okem: RT @redcrossokc: An evacuation center has been set up at the Midwest City Community Center at 100 North Midwest City Blvd. #okfire
Additionally, and importantly for the determination of annotation spans, users may comment on retweets, typically by writing material before the “RT” symbol. While content placed before the “RT” symbol is easily distinguished as emerging from the current user (e.g. “Done! RT @RedCross Text Haiti to 90999. 100% of your $10 donation to @RedCross for Haiti relief. cell carrier keeps nothing.”), content placed after a retweeted segment is considered ambiguous. While annotators were instructed to assume that text appearing after an “RT” symbol is part of the retweeted content, in certain cases such as in the example below, it was possible to define a separate annotation span (shown in bold) based upon the tweet semantics and tweet structure. In this case, annotators inferred that “Get it higher!” was appended by the current user, likely due to the presence of parentheses offsetting the span and the frequency with which websites, whether as components of Website Attribution or otherwise, appear at the end of tweets.

“RT @mashable Red Cross Raises $800 000+ for Haiti Through Text Message Campaign http://ow.ly/1n0Pbn (Get it higher!)

4.2.3.13 Discussion

Because evidentiality is the first layer of annotation coded, and therefore the annotation layer where spans are determined, it is also the annotation task within which coders must determine the constituency of words as they relate to embedded spans. This constituency may be genuinely ambiguous, as in the following example:

RT @Alyssa_Milano: Wow. 28 yr-old man pulled alive from rubble in #Haiti 4 weeks after earthquake http://bit.ly/9jttMM (via @BreakingNews)

Following the annotation guidelines previously described, we see that the tweet contains a Retweet, Website Attribute, and a User Attribution. However, the spans of these annotations are unclear. For instance, consider the following segmentations, marked in square brackets:

(1) [[RT @Alyssa_Milano: Wow. 28 yr-old man pulled alive from rubble in #Haiti 4 weeks after earthquake http://bit.ly/9jttMM] (via @BreakingNews)]
In (1), the Retweet is attributed to @BreakingNews, whereas in (2) the Retweet contains the @BreakingNews span and only the interior span (“Wow. 28 yr-old man pulled alive from rubble in #Haiti 4 weeks after earthquake http://bit.ly/9jttMM”) is attributed to @BreakingNews. In order to render such examples less confusing to annotators, the following annotation order was defined:

1. Retweet
2. User Attribution
3. Website Attribution
4. Source Attribution

In general, this corresponds to an “outside-in” approach to tweet spanning. This order was supplied as a heuristic rather than an absolute, but many tweets were amenable to this interpretation. The order may be justified by the observation that annotation ambiguity likely signals a potential ambiguity for the tweet readership. The example above, this order selects for the interpretation provided in (2).

Additionally, annotators needed to consider the constituency of hashtags, which are frequently unrelated to either the linguistic syntax or the tweet structure. While hashtags generally do not fit neatly into logical tweet spans, they serve to contextualize tweet content, and this contextualization is assumed to occur transitively, such that subspans of a subsuming span are also associated with the semantics of a hashtag marker. Therefore, annotators were instructed to include these within spans that could potentially cover them and all subsuming spans, as illustrated in the following example:

[[From MWCDF: [Eastwood addition, a lot of damage. Part has power, part doesn’t. Won’t open it back up. #OKFires]] (via @mkokc)]

Inter-annotator agreement rates for evidentiality annotation are reported in the following table.
<table>
<thead>
<tr>
<th>Dataset</th>
<th>IAA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>.824</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.719</td>
</tr>
<tr>
<td>Red River Flood (2009)</td>
<td>.796</td>
</tr>
<tr>
<td>Red River Flood (2010)</td>
<td>.870</td>
</tr>
</tbody>
</table>

Table 4.3: Evidentiality Inter-annotator Agreement (IAA)

We now turn to the speech act layer of the pragmatic annotation infrastructure, where the spans delineated by evidentiality annotation are labeled according to the type of illocutionary act they perform.

### 4.3 Speech Acts

Speech Acts are a valuable component of a pragmatic annotation infrastructure because they characterize speaker actions at the level of the utterance. Whereas IC annotations describe the disaster-relevant information contained in utterances, speech act annotations label the speaker actions to which this information is relevant. Speech Act Theory, as it has informed previous computational work relevant to a crisis tweet annotation, is based on the work of Austin (1962) and Searle (1969; 1976; 1979). Austin (1962) provides a theory of performative utterances. Unlike purely truth-conditional statements, performatives are subject to conditions of felicity (effectiveness/appropriateness) rather than simply to conditions of veracity. In order for a performative to be felicitous, it must conform to the following specifications (1962: 14-15):

1. The act must constitute a conventional procedure with an expected outcome. The utterance must be recognizable as a speech act of a certain type.
2. The act must be performed in the appropriate real-world situation. For instance, a marriage cannot be performed by just anyone, nor can it join any two people.
3. It must be performed correctly. The act must be given in its recognizable form.
4. It must be performed completely.
(5) It must be given with the proper intentions. The speaker must intend to do the act given.

(6) And it must elicit the expected subsequent action. The act must cause the change in the world that it was designed to engender.

If one or more of these conditions is violated, then a speech act performance is considered infelicitous. Infelicitous speech acts can be of various types. Violations of conditions (1) or (2) yield misinvocations; violations of (3) or (4), misapplications or misexecutions; and violations of (5) or (6), abuses (1962: 17-18). The ability to define such specifications underlines the conventional nature of speech acts. Although speech acts are by definition conventional, they need not be instantiated using a single linguistic form. Speech acts may be either explicit or implicit. While explicit (or direct) speech acts indicate the category of the act directly (e.g. an offer prefaced by “I hereby offer”), implicit (or primitive or indirect) speech acts do not strictly adhere to a certain form, but are nonetheless loosely conventional, as in the case of uttering “It’s cold in here” as a request to close an open window. Austin offers an initial speech act classification, comprised of classes of speech act verbs:

(1) Verdictives: e.g. judging
(2) Exercitives: e.g. appointing, warning
(3) Commissives: e.g. promising.
(4) Behabitives: e.g. apologizing, congratulating.
(5) Expositives: reflections on the current discourse, e.g. conceding, illustrating.

Research on speech act verbs and classes (as opposed to speech act types) is extended by Wierzbicka (1987).

Searle builds on Austin’s theory of illocutionary acts by focusing on the proper taxonomic arrangement of predicates by marking a distinction between a clustering of verbs according to semantic characteristics and a clustering based on illocutionary type. The author outlines twelve dimensions that define speech acts (Searle 1976, 1979):

(1) The purpose or point of the act.
The direction of fit between the speech act and the world (words to world, or vice-versa).

The expressed psychological state of the act.

The force of the act.

The status of the speaker and hearer.

The relation of the speech act to the intentions of the speaker and hearer.

The relation of the speech act to the discourse context.

The propositional content of the speech act.

The essential nature of the illocutionary act being a speech act as opposed to an act accomplished in some other modality.

The necessity of some institution outside of the speech act for the accomplishing of the speech act.

Whether or not the illocutionary verb has a performative use.

Differences in the style of the performance of the speech act (as for near-synonyms).

Note that these dimensions constitute a set of features rather than a taxonomy of classes. Having defined key characteristics of speech act types, Searle constructs an alternative taxonomy that includes the following act types:

1. Representatives (Assertives): assertions of the truth of propositions, including statements

2. Directives: e.g. ordering

3. Commissives: commitments to future action, e.g. promising

4. Expressives: expressions of a speaker's mental state, e.g. "I hope we win."

5. Declarations: e.g. marrying

Searle (1979: 31-32) also offers a treatment of indirect speech acts. He suggests that indirect speech acts function through complex inferencing based on mutual background information, conversational maxims dictating conversational cooperation (in accordance with Grice 1975; reprinted in Nuccetelli and Seay, eds. 2008), and convention. Like explicit speech acts, indirect speech acts are subject to preparatory conditions, essential conditions, and conditions of sincerity and propositional content. Preparatory, sincerity, and essential conditions concern the speaker's stance and ability to perform a speech act. For instance, in order to affect a marrying speech event, the speaker must be a proper
officiator to marry a set of hearers; he or she must intend to marry them; and the utterance must count as an instance of a marrying speech act. The condition on propositional content ensures that the utterance has the proper semantic components to (potentially) meet the essential condition (1979: 44). Both direct and indirect speech acts appear in tweets; the distribution of speech acts in the crisis tweet data is described in Chapter 6.

### 4.3.1 Speech Act Recognition for Computer-mediated Communication

Automatic identification of direct and indirect speech acts in computer-mediated communication is a topic of two recent studies. These efforts serve to contextualize the effort described here and motivate the specific implementation of the speech act annotation scheme. Both studies use variants of Searle’s taxonomy as presented above.

Zhang and colleagues (2011; 2012) present a supervised machine learning approach to identifying speech acts in Twitter. The authors annotate five speech acts derived from the Searlean taxonomy. The mapping to Searle’s categories is shown as Table 4.3.1.

<table>
<thead>
<tr>
<th>Zhang et. al.</th>
<th>Searle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statement</td>
<td>Representative</td>
</tr>
<tr>
<td>Question</td>
<td>Directive</td>
</tr>
<tr>
<td>Suggestion</td>
<td></td>
</tr>
<tr>
<td>Comment</td>
<td>Expressive</td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>Commissive Declarative</td>
</tr>
</tbody>
</table>

Table 4.4: Mapping to Searle’s Taxonomy (derived from Zhang et. al. 2011: 86)

Zhang and colleagues (2011: 19) classify speech acts on a per-tweet basis and assume that a tweet contains a single speech act. The authors appear to conflate the notion of a tweet’s speech act *containment* with its speech act *performance*. Consider the following examples from Zhang et. al. (2012: 19; examples include Zhang et. al. annotations).

(1) #sincewebeinghonest why u so obsessed with what me n her do?? Don’t u got ya own man???? Oh wait..... — Question
(2) RT @NaonkaMixon: I will donate 10 $ to the Red Cross Japan Earthquake fund for every person that retweets this! #PRAYFORJAPAN — Suggestion

In the annotation scheme described here, the segmentation produced during evidentiality annotation distinguishes between tweets containing and performing speech acts. Additionally, in the EPIC annotation annotators are permitted to encode multiple speech acts on a tweet span and to annotate indirect speech acts, providing a rich description of this facet of tweet pragmatics. The above examples would be annotated in the following way:

(1) #sincewebeinghonest [why u so obsessed with what me n her do?? Don’t u got ya own man???] QUESTION [Oh wait.....] B-REPRESENTATIVE

(2) RT @NaonkaMixon: [I will donate 10 $ to the Red Cross Japan Earthquake fund for every person that retweets this! #PRAYFORJAPAN] COMMISSIVE (attributed to @NaonkaMixon)

Qadir and Riloff (2011) propose a slightly different version of the Searlean taxonomy as they utilize unsupervised techniques to classify speech acts in veterinary message board posts. The authors omit Declarations from their taxonomy, which do not appear in their data, and propose a reduction in the scope of the category Representative. To qualify as a Representative, the authors require that a post express a belief about a fact (e.g. “I suspect the patient has pancreatitis” (2011: 750)) and not simply state the fact (e.g. “The cat has pancreatitis” (2011: 750-751)), as the authors observed that in context statements of fact which appeared to be assertions might actually be merely observations from the veterinary medical record (i.e. presupposed information, or information that is stated in order to be undermined or challenged by other assertions). In the interest of congruency with the Qadir and Riloff work, and in order to distinguish statements of explicit belief from other statements of fact, this study motivates the inclusion of two varieties of Representatives, as described in the following section.

A Searlean approach to speech act labeling in the EPIC data is both commensurate with previous research and provides an appropriate number of speech act categories to avoid extreme sparsity in the data while still illustrating the diversity of acts performed. We now turn to a detailed discussion of the speech act annotation guidelines.
4.3.2 Speech Act Annotation

Annotators were instructed to evaluate each span for the presence of one or more speech acts. Each speech act type, with the exception of the Representative types, is annotatable as either a direct or indirect speech act. As in the theoretical literature, direct speech acts are defined in the guidelines as utterances marked with a characteristic speech act verb signaling their instantiation of a certain speech act type, whereas indirect speech acts function via an additional inference over a direct type. A “Null” annotation for the indirect speech act indicates that a tweet segment does not instantiate an indirect speech act.

4.3.2.1 Representatives

Representatives are defined as utterances that commit a speaker to the truth of a proposition expressed. Two types of Representatives are annotated. The first type, A-Representatives, are statements of fact that also express a belief state on the part of the speaker, such as “I think,” “I believe,” or “I suppose”.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>At the moment it looks like SE Texas will dodge a bullet. New Orleans is going to be devastated again though, I think.</td>
<td>A-Representative</td>
<td>Null</td>
</tr>
</tbody>
</table>

In contrast to A-Representatives, B-Representatives express a statement of fact without also expressing a belief state on the part of the speaker.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>President Bush, Vice President Cheney to skip Republican convention because of Hurricane Gustav, White House says.</td>
<td>B-Representative</td>
<td>Null</td>
</tr>
<tr>
<td>2</td>
<td>President Bush, Vice President Cheney to skip Republican convention because of Hurricane Gustav</td>
<td>B-Representative</td>
<td>Null</td>
</tr>
</tbody>
</table>

Because Twitter contains many spans that could never occur in conversational speech, B-
Representatives as a category covers many of the phenomena; for instance, retweets and website attributions are (trivially) B-Representatives. This speech act assignment to non-conversational spans both provides a coherent treatment of otherwise unannnotatable spans and allows the annotators to follow through on the obligation to tag every span that has been inherited from evidentiality annotation. However, B-Representatives annotated over Retweet, Website Attribution, and User Attribution spans are converted to “Null” speech act values for classification, as these B-Representatives do not function as statements of fact in a straightforward fashion.

4.3.2.2 Directives

Directives instruct the reader or hearer to perform some action, and can range in intensity from suggestions to demands.

4.3.2.3 Primary Directives

Primary directives contain a verb phrase whereby a speaker explicitly requests, orders, or suggests a course of action using a verb such as “request”, “order”, “implore”, “beg”, etc.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RT @britishredcross: We have launched an emergency appeal for the #Haiti #earthquake <a href="http://bit.ly/5xg9eH">http://bit.ly/5xg9eH</a> Please donate now</td>
<td>B-Representative</td>
<td>Null</td>
</tr>
<tr>
<td>2</td>
<td>We have launched an emergency appeal for the #Haiti #earthquake <a href="http://bit.ly/5xg9eH">http://bit.ly/5xg9eH</a> Please donate now</td>
<td>Directive</td>
<td>Null</td>
</tr>
<tr>
<td>3</td>
<td>We have launched an emergency appeal for the #Haiti #earthquake</td>
<td>B-Representative</td>
<td>Null</td>
</tr>
</tbody>
</table>

4.3.2.4 Indirect Directives

Indirect directives make a request or suggestion by way of another speech act, typically a Question.
Some primary A-Representatives and B-Representatives do not qualify to be Indirect Directives. For instance, a statement such as “Conditions here are really terrible and no one is helping” are not Indirect Directives. Notice in the example above, the primary speech act is not only a B-Representative but also a Question. In contrast, given specific context other Primary Representatives may be Indirect Directives, for instance “Fire Chief said ‘Residents are now asked to evacuate’”.

4.3.2.5 Questions

Prototypically, questions appear in a conventional question format, such as the following:

(1) Wh questions, e.g. {Who(m), What, When, Where, Why, How} are you serving?

(2) Yes/No questions, e.g. “Are you going to the veterinarian today?”

(3) Declarative questions, e.g. “My nose is running?”

While many questions that occur in tweets are marked with a question mark, spans can perform as questions without the expected punctuation, as in the following example:

@BezzeraEspresso i am well. how are you. when are you coming back to christchurch. i want a lunch date.

4.3.2.6 Commissives

Commissives commit the speaker to some course of action. Commissives may be direct or indirect. Primary Commissives contain a specific verb such as “promise” (“I promise to go to the party.”), “threaten.” (“I am threatening you with divorce.”), or invite “I invite you to the party.” The speaker must be the subject of the verb phrase. Indirect Commissives commit the speaker to
future actions without using a verb phrase (containing a verb such as “promise” or “invite”) where
the speaker is the subject.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>@BezzeraEspresso i am well. how are you. when are you coming back to christchurch. i want a lunch date.</td>
<td>Expressive, Question</td>
<td>Commissive</td>
</tr>
<tr>
<td>1</td>
<td>You are invited to a Chat with Administrators of Red River Writers...</td>
<td>B-Representative</td>
<td>Commissive</td>
</tr>
</tbody>
</table>

### 4.3.2.7 Expressives

Expressives indicate the mental or psychological state of the speaker, including the speaker’s wishes, desires, or feelings. Additionally, spans performing thanking, sympathizing, apologizing, welcoming, rebuking, etc. are all Expressives.

- **(Desire)** @BezzeraEspresso i am well. how are you. when are you coming back to christchurch. i want a lunch date.

- **(Hope)** I hope the fires settle down soon. I can’t imagine what some fellow Oklahomans are going through right now. #okfires

- **(Thanking)** @wind4me wow! And thanks so far he hasn’t had to go to any of them last I heard. Lots of ours have though.
4.3.2.8 Declarations

Declarations change the state of the world through their utterance. For instance, an ordained official stating “I hereby declare that you are married” performs a Direct Declaration, in that the official uses an explicit form “declare” to perform the act and after the act is performed the two individuals are married. Indirect Declarations may be instantiated as primary B-Representatives, such as “You are married.” Declarations do not appear in the annotated data for two reasons. First, the data do not contain any Direct Declarations, which are readily identifiable though their deployment of a characteristic verb. Second, Indirect Declarations are not analyzable in this annotation context because satisfaction of the felicity conditions, particularly the status of the speaker and the hearer, cannot be established.

4.3.3 Discussion

Aggregated inter-annotator agreement for speech act annotation is reported below. Despite low agreement on infrequent labels, annotators achieved high agreement overall.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>IAA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>.851</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.863</td>
</tr>
<tr>
<td>Red River Flood (2009)</td>
<td>.941</td>
</tr>
<tr>
<td>Red River Flood (2010)</td>
<td>.817</td>
</tr>
</tbody>
</table>

Table 4.5: Speech Act Inter-annotator Agreement (IAA)

4.4 Territory of Information

Kamio (1997) introduces Territory of Information (TOI) as a framework to explain the presentational practices a conversational participant is licensed to use. Kamio introduces territory from the perspective of the natural sciences, where the term describes ownership of area or property (1997: 1-2). In discourse, the concept of territory is used to label behaviors that demonstrate relative ownership of information. Territory is meant to explain the distributions of the following
utterances (adapted from Kamio 1997: 7):

- BOSS: I have a meeting at 3:00.
- SUBORDINATE: I believe you have a meeting at 3:00.
- SUBORDINATE: ??You have a meeting at 3:00.

Kamio’s assertion is that the BOSS, as the owner of knowledge concerning her calendar, is licensed to personal scheduling information. However, a SUBORDINATE is not, and therefore must utilize an indirect form, making the third example “unnatural” (7). The indirect form places the information in the BOSS’s territory of information, whereas the alternative, direct form places the information in the SUBORDINATE’s territory. Note that the indirect form contains an evidential marker, “believe,” which signals a Belief (in Chafe’s terminology), and which also instantiates a Representative.

4.4.1 Territory and Dialogue Systems

In general, computational linguistics has not applied Territory of Information in system building. However, Yamaoka and colleagues (1992) utilize territory (speaker and hearer) as a mechanism for understanding the politeness conventions that dictate the surface forms of noun phrases in Japanese dialogue. For instance, if a participant is speaking about his or her own street address, the unmarked form “juusyo,” is used whereas the polite form “go-juusyo” is used when speaking of a hearer’s address (1153). The authors implement politeness, among other conversational practices such as anaphoric reference, in a plan-based dialogue system. Noun phrases in a hearer’s territory undergo a special processing path through the system in order to be realized as a polite form. In contrast to the current study, Territory of Information is stored as part of a knowledge base, rather than classified for an utterance.

4.4.2 Territory of Information Annotation

Territory of Information (TOI) annotation marks a tweet segment as being with Speaker, Other, or Indeterminate “territory.” The category of Indeterminate applies both to spans consid-
ered to be mutual information and to spans where it is unclear what annotation category should be ascribed. Annotators are instructed that a label of Speaker territory merely indicates that the information is presented as if the information arose from the speaker’s personal knowledge. Conversely, Other territory is applied where the information is unambiguously attributed to some other person. Annotators are permitted to label each span with only one TOI annotation.

TOI is labeled relative to the *speaker of a segment*. For instance, in a quotation, the quoted material may be Speaker TOI even if the tweet as a whole is Other TOI.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>TOI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Just saw three pieces of sleet fall. Nemo is hitting Russellville! Buy bread! Start your fireplaces! Barricade your doors! #sarcasmfont</td>
<td>Speaker</td>
</tr>
<tr>
<td>1</td>
<td>Overheard from a #TTC operator: “On time is not happening!” So, business as usual then. #snowmageddon @... <a href="http://t.co/VqsRBCRN">http://t.co/VqsRBCRN</a></td>
<td>Indeterminate</td>
</tr>
<tr>
<td>2</td>
<td>On time is not happening!</td>
<td>Speaker</td>
</tr>
<tr>
<td>1</td>
<td>did i hear hilary barry say the death toll could rise 200 more ? jesus christ this is terrible, #christchurch</td>
<td>Indeterminate</td>
</tr>
<tr>
<td>1</td>
<td>Forecasters say Saturday’s storms could be ‘life threatening’ <a href="http://t.co/3EdBFd4z">http://t.co/3EdBFd4z</a> #DFW #Dallas #Texas</td>
<td>Other</td>
</tr>
<tr>
<td>2</td>
<td>Forecasters say Saturday’s storms could be ‘life threatening’</td>
<td>Other</td>
</tr>
<tr>
<td>3</td>
<td>Saturday’s storms could be ‘life threatening’</td>
<td>Speaker</td>
</tr>
</tbody>
</table>

Agreement rates for TOI annotation are described in the following table.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>IAA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>.785</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.696</td>
</tr>
<tr>
<td>Red River Flood (2009)</td>
<td>.921</td>
</tr>
<tr>
<td>Red River Flood (2010)</td>
<td>.883</td>
</tr>
</tbody>
</table>

Table 4.6: Territory of Information Inter-annotator Agreement (IAA)

Annotator agreement is lower for the Haiti dataset which contains more complex patterns of reported information, owing to the fact that the majority of users are not local to the disaster. TOI annotation may also be a more difficult task generally, as tweets are too brief to contain the
nuanced pragmatic markers of TOI, such as hedges.

4.4.3 Summary

Each of the three layers of pragmatic annotation achieved moderate to high inter-annotator agreement by the conclusion of the coding effort. Annotators aided in refining the annotation guidelines in order to make the annotation process clearer and the annotation criteria more precise. Because of the specificity of the guidelines, certain annotation categories, including Inferred and Assumed evidentiality and the speech act Declaration are not represented in the data. Given less strict annotation criteria, it is possible Assumed and Inferred evidentiality could have been annotated, although annotators would likely have marked assumed or inferred evidence rather than evidentiality given that the specific lexical encoding needed to identify assumption or inference as the source of information was not found in the text. In contrast, Declarations are simply not represented in the data; this seems reasonable as Twitter is an unlikely forum for the issuance of declarations.

Finally, as introduced in Chapter 1, this project takes a “linguistic approach” to pragmatic analysis, meaning an investigation where only the evidence gained from an examination of tweet text is considered in forming opinions of tweet pragmatics or in the case of information retrieval, of tweet utility. Because speaker characteristics are relevant to speech act performance and TOI, the set of guidelines provided to annotators is designed solely according to text features from the perspective of each of these theories. This approach, which in some respects constrained and simplified the annotation process, also introduced hidden ambiguities. For instance, because speaker characteristics are needed in order to establish that the speaker is capable of performing a certain speech act, unconscious assumptions about the speaker of a tweet sometimes appeared to influence annotator decisions. This was particularly common in the case of website attributions where the author of the tweet appeared to be affiliated with the news agency where the website linked. While a purely linguistic approach would mark such a tweet as Website Attribution and Other TOI, annotators generally marked the tweets as Website Attribution but Indeterminate TOI.
While this seems like the correct analysis in this case, the annotation is less principled if supposed speaker characteristics are taken into account for some tweets but not for others.

This chapter has introduced the annotation layers encoded in order to produce training data to build classifiers for the automatic labeling of evidentiality, speech acts, and Territory of Information over both tweets and segments. The following chapter details these classification efforts.
Chapter 5

Systems for Pragmatic Analysis

The gold-standard annotations produced by the coding efforts described in Chapter 4, in concert with the pragmatic features annotated by Verma and colleagues (2011), provide a rich characterization of tweet pragmatics. Two applications, (1) information ownership detection and (2) information attribution, exploit various aspects of the pragmatic annotation infrastructure. While information ownership detection is a novel task designed specifically to meet a Project EPIC information extraction need, information attribution is a more general natural language processing task. This chapter provides an introduction to the general classification paradigm employed and describes each application alongside the classifiers and algorithms that support it.

5.1 Classification Approach

This project employs a supervised machine learning approach, utilizing the pragmatic annotations described in Chapter 4 in order to train systems to approximate human judgments. A classification method is implemented, such that the computational system labels a single category on the data as opposed to one or more alternative categories. Two common classification algorithms are utilized: Naïve Bayes and Maximum Entropy. As a generative machine learning algorithm, Naïve Bayes provides a probability for the assignment of each class to a data point and the classification chosen is the one with the maximum probability. In contrast, Maximum Entropy approaches train a logistic regression model on training data and use this model to discriminate between possible classifications of a data point. Implementations of both algorithms are provided by
the MALLET machine learning toolkit (McCallum 2002a). MALLET has been widely adopted for a number of natural language processing tasks and provides efficient Maximum Entropy training, which can be time-consuming (McCallum 2002b).

The classification paradigms designed for the datasets utilized here are motivated by two concerns: dataset composition and dataset size. Because the dataset in aggregate contains 1,943 instances across four distinct subsets, data sparsity can be a major consideration when designing a classification paradigm. In this section, the available training data for each annotation layer is considered in turn. Annotations are viewed from two perspectives: (1) as features of a tweet and (2) as features of a tweet segment. Where information ownership detection utilizes tweet-level features, information attribution requires features at the level of the segment.

5.2 Information Ownership Detection

Information ownership detection involves the attribution of tweet information content taken as an aggregate to a point on a spectrum between speaker ownership and other ownership. Two features are classified on a tweet in order to permit this analysis: tweet Territory of Information and information distance. Because register, subjectivity, and style are potentially relevant to TOI classification, Verma and colleagues’ (2011) classifiers are replicated for these features, as shown in the following section.

5.2.1 Tweet-level Annotations

While evidentiality, speech acts, and Territory of Information may each be described as facets of a tweet, the questions these classifications address are different for TOI versus speech acts and evidentiality. The distribution of each feature considered at the level of individual tweet is described below. Classification experiments are motivated for each annotation layer.
5.2.1.1 Tweet Territory of Information

Tweet TOI annotations answer the question “In whose territory does the information in this tweet belong?” with a single ternary annotation: speaker, other, or indeterminate. The following table provides the relative frequencies of TOI types per hazard subset.

<table>
<thead>
<tr>
<th>Type</th>
<th>Oklahoma Fires</th>
<th>Haiti Earthquake</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speaker TOI</td>
<td>.631</td>
<td>.382</td>
<td>.678</td>
<td>.624</td>
</tr>
<tr>
<td>Other TOI</td>
<td>.354</td>
<td>.528</td>
<td>.290</td>
<td>.363</td>
</tr>
<tr>
<td>Indeterminate TOI</td>
<td>.016</td>
<td>.032</td>
<td>.032</td>
<td>.012</td>
</tr>
</tbody>
</table>

Table 5.1: Tweet Territory of Information Distribution

Although Indeterminate TOI annotations are quite rare, the data provide a fairly balanced distribution of instances of speaker and other TOI. Because a single TOI annotation is applied to each tweet, a single classifier is required to distinguish between the three TOI types. In contrast, a tweet may instantiate multiple speech acts and contain many types of evidential marking. These two annotation layers therefore require a different classification approach, as outlined in the following sections.

5.2.2 Tweet Speech Acts

Tweet speech act recognition seeks to detect speech act instantiation by the speaker of a tweet. A single tweet may contain multiple segments relevant to speech act annotation, as in the following example:

Hope the Haiti single reaches #1 can it do that if it was only released today?

Here, the speaker issues an Expressive through “Hope the Haiti single reaches #1” and a Question through “can it do that if it was only released today?” To classify instances that may be assigned more than one annotation from within a given annotation layer, a common approach is to construct a series of binary (yes/no) classifiers, with one classier corresponding to each annotation type for a
given annotation layer (e.g. Morbini and Sagae 2011, for speech acts). The training data for such
classifiers treats the annotation type label (e.g. “Expressive”) as positive and all other labels as
negative (“Null”). The proportion of positive examples in a given training set is therefore equivalent
to the proportion of annotated instances that have been assigned the annotation type addressed
by the classifier consuming that training set.

The following table illustrates the distribution of speech acts considered at the level of the
tweet.\footnote{Because speech acts and evidential marking may be multiply instantiated in each tweet, the fractions presented here and in the corresponding table on evidentiality may sum to a number greater than one.}

<table>
<thead>
<tr>
<th>Type</th>
<th>Oklahoma Fires</th>
<th>Haiti Earthquake</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null</td>
<td>.313</td>
<td>.567</td>
<td>.299</td>
<td>.353</td>
</tr>
<tr>
<td>A-Representative</td>
<td>.008</td>
<td>.006</td>
<td>0.00</td>
<td>.002</td>
</tr>
<tr>
<td>B-Representative</td>
<td>.577</td>
<td>.325</td>
<td>.651</td>
<td>.618</td>
</tr>
<tr>
<td>Directive</td>
<td>.033</td>
<td>.053</td>
<td>.032</td>
<td>.022</td>
</tr>
<tr>
<td>Question</td>
<td>.037</td>
<td>.018</td>
<td>.011</td>
<td>.006</td>
</tr>
<tr>
<td>Expressive</td>
<td>.033</td>
<td>.043</td>
<td>.014</td>
<td>.008</td>
</tr>
<tr>
<td>Commissive</td>
<td>.004</td>
<td>.004</td>
<td>.005</td>
<td>.002</td>
</tr>
<tr>
<td>Declaration</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 5.2: Tweet Speech Act Distribution

With the exception of B-Representatives, the overall representation of speech act types is
generally quite sparse. While B-Representatives comprise the majority class in three of the four
datasets, tweets are much more likely to be labeled as “Null” with reference to speech act instanti-
ation than as A-Representatives, Directives, Questions, Expressives, Commissives, or Declarations.
Declarations did not appear in the data at all, and therefore this study provides no statistical meth-
ods for their detection. Large class imbalances are also shown for tweet evidentiality annotation,
### 5.2.3 Tweet Evidential Marking

Tweet evidentiality annotation provides an inventory of the evidential marking contained in a tweet, where a tweet may contain multiple types of evidential marking. The following table shows the distribution of evidential marking.

<table>
<thead>
<tr>
<th>Type</th>
<th>Oklahoma Fires</th>
<th>Haiti Earthquake</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero-evidential</td>
<td>.681</td>
<td>.488</td>
<td>.712</td>
<td>.633</td>
</tr>
<tr>
<td>Visual</td>
<td>.010</td>
<td>.004</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Non-visual</td>
<td>.012</td>
<td>.002</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Assumed</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Inferred</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Hearsay</td>
<td>.002</td>
<td>.002</td>
<td>.002</td>
<td>0.00</td>
</tr>
<tr>
<td>Quotative</td>
<td>.029</td>
<td>.004</td>
<td>.011</td>
<td>0.00</td>
</tr>
<tr>
<td>Source Attribution</td>
<td>.069</td>
<td>.087</td>
<td>.127</td>
<td>.061</td>
</tr>
<tr>
<td>Website Attribution</td>
<td>.069</td>
<td>.195</td>
<td>.156</td>
<td>.224</td>
</tr>
<tr>
<td>User Attribution</td>
<td>.040</td>
<td>.024</td>
<td>.011</td>
<td>.008</td>
</tr>
<tr>
<td>Retweet</td>
<td>.181</td>
<td>.427</td>
<td>.059</td>
<td>.173</td>
</tr>
</tbody>
</table>

Table 5.3: Tweet Evidentiality Distribution

Because the number of total training instances is limited and the data are comprised of four different datasets corresponding to three distinct hazard domains with different lexical features (as demonstrated in Verma et. al. 2011), class imbalances are not easily remedied through sampling. Viewing annotations at the level of tweet subsegments can provide more balanced training data, as shown in the following section.
5.2.4 Classification of Tweet-level Linguistic Features from ICWSM

Predicted classifications for tweet-level linguistic features informing situational awareness classification are derived from the ICWSM-11 data. Accuracies for the classification of each feature are shown in Table 5.4.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Dataset</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Register</td>
<td>Oklahoma Fires</td>
<td>.823</td>
</tr>
<tr>
<td></td>
<td>Haiti Earthquake</td>
<td>.724</td>
</tr>
<tr>
<td></td>
<td>Red River Flood (2009)</td>
<td>.846</td>
</tr>
<tr>
<td></td>
<td>Red River Flood (2010)</td>
<td>.881</td>
</tr>
<tr>
<td>Subjectivity</td>
<td>Oklahoma Fires</td>
<td>.851</td>
</tr>
<tr>
<td></td>
<td>Haiti Earthquake</td>
<td>.579</td>
</tr>
<tr>
<td></td>
<td>Red River Flood (2009)</td>
<td>.871</td>
</tr>
<tr>
<td></td>
<td>Red River Flood (2010)</td>
<td>.888</td>
</tr>
<tr>
<td>Style</td>
<td>Oklahoma Fires</td>
<td>.917</td>
</tr>
<tr>
<td></td>
<td>Haiti Earthquake</td>
<td>.884</td>
</tr>
<tr>
<td></td>
<td>Red River Flood (2009)</td>
<td>.923</td>
</tr>
<tr>
<td></td>
<td>Red River Flood (2010)</td>
<td>.924</td>
</tr>
</tbody>
</table>

Table 5.4: ICWSM Feature Classification Performance

Each of the classifiers performs with high accuracy on all datasets, with the exception of register and subjectivity classification for the Haiti dataset. For each of the classifiers proposed below, gold-standard ICWSM features are first utilized to gauge whether register, subjectivity, and style taken as a set are useful features for the classification of a given pragmatic type. In cases where these features boost system performance, predicted values for the ICWSM annotations are also utilized in a subsequent model.
5.2.5 Information Distance Calculation

Evidentiality classification of tweet segments enables a straightforward calculation of the distance between the user and the information presented in the tweet. Only evidential categories under the reported node in the taxonomy are hypothesized to contribute to distance, as these explicitly encode a source of information outside the speaker. Information distance calculation accuracy is dependent on both segmentation accuracy and segment classification accuracies. However, exact spans are not required for information distance calculation.

5.2.5.1 Tweet Evidentiality Detection

Because the training data contains a very small proportion of certain evidential types, tweet evidentiality detectors are constructed only for evidential types comprising five percent or more of the evidential annotations for at least one of the four disaster datasets, for a total of four detectors designed to discover Retweets, Source Attribution, Website Attribution and Zero-evidentiality. Features for these models include unigrams and part of speech only.

<table>
<thead>
<tr>
<th></th>
<th>Oklahoma Fires</th>
<th>Haiti</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
<td>ME</td>
<td>NB</td>
<td>ME</td>
</tr>
<tr>
<td>Baseline</td>
<td>.819</td>
<td>.573</td>
<td>.941</td>
<td>.827</td>
</tr>
<tr>
<td>(1) U</td>
<td>.853</td>
<td>.987</td>
<td>.808</td>
<td>.971</td>
</tr>
<tr>
<td>(2) U, POS</td>
<td>.860</td>
<td>.985</td>
<td>.741</td>
<td>.965</td>
</tr>
</tbody>
</table>

Table 5.5: Retweet Detector Performance
A zero-evidentiality detection task is equivalent to the binary classification of tweet as evidentially-marked or zero-evidential.

5.2.5.2 Term-Based Evidentiality Extraction

To provide coverage for evidential types with insufficient training data, a set of heuristics is defined for the identification of low-frequency evidential types, including Visual, Non-visual,
Hearsay, Quotative, and User Attribution. Because Twitter users appear to utilize a finite set of conventions to signal Quotatives and User Attribution, these types of evidential marking may be relatively straightforward to detect. However, given the small size of the dataset and the limited number of instances, it would be improper to conclude that such a short list of heuristics could capture all possible variations. Terms associated with low-frequency evidential types are included in Table 5.9 below.

<table>
<thead>
<tr>
<th>Evidential Type</th>
<th>Lexical Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual</td>
<td>see, look at</td>
</tr>
<tr>
<td>Non-visual</td>
<td>smell, hear (from)</td>
</tr>
<tr>
<td>Hearsay</td>
<td>hear</td>
</tr>
<tr>
<td>Quotative</td>
<td>“,&quot;</td>
</tr>
<tr>
<td>User Attribution</td>
<td>“@username:”, “via”, “@username reports (that)”</td>
</tr>
</tbody>
</table>

Table 5.9: Lexical Features for Evidential Extraction

5.2.5.3 Results

Average information distance per tweet and system accuracies are shown for each dataset below. In order to give a realistic estimate of system performance, the system utilizes only predicted classifications for Retweet, Website Attribution, and Source Attribution to calculate information distance, as the accuracy of lexical features for a larger dataset is unknown.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Average Information Distance</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>.388</td>
<td>.894</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.715</td>
<td>.762</td>
</tr>
<tr>
<td>Red River Flood 2009</td>
<td>.363</td>
<td>.803</td>
</tr>
<tr>
<td>Red River Flood 2010</td>
<td>.467</td>
<td>.961</td>
</tr>
</tbody>
</table>

Table 5.10: Information Distance Detection by Dataset
While information distance presents a partial perspective on information ownership, tweet information content also plays a role in the overall interpretation of information ownership. Compare the following tweets, which both received a gold-standard information distance of one:

(1) JPMA partner Kids in Distressed Situations coordinates #Haiti relief efforts:
   http://bit.ly/7Wwhq8

(2) Molly Hightower’s blog is a living memorial http://bit.ly/4EHdNI #haiti #uwmcmdm

While each tweet contains information attributed to a website, the content attributed in (2) is ambiguous between being purely attributed and being the speaker’s own opinion. For this reason, annotators tagged (2) as Indeterminate TOI whereas (1) was annotated as Other TOI. TOI therefore provides an additional level of analysis that situates evidential marking within a larger context of tweet composition. Section 5.2.7 describes classification results for the identification of tweet Territory of Information.

5.2.6 Tweet Speech Act Filtering

Both primary (direct) and indirect speech acts are annotated in the data. Because speech acts other than B-Representatives are quite infrequent in the data, in order to boost the instances for training, direct and indirect speech acts are treated equivalently (e.g. Indirect Commissives are classified as simply Commissives). This appears to be in line with current work in speech act recognition for Twitter, which ignores the direct/indirect speech act distinction entirely (e.g. Zhang 2011); however, it is unclear whether other studies collapsing this distinction assign the primary or indirect speech act labels for instances of indirect speech acts. For instance, in the case of a Commissive derived from a B-Representative, a choice could be made to classify based on the primary tag, “B-Representative,” or based on the indirect tag, “Commissive,” or both. In this study, indirect speech act spans are tagged with both the primary and indirect speech act labels, but there is no separate label for indirect speech acts versus direct speech acts. The following example illustrates how direct and indirect speech acts are collapsed into a single annotation category:
On standby all wkend in case flood breaks locally. Planning show at 6 Sunday. Fargo teams live on Newsworld too. #flood09 #redriver

**Primary Speech Act:** B-Representative  
**Indirect Speech Act:** Commissive  
**Training Data:** B-Representative, Commissive

Separate classification of indirect speech acts is discussed as future work in Chapter 8.

Because of the small number of instances available for the majority of speech acts, only two speech act types, B-Representatives and Directives, pass the five percent threshold to be piloted as detector systems. In order to provide a uniform treatment of speech acts, two speech act filtering systems are proposed. Speech act filtering is the task of determining whether or not a tweet instantiates a speech act. Following Qadir and Riloff (2011), an initial speech act filtering system is constructed in order to determine whether a tweet instantiates a non-B-Representative speech act or not. A second system is constructed that additionally includes B-Representatives as speech acts. Results of the first speech act filtering system are shown in the following table. System features include gold-standard evidentiality (“goldE”), predicted evidentiality (“predE”), and gold-standard subjectivity, register, and style taken as a set (“goldTL”), as well as unigrams (“U”) and part of speech tags (“POS”).

<table>
<thead>
<tr>
<th></th>
<th>Oklahoma Fires</th>
<th>Haiti</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
<td>ME</td>
<td>NB</td>
<td>ME</td>
</tr>
<tr>
<td>Baseline</td>
<td>.894</td>
<td>.892</td>
<td>.948</td>
<td>.965</td>
</tr>
<tr>
<td>(1) U</td>
<td>.874</td>
<td>.898</td>
<td>.848</td>
<td>.895</td>
</tr>
<tr>
<td>(2) U, POS</td>
<td>.890</td>
<td>.885</td>
<td>.886</td>
<td>.889</td>
</tr>
<tr>
<td>(3) U, POS, goldE</td>
<td>.892</td>
<td>.889</td>
<td>.887</td>
<td>.890</td>
</tr>
<tr>
<td>(4) U, POS, predE</td>
<td>.894</td>
<td>.885</td>
<td>.887</td>
<td>.887</td>
</tr>
<tr>
<td>(5) U, POS, goldTL</td>
<td>.882</td>
<td>.886</td>
<td>.886</td>
<td>.891</td>
</tr>
</tbody>
</table>

Table 5.11: Subset Speech Act Filter System Performance
Binary classification of non-B-Representative speech acts proves difficult due to the extraordinarily high majority class baselines. Therefore, a second system including B-Representatives as speech acts in also provided. The training data for this task is much more balanced.

Table 5.12: All Speech Act Filter System Performance

<table>
<thead>
<tr>
<th></th>
<th>Oklahoma Fires</th>
<th>Haiti</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
<td>ME</td>
<td>NB</td>
<td>ME</td>
</tr>
<tr>
<td>Baseline</td>
<td>.685</td>
<td>.567</td>
<td>.703</td>
<td>.647</td>
</tr>
<tr>
<td>(1) U</td>
<td>.773</td>
<td>.885</td>
<td>.783</td>
<td>.869</td>
</tr>
<tr>
<td>(2) U, POS</td>
<td>.746</td>
<td>.875</td>
<td>.781</td>
<td>.853</td>
</tr>
<tr>
<td>(3) U, POS, goldE</td>
<td>.907</td>
<td>.963</td>
<td>.905</td>
<td>.954</td>
</tr>
<tr>
<td>(4) U, POS, predE</td>
<td>.878</td>
<td>.931</td>
<td>.869</td>
<td>.918</td>
</tr>
<tr>
<td>(5) U, POS, goldTL</td>
<td>.734</td>
<td>.867</td>
<td>.792</td>
<td>.852</td>
</tr>
</tbody>
</table>

Because of the high accuracy of this system, it is included as the predicted speech act feature for tweet TOI classification, which is in turn included as part of information ownership detection detailed below. The model included for TOI classification is based on word, part of speech, and predicted evidentiality values. The derivation of predicted tweet evidentiality is described in the following section.

5.2.7 Tweet Territory of Information Classification

Territory of Information classified at the level of the tweet provides a ternary classification of information ownership between speaker, non-speaker, and mutual/indeterminate properties. System performances are detailed in the following table. The predicted speech act feature is encoded by the speech act filtering system described in the following section; predicted evidentiality values are those classified for Retweet, Source Attribution, Website Attribution, and Zero-evidentiality.
Table 5.13: Tweet Territory of Information System Performance

The data suggest that a model including word, part of speech, predicted evidentiality, and predicted binary speech act values can predict tweet TOI with high accuracy.

5.2.8 Discussion

Both speech acts and evidentiality contribute as features to the automatic identification of tweet Territory of Information. When combined with information distance, TOI annotations define a space of information ownership with three primary divisions: Speaker, Other, and Indeterminate, but with additional distinctions within territories of information based on distance calculation. For instance, a tweet annotated as Other TOI with a relatively high information distance could be said to be more in another’s territory than a tweet coded as Other TOI but with a relatively low information distance. The interaction between information distances and Territory of Information is discussed in Chapter 6.

A second application, for information attribution, focuses specifically on information that is
derived from a source outside of the speaker.

5.3 Towards a System for Tweet Information Attribution

The following sections detail the foundations of a system for tweet information attribution. Segment-based training data is described, along with systems for the classification of segment evidentiality, speech acts, and Territory of Information. Finally, attribution accuracies are provided.

5.3.1 Segment Level Annotations

The annotation work outlined in Chapter 4 suggests that tweets are reliably analyzable in terms of segments that are relevant to specific annotation types, and that these segments may be intuitively defined with reference to specific conventions of evidential marking present in Twitter communications. If a classification problem can be cast as a segment classification task rather than a tweet classification task, more balanced distributions may be provided in the training data. In the case of speech acts and Territory of Information, a more diverse set of training examples becomes available because the annotations of embedded spans are also considered. In the case of evidential marking, the class imbalances encountered in positing one-versus-all evidential classifiers are mitigated by constructing a single classifier that classifies all evidential types. Annotation type distributions over tweet segments are discussed below. For the majority of tweets, the span of the entire tweet is included in the span inventory. In cases where annotators marked a non-embedding distinction between tweet segments, the tweet itself is not included as a span.

5.3.1.1 Segment Territory of Information Annotations

While tweet-level TOI annotations provide a fairly balanced distribution over TOI types (see Table 5.1), segment annotation boosts the proportion of instances ascribed Indeterminate TOI, increasing the likelihood of their recognition. The distribution of segment TOI annotations is described by the following table; the distribution of tweet-level TOI annotations is included as
Table 5.1 above.

<table>
<thead>
<tr>
<th>Type</th>
<th>Oklahoma Fires</th>
<th>Haiti Earthquake</th>
<th>Red River 2009</th>
<th>Red River Flood</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speaker TOI</td>
<td>.641</td>
<td>.501</td>
<td>.719</td>
<td>.659</td>
</tr>
<tr>
<td>Other TOI</td>
<td>.323</td>
<td>.426</td>
<td>.254</td>
<td>.282</td>
</tr>
<tr>
<td>Indeterminate TOI</td>
<td>.034</td>
<td>.073</td>
<td>.027</td>
<td>.012</td>
</tr>
</tbody>
</table>

Table 5.14: Segment Territory of Information Distribution

Segmentation reveals a greater proportion of spans marked as Indeterminate TOI for the Oklahoma Fires and Haiti Earthquake datasets, while this proportion is reduced in Red River 2009 and remains the same in Red River 2010.

5.3.1.2 Segment Speech Act Annotation

While each segment receives only one TOI value, segments may receive one or more speech act annotations. For speech act annotations, segmentation can have a remarkable effect on the representation of Directives, as shown below (tweet-level Directive frequencies (see Table 5.2) are shown in parentheses for comparison).
Table 5.15: Segment Speech Act Distribution

<table>
<thead>
<tr>
<th>Type</th>
<th>Oklahoma Fires</th>
<th>Haiti Earthquake</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null</td>
<td>.281</td>
<td>.424</td>
<td>.263</td>
<td>.362</td>
</tr>
<tr>
<td>A-Representative</td>
<td>.008</td>
<td>.003</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>B-Representative</td>
<td>.623</td>
<td>.440</td>
<td>.695</td>
<td>.645</td>
</tr>
<tr>
<td>Directive</td>
<td>.072 (.033)</td>
<td>.191 (.053)</td>
<td>.041 (.032)</td>
<td>.053 (.022)</td>
</tr>
<tr>
<td>Question</td>
<td>.032</td>
<td>.040</td>
<td>.018</td>
<td>.016</td>
</tr>
<tr>
<td>Expressive</td>
<td>.047</td>
<td>.053</td>
<td>.039</td>
<td>.023</td>
</tr>
<tr>
<td>Commissive</td>
<td>.009</td>
<td>.012</td>
<td>.010</td>
<td>.003</td>
</tr>
<tr>
<td>Declaration</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

While the frequency of Directives is increased, other frequencies remain similar to those seen for tweet-level annotations.

5.3.1.3 Segment Evidentiality Annotation

Frequencies of types of evidential marking also shift slightly when encoded over segments, as shown in the following table (compare to Table 5.3).
Table 5.16: Segment Evidentiality Distribution

<table>
<thead>
<tr>
<th></th>
<th>Oklahoma Fires</th>
<th>Haiti Earthquake</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero-evidential</td>
<td>.703</td>
<td>.572</td>
<td>.735</td>
<td>.684</td>
</tr>
<tr>
<td>Visual</td>
<td>.007</td>
<td>.002</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Non-visual</td>
<td>.008</td>
<td>.001</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Assumed</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Inferred</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Hearsay</td>
<td>.001</td>
<td>.001</td>
<td>.002</td>
<td>0.00</td>
</tr>
<tr>
<td>Quotative</td>
<td>.020</td>
<td>.002</td>
<td>.008</td>
<td>0.00</td>
</tr>
<tr>
<td>Source Attribution</td>
<td>.050</td>
<td>.046</td>
<td>.088</td>
<td>.040</td>
</tr>
<tr>
<td>Website Attribution</td>
<td>.051</td>
<td>.103</td>
<td>.114</td>
<td>.149</td>
</tr>
<tr>
<td>User Attribution</td>
<td>.028</td>
<td>.013</td>
<td>.008</td>
<td>.005</td>
</tr>
<tr>
<td>Retweet</td>
<td>.134</td>
<td>.256</td>
<td>.042</td>
<td>.119</td>
</tr>
</tbody>
</table>

5.3.2 Discussion

While segmentation can provide richer training data for the classification of certain annotation types, the assumption of segmented data is a concern for the classification of new datasets where gold-standard segmentation is not available. In order to provide pre-segmented spans for classification, a deterministic segmentation algorithm is provided. A description of this algorithm and its accuracy is included as a component of the information attribution system reviewed later in this chapter.

The strengths and potential limitations of the training data provided by human annotations identified here motivate the classification approaches taken for the three applications identified above. The following sections describe a set of tools that utilize gold-standard annotations in order to provide representations of information ownership, information attribution, and speech act instantiation. Classifiers built in service of these applications utilize two popular machine learning
algorithms for natural language processing: Naïve Bayes (NB) and Maximum Entropy (ME) (as implemented in the Mallet machine learning software package (McCallum, 2002a). Unlike information distance calculation, which outputs a numerical value, an information attribution system is required to output spans, one corresponding to the source of information and one corresponding to the information attributed to that source. For this reason, the ceilings for information attribution performance on a given dataset are dependent on the segmentation accuracy for that dataset. However, given a segmentation and a segment classification, the information attribution process is straightforward, as the following example shows.

- RT @RTDNEWS: #RVA St Bridget’s church group is expected back in Richmond from #Haiti tomorrow. http://bit.ly/7feNqC — Reported: Retweet; Attribution: @RTDNEWS

- #RVA St Bridget’s church group is expected back in Richmond from #Haiti tomorrow. http://bit.ly/7feNqC — Reported: Website Attribution; Attribution: http://bit.ly/7feNqC

Following segment classification, an attribution algorithm is applied to a tweet segment together with its predicted classification; if either the segmentation or the classification are incorrect, then the attribution postulated will also be incorrect.

5.3.3 Tweet Segmentation

As illustrated in Chapter 4, tweets containing embedded structures have multiple spans that are relevant for annotation. In order to perform segment-based annotation, a tweet must be parsed into its component spans. Fortunately, for all the irregularity exhibited in tweet orthography or grammar (Zappavigna 2012: 19), many tweets conform to a structural (if not a linguistic) syntax that provides robust patterns for deterministic segmentation. Segmentation accuracy is important for segment speech act and TOI classification, as well as for deterministic information attribution.

A segmentation script based on regular expressions parses the tweets into relevant spans. Accuracies are shown in Table 5.3.3 below.
Table 5.17: Tweet Segmentation Accuracies By Dataset

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Precision</th>
<th>Recall</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>.807</td>
<td>.774</td>
<td>.791</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.703</td>
<td>.741</td>
<td>.722</td>
</tr>
<tr>
<td>Red River Flood 2009</td>
<td>.768</td>
<td>.736</td>
<td>.752</td>
</tr>
<tr>
<td>Red River Flood 2010</td>
<td>.816</td>
<td>.832</td>
<td>.824</td>
</tr>
</tbody>
</table>

Accuracies are higher for datasets where the average per-tweet number of spans is lower, because in such datasets a greater number of tweets contain a single span comprised of the whole of the tweet text. Because segmentation criteria are often a part of the annotation criteria used to discriminate between reported speech types (e.g. Retweet, Source Attribution), evidentiality labels could be assigned deterministically during the segmentation process. However, such a method is incapable of classifying non-obligatory embedding evidential types (Visual, Non-Visual, Assumed, Inferred, Hearsay), to say nothing of speech acts or TOI. Therefore, in the interest of implementing a uniform treatment of all evidential types, such a method is not utilized.

Additionally, despite the standardization of many patterns (Retweet is a particularly striking example), tweets exhibit a certain amount of variation, and therefore evidentiality annotation of reported speech types provides valuable data for segmentation as well as for the classification of pragmatic features; indeed, it was only by consulting annotated data that I was alerted to the presence of certain variations in the presentation of Retweet, Source Attribution, and Website Attribution behaviors. Therefore, a statistical approach to segment evidentiality classification is pursued, as described below.

### 5.3.4 Segment Evidentiality Classification

Segment evidentiality classification is the task of determining the proper evidential categorization given a gold-standard span. In contrast to evidentiality detection for tweets, because each segment is assigned a single evidential category, only one classifier is required to label segment
evidentiality. System accuracies are described by the following table. Features include unigrams ("U") and part of speech ("POS").

<table>
<thead>
<tr>
<th></th>
<th>Oklahoma Fires</th>
<th>Haiti Earthquake</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
<td>ME</td>
<td>NB</td>
<td>ME</td>
</tr>
<tr>
<td>Baseline</td>
<td>.703</td>
<td>.684</td>
<td>.735</td>
<td>.735</td>
</tr>
<tr>
<td>U</td>
<td>.627</td>
<td>.795</td>
<td>.441</td>
<td>.725</td>
</tr>
<tr>
<td>U, POS</td>
<td>.666</td>
<td>.826</td>
<td>.499</td>
<td>.729</td>
</tr>
</tbody>
</table>

Table 5.18: Segment Evidentiality Classifier Performance

The results reveal that segment evidentiality classification is a relatively difficult task, with system performances sometimes underperforming a majority class baseline. Nonetheless, results like those shown for the Oklahoma Fires dataset suggest that relatively high accuracy may be achieved depending on the lexical features associated with the dataset.

5.3.5 Segment Speech Act Filtering

Segment speech act filtering distinguishes speech acts which are not mere statements of fact (non-B-Representatives) from all other instances. For a description of information ownership, it is useful to mark, collectively, the presence of beliefs about facts, questions, directions, commitments to future action, or expressions of emotional state, as these help to further characterize the relationship of a speaker to the information expressed. System performances are described by the following table; the features utilized include unigrams (U), part of speech (POS), gold-standard evidentiality (goldE), predicated evidentiality (predE), and the gold-standard pragmatic features coded in ICWSM-11 (goldTL).
Table 5.19: Segment Speech Act Filtering Performance

<table>
<thead>
<tr>
<th></th>
<th>Oklahoma Fires</th>
<th>Haiti</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
<td>ME</td>
<td>NB</td>
<td>ME</td>
</tr>
<tr>
<td>Baseline</td>
<td>.846</td>
<td>.730</td>
<td>.910</td>
<td>.913</td>
</tr>
<tr>
<td>U</td>
<td>.824</td>
<td>.853</td>
<td>.705</td>
<td>.795</td>
</tr>
<tr>
<td>U, POS</td>
<td>.841</td>
<td>.863</td>
<td>.730</td>
<td>.806</td>
</tr>
<tr>
<td>U, POS, goldE</td>
<td>.840</td>
<td>.872</td>
<td>.768</td>
<td>.849</td>
</tr>
<tr>
<td>U, POS, predE</td>
<td>.839</td>
<td>.868</td>
<td>.762</td>
<td>.823</td>
</tr>
<tr>
<td>U, POS, goldTL</td>
<td>.834</td>
<td>.858</td>
<td>.730</td>
<td>.807</td>
</tr>
<tr>
<td>U, POS, goldE, goldTL</td>
<td>.835</td>
<td>.869</td>
<td>.779</td>
<td>.855</td>
</tr>
</tbody>
</table>

Evidentiality is a strong predictor of speech act as certain evidential annotations for spans, namely Retweet, Website Attribution, and Source Attribution, make a speech act interpretation for that segment impossible. This does not mean that such spans could not be subspans of another span that does instantiate a speech act, such as “I think that the sheriff said that the fire was under control,” which would be labeled as an A-Representative. Pragmatic features of register, subjectivity, and style, taken as an aggregate, do not appear to increase speech act classification performance. Using gold-standard spans, a Maximum Entropy unigram model outperforms most baselines, with maximal performances incorporating gold-standard evidentiality and automatic part of speech tags.

5.3.6 Segment TOI Classification

Territory of Information classified at the level of the segment provides a characterization of information ownership within attributed segments. For segments comprising an entire tweet, the task is equivalent to tweet TOI classification; therefore, segment TOI classification may be seen as an extension of tweet TOI classification. System performances for segment TOI classification are shown in the following table.
<table>
<thead>
<tr>
<th></th>
<th>Oklahoma Fires</th>
<th>Haiti</th>
<th>Red River 2009</th>
<th>Red River 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
<td>ME</td>
<td>NB</td>
<td>ME</td>
</tr>
<tr>
<td>Baseline</td>
<td>.641</td>
<td>.501</td>
<td>.719</td>
<td>.659</td>
</tr>
<tr>
<td>U</td>
<td>.654</td>
<td>.803</td>
<td>.542</td>
<td>.740</td>
</tr>
<tr>
<td>U, POS</td>
<td>.663</td>
<td>.818</td>
<td>.589</td>
<td>.738</td>
</tr>
<tr>
<td>U, POS, goldE</td>
<td>.783</td>
<td>.893</td>
<td>.752</td>
<td>.884</td>
</tr>
<tr>
<td>U, POS, predE</td>
<td>.764</td>
<td>.857</td>
<td>.689</td>
<td>.784</td>
</tr>
<tr>
<td>U, POS, goldS</td>
<td>.801</td>
<td>.898</td>
<td>.773</td>
<td>.886</td>
</tr>
<tr>
<td>U, POS, predS</td>
<td>.665</td>
<td>.816</td>
<td>.623</td>
<td>.749</td>
</tr>
<tr>
<td>U, POS, goldTL</td>
<td>.670</td>
<td>.822</td>
<td>.592</td>
<td>.733</td>
</tr>
<tr>
<td>U, POS, All Gold</td>
<td>.848</td>
<td>.899</td>
<td>.852</td>
<td>.889</td>
</tr>
<tr>
<td>U, POS, predE, predS</td>
<td>.765</td>
<td>.857</td>
<td>.710</td>
<td>.798</td>
</tr>
</tbody>
</table>

Table 5.20: Segment Territory of Information System Performance

Evidentiality and binary speech acts provide useful features for segment TOI classification, which can be performed with high accuracy. Predicted values for evidentiality and speech acts yield moderate system performance compared to the use of gold-standard features, showing between four and fourteen percent attrition in system accuracy depending on the dataset.

5.3.7 Results

An information attribution system relies upon the output of the segmentation algorithm, together with labels derived using a segment evidentiality classifier, in order to assign a source of information using a rule-based information attribution algorithm. The system assigns a source of information to a tweet span in three steps:

1) **Tweet Segmentation:** a tweet is automatically segmented using the segmentation algorithm described above.

2) **Evidentiality Classification:** a segment evidentiality classifier trained on gold-standard
(3) **Source Attribution:** an algorithm is applied to determine the span denoting a source of information for the tweet span.

For Zero-evidential, Visual, Non-Visual, Assumed, Inferred, and Hearsay segments, the source of the information may be considered “Null,” as the segment does not indicate a source of information. Information attribution accuracies for each dataset, calculated for a subset of 100 gold-standard segments, are described by the table below. Precision is defined as the number of matches divided by the number of segments proposed (the number of automatic segments); recall is defined as the number of matches divided by the number of gold-standard segments; and an $F$ score is the harmonic mean of precision and recall. In order to count as a match, both the segment and the source assigned must be identical.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Precision</th>
<th>Recall</th>
<th>$F$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>.454</td>
<td>.400</td>
<td>.426</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.643</td>
<td>.740</td>
<td>.688</td>
</tr>
<tr>
<td>Red River Flood 2009</td>
<td>.648</td>
<td>.590</td>
<td>.618</td>
</tr>
<tr>
<td>Red River Flood 2010</td>
<td>.559</td>
<td>.660</td>
<td>.606</td>
</tr>
</tbody>
</table>

Table 5.21: Information Attribution Accuracy by Dataset

### 5.3.8 Discussion

Information attribution accuracies for all datasets are relatively low, suggesting that a compounding of segmentation and evidentiality classification errors make deterministic source attribution difficult. Future work will experiment with methods of source attribution that do not rely on segment evidentiality classification, but rather take a sequence labeling approach to the determination of source spans. Until source attribution accuracies increase, more advanced information
attribution systems remain preliminary. However, segment classifications for speech acts and Territory of Information provide a framework for nuanced information attribution. In future work, given improved source attribution accuracy, it would be straightforward to provide a binary speech act characterization of the information reported by a source and to determine whether that information were owned by the source marked.

5.4 Cross-Disaster Tweet Territory of Information Classification

In order to test the portability of TOI classifiers trained on a single disaster to new disaster domains, cross-disaster classification experiments were performed. Results are described in the following table; systems utilize unigrams, POS, predicted evidentiality, and predicted binary speech act value.

<table>
<thead>
<tr>
<th>Training Set</th>
<th>OKF</th>
<th>HE</th>
<th>RR09</th>
<th>RR10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires (OKF)</td>
<td></td>
<td>.569</td>
<td>.408</td>
<td>.371</td>
</tr>
<tr>
<td>Haiti Earthquake (HE)</td>
<td>.458</td>
<td></td>
<td>.190</td>
<td>.437</td>
</tr>
<tr>
<td>Red River Flood (2009) (RR09)</td>
<td>.544</td>
<td>.373</td>
<td></td>
<td>.561</td>
</tr>
<tr>
<td>Red River Flood (2010) (RR10)</td>
<td>.508</td>
<td>.593</td>
<td>.313</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.22: Cross-disaster TOI Classification

Results demonstrate a common problem for natural language processing systems utilizing supervised machine learning: models built on a training set can be a poor fit for additional data, no matter how (conceptually) similar the data might appear. For instance, classifiers trained and tested on two different flood datasets also fair poorly. Such results can call the entire supervised machine learning approach into question, because systems may only function adequately for the training data provided. When systems fail to port to new datasets, the burden is on system designers to explain why a system fails when applied to additional data and suggest pathways of remediation.
The classification results suggest that the features informing a tweet Territory of Information classifier may be somewhat idiosyncratic, and the problem is likely exacerbated by the small size of the training sets for each disaster. Because they may lack diversity, both in linguistic form and in the annotation labels applied, small datasets can lead a classifier to make incorrect judgments because it has not encountered some linguistic phenomenon in the training data. It is possible that increasing the amount of training data for each classifier could raise system performances. Optimization of cross-domain TOI classification is a topic of future research.

5.5 Discussion

This chapter has presented system accuracies for the classification of evidentiality, speech acts, and Territory of Information, together with the system accuracies of information extraction applications built using these classifications. However, the usefulness of the annotations produced in order to supply training data for these classifiers is not limited to machine learning. The following chapter utilizes the gold-standard pragmatic annotations in a corpus study designed to explore the features associated with Speaker, Other, and Indeterminate TOI.
Chapter 6

Territory of Information: A Corpus Exploration

6.1 Motivation

The purpose of a theory of Territory of Information is to abstract over the individual presentations of markers of attribution or authority to characterize the relation of ownership between the speaker and the information he or she conveys. This chapter explores the role of speech act performance and evidentiality in establishing Territory of Information. Several hypotheses are explored for interactions between speech acts, evidential marking, and TOI, motivated by Kamio’s (1997) treatment of these features.

6.2 Territory and Evidentiality

Kamio argues that evidentiality is relevant to Territory of Information insofar as evidential forms serve as markers of territory (and not primarily as markers of source of information or of belief/certainty). The author takes the term evidential to mean not only the grammatical or lexical form denoting source of information, but also “‘evidence’ that the speaker is assumed to have and how it is related to linguistic forms” (1997: 174). Kamio proceeds by describing a number of circumstances in which no proper evidence could be provided for a zero-evidential assertion, as in “I was born in 1942” (1997: 174), where (in the absence of a birth certificate or parental eyewitnesses) the speaker would have no source of information. From an examination of these circumstances, Kamio concludes that the concept of evidentiality is intractable. To avoid this confusion, following Aikhenvald (2004), evidentiality is defined narrowly as the practice of marking source of information
rather than “evidence” per se; by this definition, and thus in the context of this study, annotators are not obligated to determine whether or not the speaker actually has evidence for the assertion made, and sentences like “I was born in 1942” are described simply as lacking evidential marking, or as zero-evidentially marked. Following Kamio, zero-evidential marking is assumed to indicate Speaker TOI and in the absence of any contradicting information, all information is assumed to be Speaker TOI. The following hypothesis is proposed:

Zero-evidentiality indicates Speaker Territory of Information.

While TOI is labeled on any span delineated during evidentiality annotation, TOI annotations must be treated differently from other annotation types in that the TOI properties of specific tweet subspans do not generally apply to their subsuming spans. For instance, information supplied as retweeted content may be Speaker TOI, but the Retweet span itself will be Other TOI, as illustrated by the following example:

[RT @NewsOK: [At least a dozen houses have burned east of Lake Draper. Area includes land between SE 119 2 SE 149 &amp; Hiawassee &amp; Anderso]SpeakerTOI]OtherTOI

Thus, as illustrated in the guidelines, TOI span annotations must be interpreted relative to the entity they are attributed to via evidential marking. For instance, in a Quotative span, the quoted material is Speaker TOI, but “Speaker” is defined as the speaker of the quotation, which is different from being the speaker of the tweet. Extrapolating from these observations, we arrive at a set of evidentiality annotations which “block” the propagation of a TOI value to a larger tweet span:

(1) Quotative
(2) Source Attribution
(3) Website Attribution
(4) User Attribution
(5) Retweet

This is not to say that subsumed TOI spans are unimportant to the overall interpretation of a tweet’s verifiability. For instance, it may be interesting to know the proportion of Speaker TOI
spans within a tweet, to include tweet subspans. However, the overall Territory of Information of a
tweet will be determined by the maximal annotation span. Frequently, this span covers the entire
tweet, and so the tweet itself receives a single TOI annotation value. More complex cases require
an additional treatment. Consider the following example:

    Seriously? RT @russellmyers: "What good is watching a city burn on three
different networks? Survivor is much more important." - Gr

In this case, the span “Seriously?”, which comprises a comment on the Retweet that follows, is not
included in the same span as the Retweet. The comment is coded Speaker TOI but the Retweet
is coded Other TOI, leaving the tweet without a unified TOI annotation. For tweets where the
maximal span emerging from evidentiality annotation did not cover the entire tweet, the tweet
was passed back through TOI annotation to code a single TOI value for the tweet. Uniformly,
annotators assigned a value of Indeterminate TOI to these instances.¹

Tweets without unified TOI annotations raise interesting questions for the utility of tweet-
level characterizations of evidentiality as a feature for TOI classification and for the quantification
of information distance. In this example, while the presence of a Retweet indeed signals speaker
distance from a portion of the tweet content, the annotation of Indeterminate Territory of Informa-
tion reveals that the presence of the comment portion of the tweet serves to mitigate this distance.
Where information distance is non-zero and Indeterminate Territory of Information is assigned,
information distance may provide a more nuanced characterization of TOI. Consider the following
examples; the information distance for each tweet is listed to the right.

(1) Seriously? RT @russellmyers: "What good is watching a city burn on three
different networks? Survivor is much more important." - Gr (+2)

(2) Thx! RT @TWCBreaking: R resident RRvr flood expert TWC meteorologist Daniel Dix
has an exlnl writeup here: http://bit.ly/dv14L7 #flood10 (+1)

(3) The photograph mapping is done on the map. RT @mahila: http://bit.ly/63pVZf #geo
    #haiti #bosai (+2)

¹ One tweet was coded Other TOI, but this violated the constituency decision annotators had made during
evidentiality annotation. I believe if the annotator had recognized that there were two subspans under consideration,
the annotation would have been Indeterminate TOI also.
Although each tweet is annotated as exhibiting Indeterminate TOI, the tweets exhibit some variation in information distance. However, as annotators assigned only a ternary set of codes for TOI, it is difficult to know what judgments annotators might have made in assigning finer-grained annotations for indeterminate territory. The examples presented here suggest that an examination of qualities of the Speaker TOI segment (the “comment”, for instance “Seriously?” in (1)), rather than information distance, might provide additional insight into Indeterminate TOI; this analysis is provided in the following section.

Tweets with a unified TOI representation may also exhibit surprising evidentiality features. While all tweets with zero information distance as derived from evidentiality (and therefore all tweets annotated as zero-evidential) are annotated as Speaker TOI, tweets containing Reported evidential marking may also be annotated as Speaker TOI, as in the following example:

I just heard that a person was rescued under a pile of rubble 11 days after the Haiti earthquake. That’s insane. I couldn’t imagine...

While this example is annotated as Hearsay, and as having an information distance of one, it is also considered to be Speaker TOI due to the comments that follow the Hearsay content. Conversely, tweets annotated as Other TOI may be marked as Zero-evidential, as in the following example, which should have been annotated as Source Attribution:


However, in contrast to the previous example, this mismatch between evidential marking and expected TOI may be an artifact of the annotation guidelines. As annotators are prohibited from assigning Website Attribution to spans containing ellipses, the information may not be attributed to the tweet-final website. Further, annotators did not consider the hashtag “#NFLHeadlines” to
be a source of information. Nonetheless, it does not seem that the speaker owns this information. Therefore, the tweet is assigned to Other TOI despite having no Reported evidentiality annotated.

The previous examples are not the only instances of tweet segments where the annotated Territory of Information is incongruent with the expected Territory of Information given the evidentiality annotated. A full inventory of all segments exhibiting either Speaker TOI with Reported evidentiality or Other TOI with zero-evidentiality is included as Appendix E; the proportion of segments exhibiting an unexpected TOI value given evidential marking, which is less than 1% in all cases, is described by the following table.

<table>
<thead>
<tr>
<th>Territory of Information</th>
<th>Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>.008</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.003</td>
</tr>
<tr>
<td>Red River Flood (2009)</td>
<td>.006</td>
</tr>
<tr>
<td>Red River Flood (2010)</td>
<td>.005</td>
</tr>
</tbody>
</table>

Table 6.1: Speaker Territory of Information Mismatch

Segments labeled as Speaker Territory of Information are labeled as a Reported evidential type in between three and eight percent of segments. Specifically, such segments are labeled as Hearsay, Source Attribution, User Attribution, or Website Attribution. In cases of Source Attribution, User Attribution, and Hearsay, Speaker TOI is assigned where it is unclear what the information is. If the primary information is thought to be contained in an embedded segment, then the subsuming segment is likely to be labeled as Other TOI; in contrast, if the subsuming segment contains some portion of the tweet’s information value, then the segment may be labeled Speaker TOI. Consider the following examples, which are all annotated as Speaker TOI for the largest span:

1. (Oklahoma Fires) [News9’s @news9wxguy says [rain is likely late tonight and tomorrow.]ZERO-EVIDENTIAL]USER ATtribution

2. (Haiti Earthquake) [I just heard that [a person was rescued under a pile of rubble 11 days
after the Haiti earthquake[ZERO-EVIDENTIAL. That’s insane. I couldn’t imagine...]HEARSAY

(3) (Red River 2009) [U researcher talks Red River flooding in MinnPost
- [“There’s just too much water.”]QUOTATIVE|SOURCE ATTRIBUTION

While in (2) the information contribution of the subsuming span is in the form of opinions about the information content of the embedded span (“That’s insane. I couldn’t imagine...”), in (1) and (3) the judgment of Speaker TOI may be based on the perceived pragmatic salience of the reporting event. Under this interpretation, (1) not only relays the information “rain is likely late tonight and tomorrow” but also provides the information that it is “@news9wxguy” who provides this prediction. Similarly, in (3) the reporting event is highlighted (“U researcher talks Red River flooding in MinnPost”) as well as the related information (“There’s just too much water”). In each of these cases, it is the salience of the non-embedded information, the information owned by the speaker of the segment, which leads the segment to be annotated as Speaker TOI. Website Attribution spans annotated as Speaker TOI often represent a type of annotation ambiguity, between information attribution to a website and direction to a website. Additionally, if a website or blog is thought to be controlled by the speaker, then Website Attribution spans may be annotated as Speaker TOI, as in the following example:

We just added a new webcam to our USGS Webcams page for Red River in Fargo ND http://go.usa.gov/lzs

In contrast to the instances described above, where the information content determines the TOI annotation applied, cases where Zero-evidential is annotated alongside Other TOI instead demonstrate complex evidential marking that may be difficult to annotate. The proportion of tweets annotated as Zero-evidential with Other TOI for each dataset is shown in the table below.
Table 6.2: Other Territory of Information Mismatch

<table>
<thead>
<tr>
<th>Segment</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Fires</td>
<td>.063</td>
</tr>
<tr>
<td>Haiti Earthquake</td>
<td>.032</td>
</tr>
<tr>
<td>Red River Flood (2009)</td>
<td>.010</td>
</tr>
<tr>
<td>Red River Flood (2010)</td>
<td>.001</td>
</tr>
</tbody>
</table>

Segments labeled as Other Territory of Information are labeled as Zero-evidential in up to six percent of segments. In these segments, a possible source of information is not marked. Consider the following examples:

(1) (Oklahoma Fires) Good news: Evacuations have been ceased and residents are being allowed back in the area. Earlier tweets were hung up in cyberspace I guess

(2) (Haiti Earthquake) I’m getting confirmations that http://www.mercycorps.org/haiti is a good choice.

(3) (Red River Flood (2010)) U.S. Coast Guard emergency response crews have begun patrolling... http://bit.ly/8ZJLP0

In (1) and (2), a possible source of information is underspecified. In (1), “earlier tweets” may have provided the information presented; similarly, in (2) the “confirmations” emerge from an unknown source. The assignment of Other TOI in (3) instead emerges from the difficulty of interpreting the ellipsis prior to the website as a cutoff versus an instance of Website Attribution as the ellipsis occurs at a possible syntactic boundary. Other TOI annotation for a Zero-evidential span may also signal a possible annotation error, as in the following example:

Gary England just said if you live SE of these fires don’t climb in your bed and think you’re safe tonight.

The proper annotation for this segment would be Source Attribution, with the embedded segment “if you live SE of these fires don’t climb in your bed and think you’re safe tonight” annotated as Zero-evidential.
In summary, a review of mismatches between segment TOI and evidentiality highlights complex spans with either ambiguous Territory of Information, ambiguous evidentiality, or potential annotation errors. Mismatches are therefore useful for annotation correction as well as targeted corpus analysis.

6.3 Territory and Speech Acts

As described in Chapter 4, speech act theory is designed to provide an account of the non-propositional content of utterances. Kamio (1997: 75-78) suggests that TOI provides an alternative account of performative utterances; the TOI account integrates performativity with epistemic modality. The author draws two distinctions among speech acts: directness and explicitness. A direct speech act form, such as “I can promise you I’ll be there” (76), suggests certainty on the part of the speaker; indirect speech act forms, such as “I believe I can assure you that the letter will be delivered by the day after tomorrow” (76), suggest less confidence. In contrast, explicit speech acts (e.g. “I order you to stand up” (77)) may highlight certain social dynamics more strongly than implicit speech acts (e.g. “Stand up.” (77)). Kamio suggests that the variation in speech act forms along these two dimensions is explained primarily by territory.

Potentially the clearest representation of an interaction between speech act instantiation and Territory of Information occurs in tweets without a unified TOI representation, where the overall TOI assigned to the tweet is not that of its component segment annotations. Consider again the following tweets annotated as Indeterminate TOI:

(1) Seriously? RT @russellmyers: &quot;What good is watching a city burn on three different networks? Survivor is much more important.&quot; - Gr

(2) Thx! RT @TWCBreaking: R resident RRvr flood expert TWC meteorologist Daniel Dix has an exnt writeup here: http://bit.ly/dv14L7 #flood10

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It is unclear from Kamio how TOI would treat such utterances; however the analysis could follow along similar lines to Searle’s description of indirect speech acts (for the example included here: via cooperation and mutual background knowledge, the hearer infers that the speaker is being cooperative and is therefore not asking a literal question concerning the hearer’s obvious physical ability to pass the salt (a fact which lies within the hearer’s TOI), and therefore the speaker must be performing some other action with his speech, an act which could lie within the speaker’s TOI (such as a request)).

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2 Kamio refers only to indirect speech act forms and not to indirect speech acts (e.g. “Could you pass the salt?”).
(3) The photograph mapping is done on the map. RT @mahila: http://bit.ly/63pVZf #geo #haiti #bosai

(4) GOOD Christians NEED to out against this HATE! - Haitian People Are Cursed/Deserved the Earthquake, Rev. Pat Robertson http://is.gd/6dgLH

(5) RT @mashable Red Cross Raises $800,000+ for Haiti Through Text Message Campaign http://ow.ly/1n0Pbn (Get it higher!)

(2), like (1) which has been examined above, is a comment on a Retweet. In each case, the user performs a speech act in the comment provided; (1) instantiates a direct Question and an indirect Expressive while (2) instantiates a direct Expressive. In contrast, (3) and (4) each instantiate direct B-Representatives. Thus, while the initial segments of the tweet comment on later material, the comments add additional information. (4) additionally instantiates an indirect Directive. Examples like (5) are more difficult to analyze as tweets without unified TOI annotations, as annotators were specifically instructed to be cautious in choosing not to include content that could potentially be associated with the retweeted segment; whereas comments appearing between an “RT” symbol clearly originate with the user, comments following a retweeted segment may be ambiguous. Here, annotators determined that the parentheses surrounding the comment were sufficient to suggest that the span was not a part of the retweeted content.

While speech acts and evidentiality may inform TOI annotation, TOI annotations may also highlight inconsistencies and ambiguities in the assignment of evidential categories; this contribution of Territory of Information is examined in the following section.

6.4 Discussion

This chapter has explored correspondences between Territory of Information and speaker deployment of evidential marking and speech acts. While classification experiments provide clear evidence of systematic correspondences between zero-evidentiality, non-representative speech act instantiation, and Speaker TOI on the one hand, and evidential marking and Other TOI on the other, corpus analysis suggests that these correspondences are not universal. An analysis of tweets without a unified TOI annotation demonstrates that Territory of Information captures an aspect
of information ownership not encoded by evidentiality. The assignment of Indeterminate TOI to
tweets containing a speaker’s comment on reported information may be interpreted in two ways.
First, speakers may attribute information to another party while simultaneously appropriating
that information, and thus placing that information within his or her own territory. Second,
indeterminacy of territory could indicate joint TOI because the information reported is presumed
to be mutually owned prior to the user commenting on the reported information. One of the primary
limitations of analyzing tweets outside of their sequential context lies in the inability to determine
whether a piece of information is discourse new or discourse old. Future investigation in this area
could seek to analyze Twitter conversations.

While this corpus investigation has been purely linguistic in nature, establishing Territory
of Information on purely linguistic grounds can be a difficult task. For instance, a piece of news
provided by a reporter, and yet attributed to a website, may be interpreted as Speaker TOI, even
though the same information presented by a user who is unaffiliated with the news organization is
likely to be interpreted as Other TOI. Such distinctions are invisible to a purely linguistic inquiry
but may be important for establishing other features of Territory of Information on non-linguistic
grounds. As Kamio asserts in his motivating example of an exchange between a boss and an office
assistant discussing the boss’s schedule, linguistic forms are presumed to be the reflexes and not the
causes of speaker observations of territory. Therefore an increased knowledge of users, as studied
in numerous Project EPIC research efforts outside the natural language processing domain, could
prove integral to the study of territory.

Finally, there are no theoretical grounds to presuppose a systematic correspondence between
Territory of Information and the value of information presented. Information that could not possi-
bly be relevant to Situational Awareness may be presented as speaker-owned, and information that
is maximally relevant to Situational Awareness may be attributed to sources outside the speaker.
Therefore, any correspondence between tweet Territory of Information and tweet utility must be
determined empirically; this is the topic of Chapter 7.
Chapter 7

Territory of Information for Crisis Information Retrieval

In order to assess the association of tweet Territory of Information with tweet utility to a citizen on the ground engaged in disaster response, a qualitative analysis was performed. This chapter describes an approach to simulating user feedback. Implications of the results for future work are explored.

7.1 Experimental Design

An annotation study was conducted in order to gather user ratings on the usefulness of the information provided by tweets. Because interaction with previous victims of the disaster events analyzed was not feasible or justifiable, a subject matter expert within Project EPIC was asked to play the role of a citizen on the ground, engaged in personal disaster response, for each disaster scenario tested. The citizen was designated as either a disaster victim only, or a victim and citizen responder; the expert was specifically instructed not to consider the citizen as a part of a formal disaster response effort. Additionally, the annotator was instructed to be charitable in considering the applicability of some information. For instance, if a tweet notes the specific street intersection where a fire is located, then this information is read as if the annotator were a user near that location.

Having established the characteristics of the role the expert was to play, an annotation task was defined to assign numeric ratings to samples from two datasets: the 2009 Oklahoma Fires and the 2010 Haiti Earthquake. The Oklahoma Fires dataset consisted of a random sample of 98
SA-relevant tweets (out of 117 SA-relevant tweets, 520 tweets total), whereas the Haiti dataset consisted of all 83 SA-relevant tweets (out of 499 tweets total). Tweets were annotated with a rating from 1 to 5. Annotations were performed in the Dualist annotation interface (Settles 2011; Settles and Zhu 2012), a browser-based annotation tool well-suited to categorical annotation tasks where annotation spans do not need to be assigned. Throughout the annotation process, the annotator was instructed to “think aloud” her reasoning for difficult annotations as an observer (in this case, the author) took notes. The notes were then provided as an aid for the annotator in completing a brief survey about the annotation task, presented as Appendix E. The annotator was not informed of the purpose of the task, other than as a data exploration for the refinement of situational awareness annotation, so as not to skew the results.

7.2 Guideline Development

In the course of the annotation process, the annotator identified key characteristics of tweets that allowed her to make a determination of their utility, as well as contextual information that, where lacking, made a determination difficult. Many of these observations were made on a tweet-by-tweet basis and are therefore relevant. Two particular concerns were identified. First, the assumed position of the citizen relative to locations described in a tweet can drastically affect the tweet’s perceived utility. For instance, at tweet like “New fires popping up at hiwassee rd and Reno ave. #OKFires”) from the Oklahoma Fires dataset could be of extreme importance and urgency to people living near the intersection but of no importance at all to residents across town. In order to treat localized information consistently, a guideline was determined such that the content of each tweet would be interpreted as if the citizen were near the location described. In this way, tweets were evaluated according to their perceived maximum relevance for citizen response. This applied equally to tweets from the Haiti Earthquake data, where specific locations appear less common. If the country or a specific city are mentioned, it is assumed that the annotator plays the role of a citizen in that location.
7.3 Results

7.3.1 Annotator Feedback

Prototypical characteristics for each rating, gathered from the annotator “think aloud” process and follow-up survey, are discussed below.

7.3.1.1 Very Low Utility Tweets (Rating: 1)

A rating of one was assigned to tweets that were considered irrelevant to the crisis scenario. Because all tweets rated in this study were said to demonstrate Situational Awareness in Verma and colleagues’ (2011) data, the identification of a tweet as irrelevant to crisis response, and therefore potentially irrelevant to situational awareness, indicates either a mistake in the situational awareness annotation of a tweet or demonstrates some variance in coder interpretation of situational awareness. Certain annotations, such as the following, appear to be mistakes:

(Haiti Earthquake) GoodNight, loved ones... Taking this moment to say a prayer of support & strength 4 those in need. Children of #Haiti. Love light Strength

In this case, although the tweet is on-topic for the disaster, Verma and colleagues’ guidelines prohibit tweets about prayer from being coded as SA-relevant. The only possible connection to situational awareness within the tweet is the naming of “Children of #Haiti” as a subset of “those in need”; this appears quite general. However, the vast majority of tweets fit the definition of SA-relevance, but would be of little use to citizens on the ground. For instance, the following tweet details a news story which, while relevant to the hazard scenario, is not directly related to personal crisis response activities:

(Haiti Earthquake) RT @SuzeOrmanShow: Check out Larry King Live tonight! They are covering Human Trafficking in Haiti with Sean Penn.

Although children in Haiti were indeed at risk of child trafficking (The Guardian, January 2, 2010), this was not considered actionable information for a citizen on the ground, either because such a citizen would not have been the audience of the tweet, due to a loss of power (The Washington
Post Live Updates, January 13, 2010) or the destruction of a home, or because the information was only tangentially related to day-to-day crisis response by members of the community. Citizens also presented personal information or opinions that the rater considered irrelevant to disaster response because they do not provide actionable information:

> the burnt grass smell is so strong it startles you; you instinctively want to look for the fire that must be near.

For all ratings higher than one, the information provided in a tweet was considered informative or actionable to varying degrees.

### 7.3.1.2 Low Utility Tweets (Rating: 2)

Tweets given a rating of two were said to be low-utility because the content provided was largely “background information,” which included information about donations or general pathways through which citizens could supply aid, such as by calling an agency to determine current needs. This included tweets expressing continuing, non-specific needs such as medical supplies or blood. Tweets commenting generally on the condition of the hazard or explaining background weather phenomena (in the case of the Oklahoma Fires data) carried this rating, as well as tweets on personal status that indicated the user was distant from the disaster area.

### 7.3.1.3 Medium Utility Tweets (Rating: 3)

A rating of three was applied to tweets with content that reported on the hazard situation with the quality and specificity of a news story. Frequently, such tweets were expressly attributed to a news source, such as CNN, but the category was also applied to tweets reporting on the status of a hazard or crisis response activities that were not clearly issued by a news organization, such as the following:

> (Oklahoma Fires) In eastoak, antique truck pulled from burnt home... Husband in navy away... #Okfire
7.3.1.4 High Utility Tweets (Rating: 4)

Tweets assigned a rating of four contained information relevant to an individual or subgroup of the population. This information was not generalizable to a broader population, however. For example, the following tweet provides valuable information concerning the safety of family members:

(Oklahoma Fires) my friend lives there too are homes burning there? They are in the middle but opposite corner from ur parents

Requests for highly specific, restricted-audience information were also rated as four:

(Oklahoma Fires) how’s gma betty’s house?

In the Haiti data, which did not contain many tweets distributing or requesting highly localized or sub-population related information, ratings of four were assigned to news content or aid-related tweets with more specific information, such as the following:

RT @wired updummies: #Haiti Western Union Co. won’t charge transfer fees to anyone sending money to Haiti from the U.S., Canada and Franc ...

While this tweet provides actionable information for friends and family members seeking to send money to contacts in Haiti, the information does not necessarily have broad appeal.

7.3.1.5 Very High Utility Tweets (Rating: 5)

Tweets given the highest rating of five supplied specific, actionable information that was also applicable to a broad audience. Tweets in this category included information on the status of the hazard, status of persons or property, and highly specific requests for aid, such as the following examples:

- (Oklahoma Fires) Shelter @ Choctaw Jr. High auditorium is closed. (via @OkCountySheriff)

- (Haiti) RT @VRWCTexan: @JTFHaiti @USNSComfort RT @lightxxx We have a lady dying of rabies we need Rabies antitoxin asap #Haiti
### 7.3.2 Analysis of Feature Correspondence

Having established annotation criteria for tweet utility and acquired ratings for a sample of tweets from two hazard datasets, additional research is conducted to explore how tweet utility is expressed as a set of pragmatic features including Speech Act labels, TOI, evidential marking, register, subjectivity, and style, and the impact of tweet content on the relevance of these features for tweet utility. While the majority of the analysis presented so far has concerned tweet segments, in this analysis only tweet-level features are considered for TOI, Speech Act, register, subjectivity, and style, and the evidential markings of tweet subsegments are considered as a set. The following example illustrates a set of features labeled on a tweet as a whole:

**Tweet:** RT @NewsOK In Carter County, officials reported at least 15 fires in progress and *several homes* destroyed. #OKFires #OKFire

**Speech Act:** Null

**TOI:** OtherTOI

**Evidential Marking:** [Retweet, Source Attribution, Quotative]

**Register:** Formal

**Subjectivity:** Objective

**Style:** Impersonal

The distribution across pragmatic categories for each tweet utility rating is described in Table 7.1 below. For a more concise representation, evidential marking is represented as information distance (ID), described in Chapter 5 as the number of measurable increments of distance between information origin and the speaker as derived from evidentiality annotations, and speech acts are described as the proportion of all non-B-Representative speech act types (“non-B”), disregarding Null instances. Recall that non-B-Representatives include statements of belief about a fact, Questions, Directives, Commissives, and Expressives.
Differences in distributions of feature values associated with each dataset may derive from differences between the hazard situations during which the data are collected. For instance, the Oklahoma Fires dataset, which contains only hand-verified local users, exhibits a much higher proportion of Speaker TOI tweets than the Haiti Earthquake dataset (.84 versus .24 respectively), which was collected during an event exhibiting international interest and response and which was not highly curated. Similarly, tweets in the Oklahoma Fires dataset have a lower average information distance than those collected during the Haiti Earthquake. In general, formal, impersonal, and objective tweets are rated as higher utility than informal, impersonal, and subjective tweets; however, this trend is weaker for the Haiti dataset.

In order to test the strength of the any correspondences between tweet utility and pragmatic features, a series of pilot classification experiments were performed. The gold-standard features
included are Territory of Information (T), Information Distance (ID), register, subjectivity, and style taken as a set (“goldTL” below), as well as part of speech tags. For contrast, Information Category (IC) annotations are also tested as a feature, independently and in concert with pragmatic features. Data are restricted to instances where an Information Category has been previously assigned, yielding 155 instances total from both the Haiti Earthquake and Oklahoma Fires datasets combined. Because of the small size of the dataset, five-fold cross-validation is utilized.

If classifiers utilizing pragmatic features outperform classifiers based on Information Category information, then this suggests that pragmatic factors may be the most important ones for determining tweet utility. In contrast, if Information Categories prove more predictive, this suggests that tweet utility is based on the differential assessment of information types. Finally, if classifiers including both pragmatic and Information Category information perform best, this may signal that it is co-occurrence of features of tweet pragmatics and information content that lead to the assignment of tweet utility. Results are shown in the following table.

<table>
<thead>
<tr>
<th></th>
<th>NB</th>
<th>ME</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>.419</td>
<td></td>
</tr>
<tr>
<td>U</td>
<td>.426</td>
<td>.439</td>
</tr>
<tr>
<td>U, POS</td>
<td>.487</td>
<td>.461</td>
</tr>
<tr>
<td>U, POS, T</td>
<td>.497</td>
<td>.468</td>
</tr>
<tr>
<td>U, POS, ID</td>
<td>.487</td>
<td>.461</td>
</tr>
<tr>
<td>U, POS, goldTL</td>
<td>.503</td>
<td>.474</td>
</tr>
<tr>
<td>U, POS, T, ID</td>
<td>.497</td>
<td>.468</td>
</tr>
<tr>
<td>U, POS, T, ID, goldTL</td>
<td>.506</td>
<td>.484</td>
</tr>
<tr>
<td>U, POS, IC</td>
<td>.561</td>
<td>.523</td>
</tr>
<tr>
<td>U, POS, T, ID, goldTL, IC</td>
<td>.582</td>
<td>.542</td>
</tr>
</tbody>
</table>

Table 7.2: Utility Classification Results
Although classification accuracies well exceed a majority class baseline, system performance for this task remains relatively low, suggesting that neither the pragmatic features encoded nor Information Category features are highly predictive of tweet utility. However, annotator feedback suggests that the specificity of information provided may affect tweet utility rating. Information specificity may be determined on semantic grounds. Compare the following examples from the Oklahoma Fires dataset:

(1) Looks like the whole town of Choctow OK is going up in flames.

(2) New fires popping up at hiwassee rd and Reno ave. #OKFires

While both tweets provide potentially useful information about the status of wildfires, (2) is rated as “5” where (1) receives a rating of only “3”, likely because (2) provides much more specific location information in the form of street intersection. Patterns of location information are marked by named entities. In addition, (1) describes a change in the hazard situation (“new fires”) where (1) describes an ongoing hazard condition. A semantic analysis of the predicates *pop up* and *go up*, using PropBank or related resources, could reveal whether a tweet describes an emerging or an existing hazard. For instance, where the PropBank frame for *pop up* denotes “appearance”, the frame for *go up* describes “becoming,” indicating a change of state but not necessarily an emergence or coming into existence. Semantic analysis for tweet specificity determination is a focus of future work. Prediction of tweet utility will therefore require an integration of all Project EPIC linguistic annotations, including named entities and semantic role labeling. However, more fine-grained semantic representations may be desirable; for instance, VerbNet class information has already shown potential for information content recognition (Vieweg 2012).

7.4 Discussion

As shown, Other TOI tweets ranked higher in general than Speaker TOI tweets, suggesting that the annotator did not have a preference for firsthand knowledge over reported information, or minimally that any preference that did exist was overcome by the need for specific, actionable
information. Nonetheless, Speaker TOI tweets can be rated very highly when they contain such information, as demonstrated in the Oklahoma Fires dataset. In general, pragmatic features are distributed somewhat evenly throughout the rating categories, suggesting that, as expected, tweet semantics plays the most important role in perceived tweet utility. The datasets explored here do not contain enough diversity to determine whether tweets with equivalent information content and specificity but differing territory would reveal a preference for first-hand information.

A final question on the annotator survey asked about the appropriateness of a five-division scale for rating tweet utility. The annotator indicated that while the granularity was adequate, the scale might be better represented as a range between zero and four, as tweets receiving a rating of one were often thought to have no utility whatsoever. This study motivates a more in-depth analysis of situational awareness annotation in order to determine what is meant by the potential “relevance” of a tweet to disaster response. For instance, while news stories and announcements of news broadcasts may provide valuable information, such information may not always be actionable. Additionally, the annotator highlighted a the value of specific actionable information that has broader applications for individual disaster response. Thus, the most useful information appears to be presented in a formal, generally impersonal and objective style, as a component of either the speaker or other’s territory of information, where the information content is specific but not related only to one’s own family or circumstance.

The analysis presented here has provided a qualitative evaluation of pragmatic features presented in this work and Verma and colleagues (2011) dataset. While the datasets of included tweets are small, the study provides future directions for situational awareness annotation and demarcates the expectations one might have for TOI and evidentiality as analytic tools for determining tweet utility. It is not surprising that some reported information was found to be high-utility, as numerous studies in the crisis informatics literature and beyond have suggested that one of the functions of social media, perhaps acutely so in hazard situations, is to propagate information perceived as valuable. Therefore in future studies of this kind, an additional variable to explore might be the user’s perception of reported speech and its value in general versus information presented as if it
were first-hand.
Chapter 8

Conclusions

Previous chapters have detailed work in corpus annotation, computational implementation, corpus linguistic study, and qualitative evaluation. This chapter provides a summary of the main findings of these studies and their significance, and provides direction for extending this research in future work.

8.1 Findings and Significance

This study provides findings relevant to three areas of research: information retrieval for crisis informatics, natural language processing, and corpus linguistics. Key contributions for each field are defined below.

8.1.1 Information Retrieval for Crisis Informatics

For crisis-oriented information retrieval, a set of codes is provided to facilitate the extraction of key pragmatic information characterizing information ownership.\footnote{Annotation guidelines are provided as Appendix D.} As shown in Chapter 6, these codes provide both an explicit, numeric representation of information distance and a ternary, nominal representation of information ownership. While information ownership by itself does not appear to be a reliable predictor of tweet utility, as Chapter 7 demonstrates, such metrics are vital to crisis information retrieval because of their contributions to a description of tweet reliability. In addition to key features of users, such as location (e.g. Vieweg et. al. 2010), information
distance and Territory of Information may demonstrate a user’s relationship to the crisis information provided and, ultimately, to the crisis situation itself. Because first-hand information provided by local users has been identified as a key source of potentially actionable information, further applications of the frameworks of information distance and Territory of Information are warranted, with particular focus on their interaction with semantic features.

8.1.2 Natural Language Processing

This study has applied natural language processing techniques to Twitter data with three foci: Territory of Information, speech acts, and evidentiality. TOI classification is a novel task for computational linguistics, and this study demonstrates the viability of a supervised machine learning approach. In contrast, speech act recognition and evidentiality detection have been the topics of previous studies, both for Twitter data and for other text genres. This work provides a resource for the classification of speech acts and evidentiality by extending the coverage of previous systems through utilizing complete taxonomies from the linguistic literature and supplying annotated data. Work presented in Chapters 4 and 5 suggests that the full inventories of key distinctions presented in the linguistic literature may be applied to tweet processing, as such categories may be reliably annotated and, in general, classified with high accuracy, both for tweets as a whole and for tweet segments. While the current corpus does not supply training data for all categories of speech acts or evidentiality, such data could be procured through targeted efforts, perhaps by utilizing search terms over a much larger corpus. A summary of top-performing classifiers for pragmatic features is included in the following table (where “OKF” stands for Oklahoma Fires, “HE” for Haiti Earthquake, and “RR09” and “RR10” for Red River Floods of 2009 and 2010 respectively). Classification features in one or more of the systems below include unigrams (“U”), part of speech (“POS”), gold-standard evidentiality (“goldE”), predicted evidentiality (“predE”), gold-standard binary speech act annotations (“goldS”), predicted binary speech act classification (“predS”), and gold-standard subjectivity, register, and style taken as a set (“goldTL”). Best performing systems for both gold-standard and predicted features are shown. In all cases, Maximum Entropy is used as the learning
Table 8.1: Summary of Classifier Performance

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>OKF</th>
<th>HE</th>
<th>RR09</th>
<th>RR10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evidentiality</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>.703</td>
<td>.684</td>
<td>.735</td>
<td>.735</td>
</tr>
<tr>
<td>Predicted: U, POS</td>
<td>.826</td>
<td>.729</td>
<td>.910</td>
<td>.913</td>
</tr>
<tr>
<td>Speech Act Filtering</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>.846</td>
<td>.730</td>
<td>.910</td>
<td>.913</td>
</tr>
<tr>
<td>Gold: U, POS, goldE, goldTL</td>
<td>.869</td>
<td>.855</td>
<td>.943</td>
<td>.936</td>
</tr>
<tr>
<td>Predicted: U, POS, predE</td>
<td>.868</td>
<td>.823</td>
<td>.914</td>
<td>.918</td>
</tr>
<tr>
<td>TOI</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>.641</td>
<td>.501</td>
<td>.719</td>
<td>.659</td>
</tr>
<tr>
<td>Gold: U, POS, goldE, goldS, goldTL</td>
<td>.899</td>
<td>.889</td>
<td>.941</td>
<td>.933</td>
</tr>
<tr>
<td>Predicted: U, POS, predE, predS</td>
<td>.857</td>
<td>.798</td>
<td>.802</td>
<td>.833</td>
</tr>
</tbody>
</table>

algorithm and accuracies are for a segment classification task. Classification experiments reveal that evidentiality and binary speech acts\(^2\) provide useful features for TOI classification, which may be performed with high accuracy using predicted feature values. Accuracy is improved when gold-standard are utilized, showing the potential benefit of improved evidentiality and speech act classification for a TOI classification task.

Additionally, systems are proposed for information distance calculation and information attribution. In service of information attribution, a tweet segmentation algorithm is offered. While information distance may be calculated with high accuracy (76% to 96%), information attribution proves much more challenging (F-scores .43 to .69). Improvements in evidentiality classification will be vital to continued gains in the accuracy of each system. Additionally, through speech act and Territory of Information classification, a framework is outlined for improved, nuanced information distance and source attribution descriptions. For information distance, Territory of Information may provide a moderated perspective on information ownership in cases where Speaker or Indeterminate TOI is annotated with greater than zero information distance. For information attribution, additional qualities of the attributed segment (the speech act quality and the information ownership) may be included in the information attribution representation.

Pragmatic features are also analyzed in terms of their relationship to tweet utility, which is related to potential relevance to situational awareness. Chapter 7 suggests that nuanced descrip-

\(^2\) Speech act annotations classified are statements of belief about facts (A-Representatives), Questions, Directives, Expressives, and Commissives, taken as a set, versus Null.
tions of tweet semantics, particularly with respect to information specificity, may be needed in order to predict tweet utility. It is possible that pragmatic features might aid in the prediction of tweet utility from within levels of tweet specificity once semantic features are fully implemented.

8.1.3 Corpus Linguistics

The primary contribution of this project to corpus linguistic study is in providing an annotated corpus for the investigation of Territory of Information. As Chapter 6 demonstrates, such a corpus permits an investigation into the contributions of speech acts and evidential constructions to speaker formulations of Territory of Information as a pragmatically-determined category. More generally, this work demonstrates the value of linguistic annotation and computational linguistics to corpus-based empirical research on TOI, which has previously been limited to theoretical research based on small sets of examples. Further investigations could explore the interactions of these categories across a wider range of data. Because tweets are very brief and therefore do not include many features relevant to Territory of Information, additional data types must be included for a complete corpus-based examination of TOI.

8.2 Evaluation of Robustness and Portability

This section details cross-linguistic and cross-domain applications of the pragmatic annotation framework employed in this study designed to test the portability of the pragmatic annotation framework and the computational systems it facilitates to new linguistic contexts.

8.2.1 Application to Spanish Tweets

Project EPIC data collected from the Copahue Volcano eruption of 2013 provides data for the analysis of Spanish-language tweets produced during a disaster event that is out of domain for the data examined in this study. The following section provides a brief empirical analysis of a selection of this data and on Spanish data for the tweet segmentation algorithm developed using the Verma et. al. (2011) dataset.
8.2.1.1 Tweet Segmentation

A deterministic segmentation algorithm based upon English Twitter data parses Spanish data with approximately 79% accuracy. The viability of cross-linguistic segmentation suggests that while tweets may contain non-standard language, tweet structure is robust and predictable across languages.

8.2.1.2 Application of Annotation Categories

Analysis of a sample of 100 tweets collected during the Copahue Volcano eruption of 2013 suggests the annotation categories implemented in this study for English data may be readily applied to Spanish language tweets. This is expected given the theories and frameworks from which the taxonomy of annotations is derived; all annotation categories utilized are either presupposed to be language-independent or mark certain language-independent features of Twitter communications. A more large-scale analysis is needed to determine whether the frequencies of individual annotation categories might vary by language.

8.2.2 Application to English Newswire Text

Recent work in computational linguistics has sought to annotate key features of events in newswire text. The shared task of the 1st Workshop on EVENTS: Definition, Detection, Coreference, and Representation\(^3\), co-located with the 2013 annual conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, involved the annotation of event spans and the assignment of event co-reference. Evidentiality is one feature of events identified in the University of Colorado guidelines for this task\(^4\), which are based in part upon the TimeML guidelines (Pustejovsky et al. 2003). The feature “evidential” is applied to “perception” and “reporting” events; Pustejovsky and colleagues (2003: 8) offer the following examples:

\(^{3}\) [https://sites.google.com/site/cfpsevent/task](https://sites.google.com/site/cfpsevent/task)

\(^{4}\) At this time the guidelines are circulated as an unpublished manuscript.
(1) John said he bought some wine.

(2) Mary saw John carrying only beer.

The label “negative evidential” is instead applied in cases where an event is perceived or reported not to have occurred (2003: 8):

(3) John denied he bought only beer.

A subset of the evidential types applied to Twitter data may be utilized for newswire text in order to provide a more nuanced description of evidential marking. For instance, (1) and (3) are examples of Source Attribution whereas (2) is an example of Visual evidentiality. The definition of evidential subclasses, even if not implemented as annotation categories in their own right, could improve annotation guidelines for event evidentiality by providing a richer set of coding criteria and a more varied set of examples. Additionally, because certain types of evidential marking, such as Visual or Non-visual, are instantiated by a restricted set of lexical items, creating evidential subtypes could facilitate the automatic extraction of many evidentials.

8.2.3 Discussion

Early experiments in porting the annotation framework to Spanish tweets and English newspaper text appear promising and motivate further research. Because a broad, language-independent framework has been adopted, which incorporates many evidential categories that are not genre-specific, it is expected that the framework studied here for English Twitter could be applied in a number of linguistic contexts with only minimal adaptation.

8.3 Directions for Future Work

This dissertation has provided initial efforts in pragmatic analysis for an understudied domain, Twitter, and for an understudied pragmatic framework, Territory of Information. Directions for future work include extensions of the speech act framework implemented, a diversification of machine learning approaches, the integration of the systems detailed here into larger Project EPIC
processing systems, and the extension of this feature set to include the semantic features already
annotated, such as named entities and semantic roles, as well as additional semantic information,
such as word sense annotations or annotations derived from lexical resources, such as VerbNet class
assignments.

8.3.1 Speech Act Recognition

Speech act recognition for Twitter is a relatively new task in natural language processing;
Zhang and colleagues (2011) appears to be the first research effort in this domain, and there are a
number of open questions concerning how well computational linguistic approaches to other types
of data, such as naturally occurring conversation, might port to the Twitter domain. The following
sections outline two potential areas for further research in tweet speech act recognition.

8.3.1.1 Speech Act Recognition and Granularity

The presumption has been, both in the work presented here and in previous work, that a
Searlean approach to speech act labeling would encode distinctions fine-grained enough to support
applications. For the data presented here, an augmented set of Searlean speech acts does appear
useful as a feature for recognizing information ownership. However, this taxonomy is quite coarse-
grained relative to the complex taxonomies included in the dialogue act literature. Experiments
with more elaborate speech act taxonomies could provide more nuanced speech act representa-
tions.

8.3.1.2 Recognition of Indirect Speech Acts in Twitter

Indirect speech acts are understudied relative to primary speech acts in computational lin-
guistics. Often, indirect speech acts are encoded by the same annotation layer as primary speech
acts, as it is often the indirect speech act that is the preferred speech act interpretation of utter-
ances (since it is the indirect speech act that motivates subsequent actions in the dialogue). The
separate annotation and treatment of primary and indirect speech acts can provide a resource for
linguists interested in the relationship between direct and indirect speech acts; the annotation of indirect speech acts in Twitter is a novel annotation task and merits further investigation, despite the low frequency of indirect speech acts in the dataset examined here.

8.3.2 Alternative Machine Learning Approaches

The machine learning experiments presented in this work each take a classification approach. However, this is not the only framework that may be applied to the data at hand. Sequence labeling approaches have been applied to quotation attribution (O’Keefe, 2012) in particular, and would be relevant to each of the annotations considered here. In contrast to the current segment classification approach, which relies on a segmentation algorithm, sequence labeling permits machine annotation of segments without parsing the tweet into its component subspans, by probabilistically judging whether a token is inside or outside a span of a given annotation type. While deterministic segmentation performs well for the data explored here, sequence labeling could outperform segmentation for tweets that do not adhere to expected structures, such as atypically-formatted retweets or website attributions where the website appears before the information attributed.

8.3.3 Integration into a Crisis Informatics Interface

Finally, while the focus of this work has been the extraction of pragmatic features for the purpose of information retrieval, the applications discussed may be of interest to information scientists studying crisis response on Twitter. McTaggart (2012) details an analysis engine in support of crisis informatics study that could be a site of integration for the tools presented here. For instance, in addition to retrieving tweets from a specific timeframe, or with specific search terms, or which are coded as relevant to situational awareness, analysts could additionally retrieve tweets demonstrating a specified information distance or where a certain pattern of information attribution were present.
Bibliography


# Appendix A

## Information Category Taxonomy

<table>
<thead>
<tr>
<th>Macro-level Information Category</th>
<th>Micro-level Information Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Environment</td>
<td>Advice - Information Space</td>
</tr>
<tr>
<td></td>
<td>Animal Management</td>
</tr>
<tr>
<td></td>
<td>Caution</td>
</tr>
<tr>
<td></td>
<td>Crime</td>
</tr>
<tr>
<td></td>
<td>Death</td>
</tr>
<tr>
<td></td>
<td>Evacuation</td>
</tr>
<tr>
<td></td>
<td>General Population Information</td>
</tr>
<tr>
<td></td>
<td>Injury</td>
</tr>
<tr>
<td></td>
<td>Missing</td>
</tr>
<tr>
<td></td>
<td>Offer of Help</td>
</tr>
<tr>
<td></td>
<td>Preparation</td>
</tr>
<tr>
<td></td>
<td>Recovery</td>
</tr>
<tr>
<td></td>
<td>Request for Help</td>
</tr>
<tr>
<td></td>
<td>Request for Information</td>
</tr>
<tr>
<td></td>
<td>Rescue</td>
</tr>
<tr>
<td></td>
<td>Response - Community</td>
</tr>
<tr>
<td></td>
<td>Response - Formal</td>
</tr>
<tr>
<td></td>
<td>Response - Miscellaneous</td>
</tr>
<tr>
<td></td>
<td>Response - Personal</td>
</tr>
<tr>
<td></td>
<td>Sheltering</td>
</tr>
<tr>
<td></td>
<td>Status - Community/Population</td>
</tr>
<tr>
<td></td>
<td>Status - Personal</td>
</tr>
<tr>
<td>Built Environment</td>
<td>Damage</td>
</tr>
<tr>
<td></td>
<td>Status - Infrastructure</td>
</tr>
<tr>
<td></td>
<td>Status - Personal Property</td>
</tr>
<tr>
<td></td>
<td>Status - Public Property</td>
</tr>
<tr>
<td>Physical Environment</td>
<td>General Area Information</td>
</tr>
<tr>
<td></td>
<td>General Hazard Information</td>
</tr>
<tr>
<td></td>
<td>Historical Information</td>
</tr>
<tr>
<td></td>
<td>Predictions</td>
</tr>
<tr>
<td></td>
<td>Status - Hazard</td>
</tr>
<tr>
<td></td>
<td>Weather</td>
</tr>
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</table>
## Appendix B

Semantic Parameters for Evidential Categories

<table>
<thead>
<tr>
<th># Choices</th>
<th>Visual</th>
<th>Sensory</th>
<th>Inference</th>
<th>Assumption</th>
<th>Hearsay</th>
<th>Quotative</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td></td>
<td></td>
<td>Firsthand</td>
<td>Non-firsthand</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A1</td>
<td></td>
<td></td>
<td>Firsthand</td>
<td>Non-firsthand</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A1</td>
<td></td>
<td></td>
<td>Firsthand</td>
<td>Non-firsthand</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A4</td>
<td>&lt;no term&gt;</td>
<td>Non-visual</td>
<td>&lt;no term&gt;</td>
<td>Reported</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>Direct</td>
<td>Inferred</td>
<td>Reported</td>
<td></td>
</tr>
<tr>
<td>B1</td>
<td></td>
<td></td>
<td>Visual</td>
<td>Non-visual</td>
<td>Inferred</td>
<td>&lt;no term&gt;</td>
</tr>
<tr>
<td>B2</td>
<td></td>
<td></td>
<td>Visual</td>
<td>Non-visual</td>
<td>Inferred</td>
<td></td>
</tr>
<tr>
<td>B3</td>
<td></td>
<td></td>
<td>Visual</td>
<td>Non-visual</td>
<td>&lt;no term&gt;</td>
<td>Reported</td>
</tr>
<tr>
<td>B4</td>
<td>&lt;no term&gt;</td>
<td>Non-visual</td>
<td>Inferred</td>
<td>Reported</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td>Direct</td>
<td>Inferred</td>
<td>Assumed</td>
<td>Reported</td>
</tr>
<tr>
<td>C1</td>
<td></td>
<td></td>
<td>Visual</td>
<td>Non-visual</td>
<td>Inferred</td>
<td>Reported</td>
</tr>
<tr>
<td>C2</td>
<td></td>
<td></td>
<td>Direct</td>
<td>Inferred</td>
<td>Assumed</td>
<td>Quotative</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>Visual</td>
<td>Non-visual</td>
<td>Inferred</td>
<td>Assumed</td>
</tr>
</tbody>
</table>

Table B.1: Aikhenvald (2004: 65)
Appendix C

Taxonomy of Twitter Evidential Marking
Appendix  D

EPIC Pragmatic Annotation Guidelines

D.1  Overview

This section introduces some useful concepts from Twitter and provides guidelines for determining annotation spans.

D.1.1  Twitter Terminology

Twitter spans may contain usernames or hashtags, and may be retweets. Characteristics of each are described below.

D.1.1.1  Usernames

Usernames are marked by the “@” symbol (@username).

When they appear at the beginning of a tweet, it generally signals that the tweet is directed to the username given (e.g. “@username Storm is coming.”). However, usernames at the beginning of a tweet may also be syntactic arguments (e.g. “@username is riding out the storm.”), and therefore do not indicate a directed tweet.

In other parts of the tweet, usernames may be listed as the syntactic subjects or objects of predicates or merely as mentions outside a potential syntactic position.

D.1.1.2  Hashtags

Hashtags, marked with the “#” symbol, are used to indicate topics.

Hashtags may appear in syntactic positions as arguments to predicates or at or near the end of tweets to mark the topic of the tweet.

D.1.1.3  Retweets

Retweeting is a method of quoting another tweet in its entirety and is marked by “RT @username: ” at the beginning of the tweet.

It is possible to retweet a retweet (potentially a number of times), so more than one “RT @username:” may appear at the beginning of a tweet.

It is possible to retweet without using the “RT” convention by instead using quotes “@username...”
It is possible (but rare) to put the “RT” at the end of the tweet instead of at the beginning.

D.1.2 Annotation Spans

Tweets may contain one or more spans that are relevant to a particular layer of annotation. For instance, the tweet “Forecasters say Saturday’s storms could be ‘life threatening’ http://t.co/3EdBFd4z #DFW #Dallas #Texas” contains three segments relevant to evidential marking:

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Forecasters say Saturday’s storms could be ‘life threatening’ <a href="http://t.co/3EdBFd4z">http://t.co/3EdBFd4z</a> #DFW #Dallas #Texas</td>
</tr>
<tr>
<td>2</td>
<td>Forecasters say Saturday’s storms could be ‘life threatening’</td>
</tr>
<tr>
<td>3</td>
<td>Saturday’s storms could be ‘life threatening’</td>
</tr>
</tbody>
</table>

Spans are determined by the principle of embedding. Certain annotations (Retweets, Website Attribution, Source Attribution, User Attribution, and Quotative) obligatorily contain embedded spans while others (Visual, Non-visual, Assumed, Inferred, Hearsay, and Zero-evidential) do not. Embedding indicates that there is an additional degree of distance between the Twitter user and a piece of information. For instance, in a Quotative, the speaker demonstrates one degree of separation from the information. In contrast, when there is no embedding, there is no linguistic encoding of additional distance from the source of information. For instance, in the Visual-evidential span “I saw that the storm had ended,” the speaker does not demonstrate distance from the information by using a Visual evidential. For annotation purposes, annotation categories with embedded spans will always have at least one additional subspan annotated within their span, whereas annotation categories without embedded spans will never contain additional subspsans within their span.

In the description and examples for each evidential category, pay attention to the various annotation spans as they nest within one another. Additionally, use the following rules as a guide.

1. Hashtags occurring at the end of a tweet (trailing hashtags) are always included in any continuous spans that cover them. These are topic markers that condition any pragmatic annotation applied.

2. Usernames occurring at the beginning of a tweet are only included in spans when they are syntactic arguments. In the case of retweets, the username is never included in an interior span (only in the outer Retweet annotation span).

3. Discontinuous spans are allowed. In ambiguous cases, a continuous span is always preferred.

4. Remember, separate spans mean separate annotations. Creating a discontinuous span is very different from creating two annotations.

5. The maximum possible span should be chosen. If you are not sure if an additional word (or hashtag) should be included, include it.
(6) Annotation spans may be subsumed by one another (this is common in evidentiality annotation), but otherwise **should not overlap**.

(7) The only time is it possible to annotate the exact same span with two annotations from the same annotation layer is during speech act annotation. If a span with zero-evidential content also contains content marked by some other non-embedding evidential category, then the whole span should be marked as the non-zero-evidential category.

(8) Some tweet sets may enclose each tweet in quotation marks. These marks should not be considered when determining spans, and should not be included in any spans.

(9) Sometimes, quotation marks may be rendered as “&quot;” and close variations. These should not be included in inner spans (but like quotation marks will be included in outer spans).

(10) It is permissible to split words in limited circumstances. If you think two words are concatenated together, then associate the various parts of the word with the annotation spans they pertain to, **only in the case of an embedding relationship** (e.g. [RT @username]it’s raining outside][ZERO-EVIDENTIAL][RETWEET (from “RT @username it’s raining outside”). In cases where the concatenated word occurs in phrases at the same level of embedding, then annotate as a single span (e.g. [I see that the cold front is coming]It’s raining outside.[VISUAL]). This follows the same logic as the following guideline: if clean sentence boundaries are not present, then the text should be annotated as a single span.

(11) Tweets may be divided into different annotation spans by **sentence boundaries** if there is more than one annotation type present. A sentence boundary is marked by sentence-final punctuation, such as a period, comma, or ellipsis (or phrase-final punctuation such as a hyphen). However, if all annotations are of the same type, then only one span should be marked. Compare the following examples:

**Clear sentence boundaries:** [Storm is coming.]ZERO-EVIDENTIAL[Weather Service says [storm will be quite strong.]ZERO-EVIDENTIAL][SOURCE ATTRIBUTION][Preparing the house.]ZERO-EVIDENTIAL

**Unclear sentence boundaries:** [I heard that the storm is coming it is so scary]HEARSAY

The following sections outline three types of pragmatic annotations designed for Project EPIC Twitter data: evidential categories (Aikhenvald 2004), Territory of Information (TOI; Kamio 1997), and speech acts (Searle 1976; 1979).

**D.2 Evidentiality Annotation**

Evidentiality annotation marks the source of the information contained in a tweet segment. Tweet segments cover both the span containing the information presented by the source and the span containing the name or description of the source itself. Most spans may be labeled with only one evidential category. Only the smallest (most embedded) of the spans in a tweet may be labeled with more than one category.
D.2.1 Annotations Without Obligatory Embedded Spans

As stated above, certain annotation categories (Visual, Non-visual, Assumed, Inferred, Hearsay, and Zero-evidential) do not have obligatory embedded spans. This means that when you code an annotation of this type, it will generally not contain any subspans. The only time one of these annotation types will contain an embedded span is if that embedded span is of a type that has an obligatory embedded span. Study the following example:

[I heard [Dan Rather say that [the hurricane is coming.]]ZERO-EVIDENTIAL]SOURCE Attribution]NON-VISUAL

In this example, the Non-Visual span has an embedded annotation only because the “thing heard” is a Source Attribution that itself has an embedded span. Compare to the following example:

[I heard that the hurricane is coming.]HEARSAY

In this example, there is no embedded span because the “thing heard” is not an embedding annotation type.

D.2.1.1 Zero-evidential

Many Zero-evidential tweet segments contain no evidential marking at all:

what a day! thanks for all the sweet tweets about dallas storms :D

Pray for the families who has lost there homes in this storm that crushed through Dallas/Ft. Worth today

Bad storms in Dallas yesterday, none here in Austin, Call ZINDLER AND SONS ROOFING for your leaky roof !!!

It is possible for a zero-evidential segment contain a sensory verb (such as “see,” “smell,” or “hear”). In order for a segment to be evidentially-marked, the sensory event (seeing, hearing, etc.) must be the event through which the speaker has knowledge of another event, circumstance, state, or characteristic. Compare the following examples; while the zero-evidential segments describe a sensory event only, evidentially-marked segments contain a sensory event plus some other event/predication/statement.

(1) I saw pictures of Christchurch. — Zero-evidential
(2) I saw pictures of Christchurch. Damage is severe. — Visual
(3) I smelled the cookies. — Zero-evidential
(4) I smelled that there were cookies in the oven. — Non-visual
(5) I smelled the cookies burning. — Non-visual
(6) I smelled that the cookies were burning. — Non-visual
(7) We’ve smelled smoke and we’re now getting ash in #Calhan Colorado from the @Waldo-CanyonFire burning in #COS right now. — Zero-evidential
(8) @LilKingTiTan We have had about 300+ wuakes in the past eight days. Personally, I don’t think we have seen the worst. :-( #eqnz — Zero-evidential

(9) #hurricanesandy I laughed so hard when I saw this. Boy hot hella stacks http://t.co/Lw6glvSp — Zero-evidential

(10) Heard from my friend. — Zero-evidential

(11) Heard from my friend. She is OK. — Non-visual

If a span is marked as zero-evidential, that span should not be marked with any other evidential category.

D.2.1.2 Visual

Tweets citing visual evidence typically use a verb like “see” to indicate the source of information, where the subject of the verb is the speaker who is cited in the span (this may be different from the speaker of the tweet). Pictures and video may constitute visual evidence. “Looks (like)” specifically does not encode a Visual evidential.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Just saw three pieces of sleet fall. Nemo is hitting Russelville! Buy bread! Start your fireplaces! Barricade your doors! #sarcasmfont</td>
<td>Visual</td>
</tr>
<tr>
<td>1</td>
<td>RT @RRFNWick: [On the way to Mankato, MN yesterday], I saw tillage has started in southern MN. Still way too wet in Red River Valley. #farm</td>
<td>Retweet</td>
</tr>
<tr>
<td>2</td>
<td>[On the way to Mankato, MN yesterday], I saw tillage has started in southern MN. Still way too wet in Red River Valley. #farm</td>
<td>Visual</td>
</tr>
<tr>
<td>1</td>
<td>@theunfocused I saw the pictures of Christchurch today. Unbelievable destruction. Be safe over there.</td>
<td>Visual</td>
</tr>
</tbody>
</table>

D.2.1.3 Non-visual

Non-visual evidential marking consists of any primary sensory data other than data perceived by visual means. This includes information attributed to hearing, touching, tasting, or smelling. Where auditory information is involved, be careful to discriminate between non-visual evidence and hearsay (described below). Non-visual evidence only involves direct perception of a hearable, touchable, tasteable, or smellable event or situation.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>did i hear hilary barry say the death toll could rise 200 more ? jesus christ this is terrible, #christchurch</td>
<td>Non-visual</td>
</tr>
</tbody>
</table>

D.2.1.4 Assumed

Assumed information is marked by one of the following: “assumed (to be),” “likely (to be),” or “believed (to be).”
Irish man ‘trapped’ in NZ quake building: It’s believed a man from the Republic of Ireland could be trapped in a ...

http://bit.ly.fPyfSN

The tragedy of the Christchurch quake has hit home for me with the horrible realisation that someone I knew is among those believed dead.

D.2.1.5 Inferred

Inferred information is usually marked by “appears (to be)” or “seems (to be).” Note that there are multiple senses of appear (“The dog appeared.”) and seem (“Final exams seem a world away at the start of the semester.”) that do not mark inferred information. To mark inferred information, a verb such as “seem” or “appear” must be a matrix verb with an embedded predication (e.g. “She seems fine.” or “Christchurch appears to be recovered.”) but not “She appeared in the hallway.”. Verbs referring to a speaker’s mental processing of information (e.g. “I gathered/understood/discovered that the weather was improving...”) may also signal an Inferred evidential.

It seems that maybe as many as a third of the buildings in central Christchurch may have to be demolished, such...
http://fb.me/Qss6lfWD

D.2.1.6 Hearsay

Hearsay evidence comes to a speaker by some means other than direct non-visual experience. Nonetheless, hearsay segments generally contain the verb “hear.” Hearsay can also be marked by expressions such as “Caught wind of...” or “Reports that X has occurred”.

@minimonos @Cade77MM I hope that everybody is safe over there a NZ. I heard there have been some deaths though. STAY SAFE NEW ZEALAND :D

D.2.2 Annotations with Embedded Spans

Annotation categories in this section contain obligatory embedded spans. This means that if you annotate with one of these labels, you will always annotate a subspan.

D.2.2.1 Website Attribution

Information in spans may be attributed to websites by listing the website after the information given. However, not every website listed in a tweet is the object of information attribution. For instance, in tweets where a span explicitly directs the reader to a website or merely mentions website content(e.g. “Friends from home took these pictures! – Storm Pictures from the Dallas-Fort Worth Metroplex http://t.co.LvMQZcnM” or “Stuff have photos here,
including Press office http://www.stuff.co.nz/4688231/Deaths-destruction-in Christchurch-quake OMG”), that span does not demonstrate Website Attribution unless there is another statement before or after the span that the website for which the website provides evidence (e.g. “(Emma) Also: NZ Book Month voucher spending begins - with photos - correct link: http://bit.ly.gTvvXn”). Additionally, some tweets ending in a website may be cutoffs, where the website provides a link to a continuation of the tweet content and not to the information source (e.g. “Overheard from a #TTC operator: “On time is not happening!” So, business as usual then. #snowmageddon @... http://t.co/VqsRBCRN”); these should not be marked as Website Attribution. Assume that any ellipsis before a website indicates a cutoff and should not be tagged as Website Attribution.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RT @wildfiretoday: Body of 3rd victim found in #LowerNorthForkFire in Colo. <a href="http://t.co/bq71BTfx">http://t.co/bq71BTfx</a> <a href="http://t.co/V917TWhh">http://t.co/V917TWhh</a></td>
<td>Retweet</td>
</tr>
<tr>
<td>2</td>
<td>Body of 3rd victim found in #LowerNorthForkFire in Colo. <a href="http://t.co/bq71BTfx">http://t.co/bq71BTfx</a> <a href="http://t.co/V917TWhh">http://t.co/V917TWhh</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Body of 3rd victim found in #LowerNorthForkFire in Colo.</td>
<td>Zero-evidential</td>
</tr>
</tbody>
</table>

In some cases, the website may contain media that provide supporting evidence for a statement. This is also Website Attribution.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
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</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mike Francesa on Nemo: 'Don’t overreact.' #video <a href="http://t.co/7QaTttvZ">http://t.co/7QaTttvZ</a> via @BobsBlitz</td>
<td>User Attribution</td>
</tr>
<tr>
<td>2</td>
<td>Mike Francesa on Nemo: 'Don’t overreact.' #video <a href="http://t.co/7QaTttvZ">http://t.co/7QaTttvZ</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Mike Francesa on Nemo: 'Don’t overreact.'</td>
<td>Quotative</td>
</tr>
<tr>
<td>4</td>
<td>Don’t overreact.</td>
<td>Zero-evidential</td>
</tr>
</tbody>
</table>

D.2.2.2 User Attribution

Information may be attributed to a user by listing the username after the word “via” or “from” or through other means of citation, such as putting a username in parentheses after the span containing the information. In order or to be marked as User Attribution, a span must have explicit marking (e.g. “via” or “from” or the username in parentheses); merely mentioning a username near a proposition does not constitute User Attribution.
<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>'Nemo’ storms Twitter - <a href="http://t.co.zL0Gt5v9">http://t.co.zL0Gt5v9</a> <a href="http://t.co.rGYm5gEU">http://t.co.rGYm5gEU</a> via @nypost (I’m sure Buzzfeed is on this too)</td>
<td>User Attribution</td>
</tr>
<tr>
<td>2</td>
<td>'Nemo’ storms Twitter - <a href="http://t.co.zL0Gt5v9">http://t.co.zL0Gt5v9</a> <a href="http://t.co.rGYm5gEU">http://t.co.rGYm5gEU</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>'Nemo’ storms Twitter</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Overheard from a #TTC operator: “On time is not happening!” So, business as usual then. #snowmageddon @... <a href="http://t.co/VqsRBCRN">http://t.co/VqsRBCRN</a></td>
<td>Non-visual</td>
</tr>
<tr>
<td>1</td>
<td>Update: Power outages at 350,000 as winter storm batters New York, New England. (@AP) #Nemo</td>
<td>User Attribution</td>
</tr>
<tr>
<td>2</td>
<td>Update: Power outages at 350,000 as winter storm batters New York, New England.</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>PM: Boosing efforts to locate backpackers missing in NZ quake: <a href="http://bit.ly/hHhniC">http://bit.ly/hHhniC</a> YNet</td>
<td>Website Attribution</td>
</tr>
<tr>
<td>2</td>
<td>PM: Boosing efforts to locate backpackers missing in NZ quake</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Boosing efforts to locate backpackers missing in NZ quake</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Two crew missing from movie ship in Sandy - CNN: CTV NewsTwo crew missing from movie ship in SandyCNNNEW: Surviv... <a href="http://t.co/VRIknxBw">http://t.co/VRIknxBw</a></td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>Two crew missing from movie ship in Sandy</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Officials reporting that the fire is spreading south</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>the fire is spreading south</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Fire department says it sees that everybody is safe.</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>it sees that everybody is safe</td>
<td>Visual</td>
</tr>
</tbody>
</table>

### D.2.2.3 Source Attribution

Information may be attributed to a source outside of Twitter, such as a person or news organization. Source attribution should never be used to attribute information to a username (which are instances of User Attribution). It is important to remember that Source Attribution is an evidential marker indicating *where the information in a tweet segment has come from*; for instance, a span like ”Bushfire WATCH AND ACT just issued by DEC for Shire of Upper Gascoyne” is Zero-evidential, not Source Attribution, because the evidential category marks the source of this information, not the source of the “Bushfire WATCH AND ACT” (the DEC). In contrast, “Fire department says it sees neighborhood is safe” *is* Source Attribution, with an embedded Visual span.

<table>
<thead>
<tr>
<th>Segment</th>
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</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PM: Boosing efforts to locate backpackers missing in NZ quake: <a href="http://bit.ly/hHhniC">http://bit.ly/hHhniC</a> YNet</td>
<td>Website Attribution</td>
</tr>
<tr>
<td>2</td>
<td>PM: Boosing efforts to locate backpackers missing in NZ quake</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Boosing efforts to locate backpackers missing in NZ quake</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Two crew missing from movie ship in Sandy - CNN: CTV NewsTwo crew missing from movie ship in SandyCNNNEW: Surviv... <a href="http://t.co/VRIknxBw">http://t.co/VRIknxBw</a></td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>Two crew missing from movie ship in Sandy</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Officials reporting that the fire is spreading south</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>the fire is spreading south</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Fire department says it sees that everybody is safe.</td>
<td>Source Attribution</td>
</tr>
<tr>
<td>2</td>
<td>it sees that everybody is safe</td>
<td>Visual</td>
</tr>
</tbody>
</table>

### D.2.2.4 Retweet

Retweets always occur at the beginning of a tweet (RT @username ( RT @username):...). A tweet may be retweeted one or more times. There are several conventions for retweeting, including “@username:”, “RT @username”, “RT @username:”, and “RT @username”. Each retweet span begins at the “RT” or quotation mark. *Any content before one of these tokens is not part*
of the retweet span and will be annotated with a separate annotation span.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
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</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RT @wildfiretoday: Body of 3rd victim found in #LowerNorthForkFire in Colo. <a href="http://t.co/bq71BTfx">http://t.co/bq71BTfx</a> <a href="http://t.co/V917TWhh">http://t.co/V917TWhh</a></td>
<td>Retweet</td>
</tr>
<tr>
<td>2</td>
<td>Body of 3rd victim found in #LowerNorthForkFire in Colo. <a href="http://t.co/bq71BTfx">http://t.co/bq71BTfx</a> <a href="http://t.co/V917TWhh">http://t.co/V917TWhh</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Body of 3rd victim found in #LowerNorthForkFire in Colo.</td>
<td>Zero-evidential</td>
</tr>
</tbody>
</table>

D.2.2.5 Quotative

Many tweet spans containing Quotatives are similar to Hearsay spans. However, typically Quotatives must contain quotation marks. In rare circumstances, it may be possible to signal quotation without quotation marks, as in “The Fire Chief used these exact words: the fire has been contained.” Where it is unclear whether the exact words are cited, the span should be labeled Hearsay. If any portion of a span is quoted, it should be labeled as Quotative. However, in order for a span to be labeled as a Quotative, the source must be marked; if there is no source marked in the tweet, then despite the presence of quotation marks, there is no Quotative annotation.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Evidentiality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mike Francesa on Nemo: 'Don’t overreact.' #video <a href="http://t.co/7QaTttvZ">http://t.co/7QaTttvZ</a> via @BobsBlitz</td>
<td>Attribution to User</td>
</tr>
<tr>
<td>2</td>
<td>Mike Francesa on Nemo: 'Don’t overreact.' #video <a href="http://t.co/7QaTttvZ">http://t.co/7QaTttvZ</a></td>
<td>Website Attribution</td>
</tr>
<tr>
<td>3</td>
<td>Mike Francesa on Nemo: 'Don’t overreact.'</td>
<td>Quotative</td>
</tr>
<tr>
<td>4</td>
<td>Don’t overreact.</td>
<td>Zero-evidential</td>
</tr>
<tr>
<td>1</td>
<td>Overheard from a #TTC operator: “On time is not happening!” So, business as usual then. #snowmageddon @... <a href="http://t.co/VqsRBCRN">http://t.co/VqsRBCRN</a></td>
<td>Quotative</td>
</tr>
<tr>
<td>2</td>
<td>On time is not happening!</td>
<td>Zero-evidential</td>
</tr>
</tbody>
</table>

Partial Quotatives occur when only a few words of a span are placed within quotation marks. In these cases, the entire span should be tagged as Source Attribution. Then the quoted material only should be tagged as Quotative and annotated as a discontinuous span as appropriate.

D.3 Territory of Information Annotation

Territory of Information (TOI) annotation marks a tweet segment as being with speaker, other, or indeterminate “territory.” The concept of territory is based upon a spatial metaphor for information ownership. Information is said to be a speaker’s territory if the speaker presents the informations as if the information arose from personal knowledge. Conversely, information belongs to Other territory if the information is unambiguously attributed to some other person. Information that is presented as being both within the speaker and hearer’s territory is marked as Indeterminate. Indeterminate TOI is hypothesized to occur most frequently in cases where a user comments on information that comes from another’s TOI. Each span will receive only one
TOI annotation. Finally, TOI is labeled relative to the speaker of a segment. For instance, in a quotation, the quoted material may be Speaker TOI even if the tweet as a whole is Other TOI.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>TOI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Just saw three pieces of sleet fall. Nemo is hitting Russelville! Buy bread! Start your fireplaces! Barricade your doors! #sarcasmfont</td>
<td>Speaker</td>
</tr>
<tr>
<td>1</td>
<td>Overheard from a #TTC operator: “On time is not happening!” So, business as usual then. #snowmageddon @... <a href="http://t.co/VqsRBCRN">http://t.co/VqsRBCRN</a></td>
<td>Indeterminate</td>
</tr>
<tr>
<td>2</td>
<td>On time is not happening!</td>
<td>Speaker</td>
</tr>
<tr>
<td>1</td>
<td>did i hear hilary barry say the death toll could rise 200 more ? jesus christ this is terrible, #christchurch</td>
<td>Indeterminate</td>
</tr>
<tr>
<td>1</td>
<td>Forecasters say Saturday’s storms could be ‘life threatening’ <a href="http://t.co/3EdBFd4z">http://t.co/3EdBFd4z</a> #DFW #Dallas #Texas</td>
<td>Other</td>
</tr>
<tr>
<td>2</td>
<td>Forecasters say Saturday’s storms could be ‘life threatening’</td>
<td>Other</td>
</tr>
<tr>
<td>3</td>
<td>Saturday’s storms could be ‘life threatening’</td>
<td>Speaker</td>
</tr>
</tbody>
</table>

D.4 Speech Act Annotation

Speech act labels mark tweets or tweet segments where the tweet content performs an action. Six categories of speech acts are annotated:

1. Representatives (Assertives): assertions of the truth of propositions, including statements
2. Directives: e.g. ordering
3. Questions: interrogatives that solicit an answer or information
4. Commissives: commitments to future action, e.g. promising
5. Expressives: expressions of a speaker’s mental state, e.g. I hope we win.
6. Declarations: e.g. marrying

Both primary (direct) and indirect speech acts are annotated where present. While primary speech acts contain explicit words signaling the type of act performed (e.g. “I promise...” as a Commissive), indirect speech acts do not contain such explicit marking. Consider the question “Could you pass the salt?” While the primary (surface) act is a Question, the indirect speech act, which the hearer intuits by observing that the speaker is likely not asking about his or her ability to pass salt, is a Directive to transfer salt to the hearer. Only certain speech act types are expected to produce indirect speech acts, and these are specified below.

A segment may be annotated with **one or more** primary and indirect speech act categories.

D.4.1 Representatives

Representatives commit a speaker to the truth of a proposition expressed. We annotate two types of Representatives, as outlined below.
D.4.1.1 A-Representatives

A-Representatives are statements of fact that also express a belief state on the part of the speaker, such as “I think,” “I believe,” or “I suppose.” Note that this is different from a speaker expressing an opinion (e.g. “That is probably the cutest puppy here.”). If the belief state is not encoded in some syntactic variation of the pattern “(I) VERB (that) PROPOSITION” or “PROPOSITION, I VERB,” then the span is a B-Representative, not an A-Representative.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>At the moment it looks like SE Texas will dodge a bullet. New Orleans is going to be devastated again though, I think.</td>
<td>A-Representative</td>
<td>Null</td>
</tr>
</tbody>
</table>

D.4.1.2 B-Representatives

In contrast to A-Representatives, B-Representatives express a statement of fact without also expressing a belief state on the part of the speaker. Twitter contains many spans that could never occur in conversational speech. B-Representative as a category covers many of the phenomena; for instance, retweets and website attributions are B-Representatives.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>President Bush, Vice President Cheney to skip Republican convention because of Hurricane Gustav, White House says.</td>
<td>B-Representative</td>
<td>Null</td>
</tr>
<tr>
<td>2</td>
<td>President Bush, Vice President Cheney to skip Republican convention because of Hurricane Gustav</td>
<td>B-Representative</td>
<td>Null</td>
</tr>
</tbody>
</table>

D.4.2 Questions

Prototypically, questions appear in one of the following question formats:

1. **Wh questions**, e.g. {Who(m), What, When, Where, Why, How} are you serving?
2. **Yes/No questions**, e.g. “Are you going to the veterinarian today?”
3. **Declarative questions**, e.g. “My nose is running?”

While many questions are marked with a question mark, spans can perform as questions without a mark, as in the following example:

@BezzerEspresso i am well. how are you. when are you coming back to christchurch. i want a lunch date.

D.4.3 Commissives

Commissives commit the speaker to some course of action. Commissives may be direct or indirect.
### D.4.3.1 Primary Commissives

Primary Commissives contain a specific verb such as “promise” (“I promise to go to the party.”), “threaten.” (“I am threatening you with divorce.”), or invite “I invite you to the party.” The speaker must be the subject of the verb phrase.

### D.4.3.2 Indirect Commissives

Indirect Commissives commit the speaker to future actions without using a verb phrase (containing a verb such as “promise” or “invite”) where the speaker is the subject.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>@BezzeraEspresso i am well. how are you. when are you coming back to christchurch. i want a lunch date.</td>
<td>Expressive, Question</td>
<td>Commissive</td>
</tr>
<tr>
<td>1</td>
<td>You are invited to a Chat with Administrators of Red River Writers...</td>
<td>B-Representative</td>
<td>Commissive</td>
</tr>
</tbody>
</table>

### D.4.4 Expressives

Expressives indicate the mental or psychological state of the speaker, including the speaker’s wishes, desires, or feelings. Additionally, spans performing thanking, sympathizing, apologizing, welcoming, rebuking, etc. are all Expressives.

(Desire) @BezzeraEspresso i am well. how are you. when are you coming back to christchurch. i want a lunch date.

(Hope) I hope the fires settle down soon. I can’t imagine what some fellow Oklahomans are going through right now. #okfires

(Thanking) @wind4me wow! And thanks so far he hasn’t had to go to any of them last I heard. Lots of ours have though.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>@BezzeraEspresso i am well. how are you. when are you coming back to christchurch. i want a lunch date.</td>
<td>Expressive, Question</td>
<td>Commissive</td>
</tr>
<tr>
<td>1</td>
<td>I hope the fires settle down soon. I can’t imagine what some fellow Oklahomans are going through right now. #okfires</td>
<td>Expressive</td>
<td>Null</td>
</tr>
<tr>
<td>1</td>
<td>@wind4me wow! And thanks so far he hasn’t had to go to any of them last I heard. Lots of ours have though.</td>
<td>Expressive, B-Representative</td>
<td>Null</td>
</tr>
</tbody>
</table>
D.4.5 Directives

Directives instruct the reader or hearer to perform some action, and can range in intensity from suggestions to demands.

D.4.5.1 Primary Directives

Primary directives contain a verb phrase whereby a speaker explicitly requests, orders, or suggests a course of action using a verb such as “request”, “order”, “implore”, “beg”, etc.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RT @britishredcross: We have launched an emergency appeal for the #Haiti #earthquake <a href="http://bit.ly/5xg9eH">http://bit.ly/5xg9eH</a> Please donate now</td>
<td>B-Representative</td>
<td>Null</td>
</tr>
<tr>
<td>2</td>
<td>We have launched an emergency appeal for the #Haiti #earthquake <a href="http://bit.ly/5xg9eH">http://bit.ly/5xg9eH</a> Please donate now</td>
<td>Directive</td>
<td>Null</td>
</tr>
<tr>
<td>3</td>
<td>We have launched an emergency appeal for the #Haiti #earthquake</td>
<td>B-Representative</td>
<td>Null</td>
</tr>
</tbody>
</table>

D.4.5.2 Indirect Directives

Indirect directives make a request or suggestion by way of another speech act, typically a Question.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Text</th>
<th>Primary</th>
<th>Indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>can you volunteer or offer a place to stay? <a href="http://redriver.gather.com/">http://redriver.gather.com/</a> is an open online community. #fargoflood #flood09</td>
<td>Question, B-Representative</td>
<td>Directive</td>
</tr>
</tbody>
</table>

Some primary A-Representatives and B-Representatives do not qualify to be Indirect Directives. For instance, a statement such as “Conditions here are really terrible and no one is helping” are not Indirect Directives. Notice in the example above, the primary speech act is not only a B-Representative but also a Question. In contrast, given specific context other Primary Representatives may be Indirect Directives, for instance “Fire Chief said ‘Residents are now asked to evacuate’”.

D.4.6 Declarations

Declarations are quite rare in our data; therefore, the examples given here are not from actual tweets. Be careful not to tag segments as declarations when they merely describe some event where a declaration happened (e.g. “Gov. Henry declares State of Emergency in Oklahoma”).
D.4.6.1 Primary Declarations

For a segment to be labeled as a Primary Declaration, it must contain a verb phrase explicitly denoting a declaring event where the speaker is the subject (e.g. “I declare a state of emergency”).

D.4.6.2 Indirect Declarations

In order for a segment to be an Indirect Declaration, speaker of the Indirect Declaration (note: this is different from the speaker of the tweet) must be capable of issuing the declaration, as in “A state of emergency has been declared,” the governor stated. If the span is not attributed to a capable speaker (e.g. “A state of emergency has been declared.”), then that span is tagged as A- or B-Representative as appropriate.
Appendix E

Annotation Survey

Annotation Task: Playing the role of a citizen on the ground experiencing a disaster scenario, rate tweets on a one through five scale according to their usefulness to you in responding to the crisis event and its aftermath.

(1) In general, what did you take into consideration in assigning utility codes to tweets?

(2) For a tweet rated as “1,” were there any specific features that allowed you to make this determination?

(3) For a tweet rated as “5,” were there any specific features that allowed you to make this determination?

(4) For a tweet rated as “2,” what made it better than a tweet rated as “1”?

(5) For a tweet rated as “3,” what made it better than a tweet rated as “1” or “2”?

(6) Similarly, for a tweet rated as “4,” what made it better than a tweet rated “3” or below? What made it less useful than a tweet rater “5”?

(7) Do you have any feedback about this annotation exercise? For instance, did the granularity of the rating scale seem appropriate?
Appendix F

Examples: Segment Territory of Information and Evidentiality

F.1 Speaker TOI with Reported Evidentiality

F.1.1 Oklahoma Fires

(1) officials in Midwest City say situation is worse than May 3rd. #OKFires #OKFire #wildfire — Source Attribution

(2) News9’s @news9wxguy says rain is likely late tonight and tomorrow. — User Attribution
OKC Sherrif John Whetsel isn’t sure how many houses have burned in the Choctaw area, but said it’s more than 20. #OKFire #OKFires — Source Attribution

(3) Numerous wild fires cause evacuations across Oklahoma. Check on your area: http://tinyurl.com/cpewlj — Website Attribution

(4) Listening to: “Fire Flare ups” 2 days after wildfires burnt 80 home, winds flare up same fires. ( http://tinyurl.com/dbofqc ) — Website Attribution

F.1.2 Haiti Earthquake

(1) Evil tool @nytimes Pat Robertson says reasons for Haiti’s misfortunes? Haiti swore a pact to the devil? two centuries ago. — Source Attribution

(2) We are happy to provide assistance to Haiti relief efforts. Read more: http://kl.am/WSHaiti — Website Attribution

(3) I just heard that a person was rescued under a pile of rubble 11 days after the Haiti earthquake. That’s insane. I couldn’t imagine... — Hearsay

F.1.3 Red River Flood (2009)

(1) New blog post: Red River receding; 2 dead in North Dakota flooding http://tinyurl.com/cdwxqb — Website Attribution

(2) U researcher talks Red River flooding in MinnPost - “There’s just too much water. — Source Attribution

(3) Red River Flooding: These pics sure bring it home. http://tinyurl.com/cqpbqa (via @thepipers) — User Attribution

(4) http://www.mnlakeplace.com wishing the people up by red river the best of luck with river. they need help if anyone can get up there. — Website Attribution
F.1.4 Red River Flood (2010)

(1) Some photos of the flood that we took this morning. We think the river has crested. http://bit.ly/aUTgn9 — Website Attribution

(2) We just added a new webcam to our USGS Webcams page for Red River in Fargo ND http://go.usa.gov/lzs — Website Attribution

(3) Flood fight in #Fargo ND http://tweetphoto.com/15410133 — Website Attribution

(4) Check this video out – Time-lapse of Red River flooding at Fargo from 15.75 ft to 35.5 ft http://youtu.be/Q6dUqD3I3P8 — Website Attribution

F.2 Other TOI with Zero-evidentiality

F.2.1 Oklahoma Fires

(1) Gary England just said if you live SE of these fires don’t climb in your bed and think you’re safe tonight.

(2) Good news: Evacuations have been ceased and residents are being allowed back in the area. Earlier tweets were hung up in cyberspace I guess

(3) Thanks for the RT. News has not said if they reached the house or not. Fires advancing fast, house would be gone now

(4) “Fire Flare ups” 2 days after wildfires burnt 80 home, winds flare up same fires.

(5) They aren’t weighted down with water. That’s what the officials were telling us yesterday.

(6) There are Nine major fires burning in Oklahoma and many smaller fires. Please go to KFOR.com for LIVE streamed #okfires

(7) Cool, because they said on KOCO that there were fires at Reno and Anderson, and that they were evacuating Oakwood East, again.

F.2.2 Haiti Earthquake

(1) I’m getting confirmations that http://www.mercycorps.org/haiti is a good choice.

(2) RedCross You can text HAITI to 90999 to donate $10 to Red Cross relief efforts in #haiti.&lt;== Did my part. now go mak ...

(3) RedCross You can text HAITI to 90999 to donate $10 to Red Cross relief efforts in #haiti.&lt ...

(4) Sounds of Haiti’s Earthquake. Watch: http://ow.ly/W84o Help Haiti


(6) #Haiti’s PM and also the consul general to the UN are saying the death toll could top 100,000
(7) More than 100,000 feared dead in Haiti quake, officials say

(8) People are sleeping among the dead - Matthew Price’s distressing report from a hospital in #Haiti.

(9) Doctors Without Borders report from #Haiti, has 800 staff, 70 more soon http://tinyurl.com/yddq2yu and http://tinyurl.co ...

(10) Red Cross Raises $800,000+ for Haiti Through Text Message Campaign http://ow.ly/1n0Pbn

(11) Israel’s envoy to Dominican Republic describes shocking Haiti scenes: Israel’s ambassador to the... http://bit.ly/8wZWNl #israel #palestine

(12) Text â€œHAITIâ€? to 90999 to donate $10 to American Red Cross relief for Haiti http://j.mp/6VuLQH

(13) Earthquake in #Haiti by The Big Picture http://tumblr.com/xyq5j86sa 48 fotos Boston.com

(14) Philanthropy News: Zynga Gamers Chip in for Haiti Quake Relief [Philanthropy]

(15) US could take larger security role in Haiti: The top U.S. military officer is leaving open the possibility of a gr... http://bit.ly/85cn4X

(16) AAirwaves PLS RD: Cant fly individual drs/nurses to #haiti, working w/ Red Cross & other agencies 2 provide aid. Donat ...

(17) Beck says Obama is dividing the country in Haiti response

(18) Wyclef Jean Responds to Yele Haiti Accusations [YOUTUBE VIDEO]


(20) [Social Networks] Haiti text message charity fundraising sets record - Charity Technology Trust: Haiti te... http://bit.ly/7psnOZ #jondavey

(21) The Big Picture: Haiti six days later: Haiti remains a place of profound need, anguish, desperatio... http://bit.ly/8F6LIB #photojournalism

(22) Watch performances from last night’s #Hope for Haiti telethon & find out how u can still donate http://bit.ly/8KgXYL TT @Billboarddotcom

(23) Haiti 360: Interactive Post-Earthquake Video Panoramas: Technology has played an important role not only in gettin... http://bit.ly/7rlkuC

(24) After Amputations, Victims With No Place to Go Fill Haitis Hospitals: Health officials are facing a ... http://bit.ly/6hWruC #hacerfortuna

(25) Donations to Aid Haiti Exceed $470-Million, Chronicle Tally Finds

(26) jesus disease: What Indian Media censord: xian child trafficking http://is.gd/7MSTV in Haiti punished: In India it g ...

(27) Haiti News: Government matches Canadians’ $113M for Haiti

(28) Pulled survivor from rubble in #Haiti *this
F.2.3   Red River Flood (2009)

(1) #Flood #RedRiver #GrandForks added you to Fav Gerry http://bit.ly/BAgU

(2) DisasterCenter: April 5, 2009 – The North Dakota’s Red River Links: FEMA– ND:  
http://tinyurl.com/da8pv7 Full http://tinyurl.com/7usdc

(3) WEEKENDER: The ebb and flow of the Red River of the north since 1826 -  
http://www.water.ca/index.asp #redriver #flood09

(4) Bitter cold slows rise of swollen Red River - Forbes.. http://tinyurl.com/62tlko

(5) USA TodayChilly temperatures slow ris.. http://tinyurl.com/cxh5eu

(6) Paddling Instructor Blog: Moving Red River Flooding Photos . The Big Picture is ..   
http://tinyurl.com/dyh6bu

F.2.4   Red River Flood (2010)

(1) U.S. Coast Guard emergency response crews have begun patrolling... http://bit.ly/8ZJLP0