Geotagging with Local Lexicons to Build Indexes for Textually-Specified Spatial Data

Michael D. Lieberman, Hanan Samet, Jagan Sankaranarayanan

Center for Automation Research, Institute for Advanced Computer Studies,
Department of Computer Science, University of Maryland
College Park, MD 20742, USA
{codepoet, hjs, jagan}@cs.umd.edu

***Abstract*— The successful execution of location-based and feature-based queries on spatial databases requires the construction of spatial indexes on the spatial attributes. This is not simple when the data is unstructured as is the case when the data is a collection of documents such as news articles, which is the domain of discourse, where the spatial attribute consists of text that can be (but is not required to be) interpreted as the names of locations. In other words, spatial data is specified using text (known as a *toponym*) instead of geometry, which means that there is some ambiguity involved. The process of identifying and disambiguating references to geographic locations is known as *geotagging* and involves using a combination of internal document structure and external knowledge, including a document-independent model of the audience's vocabulary of geographic locations, termed its *spatial lexicon*. In contrast to previous work, a new spatial lexicon model is presented that distinguishes between a *global lexicon* of locations known to all audiences, and an audience-specific *local lexicon*. Generic methods for inferring audiences' local lexicons are described. Evaluations of this inference method and the overall geotagging procedure indicate that establishing local lexicons cannot be overlooked, especially given the increasing prevalence of highly local data sources on the Internet, and will enable the construction of more accurate spatial indexes.**

I. Introduction

Spatial databases are differentiated from conventional databases by virtue of the presence of spatial attributes. In some applications this difference is minimized by noting the similarity of spatial point data to conventional data as database records can be viewed as multidimensional points. However, spatial data is much more than points as it also has extent (e.g., line segments, regions, surfaces, volumes, etc.). These databases enable responding to location-based queries (e.g., given a location or set of locations, what features are present) and feature-based queries or spatial data mining (e.g., given a feature, where is it? [2]) in geographic search engines [4] and other systems of interest. Executing these queries involves the efficient retrieval of spatial data which requires the construction of appropriate spatial indexes, some examples of which are R-trees, quadtrees, etc. (e.g., [18]). These indexes are relatively easy to construct when such data is readily available. However, this is not the case when the data is unstructured, as in a collection of documents such as news articles, where the spatial data is really words of text that can be (but are not required to be) interpreted as the names of locations. In other words, the spatial data is specified using text (called *toponyms*) rather than geometry, which means that there is some ambiguity involved. This ambiguity has an advantage in that from a geometric standpoint, the textual specification captures both the point and spatial extent interpretations of the data (analogous to a polymorphic type in parameter transmission which serves as the cornerstone of inheritance in object-oriented programming languages). On the other hand, the disadvantage is that we are not always sure which of many instances of geographic locations with the same name is meant, and this paper focuses on overcoming this disadvantage.

This work was supported in part by the National Science Foundation under grants IIS-08-12377, CCF-08-30618, and IIS-07-13501, as well as NVIDIA Corporation, Microsoft Research, the E.T.S. Walton Visitor Award of the Science Foundation of Ireland, and the National Center for Geocomputation at the National University of Ireland at Maynooth.

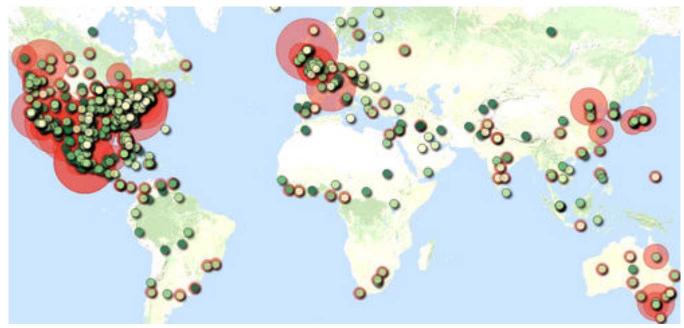


Fig. 1. Locations mentioned in news articles about the May 2009 swine flu pandemic, obtained by geotagging related news articles. Large red circles indicate high frequency, and small circles are color coded according to recency, with lighter colors indicating the newest mentions.

The process of identifying and disambiguating references to geographic locations (i.e., toponyms), known as *geotagging* [1], consists of two steps: *toponym recognition*, where all toponyms (e.g., "Paris") are identified, and *toponym resolution*, where each toponym is assigned to the correct geographic coordinates among the many possible interpretations (e.g., "Paris" which can be one of over 140 places including France and also Texas). Geotagging is difficult because the first step involves understanding natural language, while the second step requires a good understanding of the document's content to make an informed decision as to which of the many possible locations is being referenced. Enabling the construction of indexes based on toponyms through geotagging is the motivation for this paper. For example, Figure 1 illustrates worldwide outbreaks of swine flu in May 2009, obtained by geotagging news articles written about that topic, which can then be indexed spatially.

Fig. 2. An illustration of the local lexicon for readers living in the vicinity of Columbus, Ohio, USA. Notice the many local places that share names with more prominent places elsewhere.

There are many approaches to the geotagging process (e.g., [1], [9], [10], [15], [16]). Two prominent ones are MetaCarta [16] and Web-a-Where [1]. MetaCarta assumes that a toponym such as "Paris" corresponds to "Paris, France" approximately 95% of the time, and thus reasonably good geotagging can be achieved by placing it in "Paris, France", unless there exists strong evidence to the contrary. On the other hand, Web-a-Where assumes that the text document being geotagged contains a number of proximate geographic locations often of the nature of a container (e.g., the presence of both "Paris" and "Texas") that lend supporting evidence to each other. These approaches performed quite poorly in our evaluation domain of corpora of news articles, which motivated our research.

The key observation that we make in this paper is that news articles (and more generally, documents on the Internet) are written to be understood by a human audience, and therefore geotagging will benefit from processing (i.e., reading) the document in the same way as an intended reader. In doing so, the geotagger's seemingly daunting task of identifying the correct instance of "Paris" out of the more than 140 possible interpretations will be much easier when we note that the reader is unlikely to even be aware of most of these interpretations, and thus there is no need to even consider them as possibilities in the toponym resolution step.

This leads to the key point in this paper which is that the reader's *spatial lexicon* — those locations that the reader can identify and place on the map without any evidence — is very limited. In fact, even more importantly, this inherent limitation means that a common spatial lexicon shared by all humans cannot exist, which is one of the key principles used by systems such as MetaCarta and Web-a-Where. To illustrate the importance of understanding readers' spatial lexicons, consider the following opening in an online May 2009 newspaper article[1]:

> PARIS — Former champion Serena Williams and Jelena Jankovic led Saturday's women's winners at the French Open tennis tournament in Paris.

[1]http://www.upi.com/Sports_News/2009/05/30/Serena-Jankovic-win-at-French-Open/UPI-42361243724411/

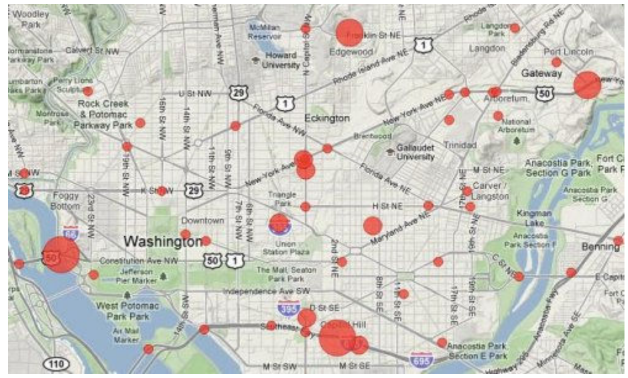


Fig. 3. Traffic hotspots in the Washington, DC area obtained by geocoding address intersections from Twitter messages.

For this article, "Paris" does refer to "Paris, France". However, consider the following contemporary article[2], published in the Paris News, a local newspaper in Texas:

> Restoration of the historic Grand Theater marquee in downtown Paris is gaining momentum.

This instance of "Paris" actually refers to the city in "Texas", which typical readers would recognize immediately, since the correct interpretation of "Paris" exists in their spatial lexicon.

For these articles, MetaCarta would erroneously place "Paris" in "France" as it assumes that "Paris" refers to "Paris, France" 95% of the time, even to readers living in "Paris, Texas", which is clearly not true. On the other hand, Web-a-Where assumes a single spatial lexicon consisting only of very prominent places around the world and does not consider local possibilities, such as "Paris, Texas", at all.

In essence, our key premise is the existence of a reader's *local spatial lexicon* or simply *local lexicon* that differs from place to place, and that it is separate from a *global lexicon* of prominent places known by everyone. In other words, to readers in Texas, "Paris" refers primarily to "Paris, Texas", rather than the distant, but more prominent, geographic location — "Paris, France". Furthermore, in most cases, the local lexicon supersedes the global lexicon. For example, as shown in Figure 2, the local lexicon of readers living in "Columbus, Ohio" includes places such as "Dublin", "Amsterdam", "London", "Delaware", "Africa", "Alexandria", "Baltimore", and "Bremen". In contrast, readers outside the Columbus area, lacking the above places in their local lexicons, would think first of the more prominent places that share their names. The local lexicon is even more necessary when geographically indexing locations with smaller spatial extent which correspond to address intersections as shown in Figure 3, since street names are even more ambiguous than regular toponyms. In this paper we present algorithms developed in tandem with NewsStand [23], a system we have constructed for visualizing news articles using the locations mentioned in them, to automatically identify the local lexicons of document sources on the Internet, which, according to our experimental analysis, leads to significant improvements in geotagging accuracy.

[2]http://theparisnews.com/story.lasso?ewcd=09b627849e99d1fa

The rest of this paper is organized as follows. We start with a survey of related work in geotagging (Section II). Next, we describe our local lexicon inference procedure, (Section III). We then outline our toponym recognition methods (Section IV) which have been tuned for geotagging, and show how we use inferred local lexicons to improve toponym resolution (Section V). This is verified through the use of experiments on two corpora of news articles (Section VI). Finally, we discuss several applications of our methods, future research directions, and present concluding remarks (Section VII).

II. Related Work

Geotagging consists of toponym recognition and toponym resolution. We now provide a brief survey of existing work on geotagging. For further overviews, refer to Leidner [9] and Purves et al. [15].

To be effective, a toponym recognition procedure must cope with *geo/non-geo ambiguity*, i.e., deciding whether a mention of "Washington" refers to a location or some other entity such as a person's name. Many different approaches to toponym recognition have been undertaken, but share similar characteristics. The most common strategy is simply to find phrases in the document that exist in a *gazetteer*, or database of geographic locations, and many researchers have used this as their primary strategy [1], [14], [19], [25], [26]. In particular, Web-a-Where [1] uses a small, well-curated gazetteer of about 40000 locations, created by collecting countries and cities with populations greater than 5000. This small size imposes a serious limitation on Web-a-Where's practical geotagging capabilities, as it is unable to recognize the small, highly local places that are commonplace in articles from local newspapers. Furthermore, because it was designed with such a small gazetteer, Web-a-Where has no means of correcting toponym recognition errors that arise from the increased geo/non-geo ambiguity when using larger gazetteers. In contrast, our own gazetteer (described in Section IV) contains almost 7 million entries and thus is suitable for recognizing highly local toponyms.

To deal with the ambiguity inherent in larger gazetteers, researchers [7], [13], [16], [20], [21], [22] have proposed a variety of heuristics for filtering potentially erroneous toponyms. MetaCarta [16] recognizes spatial cue words (e.g., "city of") as well as certain forms of postal addresses and textual representations of geographic coordinates. Unfortunately, this strategy causes serious problems when geotagging newspaper articles, as often the address of the newspaper's home office is included in each article. Given MetaCarta's primary focus on larger, prominent locations, these properly-formatted address strings play an overlarge role in its geotagging process, resulting in many geotagging errors.

Other approaches to toponym recognition are rooted in solutions to related problems in Natural Language Processing (NLP), namely Named-Entity Recognition (NER) and Part-Of-Speech (POS) tagging [8]. These approaches can be roughly classified as either rule-based [3], [5], [6], [15], [17], [27] or statistical [9], [10], [23] in nature. While statistical NER methods can be useful for analysis of static corpora, they are not well-suited to the dynamic and everchanging nature of the news, as has been noted by Stokes et al. [22]. Therefore, for our own toponym recognition procedure, we do not overly rely on any single method, instead opting for a hybrid approach involving multiple sources of evidence (see Section IV).

Once toponyms have been recognized, a toponym resolution procedure resolves *geo/geo ambiguity*, i.e., decides which "Washington" is the correct interpretation. Perhaps the simplest toponym resolution strategy is to assign a default sense to each recognized toponym, using some prominence measure such as population, and many researchers [1], [5], [13], [15], [16], [22], [27] have done so in combination with other methods. MetaCarta [16] assigns default senses in the form of probabilities based on how often each interpretation of a given toponym appeared in a precollected corpus of geotagged documents. It then alters these probabilities based on other heuristics such as cue words and cooccurrence with nearby toponyms. This probability-based paradigm makes it nearly impossible for the less prominent places that so often frequent articles in local newspapers to be selected as correct interpretations, since these smaller places will have appeared in very few precreated corpora of news articles. By contrast, our understanding of readers' local lexicons captures these smaller locations and allows their use for toponym resolution (described in Section V).

Another very popular [1], [5], [13], [14], [15], [19], [22], [26] strategy for toponym resolution is to settle on a "resolving context" within a hierarchical geographic ontology, which involves finding a geographic region in which many of the document's toponyms can be resolved. Web-a-Where [1] searches for several forms of hierarchical evidence in documents, including finding minimal resolving contexts and checking for containment of adjacent toponyms (e.g., "College Park, Maryland"). Note that the central assumption behind finding a minimal resolving context is that the document under consideration has a single geographic focus, which will be useful for resolving toponyms in that focus, but will not help in resolving distant toponyms mentioned in passing. Other resolution strategies involve the use of geospatial measures such as minimizing total geographic coverage [9], [21] or minimizing pairwise toponym distance [10]. Our own toponym resolution uses a variety of heuristics inspired by how humans resolve toponyms (see Section V and Table I).

Finally, inferring local lexicons for a given news source's audience is related to finding the *geographic focus* of a single document, i.e., the geographic coverage of toponyms in the document. A number of approaches [1], [6], [20], [26], including Web-a-Where [1], again use a hierarchical ontology to determine geographic focus, with each resolved toponym contributing a score to its parents in the hierarchy, and settling on the ontology node with highest score as the geographic focus. This approach suffers from the same problem outlined above for situations where the document contains multiple geographic foci. Another common strategy is to select the most frequent toponyms as geographic foci [6], [10], [23], [25]. Our local lexicon inference procedure, which essentially determines the geographic focus of a news source, relies on several innate properties of local lexicons to aid their discovery.

III. Inferring Local Lexicons

As noted earlier, an audience's local lexicon plays a key role in how news authors write for their audiences. We therefore require an automated, scalable method for extracting local lexicons from online news sources, which includes not only online newspapers, but also the multiple millions of blogs and Twitter users. To automatically infer local lexicons, we rely on three key characteristics of them:

1) **Stability**: A local lexicon is constant across articles from its news source.
2) **Proximity**: Toponyms in a local lexicon are geographically proximate.
3) **Modesty**: A local lexicon contains a considerable but not excessive number of toponyms.

The first property tells us that by observing and analyzing toponyms in a collection of articles from a news source, we should be able to determine the local lexicon as a common geographic theme among these articles. Note that this stability applies not only to local lexicons, but also to global lexicons as well. We must therefore use the second property of proximity to distinguish between local lexicons and more general spatial lexicons. In other words, a spatial lexicon can be classified as a local lexicon if and only if the toponyms within it are geographically proximate. The proximity property thus serves as a means of filtering and validation on an audience's local lexicon. The final modesty property highlights the notion that a person's local lexicon, while limited geographically, should at least contain several toponyms. In other words, it would be rare for a person to know of only one or two local toponyms. We will enforce the modesty property by specifying a minimum local lexicon size.

Note that we may infer local lexicons for a news source in a way analogous to geotagging a single article, but on a larger scale. In other words, we can simply geotag each article in the collection, thereby collecting a set of resolved toponyms, select the most frequent toponyms in the collection, and check whether the toponyms are geographically proximate and reasonable in number. However, this presents a bootstrapping problem, in that determining a local lexicon relies on correct geotagging of individual articles in the collection, but correct geotagging relies on knowing the local lexicon.

To break this dependency cycle, we use a geotagging process termed *fuzzy geotagging* that does not fully resolve toponyms in a single article, instead returning sets of possible interpretations for ambiguous toponyms. Fuzzy geotagging can best be understood as a variant of a traditional heuristic-based geotagging process. In such a traditional process, a toponym recognition system first finds the toponyms T in an article a. A *gazetteer*, or database of geographic locations, is then used to associate each $t \in T$ with the set of all possible interpretations R_t for t. Next, the geotagging process uses toponym resolution heuristics to filter interpretations from the set of R_t. Finally, for all t that are still ambiguous (i.e., $|R_t| > 1$), all but a single "default sense" r are filtered from R_t. This default sense is usually based on another heuristic, such as the resolution with largest population or largest geographic scope in terms of a geographic hierarchy. In this way, each recognized toponym t is resolved to a single pair of geographic coordinates. To accomplish fuzzy geotagging, the final default sense assignment is removed. Then, for each t and $r \in R_t$, a weight w_r is assigned to r, either uniformly or using default sense heuristics. Note that fuzzy geotagging is mostly independent of the underlying geotagging implementation, as long as it performs reasonably across the articles in A. Of course, a high quality underlying geotagger will result in better performance when inferring local lexicons. For fuzzy geotagging, we use our own toponym recognition and resolution methods, described in Sections IV and V, respectively. Furthermore, for each toponym t, we assign weights uniformly among the plausible interpretations R_t, and sum weights across all the articles in A.

Algorithm 1 Infer an intended audience's local lexicon.

Input: Set of articles A, Maximum diameter D_{max}, Minimum lexicon size S_{min}

Output: Local lexicon L, or $\emptyset$ if none

1: **procedure** INFERLOCALLEXICON(A, D_{max}, S_{min})
2:     $G \leftarrow \emptyset$
3:     $L \leftarrow \emptyset$
4:     **for all** $a \in A$ **do**
5:         $G \leftarrow G \cup$ FUZZYGEOTAG(a)
6:     **end for**
7:     $G \leftarrow$ ORDERBYWEIGHT(G)
8:     **for** $i \in \{1 \ldots |G|\}$ **do**
9:         $H \leftarrow$ CONVEXHULL($L \cup G_i$)
10:         **if** DIAMETER(H) $> D_{max}$ **then**
11:             **break**
12:         **end if**
13:         $L \leftarrow L \cup G_i$
14:     **end for**
15:     **if** $|L| < S_{min}$ **then**
16:         $L \leftarrow \emptyset$
17:     **end if**
18:     **return** L
19: **end procedure**

With the above in mind, we may infer local lexicons using Procedure INFERLOCALLEXICON, listed as Algorithm 1. The procedure takes as input a set of articles A from a single news source, as well as parameters D_{max}, used to determine the measure of geographic locality of an inferred spatial lexicon, and S_{min}, the minimum allowed size of a local lexicon. We determined appropriate values for these parameters experimentally (described in Section VI-C). We begin by initializing a set of resolved toponyms G and the eventual inferred local lexicon L to the empty sets. (lines 2–3). Next, we loop over all articles $a \in A$ (lines 4–6), recognizing and resolving toponyms from each article in turn. We subject each article a to the aforementioned fuzzy geotagging process with Procedure FUZZYGEOTAG, which returns a set of toponyms found in a, and their potential interpretations and weights (line 5). We aggregate these resolved and weighted toponyms into G, merging repeated interpretations and summing their weights. For example, if articles $a_1 \ldots a_k$ in the collection each contain

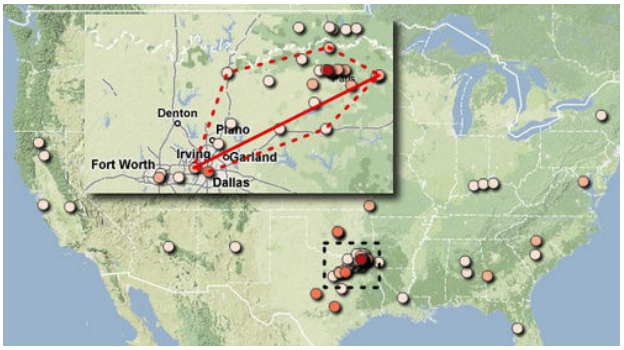


Fig. 4. The local lexicon inferred for the Paris News, a small newspaper in Paris, Texas (upper right in inset), with $D_{max} = 150$ miles and $S_{min} = 5$. The final convex hull (dashed red) has a diameter (solid red) of about 130 miles.

a mention of "College Park", and the fuzzy geotagging process assigned these toponyms to College Park, MD with weights $w_1 \dots w_k$ (not necessarily equal), we merge these k interpretations in G to a single grounded toponym with weight $\sum_i w_i$.

At this point, G serves as a weighted spatial lexicon for the articles in A. We proceed to extract a local lexicon from the resolved toponyms $r \in G$ by noting that the most heavily weighted $r \in G$ are common to a large number of articles in A, and should be considered as part of a potential local lexicon. To this end, we first order the resolved toponyms in G by decreasing order of weight (line 7), and consider adding each toponym in turn to the local lexicon L (lines 8–14). For each resolved toponym G_i, we determine the *convex hull* H of the geographic coordinates of the toponyms in L combined with the new toponym G_i (line 9). We then measure the diameter of H, and check whether it exceeds D_{max}; if so, we cease adding toponyms to L (lines 10–12). We do so to enforce the proximity property of local lexicons. Otherwise, we add G_i to L (line 13), and continue with G_{i+1}. After G's toponyms have been considered, we check whether the collected lexicon is larger than S_{min}, which qualifies it as a true local lexicon, and nullify L if it does not reach our minimum limit (lines 15–17). Finally, we return L, which is the extracted local lexicon, or $\emptyset$ if no local lexicon was found (line 18).

To illustrate this procedure, Figure 4 shows the local lexicon inferred by InferLocalLexicon for 137 articles from the Paris News, a small newspaper in Paris, Texas, which is approximately 100 miles northeast of Dallas, Texas. In the figure, Paris lies in the northeast quadrant of the inset. Each point represents a toponym found in an article published in the Paris News, with the color indicating its frequency across all articles in the collection. By far, the most frequently geotagged toponym was Paris (22 mentions). Other toponyms included Lamar County (13 mentions) and Dallas (5 mentions), in addition to a variety of toponyms unrelated to the local lexicon. Starting with Paris, the most frequently occurring toponym, we add toponyms to L in decreasing order of frequency until the diameter of the convex hull of $L > D_{max}$ (for this example, D_{max} was set to 150 miles). The final convex hull is shown in dashed red, with its diameter of approximately 130 miles highlighted in solid red. A final test ensures that $|L| > S_{min}$ (for this example, S_{min} was chosen to be 5).

By considering resolved toponyms in order of decreasing weight, Procedure InferLocalLexicon makes use of the stability property of local lexicons, since the most heavily weighted toponyms will have been resolved consistently across many articles in A. It also ensures that the returned local lexicon L falls within a geographic footprint with diameter smaller than D_{max}, thus enforcing the proximity property, and nullifies L if it violates the modesty property by having $|L| < S_{min}$. In our evaluation of InferLocalLexicon (see Section VI-C), we determine suitable parameter values for D_{max} and S_{min} and find that the overall procedure performs well.

IV. Toponym Recognition

The first step toward successful geotagging is finding toponyms within the document to be geotagged, referred to as *toponym recognition*. Toponym recognition is difficult because many names of places are also common names of people and other entities. For example, "Washington" is the name of many cities in the USA, but is a very common surname as well. Note that while geotagging relies on toponym recognition, it is only one stage in the process and should be regarded as a means to an end. Therefore, we will not overly concern ourselves with toponym recognition performance in isolation, but rather with the performance of our geotagging system as a whole. This observation informs us against overly relying on algorithms specifically tuned for the toponym recognition problem.

To enable toponym recognition and resolution, we use a *gazetteer*, or database of geographic locations with geographic coordinates and associated metadata — essentially, an ontology of geographic knowledge. We use the GeoNames[3] gazetteer, an open gazetteer originally built from multiple gazetteers and maintained by volunteers around the world. GeoNames contains almost 7 million entries with a variety of metadata such as feature type (country, city, river, mountain, etc.), population, elevation, and positions within a political geographic hierarchy. For example, the College Park entry contains pointers to its containers at increasing levels of scope: Prince George's County, Maryland, United States, North America. We store and query the GeoNames gazetteer in a PostgreSQL database.

For toponym recognition, we also make use of approaches built for solving problems from the natural language processing community, and in particular the problems of Part-Of-Speech (POS) tagging and Named-Entity Recognition (NER) [8]. The purpose of POS tagging is to assign a part of speech to each word given as input, while NER requires that a limited set of typed entities (typically people, organizations, locations, dates, etc.) are found and reported. Most state-of-the-art POS taggers and NER systems use statistical machine learning methods to train a language model from an annotated language corpus. Once trained, the model is used to determine the most likely sequence of parts of speech, or most likely set of named entities. Of course, these models will be inherently limited by the size, contents, and availability of suitable training data, which in many cases is quite limited.

At this point, it is worth noting that toponym recognition is a subtask of NER. Given this fact, it may be tempting to

[3]`http://geonames.org/`

simply use a NER system to find toponyms. However, being a more general task, most NER systems sacrifice recall in favor of precision (see Section VI-A for the definitions of precision and recall). In other words, they miss many toponyms so that the ones that they report are valid. Also, statistical NER systems are usually trained on corpora of tagged news wire text containing few less-prominent toponyms. As a result, the toponyms in an NER training corpus essentially serve as a very limited gazetteer, which in turn limits the breadth of a toponym recognizer using models trained on the corpus. This limitation drastically reduces their performance on articles from local newspapers, as noted by Stokes et al. [22]. Therefore, we do not overly rely on POS tagger and NER output, instead using them in more advisory roles.

With this in mind, we proceed with a hybrid toponym recognition technique. Given a news article, we tag each word with its part of speech, using the POS tagger, and collect all word phrases consisting of proper nouns. We also apply NER to the article, and collect all phrases tagged as locations. As a final measure, we gather probable toponyms using rules based on our toponym resolution heuristics (see Table I) as well as geographic *cue words* that occur frequently in news articles. For example, phrases such as "city of *X*", "just outside of *X*", "*X*-based", and "*X* Ocean" are strong indicators that *X* is a full or partial toponym. Then, for each collected phrase, we query the gazetteer, and report phrases that exist in the gazetteer as toponyms. We use TreeTagger[4] trained on the Penn TreeBank corpus for tagging parts of speech, and the Stanford NLP Group's NER system[5] for finding location entities.

This optimistic toponym recognition process results in many more reported toponyms than actually exist in the article, due to the aforementioned ambiguity and potentially misleading contextual geographic clues, which results in low toponym precision. However, because toponym recognition is only one part of the geotagging process, it is most important at the toponym recognition stage to maximize recall, since local lexicons serve as a powerful way to filter and temper precision errors.

V. Toponym Resolution

Having established a method for determining local lexicons, we are now prepared to apply these lexicons for toponym resolution. The main idea behind our geotagging process is to model how an article author establishes a geographic framework within an article, to make it easier for human readers in the author's intended audience to recognize and resolve toponyms. Authors create this framework by using linguistic contextual clues that we can detect using heuristic rules. Furthermore, readers are expected to read articles linearly, so article language has a contextual and geographic flow. Toponyms mentioned in a sentence will establish a geographic framework for subsequent text. To ensure correct geotagging, we therefore process the article text in a linear fashion.

Finally, and of greatest importance, an article author will keep in mind the nature of the expected audience's spatial lexicon, and in particular the local lexicon, to underspecify those toponyms in situations where adding geographic context would be redundant. For these underspecified toponyms, we will only consider those possible interpretations that are known to intended readers, either due to relative prominence (such as countries and capital cities) or existence in their local lexicon, rather than all possible interpretations from the multiple millions of entries in our gazetteer, which is a much larger set of locations than any human could possibly know. If no resolution is found that satisfies our constraints, we drop the toponym as a false positive, rather than assuming the toponym recognition process was correct and hence assigning it a default sense (e.g., the most populous interpretation). In a more general sense, unlike many existing geotagging approaches, we view successful geotagging as a single integrated process, rather than as separate toponym recognition and resolution systems that are chained together.

After recognizing toponyms from an article to be geotagged (see Section IV), we proceed to resolve toponyms using a number of heuristic rules. Table I lists the set of heuristics used in our toponym resolution process, as well as examples of when each heuristic would be applied. These heuristics are inspired by how humans normally read news articles. We apply the heuristics in the order listed in Table I. For toponyms that can be resolved by multiple heuristics, we use the resolution suggested by the highest ranked heuristic. Our highest-ranked heuristics establish a geographic context for large portions of the article, i.e., Dateline ($\mathcal{H}_1$) and Relative Geography ($\mathcal{H}_2$). We continue with heuristics favoring contextual language clues, namely Comma Group ($\mathcal{H}_3$) and Location/Container ($\mathcal{H}_4$). Finally, we conclude with default sense heuristics using the reader's Local Lexicon ($\mathcal{H}_5$) and Global Lexicon ($\mathcal{H}_6$). In addition, we use a One Sense ($\mathcal{H}_7$) heuristic modeled after the "one sense per discourse" assumption that all instances of a repeated toponym will have the same resolution. We apply $\mathcal{H}_7$ after each of $\mathcal{H}_1$–$\mathcal{H}_6$, which propagates a toponym resolution to all later repeated mentions of the toponym. This heuristic enforces a consistent resolution of the same toponym in the same article. Note that despite the Local Lexicon heuristic's low ranking as $\mathcal{H}_5$, several other heuristics, namely $\mathcal{H}_1$–$\mathcal{H}_3$, appeal to the Local Lexicon heuristic for correct resolution. The local lexicon thus plays a large role in our toponym resolution procedure. In our evaluation, we measure how often each heuristic was used in geotagging our evaluation corpora (see Section VI-E).

For the sake of clarity, we now provide more detailed descriptions of heuristics $\mathcal{H}_1$–$\mathcal{H}_6$, and give examples of each.

$\mathcal{H}_1$, *Dateline*

We examine the article, checking for the presence of dateline toponyms, which if present appears at the article's beginning and establishes the general geographic locality of the events described in the article. If happening in a place unfamiliar to the author's audience, authors generally use location/container clues (e.g., "LONDON, Ont. —"). Otherwise the location will be underspecified (e.g., "LONDON —"), since it already exists in the audience's global lexicon, or frequently its local lexicon. We therefore attempt to resolve dateline toponyms using the Lo-

[4]http://www.ims.uni-stuttgart.de/projekte/corplex/TreeTagger/

[5]http://nlp.stanford.edu/ner/

TABLE I

A SET OF HEURISTICS USED IN OUR TOPONYM RESOLUTION PROCESS.

	Heuristic	Description	Examples
$\mathcal{H}_1$	Dateline	Resolve dateline toponyms using: $\mathcal{H}_4$, $\mathcal{H}_5$, $\mathcal{H}_6$. Resolve other toponyms geographically proximate to resolved dateline.	**LONDON, Ont.** - A police... **Paris, TX** (AP) - New...
$\mathcal{H}_2$	Relative Geog.	Resolve anchor toponym using: $\mathcal{H}_1$, $\mathcal{H}_4$, $\mathcal{H}_5$, $\mathcal{H}_6$. Resolve other toponyms proximate to defined geographic point or region.	**...4 miles east of Athens, Texas.** ...lives **just outside of Lewistown**...
$\mathcal{H}_3$	Comma Group	Resolve toponym group using: $\mathcal{H}_6$, $\mathcal{H}_5$, Geographic Proximity.	...**California, Texas** and **Pennsylvania**.
$\mathcal{H}_4$	Loc/Container	Resolve toponym pairs with a hierarchical containment relationship.	...priority in **Jordan, Minn.**, ...
$\mathcal{H}_5$	Local Lexicon	Resolve toponyms geographically proximate to local lexicon centroid.	*(news source dependent)*
$\mathcal{H}_6$	Global Lexicon	Resolve toponyms found in a curated list of globally-known places.	...issues with **China**, knowing...
$\mathcal{H}_7$	One Sense	Resolve toponyms sharing names with earlier resolved toponyms.	*(article dependent)*

cation/Container ($\mathcal{H}_4$), Local Lexicon ($\mathcal{H}_5$), and finally Global Lexicon ($\mathcal{H}_6$) heuristics. If we are able to successfully resolve dateline toponyms, we then resolve additional toponyms from the article that are geographically proximate to the resolved dateline toponyms.

$\mathcal{H}_2$, *Relative Geography*

Certain phrases in article text denote relative geography, which is language that defines a usually imprecise geographic region in terms of distance from or proximity to another geographic location. These imprecise regions are important because they usually target the geographic areas where the events in an article took place, and therefore are useful for resolving the article's toponyms. Example instances of relative geography include "4 miles east of Athens, Texas" and "just outside of Lewistown". We refer to the toponyms in such phrases as *anchor toponyms*, and we term the resulting regions as *target regions*.

Notice that anchor toponyms follow the same specification patterns as those used for dateline toponyms. Therefore, to resolve target regions, we first resolve the anchor toponyms, using the same heuristics as used for the Dateline ($\mathcal{H}_1$) heuristic, namely Location/Container ($\mathcal{H}_4$), Local Lexicon ($\mathcal{H}_5$), and Global Lexicon ($\mathcal{H}_6$). After resolving the anchor toponym, we set the target region in terms of proximity to the anchor toponym (as in "just outside of Lewistown") or proximity to a geographic point defined relative to the anchor toponym (as in "4 miles east of Athens, Texas"). Finally, we resolve all toponyms in the article that are geographically proximate to the target region.

$\mathcal{H}_3$, *Comma Group*

Lists of toponyms in articles are a frequent occurrence, and we refer to these lists as comma groups. Authors generally organize toponyms into concise groups when they share a common characteristic, such as all being prominent places (e.g., "California, Texas and Pennsylvania", all states in the USA) or all being mutually geographically proximate (e.g., "College Park, Greenbelt and Bladensburg", all small places near College Park, MD). We resolve all toponyms in comma groups by applying a heuristic uniformly across the entire group. First, we check whether all toponyms exist in the Global Lexicon ($\mathcal{H}_6$) or the Local Lexicon ($\mathcal{H}_5$). We also check whether interpretations exist that are all constrained to a small geographic area, not necessarily the same as the local lexicon region.

$\mathcal{H}_4$, *Location/Container*

Authors commonly provide contextual evidence for a toponym by specifying its containing toponym, in terms of a geographic hierarchy. For example, an author might mention "College Park, Maryland", which indicates that the correct instance of College Park lies within its container toponym, Maryland. They may also use abbreviations for the container, such as "Jordan, Minn." (referring to Minnesota). To resolve these toponyms, we appeal to our gazetteer and choose a pair of interpretations that satisfies the hierarchy constraint.

$\mathcal{H}_5$, *Local Lexicon*

If we inferred a local lexicon for the article's news source (see Section III), we now use the local lexicon to resolve article toponyms. We first compute the geographic centroid of the source's inferred local lexicon, which has meaning because of the proximity property of toponyms in the local lexicon. We then resolve those toponyms that are geographically proximate to the centroid. If the news source has no local lexicon, as would occur for a newspaper with a widely dispersed audience, we do not apply this heuristic.

$\mathcal{H}_6$, *Global Lexicon*

Our final heuristic uses a curated global lexicon of toponyms which we regard as prominent enough to be known by audiences regardless of their geographic location. We created an initial global lexicon by adding prominent geopolitical divisions such as continents and country names, as well as large regions and cities with over 100k population. Note that population is a coarse measure and finally serves as a substitute for "prominence", but works adequately for our purposes.

VI. EVALUATION

A. *Evaluation Measures*

Like many natural language and text processing problems, toponym recognition performance can be cast in terms of two widely-used measures called *precision* and *recall* [24]. For a set of ground truth toponyms G and a set of system-generated toponyms S, precision and recall are defined as:

$$P(G,S) = \frac{|G \cap S|}{|S|}, R(G,S) = \frac{|G \cap S|}{|G|}$$

Put simply, precision measures how many reported toponyms are correct, but says nothing of how many went unreported. In contrast, recall measures how many ground truth toponyms

TABLE II

EVALUATION CORPUS STATISTICS.

	ACE	LGL
Number of data sources	4	78
Number of articles	104	588
Number of tokens	48036	213446
Number of toponyms	5813	4793
Distinct toponyms	915	1297
Prevalent Toponym Types		
Countries	1685	961
Administrative divisions	255	1322
Capital cities	454	318
Populated places	178	1968

were reported and correct, but does not indicate how many of all reported toponyms are correct.

To combine precision and recall into a single measure for comparative purposes, we use the F_1-score [24], which is simply the harmonic mean of precision and recall:

$$F_1 = \frac{2PR}{P+R}$$

B. Datasets

We used two datasets of news articles in our evaluation. The first is a subset of the ACE 2005 English SpatialML Annotations [11], available from the Linguistic Data Consortium, which we will refer to as *ACE*. ACE contains 428 documents in total that represent a variety of spatially-informed data sources, including news wire and blog text, as well as online newsgroups and transcripts of broadcast news. Each document is annotated using SpatialML, an XML-based language which allows the recording of toponyms and their geographically-relevant attributes, such as their lat/lon position, feature type, and corresponding entry in a gazetteer. For this evaluation, we limited our test collection to news stories, resulting in 104 news articles from prominent newspapers and news wire sources.

Unfortunately, since news wire is usually written and edited for a broadly distributed geographic audience, the ACE corpus is quite limited for the purposes of evaluating local lexicons' impact on geotagging, and is hardly representative of data from smaller newspapers with a more localized audience, which have a large presence on the Internet. As a result, we created our own corpus of news articles by sampling from the collection of over 4 million articles indexed by the NewsStand system [23], which we call the *Local-Global Lexicon* corpus, or simply *LGL*. We focused on articles from a variety of smaller, geographically-distributed newspapers. To find this set of smaller newspapers and thereby ensure a more challenging toponym resolution process, we first ranked toponyms in our gazetteer by ambiguity, and selected highly ambiguous toponyms such as Paris and London. We then selected newspapers based near these ambiguous toponyms. For example, some US-based newspapers located near a Paris include the Paris News (Texas), the Paris Post-Intelligencer (Tennessee), and the Paris Beacon-News (Illinois). For each newspaper, we chose several articles to include in LGL, and manually annotated the toponyms in these articles, including the corresponding entries from our gazetteer.

TABLE III

FOR A GIVEN NEWS SOURCE N, SITUATIONS IN WHICH WE CONSIDER OUR LOCAL LEXICON INFERENCE PROCEDURE'S FOCUS N_S TO MATCH THE GROUND TRUTH FOCUS N_G.

N_G exists	N_S exists	$D(N_G, N_S) \leq \delta$	Match
No	No	—	Yes
Yes	No	—	No
No	Yes	—	No
Yes	Yes	No	No
Yes	Yes	Yes	Yes

Table II summarizes statistics for the ACE and LGL corpora. These statistics show the limitations of ACE in terms of source breadth, as only four news sources are represented in the corpus — Agence France-Presse (AFP), Associated Press World, New York Times, and Xinhua — with 42, 40, 5, and 17 annotated articles from each source, respectively. LGL contains 588 articles from 78 newspapers, with an average of 5 articles per newspaper. Also, as the toponym counts show, the articles in ACE tend to be more toponym-heavy, with over 50 toponyms per article, in contrast to LGL articles with an average of 8 toponyms per article. Examining the prevalent toponym types in both data sources reveals that the ACE collection is also very international in scope, with 1685 of 5813 toponyms (29%) corresponding to country names. In contrast, LGL's set of toponyms are more local. Out of 4793 total toponyms, 1968 (41%) are smaller populated places, and 1322 (28%) are administrative divisions such as states and counties. These statistics show that the ACE corpus is better suited for evaluating geotagging on an international scope, while LGL is better-suited for testing geotagging on a local level.

C. Inferring Local Lexicons

We tested our local lexicon inference procedure with fuzzy geotagging, described in Section III. The idea behind our evaluation procedure is that for a small, local newspaper, the newspaper's audience will be geographically proximate to the newspaper's geographic focus. As a result, the local lexicon of the newspaper's audience will consist of multiple places near the newspaper's geographic focus. We can measure how successful we are in establishing a given newspaper's audience's local lexicon by checking whether the centroid of our inferred local lexicon is within a given distance δ to a ground truth annotation of the newspaper's geographic focus. For larger newspapers annotated with no geographic focus and hence no assumed local lexicon, we check that our local lexicon inference procedure also returned no local lexicon. In other words, we test our inference procedure first in terms of binary classification ("has local lexicon" or "no local lexicon") and second in terms of geographic distance from the ground truth focus. As earlier, we use precision and recall to measure performance, with the ground truth foci and the local lexicon foci returned by our inference procedure serving as the ground truth and system-generated sets, respectively.

Table III summarizes the situations in which we will consider the ground truth N_G to match our system-generated local lexicon N_S for a given news source N. We consider the results

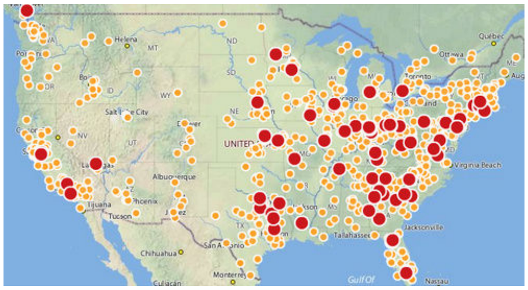
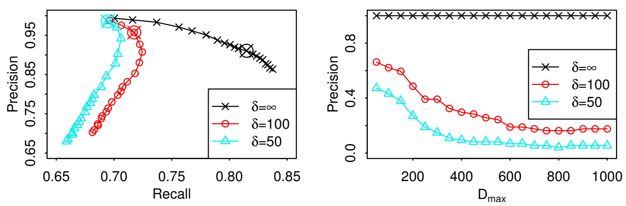
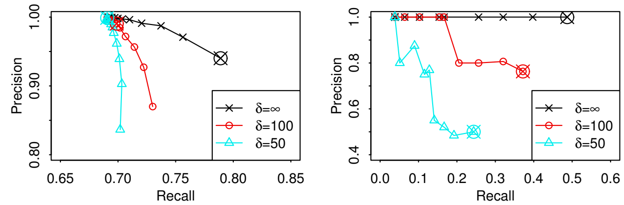


Fig. 5. Local lexicon foci for news sources in the USA (LGL in red).



(a) All news sources (b) Only LGL sources

Fig. 6. Performance on local lexicon inference by varying maximum hull diameter D_{max} between 50–1000 miles and keeping minimum lexicon size S_{min} fixed at (a) 5 and (b) 3.



(a) All news sources (b) Only LGL sources

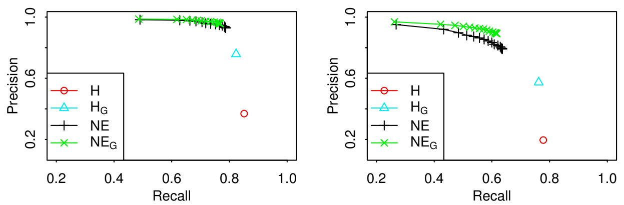
Fig. 7. Performance on local lexicon inference by varying minimum lexicon size S_{min} between 4–15 and keeping maximum hull diameter D_{max} fixed at (a) 200 and (b) 150.

to match if both N_G and N_S do not exist (i.e., the ground truth had no geographic focus for news source N and our inference procedure did not return a local lexicon). Also, the results match if both N_G and N_S exist, and further, that the distance between the geographic centroids of N_G and N_S is less than a distance threshold δ. Otherwise, we consider the results to differ, and penalize precision and recall as appropriate.

To establish our ground truth, we manually examined each of the 4867 active newspaper sources in the NewsStand system, and annotated news sources with geographic foci as appropriate. Figure 5 shows the mapped geographic foci of news sources in the USA, highlighting those with articles in LGL. To create a collection of news stories to use for determining local lexicons, we gathered approximately two months' worth of news stories in February and March 2009, resulting in a total of 1266119 articles. From this large collection of articles, 7654 were from the 78 news sources in LGL. However, the distribution of articles in sources is highly skewed, with over half of 78 news sources having under 50 articles total. For each news source (regardless of whether it is in LGL) we then tried to detect a valid local lexicon using procedure INFERLOCALLEXICON.

The goal for our first test is to evaluate the efficacy of procedure INFERLOCALLEXICON in terms of determining how far, measured by δ in the ranges $[0, 50)$, $[50, 100)$, and $[100, \infty)$, it placed the geographic focus of a source's local lexicon from its ground truth value, while also varying the maximum diameter D_{max} of the convex hull of the locations in the lexicon found between 50 and 1000 miles in 50 mile increments. Note that setting $\delta = \infty$ effectively results in a test for local lexicon inference without regard to its distance from the true geographic focus, i.e., whether the corresponding source was classified correctly as having a local lexicon or not. For this test, we kept the minimum lexicon size, S_{min}, fixed at 5 for our test on all feeds and 3 for our test on only LGL feeds. Figures 6a and 6b show our performance results for inferring local lexicons on all news sources and only those sources in LGL, respectively. In Figure 6a, the point where all three lines coincide corresponds to the minimum value of D_{max} tested, namely 50 miles. Each successive plotted point corresponds to a 50 mile increase in D_{max}. Also, the points with maximum F_1-score are highlighted. Observe that a smaller value of D_{max} results in higher precision at the expense of recall, corresponding to the high precision points in the left portion of each plot. For all sources and D_{max} values tested, we obtained precision between 0.65–1.00, and recall between about 0.65–0.85. The performance results indicate that our local lexicon inference procedure tends to have high precision overall, with values well above 0.90 for both sets for relatively small $D_{max} < 200$ miles. Above this value, precision suffers, but with little corresponding gain in recall. In fact, for $D_{max} > 150$ ($\delta = 50$) and $D_{max} > 250$ ($\delta = 100$), both precision and recall decrease, because any gains in recall from detecting a local lexicon are more than offset by penalties from having local lexicon centroids too distant from the ground truth. Figure 6b shows a plot of D_{max} values and the corresponding precision of our inference process for news sources in LGL. Recall was omitted because all sources in LGL were marked with a geographic focus in the ground truth, and furthermore, our local lexicon inference procedure always found a local lexicon for all sources as well. As a result, recall always equalled precision in this test. We found that the minimum value of D_{max} tested, 50 miles, resulted in the best precision of 0.46 for $\delta = 50$ and 0.66 for $\delta = 100$. In general, our inference algorithm performed well when simply detecting the presence of a local lexicon, as evidenced by the high precision and recall values of the $\delta = \infty$ curves in both figures. Also, performance was better across all news sources than for those only in LGL, mainly due to the relative scarcity and highly skewed distribution of stories produced by the LGL news sources. The tests indicate that a value of $D_{max} = 200$ miles is reasonable for inferring local lexicons with INFERLOCALLEXICON.

For our second test of procedure INFERLOCALLEXICON, we varied the minimum acceptable local lexicon size, S_{min}, between 4–15, while keeping the maximum convex hull diameter D_{max} fixed at 200 for all feeds and 150 for LGL feeds, to discover a suitable value for our use. Figures 7a and 7b show the results of our tests on all feeds and only LGL feeds, respectively. The smallest value of S_{min} tested (4) corresponds to the rightmost points of each curve in the graphs, which demonstrates that small S_{min} results in higher recall at the expense of precision. For all feeds (Figure 7a), a small increase



(a) ACE (b) LGL

Fig. 8. Precision-recall diagrams for toponym recognition performance using both our hybrid procedure (H) and a statistical named-entity recognizer (NE).

in S_{min} to the range of values 5–7 results in a large jump in precision with little drop in recall, and for larger values of S_{min}, the inference procedure quickly converges to near 1.00 precision and about 0.70 recall. Similar results can be seen for only LGL sources (Figure 7b), where the points with smallest value of S_{min} (4) have the highest recall and also highest F_1-scores. When increasing S_{min}, precision rapidly jumps, but at the heavy expense of recall. Again, we attribute the relatively low recall numbers for LGL sources to the skewed distribution of news articles in LGL. In general, both plots show that procedure INFERLOCALLEXICON is a high precision procedure, so small values of S_{min} such as 5 are best. This relatively small number makes sense when considering that it is rare for even a few toponyms to occur frequently in articles from a given news source to also be geographically proximate, unless the news source's geographic focus is in the area.

D. Toponym Recognition

Next, we evaluated our hybrid toponym recognition procedure described in Section IV against a simpler method using only the Stanford named-entity recognizer, trained on a variety of news corpora. For the named-entity recognizer, we varied a threshold parameter that controls the minimum confidence level of output by the recognizer. Varying this parameter allowed control over whether precision or recall was to be favored. As is typical for statistical named-entity recognizers, setting a high value for the threshold parameter favors precision at the expense of recall, while a low threshold value favors recall at the expense of precision. Also, we considered toponyms to match only if they coincided exactly in the text; partial or otherwise overlapping toponyms were considered errors.

Figure 8 details performance results of the hybrid (H) and named-entity (NE) recognition procedures in the form of precision-recall diagrams. We also tested variants of the hybrid and named-entity procedures where the system-generated toponyms were filtered to only those toponyms that have entries in our gazetteer, labeled as H_G and NE_G, respectively. In other words, rather than blindly using the set of toponyms returned by the recognition process as our system-generated set, we remove those toponyms that are not present in the gazetteer. We do so to test our toponym recognition procedure as a standalone process, separate from its purpose as the first stage in a combined geotagging process. Note that our hybrid recognition procedure (H and H_G) does not have an explicit tuning parameter to adjust the precision/recall tradeoff, and so Figure 8 contains a single data point for each.

Figure 8a shows recognition results on the ACE corpus. As can be seen, the named-entity recognizer is highly tuned for precision. At all values of the threshold parameter, recognition precision was above 0.920, with the corresponding recall ranging between 0.490–0.787. Notice that gazetteer filtering did not have much of an effect on the NE method. This is not surprising, because in essence the training set which it uses plays a similar role to a gazetteer, but is very limited in scope. This limitation serves to ensure high precision but at the expense of recall as we have observed. In contrast, our hybrid recognition procedure emphasized toponym recall, with 0.369 precision and 0.851 recall before and 0.758 precision and 0.823 recall after gazetteer filtering. Though the precision greatly increases by almost 0.39, recall drops slightly by about 0.03. This drop reflects the fact that most gazetteers are still rather incomplete or at least not in sync with the frequency of use of location descriptions that do not have formally defined boundaries, such as "New England" and "Upper West Side".

Figure 8b shows similar results from our LGL corpus, although the difficulty of recognizing smaller, less prominent toponyms is reflected in both methods' decreased performance relative to the ACE corpus. The named-entity recognizer again garnered high precision, varying between 0.892–0.969, and had recall between 0.262–0.617. In contrast, our hybrid recognition method resulted in 0.762 recall and 0.573 precision. These performance numbers indicate clearly that our hybrid procedure is much better-suited for toponym recall than purely statistical recognition methods.

E. Toponym Resolution

Our measure of correctness for toponym resolution is the same as that in our toponym recognition evaluation, except that in addition to an exact toponym match, for a grounded toponym to be considered correct, it must have been placed a maximum of 10 miles from the ground truth toponym. This small distance range is required to account for small lat/lon differences in the gazetteers used in annotating our evaluation corpora (IGDB [12] for ACE, GeoNames for LGL). Exceptions to this rule include features with extent, such as countries and states. We measured precision, recall, and F_1 of the entire toponym recognition and resolution process. In addition, we took two sets of measurements using different toponym recognition procedures to evaluate different stages of our geotagging process. Our first set of measurements used our own toponym recognition procedure, described in Section IV, which resulted in measurements of our entire geotagging procedure's accuracy. For our second set of measurements, we assumed a *toponym oracle* for toponym recognition that ensures perfect toponym recognition. That is, we tested our toponym resolution procedure in isolation using the annotated ground truth toponyms.

We compared our own geotagging procedure, referred to as IGeo, with implementations inspired by other noted geotagging methods. In particular, we created implementations using MetaCarta's [16] confidence-based toponym resolution, Web-a-Where's [1] gazetteer hierarchy resolution procedure, and Volz et al.'s [25] class-based weight heuristics, henceforth referred to as MC, WaW, and VKM, respectively. In cases where

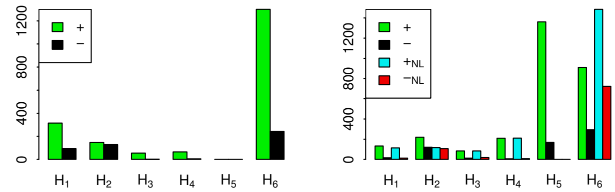
TABLE IV
TOPONYM RESOLUTION PERFORMANCE RESULTS.

	Toponym recognition			Toponym oracle		
	P	R	F_1	P	R	F_1
ACE						
IGeo	**0.800**	**0.774**	**0.787**	**0.968**	0.890	**0.928**
WaW	0.795	0.773	0.784	0.962	**0.891**	0.925
MC	0.731	0.752	0.741	0.945	0.870	0.906
VKM	0.603	0.709	0.652	0.859	0.816	0.837
LGL						
IGeo	**0.826**	**0.654**	**0.730**	**0.964**	**0.817**	**0.885**
IGeo$_{\mathrm{NL}}$	0.698	0.450	0.548	0.788	0.546	0.645
WaW	0.651	0.452	0.534	0.761	0.628	0.689
MC	0.477	0.494	0.485	0.712	0.629	0.668
VKM	0.351	0.475	0.404	0.590	0.567	0.578

the authors' implementations were loosely specified, we used defaults that ensured reasonable performance. Also, despite our best efforts, we were unable to obtain the annotated corpora used by these previous researchers, either due to inactivity or restrictive copyright policies, and hence could not directly validate our implementations.

Table IV details toponym resolution performance across both the ACE and LGL corpora. Maximum values for each evaluation method and corpus are highlighted in the table. For LGL, we also tested our IGeo procedure without using local lexicon evidence, listed as IGeo$_{\mathrm{NL}}$. Using our own toponym recognition, IGeo outperformed the other implementations across both corpora, in terms of precision, recall, and F_1-score. For the ACE corpus, all the geotagging methods performed reasonably, with precision and recall values generally above 0.70. WaW most closely approached IGeo's precision and recall, with nearly identical values. These performance numbers reflect the relative ease of geotagging news wire text, since toponyms are usually prominent places or well-specified with geographic contextual clues. However, examining performance in the LGL corpus, we can see significant performance penalties for competing methods that neglect the local lexicon. IGeo outperforms its nearest competitor WaW by almost 0.20 in terms of precision, recall, and F_1-score. Notice that adding the local lexicon caused a large increase of about 0.13 precision and 0.20 recall over IGeo$_{\mathrm{NL}}$. This increase in both precision and recall stands in contrast to many information retrieval techniques, which usually increase either precision or recall at the expense of the other.

With a toponym oracle, performance results for all resolution methods are much higher, with F_1-scores for ACE approaching or exceeding 0.90. In particular, WaW's performance nearly matched that of IGeo, in some cases being slightly better. However, when moving to the more difficult LGL, we again see a large performance difference of about 0.20 in terms of F_1-score between IGeo and competing methods. Again, for LGL, both precision and recall improve as a result of using local lexicon evidence. Interestingly, we see that IGeo's precision for both the ACE and LGL corpora stays constant at approximately 0.96, which indicates that local lexicons serve as a high precision source of evidence for geotagging. Comparing performance results between our own toponym recognition procedure and the toponym oracle, IGeo's performance gain using the toponym oracle in terms of F_1-score was about 0.10



(a) ACE (b) LGL

Fig. 9. Heuristic usage in toponym resolution for both corpora.

for ACE, and about 0.15 for LGL. This difference reflects the greater difficulty in toponym recognition and resolution of the smaller, less prominent toponyms in LGL, which affects the performance of the non-IGeo methods. Furthermore, IGeo's performance difference in terms of F_1-score between using toponym recognition and the toponym oracle was the least of all resolution methods (excepting IGeo$_{\mathrm{NL}}$), being 0.141 for ACE and 0.155 for LGL. This finding indicates that of all resolution methods, IGeo depended the least on using the toponym oracle for toponym recognition, which is artificial.

F. Heuristic Usage

Our final experiment measured how much each heuristic listed in Table I played a part in geotagging precision across our evaluation corpora. Figures 9a and 9b show our usage results. In the figures, each column represents a different heuristic, labeled H$_1$–H$_6$, and corresponding to $\mathcal{H}_1$–$\mathcal{H}_6$ in Table I. The One Sense heuristic ($\mathcal{H}_7$) is not shown as it was applied after each of $\mathcal{H}_1$–$\mathcal{H}_6$. Toponyms resolved using $\mathcal{H}_7$ were counted toward whichever of $\mathcal{H}_1$–$\mathcal{H}_6$ was responsible for the propagated resolution. Figure 9a shows the usage distribution for ACE. In each column, the first bar ($+$) shows how often the heuristic contributed to a correctly resolved toponym, while the second bar ($-$) counts instances where the heuristic led to an error. Examining Figure 9a reveals that the most important heuristics for toponym resolution were Global Lexicon ($\mathcal{H}_6$) and Dateline ($\mathcal{H}_1$). This is not overly surprising, as ACE consists mostly of news wire of international scope, so most toponyms mentioned in ACE articles will be prominent places. Also, being news wire, the Local Lexicon ($\mathcal{H}_5$) played no role in toponym resolution.

Figure 9b shows heuristic usage in the LGL corpus. In each column, the first two bars are successes ($+$) and errors ($-$) as before, while the second two show successes ($+_{\mathrm{NL}}$) and errors ($-_{\mathrm{NL}}$) when disregarding local lexicon evidence. It is clear that the Local Lexicon ($\mathcal{H}_5$) plays a large role in correct toponym resolution, and suffers from relatively few errors. This result is in keeping with our earlier observation that using the local lexicon affords high precision. Interestingly, the Global Lexicon ($\mathcal{H}_6$) plays an even larger role in correct toponym resolution when used without a Local Lexicon ($\mathcal{H}_5$) but it also causes even more errors, but the relative difference is surprisingly the same as when used with a Local Lexicon ($\mathcal{H}_5$). We can also see that the Dateline heuristic ($\mathcal{H}_1$) has less use in LGL than in ACE, which reflects the lack of dateline toponyms in many smaller newspapers. From both figures, we note that Relative Geography ($\mathcal{H}_2$) provides some resolution benefit, but is also noisy in that it causes almost as many precision errors as successes in the case of ACE and in LGL when ignoring the Local Lexicon ($\mathcal{H}_5$). We also observe that for LGL, using the Local Lexicon ($\mathcal{H}_5$) improved the performance of the Dateline ($\mathcal{H}_1$) and Comma Group ($\mathcal{H}_3$) heuristics, which partly rely on $\mathcal{H}_5$.

VII. Discussion

Associating a single local lexicon with each data source allows for a variety of applications. However, it may be possible to fine-tune the use of spatial lexicons in situations involving different types of content. For example, a blog may track several different topics simultaneously, and use different spatial lexicons for each topic. Furthermore, individual authors may write for specific audiences as well, as in the case of journalists stationed in certain geographic areas and concentrating on stories in that area. It thus might be beneficial to determine separate spatial lexicons assumed by different authors, and further improve geotagging performance. More generally, we might associate a particular spatial lexicon with any type of entity found in each document, be they authors, persons, organizations, or particular keywords. For example, upon finding a mention of "Robert Mugabe", we might assume a spatial lexicon including Zimbabwe and nearby locations, even without specific mentions in the text.

It would also be interesting to detect and observe evolving spatial lexicons over time for data sources with evolving geographic interests, thus further improving geotagging on these sources. For example, the first few articles of an ongoing, prominent news story will often fully specify the toponyms relevant to the story. Later articles in the series, however, will often underspecify the same toponyms, since they had already been introduced into the audience's spatial lexicon and been fully resolved in earlier articles.

Finally, we plan to further investigate improvements to our heuristics for better performance on a variety of data sources, such as mailing lists (e.g., ProMED[6]) and custom document repositories. Each different data source has different structure and a different audience, which will consequently affect any resulting spatial lexicon. We plan to develop additional annotated corpora to allow measurement of heuristic performance across several domains.

We have shown that modeling and using spatial lexicons, and in particular local lexicons, are vital to ensure successful geotagging. As newspapers and other data sources continue to move into the virtual space of the Internet, knowing and using spatial lexicons will be ever more important. Previously localized newspapers will cater to a broader, global audience, and thus will adjust their notion of their audiences' spatial lexicons, perhaps limiting or doing away with an assumed local lexicon altogether. On the other hand, as more and more people publish highly individual and geographically local content, inferring individual local lexicons will be a necessity for correct geotagging. Geotagging with knowledge of local lexicons will thus continue to play a large role in enabling interesting geospatial applications.

[6] `http://promedmail.org/`

References

[1] E. Amitay, N. Har'El, R. Sivan, and A. Soffer, "Web-a-Where: Geotagging web content," in *Proc. of SIGIR*, Sheffield, UK, Jul. 2004, 273–280.

[2] W. G. Aref and H. Samet, "Efficient processing of window queries in the pyramid data structure," in *Proc. of PODS*, Nashville, TN, Apr. 1990, 265–272.

[3] D. Buscaldi and P. Rosso, "A conceptual density-based approach for the disambiguation of toponyms," *IJGIS*, vol. 22(3), 301–313, Mar. 2008.

[4] Y.-Y. Chen, T. Suel, and A. Markowetz, "Efficient query processing in geographic web search engines," in *Proc. of SIGMOD*, Chicago, IL, Jun. 2006, 277–288.

[5] P. Clough, "Extracting metadata for spatially-aware information retrieval on the internet," in *Proc. of GIR*, Bremen, Germany, Nov. 2005, 25–30.

[6] J. Ding, L. Gravano, and N. Shivakumar, "Computing geographical scopes of web resources," in *Proc. of VLDB*, Cairo, Egypt, Sep. 2000, 545–556.

[7] E. Garbin and I. Mani, "Disambiguating toponyms in news," in *Proc. of HLT-EMNLP*, Vancouver, BC, Oct. 2005, 363–370.

[8] D. Jurafsky and J. H. Martin, *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics and Speech Recognition*. Upper Saddle River, NJ: Prentice Hall, Jan. 2000.

[9] J. L. Leidner, "Toponym resolution in text: Annotation, evaluation and applications of spatial grounding of place names," Ph.D. dissertation, University of Edinburgh, Edinburgh, UK, 2007.

[10] M. D. Lieberman, H. Samet, J. Sankaranaranayan, and J. Sperling, "STEWARD: Architecture of a spatio-textual search engine," in *Proc. of ACMGIS*, Seattle, WA, Nov. 2007, 186–193.

[11] I. Mani, J. Hitzeman, J. Richer, and D. Harris, *ACE 2005 English SpatialML Annotations*. Philadelphia, PA: Linguistic Data Consortium, 2008.

[12] S. Mardis and J. Burger, "Design for an integrated gazetteer database," MITRE Corporation, Tech. Rep. MTR-05B0000085, Nov. 2005.

[13] B. Martins, H. Manguinhas, J. Borbinha, and W. Siabato, "A geo-temporal information extraction service for processing descriptive metadata in digital libraries," *e-Perimetron*, vol. 4(1), 25–37, 2009.

[14] B. Pouliquen, M. Kimler, R. Steinberger, C. Ignat, T. Oellinger, K. Blackler, F. Fuart, W. Zaghouani, A. Widiger, A.-C. Forslund, and C. Best, "Geocoding multilingual texts: Recognition, disambiguation, and visualization," in *Proc. of LREC*, Genoa, Italy, May 2006, 53–58.

[15] R. S. Purves, P. Clough, C. B. Jones, A. Arampatzis, B. Bucher, D. Finch, G. Fu, H. Joho, A. K. Syed, S. Vaid, and B. Yang, "The design and implementation of SPIRIT: A spatially aware search engine for information retrieval on the internet," *IJGIS*, vol. 21(7), 717–745, Aug. 2007.

[16] E. Rauch, M. Bukatin, and K. Baker, "A confidence-based framework for disambiguating geographic terms," in *Proc of HLT-NAACL*, Edmonton, AB, May 2003, 50–54.

[17] C. Sallaberry, M. Gaio, J. Lesbegueries, and P. Loustau, "A semantic approach for geospatial information extraction from unstructured documents," in *The Geospatial Web*, London, UK: Springer, 2007, 93–104.

[18] H. Samet, *Foundations of Multidimensional and Metric Data Structures*, San Francisco, CA: Morgan-Kaufmann, 2006.

[19] F. Schilder, Y. Versley, and C. Habel, "Extracting spatial information: grounding, classifying and linking spatial expressions," in *Proc. of GIR*, Sheffield, UK, Jul. 2004.

[20] M. J. Silva, B. Martins, M. Chaves, A. P. Afonso, and N. Cardoso, "Adding geographic scopes to web resources," *Computers, Environment and Urban Systems*, vol. 30(4), 378–399, Jul. 2006.

[21] D. A. Smith and G. Crane, "Disambiguating geographic names in a historical digital library," in *Proc. of ECDL*, Darmstadt, Germany, Sep. 2001, 127–136.

[22] N. Stokes, Y. Li, A. Moffat, and J. Rong, "An empirical study of the effects of NLP components on geographic IR performance," *IJGIS*, vol. 22(3), 247–264, Mar. 2008.

[23] B. E. Teitler, M. D. Lieberman, D. Panozzo, J. Sankaranarayanan, H. Samet, and J. Sperling, "NewsStand: A new view on news," in *Proc. of ACMGIS*, Irvine, CA, Nov. 2008, 144–153.

[24] C. J. van Rijsbergen, *Information Retrieval*. London, UK: Butterworths, 1979, ch. 7.

[25] R. Volz, J. Kleb, and W. Mueller, "Towards ontology-based disambiguation of geographical identifiers," in *Proc. of I3*, Banff, AB, May 2007.

[26] C. Wang, X. Xie, L. Wang, Y. Lu, and W.-Y. Ma, "Detecting geographic locations from web resources," in *Proc. of GIR*, Bremen, Germany, Nov. 2005, 17–24.

[27] W. Zong, D. Wu, A. Sun, E.-P. Lim, and D. H.-L. Goh, "On assigning place names to geography related web pages," in *Proc. of JCDL*, Denver, CO, Jun. 2005, 354–362.