LOCATION MINING IN ONLINE SOCIAL NETWORKS

by

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To My Family and The Almighty

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March 2013

PREFACE

This dissertation was produced in accordance with guidelines which permit the inclusion as part of the dissertation the text of an original paper or papers submitted for publication. The dissertation must still conform to all other requirements explained in the “Guide for the Preparation of Master’s Theses and Doctoral Dissertations at The University of Texas at Dallas.” It must include a comprehensive abstract, a full introduction and literature review and a final overall conclusion. Additional material (procedural and design data as well as descriptions of equipment) must be provided in sufficient detail to allow a clear and precise judgment to be made of the importance and originality of the research reported.

It is acceptable for this dissertation to include as chapters authentic copies of papers already published, provided these meet type size, margin and legibility requirements. In such cases, connecting texts which provide logical bridges between different manuscripts are mandatory. Where the student is not the sole author of a manuscript, the student is required to make an explicit statement in the introductory material to that manuscript describing the student’s contribution to the work and acknowledging the contribution of the other author(s). The signatures of the Supervising Committee which precede all other material in the dissertation attest to the accuracy of this statement.

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Bhavani Thuraisingham, Co-Chair

Geosocial Networking has seen an explosion of activity in the past year with the coming of services that allow users to submit information about where they are and share that information with other users. But, because of privacy and security reasons, most of the people on social networking sites like Twitter are unwilling to specify their locations in the profiles. Just like time, location is one of the most important attributes associated with a user. The dissertation presents three novel approaches that rely on supervised and semi-supervised learning algorithms to predict the city level home location of the user purely on the basis of his/her social network. We firstly begin by establishing a relationship between geospatial proximity and friendship. The first approach, Tweethood, describes a fuzzy *k*-closest neighbor method with variable depth, a supervised learning algorithm, for determining the location. In our second approach, Tweecalization, we improve the previous work and show how this problem can be mapped to a semi-supervised learning problem and apply a label propagation algorithm. The previous approaches have a drawback in that they do not consider geographical migration of users. For our third algorithm, we begin by understanding the social phenomenon of migration and then perform graph partitioning for identifying social groups allowing us to implicitly consider time as a factor for prediction of the user’s most current city location. Finally, as an application for location mining, we build TWinner, which focuses on understanding news queries and identifying the intent of the user so as to improve the quality of web search. We perform extensive experiments to show the validity of our systems in terms of both accuracy and running time.

TABLE OF CONTENTS

VITA

LIST OF TABLES

LIST OF FIGURES

LIST OF ALGORITHMS

CHAPTER 1

INTRODUCTION

Online Social Networks (OSNs) have gained a lot of popularity on the Internet and become a hot research topic attracting many professionals from diverse areas. Since the advent of online social networking (OSN) sites like Facebook, Twitter and LinkedIn, OSNs continue to impact and change every aspect of our lives. From politics to business marketing, from celebrities to newsmakers, everyone is hooked to the phenomenon.

Twitter is a free social networking and micro-blogging service that enables users to send and read messages known as tweets. Tweets are text posts of up to 140 characters displayed on the author's profile page and delivered to the author's subscribers who are known as *followers.*

Adrianus Wagemakers, the founder of the Amsterdam-based Twopcharts (Twopcharts), analyzed Twitter (Wasserman, 2012) and reported the following findings:

- Twitter has about 640 million existing accounts.
- Some 100 million of them are suspended.
- There are roughly 72 million active Twitter accounts. These accounts average five tweets a day for a total of around 360 million tweets a day. That's in line with Twitter's claim earlier this year of 400 million tweets per day.
- Twitter had 36 million protected accounts, i.e. accounts whose tweets can only be seen by followers and who can approve or deny follower requests.

- 357 million accounts have posted at least once.
- 96 million accounts have tweeted at least once in the last 30 days.

San Antonio-based market research firm Pear Analytics (Kelly, 2009) analyzed 2,000 tweets (originating from the US and in English) over a two week period from 11:00am to 5:00pm (CST) and categorized them as:

- News
- Spam
- Self-promotion
- Pointless babble
- Conversational
- Pass-along value

Tweets with news from mainstream media publications accounted for 72 tweets or 3.60 percent of the total number (Kelly, 2009). Realizing the importance of Twitter as a medium for news updates, the company emphasized news and information networking strategy in November 2009 by changing the question it asks users for status updates from "What are you doing?" to "What's happening?".

So, what makes Twitter so popular? It's free to use, highly mobile, very personal and very quick (Grossman, 2009). It's also built to spread, and spread fast. Twitter users like to append notes called hash tags — #theylooklikethis — to their tweets, so that they can be grouped and searched for by topic; especially interesting or urgent tweets tend to get picked up and retransmitted by other users, a practice known as re-tweeting, or RT. And Twitter is promiscuous by nature: tweets go out over two networks, the Internet and SMS, the network that cell phones use for text messages, and they can be received and read on practically anything with a screen and a network connection (Grossman, 2009). Each message is associated with a time stamp and additional information, such as user location and details pertaining to his or her social network, can be easily derived.

1.1 Importance of Location

The advances in location-acquisition and mobile communication technologies empower people to use location data with existing online social networks. The dimension of location helps bridge the gap between the physical world and online social networking services (Cranshaw, Toch, Hong, Kittur, & Sadeh, 2010). The knowledge of location allows the user to expand his or her current social network, explore new places to eat, etc. Just like time, location is one of the most important components of user context, and further analysis can reveal more information about an individual's interests, behaviors, and relationships with others. In this section, we look at three reasons that make location such an important attribute.

1.1.1 Privacy and Security

Location Privacy is the ability of an individual to move in public space with the expectation that under normal circumstances their location will not be systematically and secretly recorded for later use (Blumberg & Eckersley, 2009). It is no secret that many people apart from friends and family are interested in the information users post on social networks. This includes identity thieves, stalkers, debt collectors, con artists, and corporations wanting to know more about the consumers. Sites and organizations like http://pleaserobme.com/ are generating awareness about the possible consequences of over-sharing. Once collected, this sensitive information can be left vulnerable to access by the government and third parties. And unfortunately, the existing laws give more emphasis to the financial interests of corporations than to the privacy of consumers.

1.1.2 Trustworthiness

Trustworthiness is another reason which makes location discovery so important. It is well-known that social media had a big role to play in the revolutionary wave of demonstrations and protests occurring in the Arab world termed as the “Arab Spring” to accelerate social protest (Kassim, 2012) (Sander, 2012). The Department of State has effectively used social networking sites to gauge the sentiments within societies (Grossman, 2009). Maintaining a social media presence in deployed locations also allows commanders to understand potential threats and emerging trends within the regions. The online community can provide a good indicator of prevailing moods and emerging issues. Many of the vocal opposition groups will likely use social media to air grievances publicly. In such cases and others similar to these, it becomes very important for organizations (like the US State Department) to be able to verify the correct location of the users posting these messages.

1.1.3 Marketing and Business

Finally, let us discuss the impact of social media in marketing and garnering feedback from consumers. First social media facilitates marketers to communicate with peers and customers (both current and future). It is reported that 93% of marketers use social media (Stelzner & Mershon, 2012). It provides significantly more visibility for the company or the product and helps you to spread your message in a relaxed and conversational way (Lake). The second major contribution of social media towards business is for getting feedback from users. Social media gives you the ability to get the kind of quick feedback inbound marketers require to stay agile. Large corporations from Walmart to Starbucks are leveraging social networks beyond your typical posts and updates to get feedback on the quality of their products and services, especially ones that have been recently launched on Twitter (March, 2012).

1.2 Understanding New Intent

It's 12th November 2009, and John is a naïve user who wants to know the latest on the happenings related to the shootings that occurred at the army base in Fort Hood . John opens his favorite search engine site and enters "Fort Hood", expecting to see the news. But unfortunately, the search results that he sees are a little different from what he had expected. Firstly, he sees a lot of timeless information such as Fort Hood on maps, the Wikipedia article on Fort Hood, the Fort Hood homepage, etc., clearly indicating that the search engine has little clue as to what the user is looking for. Secondly, among the small news bulletins that get displayed on the screen, the content is not organized and the result is that he has a hard time finding the news for 12th November 2009.

Companies like Google, Yahoo, and Microsoft are battling to be the main gateway to the Internet (NPR, 2004). Since a typical way for internet users to find news is through search engines and a rather substantial portion of the search queries is news-related where the user wants to know about the latest on the happenings at a particular geo-location, it thus becomes necessary for search engines to understand the intent of the user query, based on the limited user information available to it and also the current world scenario.

The impact of *Twitter* on news can be understood further by its coverage of two very crucial recent events: the July 2008 earthquake in Southern California and the turbulent aftermath of Iran's Elections in June 2009.

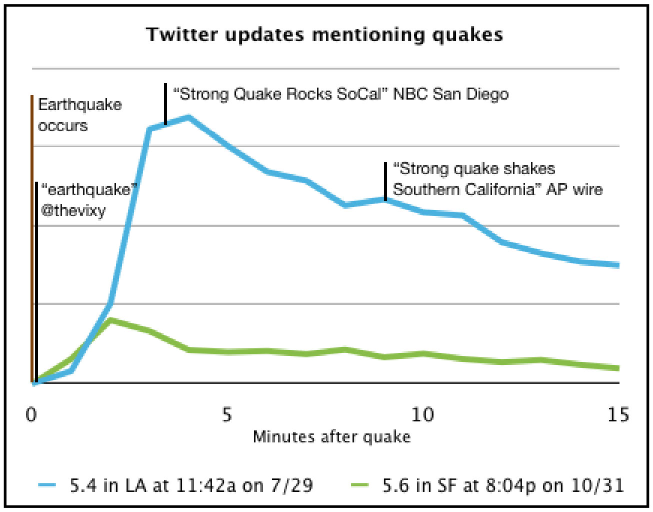


Figure 1.1. Twitter message graph after the Southern California earthquakes (Twitter, Twitter As News-wire, 2008).

Figure 1.1 illustrates the beginning of the earthquake followed seconds later by the first *Twitter* update from Los Angeles. About four minutes later, official news began to emerge about the quake. By then, "Earthquake" was trending on *Twitter* Search with thousands of updates and more on the way. Many news agencies get their feed from a news wire service such as the Associated Press. "Strong quake shakes Southern California" was pushed out by AP about 9 minutes after people began *Twittering* primary accounts from their homes, businesses, doctor's appointments, or wherever they were when the quake struck (Twitter, Twitter As News-wire, 2008).

The second example would be that of the elections in Iran in 2009. Time, in partnership with CNN, discussed the impact of *Twitter* on the coverage of developments after the Iran elections of

2009 (Grossman, 2009). On June 12th 2009, Iran held its presidential elections between incumbent Ahmadinejad and rival Mousavi. The result, a landslide for Ahmadinejad, led to violent riots across Iran, charges of voting fraud, and protests worldwide. Even as the government of that country was evidently restricting access to opposition websites and text-messaging, on *Twitter,* a separate uprising took place, as tweets marked with the hash tag *#cnnfail* began tearing into the cable-news network for devoting too few resources to the controversy in Iran. US State Department officials reached out to *Twitter* and asked them to delay a network upgrade that was scheduled for Monday (June 15th) night. This was done to protect the interests of Iranians using the service to protest the presidential election that took place on June 12, 2009.

1.3 Contributions of the Dissertation

We make an important contribution in the field of identifying the current location of a user using the social graph of the user. The dissertation describes in detail three techniques for location mining from the social graph of the user and each one is based on a strong theoretical framework of machine learning. We demonstrate how the problem of identification of location of a user can be mapped to a machine learning problem. We conduct a variety of experiments to show the validity of our approach and how it outperforms previous approaches and the traditional content-based text mining approach in accuracy.

- We perform extensive experiments to study the relationship between geospatial proximity and friendship on Twitter and show that with increasing distance between two users, the probability of friendship decreases.

- The first algorithm, Tweethood, looks at the *k*-Closest friends of the user and their locations for predicting the user's location. If the locations of one or more friends are not known, the algorithm is willing to go further into the graph of that friend to determine a location label for him. The algorithm is based on the *k*-Nearest Neighbor approach, a supervised learning algorithm commonly used in pattern recognition (Coomans & Massart, 1982).
- The second approach described, Tweecalization, uses label propagation, a semi-supervised learning algorithm, for determining the location of a user from his or her social network. Since only a small fraction of users explicitly provide a location (labeled data), the problem of determining the location of users (unlabeled data) based on the social network is a classic example of a scenario where the semi-supervised learning algorithm fits in.
- For our final approach, Tweeque, we do an analysis of the social phenomenon of migration and describe why it is important to take time into consideration when predicting the most current location of the user.
- Tweeque uses graph partitioning to identify the most current location of the user by taking migration as the latent time factor. The proposed efficient semi-supervised learning algorithm provides us with the ability to intelligently separate out the current location from the past locations.
- All the three approaches outperform the existing content-based approach in both accuracy and running time.
- We develop a system, TWinner, that makes use of these algorithms and helps the search engine to identify the intent of the user query, whether he or she is interested in general

information or the latest news. Second, TWinner adds additional keywords to the query so that the existing search engine algorithm understands the news intent and displays the news articles in a more meaningful way.

1.4 Outline of the Dissertation

This dissertation discusses various challenges in location mining in online social networks, and proposes three unique and efficient solutions to address those challenges. The rest of the dissertation is organized as follows.

Chapter 2 surveys the related work in detail for this domain and points out the novelty in our approach. The first section of the chapter focuses on prior works in the field of location extraction from both web pages and social networks. The second portion of the chapter discusses related works for determining intent from search queries.

In Chapter 3, we discuss the various challenges faced in identifying the location of a user in online social networks (OSNs). We begin by looking at the various drawbacks of using the traditional content-based approach for OSNs and then go on to describe the challenges that need to be addressed when using the social graph based approach.

Chapter 4 studies the relationship between geospatial proximity and friendship.

Chapter 5 discusses our first algorithm, Tweethood, in detail. We show the evolution of the system from a simple majority algorithm to a fuzzy *k*-closest neighbor approach.

In Chapter 6 we propose the algorithm, Tweecalization, which maps the task of location mining to a semi-supervised learning problem. We, then, describe a label propagation algorithm that uses both labeled and unlabeled data for determining the location of the central user.

In Chapter 7, we first describe in detail the importance of geographical mobility among users and make a case for why it is important to have an algorithm that performs some spatio-temporal data mining. In the latter half of the chapter, we describe an algorithm Tweeque that uses migration as latent time factor for determining the most current location of a user.

Chapter 8, briefly describes the agglomerative clustering algorithm that we employ at the end of each of the three location mining algorithms, so as to make our results more meaningful and have higher confidence values.

Chapter 9 shows the development of an application, TWinner, which combines social media in improving the quality of web search and predicting whether the user is looking for news or not. We go one step beyond the previous research by mining Twitter messages, assigning weights to them and determining keywords that can be added to the search query to act as pointers to the existing search engine algorithms suggesting to it that the user is looking for news.

We conclude in Chapter 10 by summarizing our proposed approaches and by giving pointers to future work.

CHAPTER 2

LITERATURE REVIEW

In this chapter, we first review the related research in the fields of location mining from semi-structured text such as web pages and then from online social networks such as Twitter and Facebook. Also, we survey a wide range of existing work for determining intent from search queries.

2.1 Location Mining

It is important to understand that location of the user is not easily accessible due to security and privacy concerns, thus impeding the growth of location-based services in the present world scenario. By conducting experiments to find locations of 1 million users, we found that only 14.3% specify their locations explicitly.

Twitter introduced a new feature in 2010 whereby users can associate a location (identified from the IP address) with their tweets as shown in Figure 2.1. But unfortunately, a very small fraction of the users use this service. (Martin, 2010) report that only 0.23% of the total tweets were found to be geo-tagged.

That leaves us with the option to mine the location of the user which is not an easy task in itself.

There has been a lot of prior work done on location identification and geo-tagging of documents and web pages. Social Networking, on the other hand, is still a very new field of computer science and little work has been done towards identifying the location of users based on their social activity. In this section, we do a brief survey of the previous works.

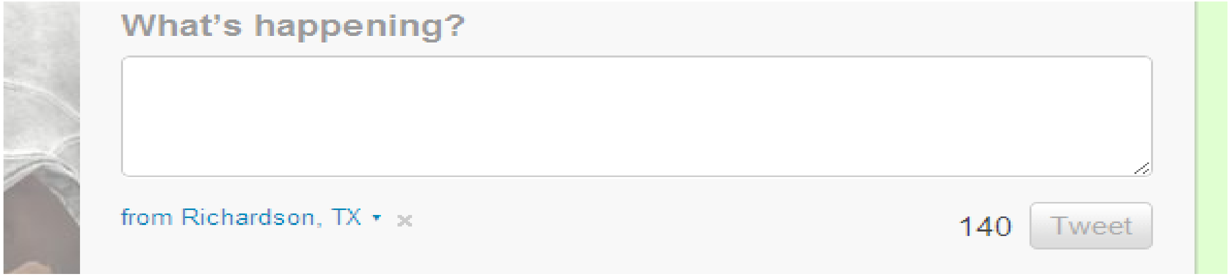


Figure 2.1. The new feature by Twitter to provide location with messages

The problem of geographic location identification and disambiguation has been dealt with mostly using two approaches. One approach involves the concepts of machine learning and natural language processing (NLP) and the other approach involves the use of data mining with the help of gazetteers. In NLP and machine learning, a lot of previous work is done on the more general topic of Named Entity Recognition (NER). Most of the work makes use of structured and well-edited text from news articles or sample data from conferences.

Most research work relies on NLP algorithms and less on machine learning techniques. The reason for this is that machine learning algorithms require training data that is not easy to obtain. Also, their complexity makes them less efficient as compared to the algorithms using the gazetteers.

Other researchers use a 5-step algorithm, where the first two steps of the algorithm are reversed. First, only terms appearing in the gazetteer are short listed. Next, they use NLP techniques to remove the non-geo terms. Li et al (Li, Srihari, Niu, & Li, 2002) report a 93.8% precision on news and travel guide data.

McCurley (McCurley, 2001) analyzes the various aspects of a web page that could have a geographic association, from its URL, the language in the text, phone numbers, zip codes, etc. Names appearing in the text may be looked up in White Pages to determine the location of the person. His approach is heavily dependent on information like zip codes, etc., and is hence successful in USA, where it is available free, but is hard to obtain for other countries. Their techniques rely on heuristics and do not consider the relationship between geo-locations appearing in the text.

The gazetteer-based approach relies on the completeness of the source and, hence, cannot identify terms that are not present in the gazetteer. But, on the other hand, they are less complex than NLP, and machine learning techniques are hence faster.

Amitay et al. (Amitay, Har'El, Sivan, & Soffer, 2004) present a way of determining the page focus of web pages using the gazetteer approach and after using techniques to prune the data. They are able to correctly tag individual name place occurrences 80% of the time and are able to recognize the correct focus of the pages 91% of the time. But they have a low accuracy for the geo/non geo disambiguation.

Lieberman et al. (Lieberman, Samet, Sankaranarayanan, & Sperling, 2007) describe the construction of a spatio-textual search engine using the gazetteer and NLP tools, a system for extracting, querying and visualizing textual references to geographic locations in unstructured text documents. They use an elaborate technique for removing the stop words, using a hybrid model of Part-of-Speech (POS) and Named-Entity Recognition tagger. POS helps to identify the nouns and NER tagger annotates them as person, organization, and location. They consider the proper nouns tagged as locations. But this system doesn’t work well for text where name of a person is ambiguous with a location. E.g., Jordan might mean Michael Jordan, the basketball player or it might mean the location. In that case the NER tagger might remove Jordan, considering it to be the name of a person. For removing geo-geo ambiguity, they use the pair strength algorithm. Pairs of feature records are compared to determine whether or not they give evidence to each other, based on the familiarity of each location, frequency of each location, as well as their document and geodesic distances. They do not report any results for accuracy of the algorithm so comparison and review is not possible.

The most relevant related work in social networks using the content-based approach is the one proposed in (Cheng, Caverlee, & Lee, You are where you tweet: a content-based approach to geo-locating twitter users, 2010) to estimate the geo-location of a Twitter user. For estimating the city level geo-location of a Twitter user, they consider a set of tweets from a set of users belonging to a set of cities across the United States. They estimate the probability distribution of terms used in these tweets, across the cities considered in their data set. They report accuracy in placing 51% of Twitter users within 100 miles of their actual location.

Hecht et al. (Hecht, Hong, Suh, & Chi, 2011) performed a simple machine learning experiment to determine whether they can identify a user's location by only looking at what that user tweets. They concluded that a user's country and state can be estimated with a decent accuracy, indicating that users implicitly reveal location information, with or without realizing it. The approach used by them only looks to predict the accuracy at the country and state levels and the accuracy figures for the state level are in the 30's and hence are not very promising.

It is vital to understand here that identifying the location mentioned in documents or messages is very different from identifying the location of user. That is, even if page focus of the messages is identified correctly, that may not be the correct location of the user. E.g., people express their opinions on political issues around the world all the time. The recent catastrophic earthquake in Haiti led to many messages having references to the country. Another example is that of the volcano in Iceland that led to flights being cancelled all around the world. In addition to this, the time complexity of text-based geo-tagging messages is very large making it unsuitable for real time applications like location-based opinion mining. Thus, as we shall show in later sections, the geo-tagging of user messages is an inaccurate method and has many pitfalls.

Recently, some work has been done in the area of establishing the relation between geospatial proximity and friendship. In (Backstrom, Sun, & Marlow, 2010), the authors perform extensive experiments on data collected from Facebook and come up with a probabilistic model to predict the location. They show that their algorithm outperforms the IP-based geo-location method. Liben-Nowell et al in (Liben-Nowell, Novak, Kumar, Raghavan, & Tomkins, 2005) focus their research on LiveJournal and establish the fact that the probability of befriending a particular person is inversely proportional to the number of closer people.

A major drawback of all the previous location extraction algorithms, including the ones discussed before, is that they do not consider time as a factor. As we shall later discuss in the dissertation, migration is an important social phenomenon with a significant fraction of people in the US changing cities every year. It is, therefore, very important to design algorithms that use some intelligent criteria for distinguishing between the current location of a user from different locations he or she may have lived in the past.

2.2 Geographic Information Retrieval

Geographic information retrieval is a well discussed topic in the past, where a lot of research has been done to establish a relationship between the location of the user, and the type of content that interests him or her. Researchers have analyzed the influence of user's location on the type of food he or she eats, the sports he or she follows, the clothes he or she wears, etc. But it is important to note here that most of the previous research does not take into account the influence of 'time' on the preferences of the user.

Liu et al. (Liu & Birnbaum, 2008) do a similar geo-analysis of the impact of the location of the source on the viewpoint presented in the news articles. Sheng et al. (Sheng, Hsu, & Lee, 2008) discussed the need for reordering the search results (like food, sports, etc.) based on user preferences obtained by analyzing user's location.

Other previous research attempts (Zhuang, Brunk, & Giles, 2008) (Backstrom, Kleinberg, Kumar, & Novak, 2008) focused on establishing the relationship between the location obtained from IP address and the nature of the search query issued by the user. In our work, we do not include the location of the user in our consideration, since it may not be very accurate in predicting the intent of the user.

Hassan et al. in (Hassan, Jones, & Diaz, 2009) focus their work on establishing a relationship between the geographic information of the user and the query issued. They examine millions of web search queries to predict the news intent of the user, taking into account the query location confidence, location type of the geo-reference in the query and the population density of the user location. But they do not consider the influence of the time at which the user issued the query, which can negatively affect the search results for news intent. For example, a query for 'Fort

Hood’ 5 months before November 2009 would have less news intent and more information intent than a query made in second week of November 2009 (after the Ft. Hood shootings took place).

Twitter acts as a popular social medium for internet users to express their opinions and share information on diverse topics ranging from food to politics. A lot of these messages are irrelevant from an information perspective and are either spam or pointless babble. Another concern while dealing with such data is that it consists of a lot of informal text including words such as ‘gimme’, ‘wassup’, etc., and need to be processed before traditional NLP techniques can be applied to them.

Nagarajan et al. (Nagarajan, Baid, Sheth, & Wang, 2009) explore the application of restricted relationship graphs or resource description framework (RDF) and statistical NLP techniques to improve named entity annotation in challenging informal English domains. (Sheth & Nagarajan, Semantics-empowered social computing, 2009), (Sheth, Bertram, Avant, Hammond, Kochut, & Warke, 2002) and (Nagarajan, Baid, Sheth, & Wang, 2009) are aimed at characterizing what people are talking about, how they express themselves and why they exchange messages.

It is vital to understand the contribution of TWinner in establishing a relationship between the search query and the social media content. In order to do so, we suggest Twitter, a popular social networking site to predict the news intent of the user search queries.

CHAPTER 3

CHALLENGES IN LOCATION MINING

As discussed previously, a lot of efforts are being made on the part of the social networking companies to incorporate location information in the communication. Twitter, in 2009, acquired Mixer Labs (Parr, 2009), a maker of geo-location Web Services, to boost up its location-based services campaign and compete with the geo savvy mobile social networking sites like Foursquare and Gowalla. Nowadays, on logging into your Twitter account, you are given the option to add location (city level) to your messages.

But still, these efforts are not paying dividends, simply because of several security and privacy reasons. And there is no incentive for users. We conducted an experiment and found that out of 1 million users on Twitter; only 14.3% actually share their location explicitly. Since, the location field is basically a text field, many of times the information provided is not very useful (Hecht, Hong, Suh, & Chi, 2011). The various problems in using the location provided by the user himself or herself include:

- *Invalid Geographical Information*: Users may provide locations which are not valid geographic information and hence cannot be geo-coded or plotted on a map. Examples include “Justin Biebers heart”, “NON YA BISNESS!!”, “looking down on u people”.
- *Incorrect Locations Which May Actually Exist*: At times a lot of users may provide information which is not meant to be a location but is mapped to an actual geographical location. Examples include “Nothing” in Arizona, “Little Heaven” in Connecticut.

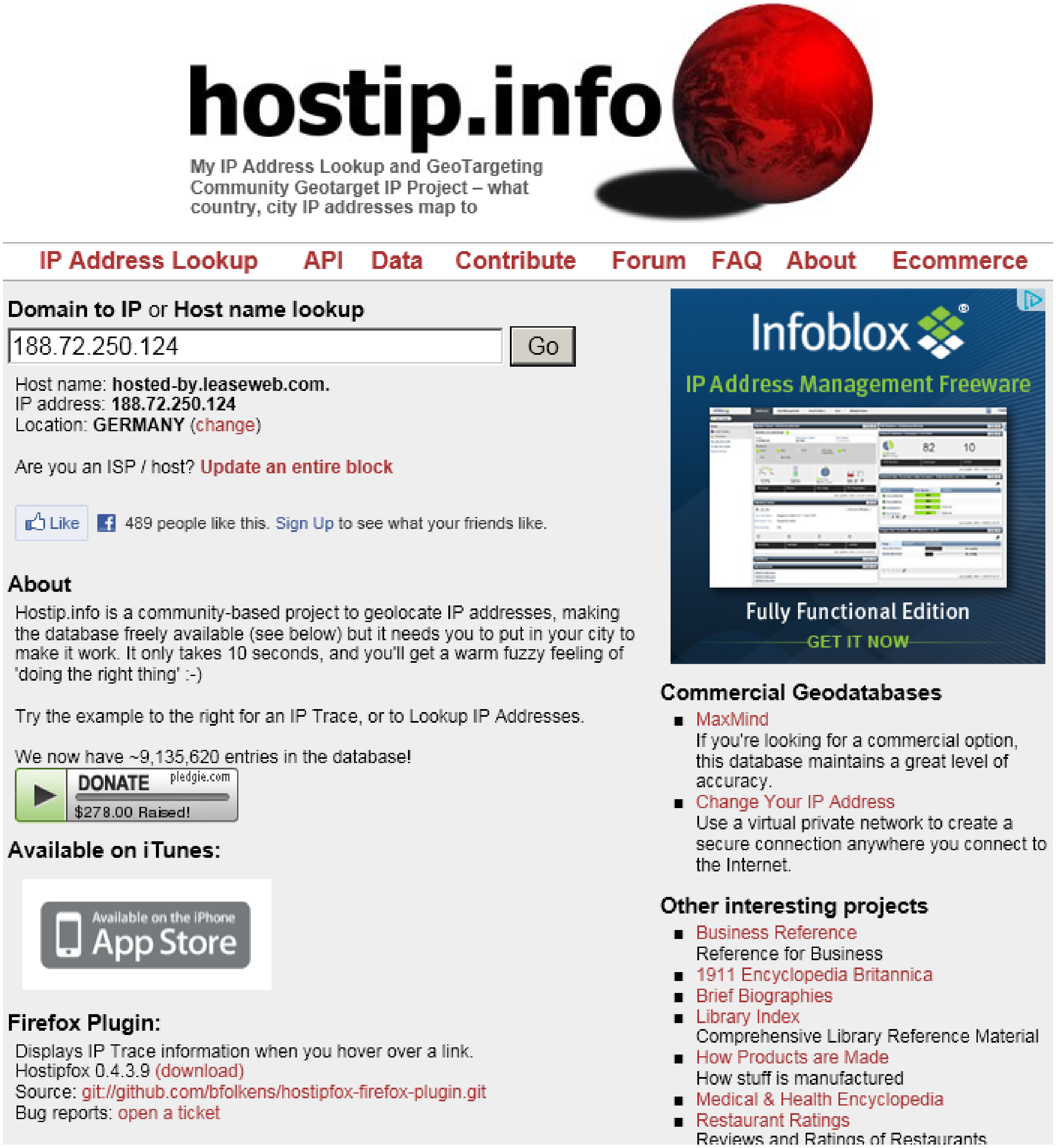
- *Provide Multiple Locations*: There are other users who provide several locations and it becomes difficult for the geo-coder to single out a unique location. Examples include “CALi b0Y $TuCC iN V3Ga$”, who apparently is a California boy stuck in Las Vegas, NV.
- *Absence of Finer Granularity*: Hecht et al. (Hecht, Hong, Suh, & Chi, 2011) report that almost 35% of the users just enter their country or state and there is no reference to the finer level location such as city, neighborhood, etc.

Hence explicitly-mentioned locations are rare and maybe untrustworthy in certain cases where the user has mal-intent. That leaves us with the question; can the location be mined from implicit information associated with the users like the content of messages posted by them and the nature of their social media network?

A commonly used approach to determine the location of the user is to map the IP address to geographic locations using large gazetteers such as hostip.info (hostip.info). Figure 3.1 shows a screenshot where a user is able to determine his or her location from the IP address by using the hostip.info website. But Bradley Mitchell (Mitchell, 2013) argues that using the IP address for location identification has its limitations:

- IP addresses may be associated with the wrong location (e.g., the wrong postal code, city or suburb within a metropolitan area).
- Addresses may be associated only with a very broad geographic area (e.g., a large city, or a state). Many addresses are associated only with a city, not with a street address or latitude/longitude location.

- Some addresses will not appear in the database and therefore cannot be mapped (often true for IP numbers not commonly used on the Internet).



hostip.info

My IP Address Lookup and GeoTargeting Community Geotarget IP Project – what country, city IP addresses map to

IP Address Lookup | API | Data | Contribute | Forum | FAQ | About | Ecommerce

Domain to IP or **Host name lookup**

188.72.250.124 [Go]

Host name: **hosted-by.leaseweb.com.**
IP address: **188.72.250.124**
Location: **GERMANY** (change)

Are you an ISP / host? **Update an entire block**

Like 489 people like this. Sign Up to see what your friends like.

About

Hostip.info is a community-based project to geolocate IP addresses, making the database freely available (see below) but it needs you to put in your city to make it work. It only takes 10 seconds, and you'll get a warm fuzzy feeling of 'doing the right thing' :-)

Try the example to the right for an IP Trace, or to Lookup IP Addresses.

We now have ~9,135,620 entries in the database!

DONATE pledgie.com
$278.00 Raised!

Available on iTunes:

Available on the iPhone App Store

Firefox Plugin:

Displays IP Trace information when you hover over a link.
Hostipfox 0.4.3.9 (download)
Source: git://github.com/bfolkens/hostipfox-firefox-plugin.git
Bug reports: open a ticket

Commercial Geodatabases

- MaxMind
  If you're looking for a commercial option, this database maintains a great level of accuracy.
- Change Your IP Address
  Use a virtual private network to create a secure connection anywhere you connect to the Internet.

Other interesting projects

- Business Reference
  Reference for Business
- 1911 Encyclopedia Britannica
- Brief Biographies
- Library Index
  Comprehensive Library Reference Material
- How Products are Made
  How stuff is manufactured
- Medical & Health Encyclopedia
- Restaurant Ratings
  Reviews and Ratings of Restaurants

Figure 3.1. Hostip.info allows user to map IP addresses to geo-locations.

Additionally, only the hosting companies (in this case the social networking sites) have access to the user's IP address. Whereas, we want to design algorithms that are generic so that any third party people can implement and use them. And since majority of Twitter users have public profiles, such analysis of user profiles is very much possible.

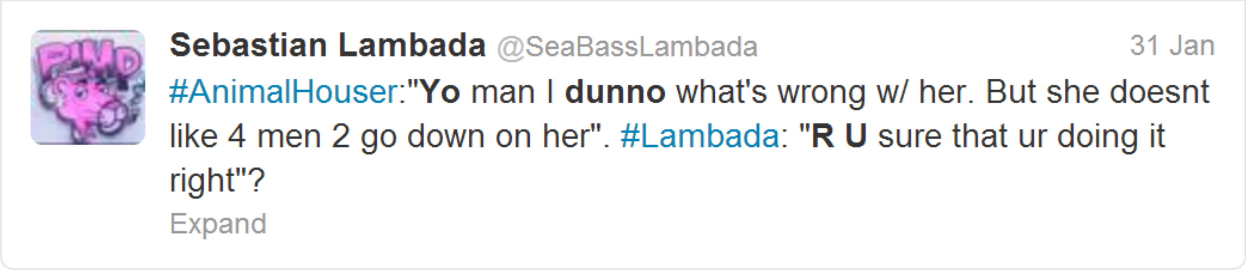
In this chapter, we will first discuss the problems related to mining location from text and why we find it to be a rather unreliable way for location determination. Second, we discuss the challenges associated with the social graph network-based location extraction technique.

3.1 What Makes Location Mining From Text Inaccurate?

Twitter, being a popular social media site, is a way by which users generally express their opinions, with frequent references to locations including cities, countries, etc. It is also intuitive in such cases to draw a relation between such locations mentioned in the tweets and the place of residence of the user. In other words a message from a user supporting the Longhorns (Football team for the University of Texas at Austin) is most likely from a person living in Austin, Texas, USA than from someone in Australia.

3.1.1 Twitter's Noisy and Unique Style – Unstructured Data

As previously mentioned, the identification of the location of a user from the messages is a very different task from identification of the locations in web pages or other media. Twitter messages consist of text that is unstructured and more often than not have grammatical and spelling errors. And these characteristics distinguish micro-text from traditional documents or web pages (Rosa & Ellen, 2009) (Dent & Paul, 2011). Therefore, it becomes more difficult to identify the location from them. Figure 3.2 shows one such tweet (Twitter Search, 2013).



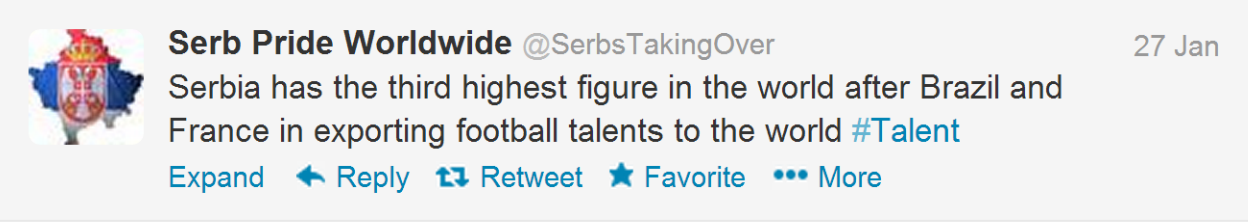
Sebastian Lambada @SeaBassLambada 31 Jan

#AnimalHouser:"**Yo** man I **dunno** what's wrong w/ her. But she doesnt like 4 men 2 go down on her". #Lambada: "**R U** sure that ur doing it right"?

Figure 3.2. An example of a tweet containing slang and grammatically incorrect sentences.

3.1.2 Presence of Multiple Concept Classes

The other major issue that one faces in identification of a location concept is that unlike other sources of information like web pages, news articles, etc., Twitter messages consist of multiple concept classes, i.e. several locations may be mentioned in the messages collected from a single user. In such a case, identification of a single location that acts as a page focus can be a difficult problem. Figure 3.3 shows one such tweet, where the user is actually from Serbia, but the message mentions multiple locations (Serbia, Brazil, and France).



Serb Pride Worldwide @SerbsTakingOver 27 Jan

Serbia has the third highest figure in the world after Brazil and France in exporting football talents to the world #Talent

Figure 3.3. An example of a tweet containing multiple locations.

3.1.3 Geo/Geo Ambiguity and Geo/Non-Geo Ambiguity

Even if the algorithm is able to identify words that are possible candidates for location concepts, we still need to disambiguate them correctly. There are two types of ambiguities that exist: Geo/Non-Geo and Geo/Geo ambiguities (Amitay, Har'El, Sivan, & Soffer, 2004) (Smith & Crane, 2001) (Brunner & Purves, 2008) (Volz, Kleb, & Mueller, 2007).

Geo/Non-Geo Ambiguity: Geo/Non-Geo ambiguity is the case of a place name having another, non-geographic meaning, e.g., Paris might be the capital of France or might refer to the socialite, actress Paris Hilton. Another example is Jordan, which could refer to the Arab kingdom in Asia or Michael Jordan, the famous basketball player.

Geo/Geo Ambiguity: Geo/Geo ambiguity arises from the two having the same name but different geographic locations, e.g., Paris is the capital of France and is also a city in Texas. Another example is Amsterdam, which could refer to the capital and largest city of the Netherlands or Amsterdam, a city located in Montgomery County, New York, USA. Figure 3.4 shows an example of Geo/Geo Ambiguity arising from a query for 'Lancaster' (MapQuest, 2009).

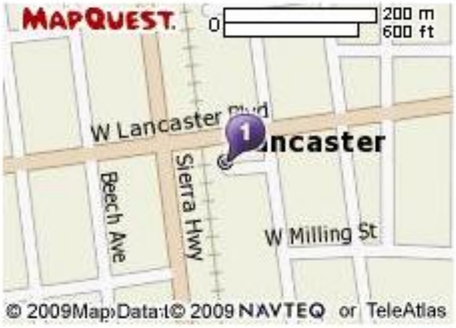
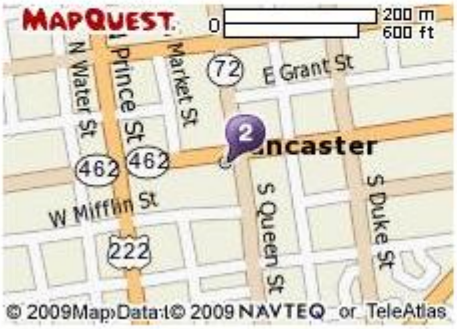
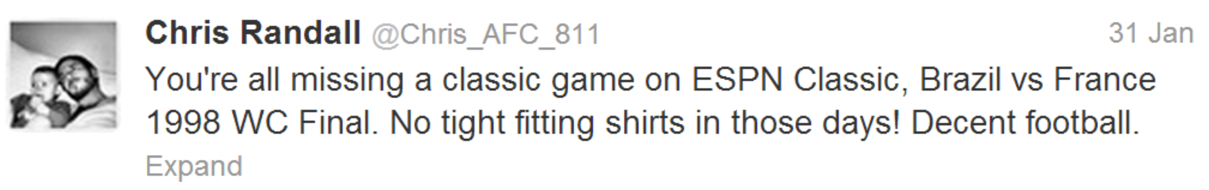
Lancaster Los Angeles County CA US	
Lancaster Lancaster County PA US	

Figure 3.4. Geo/Geo Ambiguity as shown by the MapQuest API.

3.1.4 Location in Text is Different from Location of User

Unlike location mining from web pages, where the focus of the entire web page is a single location (Amitay, Har'El, Sivan, & Soffer, 2004) and we do not care about the location of the author, in social networking sites the case is very different. In online social networks, when we talk about location, it could mean two things. The first is the location of the user (which we are trying to predict) and the other, the location in a message. And in some cases, these two could be two totally different locations. Figure 3.5 shows one such tweet in which the person talks about a football game between Brazil and France, but it is actually from Hemel Hempstead, Hertfordshire, UK.



Chris Randall @Chris_AFC_811 31 Jan

You're all missing a classic game on ESPN Classic, Brazil vs France 1998 WC Final. No tight fitting shirts in those days! Decent football.

Expand

Figure 3.5. A tweet from a user who is actually from Hemel Hempstead, Hertfordshire, UK but talks about a football game between Brazil and France (Twitter, Twitter Search, 2013).

As evident, the content-based approach may prove to be inaccurate in cases where the user talks about news-making incidents in other parts of the world. Another example is for Haiti. Haiti was a popular geo-reference in tweets after the earthquake in 2010. In another case, someone who talks about going to Venice for a vacation is not necessarily Italian.

3.2 Technical Challenges in Location Mining From Social Network of User

This approach makes use of the social network of the user. Here, the social network of the user comprises of followers (people following the user) and following (people he or she is following).

This approach gives us an insight on a user’s close friends and the celebrities he or she is following. Intuitively, most of a person’s friends are from the same country and also, a person is more likely to follow celebrities that are from his or her own country. In other words, an American’s friends are mostly Americans and he or she has a higher probability of following President Barack Obama than Asian users.

There are certain technical challenges that need to be solved before we can mine the location from the social network.

3.2.1 Small Percentage of Users Reveal Location, Others Provide Incorrect Locations

As stated earlier in this chapter, only a small percentage of the users with public profiles are willing to share their location on Twitter for privacy and security reasons. And since the location field is just a text field, there are others who provide location(s) that are not valid geographic information, or are incorrect but may actually exist, or consist of several locations.

3.2.2 Special Cases: Spammers and Celebrities

It is necessary to identify spammers and celebrities since they cannot be dealt in the same way as other users because of the differences in the properties associated with their social graphs.

At the country level, it is not always safe to assume that a person always follows celebrities from his own country. Queen Rania of Jordan advocates for global education and thus has followers around the world. In such cases, judging the location of a user based on the celebrities he or she is following can lead to inaccurate results.

3.2.3 Defining the Graph

We need to come up with an objective function that captures ‘friendship’ in the best manner for constructing the graphs for application of the algorithms.

3.2.4 Geographical Mobility: Predicting Current Location

As we shall show in Chapter 7, social migration is a very important phenomenon. And a significant percentage of users move from one county to another. It is therefore very crucial for us to design algorithms that do temporal analysis and are able to separate out the most recent location from previous locations.

CHAPTER 4

GEOSPATIAL PROXIMITY AND FRIENDSHIP

We hypothesize that there is a direct relation between geographical proximity and probability of friendship on Twitter. In other words, even though we live in the internet age, where distances actually don't matter and people can communicate with people across the globe, users tend to bring people from their offline friends into their online world. The relationship between friendship and geographic proximity in OSNs has been studied in detail previously also in (Backstrom, Sun, & Marlow, 2010) for Facebook and in (Liben-Nowell, Novak, Kumar, Raghavan, & Tomkins, 2005) for LiveJournal. We perform our own set of experiments to understand the nature of friendships on Twitter, and study the effect of geographical proximity on friendship.

We formulate 10 million friendship pairs in which location of both users is known. It is important to understand that our initial definition of friendship on Twitter is that A and B are friends if A follows B or B follows A. We divide the edge distance for the pairs into buckets of 10 miles. We determine the Cumulative Distribution Function, to observe the probability as a continuous curve. Figure 4.1(a) shows the results of our findings. It is interesting to note that only 10% of the pairs have the users within 100 miles and 75% of the users are at least 1000 miles from each other. That is, the results are contrary to the hypothesis we proposed and to the findings of Backstrom et al. for Facebook, Liben-Nowell et al. for LiveJournal. Next, we study the nature of relationships on Twitter and find it to be very different from other OSNs like

Facebook, LiveJournal, etc. We make several interesting observations that distinguish Twitter from other OSNs like Facebook and LiveJournal:

- A link from A to B (A following B) does not always mean there is an edge from B to A (B follows A back).
- A link from A to B (A following B), unlike Facebook or LinkedIn, does not always indicate friendship, but sometimes means that A is interested in the messages posted by B.
- If A has a public profile (which is true for a large majority of profiles), then he or she has little control over who follows him or her.
- Twitter is a popular OSN used by celebrities (large follower to following ratio) to reach their fans and spammers (large following to followers ratio) to promote businesses.

These factors make us redefine the concept of friendship on Twitter to make it somewhat stricter. Two users, A and B, are friends if and only if A is following B and B also follows A back.

To put it plainly, from the earlier set of friends for a user A, we are taking a subset, called associates of A which are more likely to be his or her actual friends than the other users. By ensuring the presence of two way edge, we ensure that the other user is neither a celebrity (since celebrities don’t follow back fans) nor a spammer (because no one wants to follow a spammer!). And a two way edge also means that the user A knows B and thus B is not some random person following A. And finally, the chances of A being interested in messages of B and vice versa without them being friends are pretty slim.

We re-run the earlier experiments to study the relation between association probability and geographic distance.

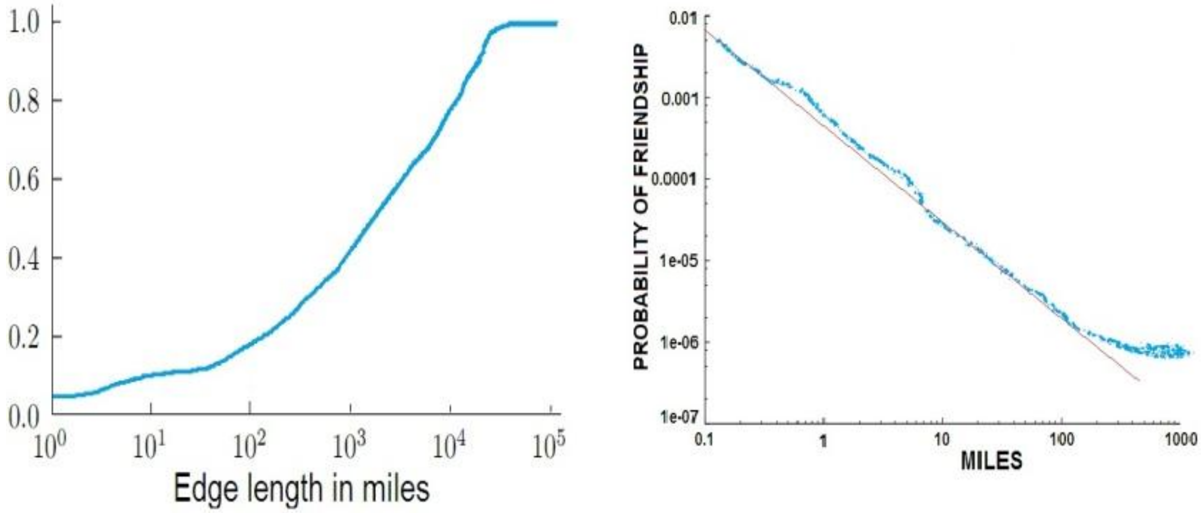


Figure 4.1. Cumulative Distribution Function to observe the probability as a continuous curve and (b) Probability vs. distance for 10^{12} Twitter user pairs.

We form 10^{12} user pairs and identify the geographical distance between them. And then, we divide the dataset into buckets of 0.1 miles and determine what percentage of them actually have an edge (are friends). Figure 4.1 (b) shows the probability of friendship versus the distance (in miles) distribution. The results for Twitter are very similar to those for LiveJournal (Liben-Nowell, Novak, Kumar, Raghavan, & Tomkins, 2005) and Facebook (Backstrom, Sun, & Marlow, 2010). The curve follows the power law having a curve of the form $\mathrm{a}(\mathrm{x}+\mathrm{b})^{-c}$ with exponent of -0.87 and for distances greater than 1000 miles becomes a straight line.

CHAPTER 5

TWEETHOOD: AGGLOMERATIVE CLUSTERING ON FUZZY K-CLOSEST FRIENDS WITH VARIABLE DEPTH[*]

Graph related approaches are the methods that rely on the social graph of the user while deciding on the location of the user. In this chapter, we describe three such methods that show the evolution of the algorithm currently used in TweetHood. Figure 5.1 shows an undirected graph with a depth d=2 used to represent the social network of a user.

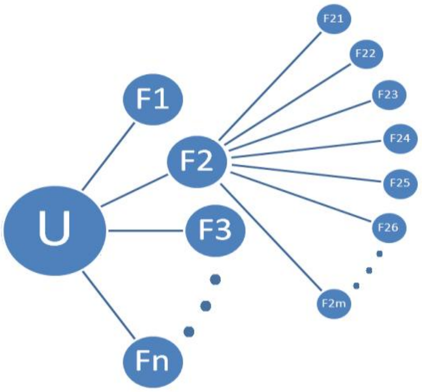


Figure 5.1. An undirected graph for a user U showing his friends

[*] © 2010 IEEE. Reprinted, with permission, from Satyen Abrol, Latifur Khan, Tweethood: Agglomerative Clustering on Fuzzy k-Closest Friends with Variable Depth for Location Mining, 2010 IEEE Second International Conference on Social Computing (SocialCom), August 2010.

Each node in the graph represents a user and an edge represents friendship. The root represents the user U whose location is to be determined, and the F_1, F_2,..., F_n represents the n friends of the user. Each friend can have his or her own network, like F_2 has a network comprising of m friends F_{21}, F_{22},...., F_{2m}.

5.1 Simple Majority with Variable Depth

A naïve approach for solving the location identification problem would be to take simple majority on the locations of friends (followers and following) and assign it as the label of the user. Since a majority of friends will not contain a location explicitly, we can go further into exploring the social network of the friend (friend of a friend). For example, in Figure 5.1, if the location of Friend F_2 is not known, instead of labeling it as *null*, we can go one step further and use F_2's friends in choosing the label for it. It is important to note here that each node in the graph will have just one label (single location) here.

Algorithm 1: Simple_Majority (userId, depth)

Input: User Id of the User and the current depth

Output: Location of the User

```
If ($Twitter\_Location(userId)! = null$)
        then return ($Twitter\_Location(userId)$);
Else If ($depth = 0$)
        then return $null$;
Else {
```

```
6:          $All\_Friends[\,] = Get\_Friends(userId)$;
7:          For each friend in $All\_Friends[\,]$
8:              $Location[i] = Simple\_Majority(All_{Friends[i]}, depth - 1)$;
9:          Aggregate($Location$ [ ]);
10:         Boost($Location$ [ ]);
11:         Return $Max\_Location(Location$ [ ]);
12:     }
```

The algorithm Simple_Majority (userId, depth) is divided into several steps as shown in Algorithm 1. In steps 1 and 2, we check for the explicitly specified location, and if it is present, the node is given that label. At Step 3, if the algorithm on being called recursively has reached a depth of 0 and is unable to find a location, the algorithm returns null to the calling method. It is important to note here that the above two conditions specify the boundary conditions of the recursive function. If either of the two conditions is not met, then we try to determine the location on the basis of the simple majority of the labels of the friends. In Step 6, we collect the list of all friends of the user. Next, for each of the friends we determine the location by recursively calling Simple_Majority with the friend's user id and decreasing the depth by 1. Once, we have the locations for all the friends, in step 6 we perform an aggregation of the locations to obtain unique locations. Next, we perform the boosting of the concepts in which a more specific concept is boosted by a more general concept. That is, the state concepts boost all the city concepts in which the city belongs to that state. Similarly, the country level concepts boost the state and city level concepts. Finally, the algorithm chooses the one with the maximum frequency and assigns it to the node.

5.2 k- Closest Friends with Variable Depth

As Twitter has a high majority of users with public profiles, a user has little control over the people following him or her. In such cases, considering spammers, marketing agencies, etc., while deciding on the user's location can lead to inaccurate results. Additionally, it is necessary to distinguish the influence of each friend while deciding the final location. We further modify this approach and just consider the k closest friends of the user.

Algorithm 2: Closeness (userId, friendId)

Input: User Id of the User and User Id of the Friend

Output: CF, the Closeness between the user and the friend

```
$CF = 0$; //initialize
$All\_Friends1\,[\,] = Get\_Friends\ (userId)$;
$All\_Friends2\,[\,] = Get\_Friends\ (friendId)$;
$CF = Common_{Friends}(All_{Friends1}[\,], All_{Friends2}[\,])$;
If $(SR > N_{spammer})$// spammer
        then $CF = 0$;
If $(Followers\ (friendId) > N_{celebrity})$
        then $CF = CF \times \frac{|\mathrm{All}_{\mathrm{Friends}_1}|}{Followers\ (friendId)}$;
Return CF;
```

Before we explain k_Closest_Friends () algorithm, let us define closeness amongst users. Closeness among two people is a subjective term and we can implement it in several ways including number of common friends, semantic relatedness between the activities (verbs) of the two users collected from the messages posted by each one of them, etc. Based on the experiments we conducted, we adopted the number of common friends as the optimum choice because of the low time complexity and better accuracy. Algorithm 2 illustrates the detailed explanation of the closeness algorithm. The algorithm takes as input the ids of the user and the friend and returns the closeness measure. In steps 2 and 3, we calculate obtain the ids of the ids of both the user and his or her friend. Next, we calculate their common friends and assign it as CF. In certain cases we need to take care of spammers and celebrities. The algorithm has zero tolerance towards spammers. A spammer is typically identified by the vast difference between the number of users he or she is following and the number of users following him or her back. We define the Spam Ratio of a friend as

$$SR(friendId) = \frac{Following(friendId)}{Followers(friendId)} \qquad (1)$$

And if SR is found to be greater than a threshold $N_{spammer}$, we identify the friend as a spammer and set CF as 0. Finally, we would like to control the influence of celebrities in deciding the location of the user because of previously mentioned problems. But, it is also important to note here that in certain cases the celebrities he or she is following are our best bet in guessing the user’s location. In step 6 we abbreviate the closeness effect a celebrity has on a user.

Algorithm 3 shows the steps involved in the k_Closest_Friends (userid, depth). Steps 1 through 7 remain the same as that of the Simple_Majority (userid, depth). Next, we call the method k-CF (userid, AllFriends [ ], k). The method returns an array consisting of userids of k closest friends of the user along with their pair wise closeness to the user as described in Algorithm 2. In the next step, for each of the k closest friends, we determine the location by recursively calling k_Closest_Friends () with the friend's user id and decreasing the depth by 1. Once, we have all locations of k closest friends, supported by their individual closeness as specified by Algorithm 2 we aggregate and boost the scores of the concepts and the concept with the maximum weight is returned.

Algorithm 3: k_Closest_Friends (userId, depth)

Input: User Id of the User and the current depth

Output: Location of the User

```
1:   If $Twitter\_Location(userId) \; != null)$
2:           then return $Twitter\_Location(userId)$;
3:   Else If $(depth = 0)$
4:           then return $null$;
5:   Else {
6:           $All\_Friends[\,] = \; Get\_Friends(userId)$;
7:           $k\_ClosestFriends[\,][2] = k\_CF(userdId, Friends[\,], k)$;
8:           For each friend in $k\_ClosestFriends[i][\,]$
9:                   $Location[i][1] = k\_ClosestFriends(k\_ClosestFriends[i], depth - 1)$;
```

```
            $Location[i][2] = k\_ClosestFriends[i][2];$
        Aggregate($Location$ [ ]);
        Boost($Location$ [ ]);
        Return $Max\_Location(Location[\,][\,]);$
    }
```

5.3 Fuzzy k- Closest Friends with Variable Depth

As mentioned previously, in Simple_Majority () and k_Closest_Friends (), each node in the social graph has a single label, and at each step, the locations with lower probabilities are not propagated to the upper levels of the graph. The disadvantage of this approach is that first, it tells us nothing about the confidence of the location identification of each node; and second, for instances where there are two or more concepts with similar score, only the location with highest weight is picked up, while the rest are discarded. This leads to higher error rates.

The idea behind the Fuzzy k closest friends with variable depth is the fact that each node of the social graph is assigned multiple locations of which each is associated with a certain probability. And these labels get propagated throughout the social network; no locations are discarded whatsoever. At each level of depth of the graph, the results are aggregated and boosted similar to the previous approaches so as to maintain a single vector of locations with their probabilities.

Algorithm 4: Fuzzy_k_Closest_Friends (userId, depth)

Input: User Id of the User and the current depth

Output: Location of the User

```
1:  If $Twitter\_Location(userId) \; != null)$
2:      then return $[Twitter\_Location(userId), 1.0]$;
3:  Else If $(depth = 0)$
4:      then return [$null$, 1.0];
5:  Else {
6:      $All\_Friends[\,] = \; Get\_Friends(userId)$;
7:      $k\_ClosestFriends[\,][2] = k\_CF(userdId, Friends[\,], k)$;
8:      For each friend in $k\_ClosestFriends[i][\,]$
9:          $Location[i][1] = k\_ClosestFriends(k\_ClosestFriends[i], depth - 1)$;
10:         $Location[i][2] = k\_ClosestFriends[i][2]$;
11:     Aggregate($Location$ [ ]);
12:     Boost($Location$ [ ]);
13:     Return $Max\_Location(Final\_Location[\,][\,])$;
14:   }
```

Algorithm 4 shows the steps involved in the algorithm. The initial input to the algorithm is the userid of the user and the maximum depth. In step 1, at any depth of recursion, the algorithm tries to determine the explicitly specified location. If the location is mentioned explicitly, then it is returned with confidence 1.0. Otherwise on reaching a depth of 0, if the algorithm is not able to find the location, it returns *null* with a confidence 1.0. If the location is not mentioned explicitly, then the algorithm tries to determine it on the basis of the locations of the k-Closest Friends of the user. In step 5 we collect the list of all the friends of the user comprising of the people he or she is following and the people following him or her. Next, we call the method k-CF (userid, AllFriends [], k) described in the k_Closest_Friends () algorithm. In the next step, for each of the *k* closest friends, we determine the list of locations, each associated with a probability, by recursively calling k_Closest_Friends () with the friend's user id and decreasing the depth by 1. Once, we have all locations-probability distribution of k-closest friends, supported by their individual closeness as specified by Algorithm 2, we aggregate and boost the scores of the concepts as discussed in Simple_Majority () algorithm. The method finally returns a vector of location concepts with individual probabilities.

5.4 Experiments and Results

5.4.1 Data

For the experiments, we randomly choose 1000 users from all different countries and cities who explicitly mention their location. But to the algorithms, we do not mention the same. It is important to note here, for uniformity, we ensure that each has at least 50 friends so that the 50-closest friends approach can be applied.

Our evaluation is designed with the following goals in mind. First, we aim to compare the accuracy of different approaches both at the city as well as the country level and show the effectiveness of TweetHood. Second, we want to show the tradeoff between accuracy and time as a function of depth. Finally, we wish to show the affect the choice of number of closest friends (k) has on accuracy and time. For all experiments, we choose the gazetteer-based approach discussed in the appendix as the baseline.

5.4.2 Experiment Type 1: Accuracy vs Depth

Figure 5.2 shows the accuracy as a function of the depth for the city level location identification for the Agglomerative clustering on Fuzzy *k* closest Friends. We make two key observations. First, with the increasing depth, the accuracy increases monotonically. This is obvious because for *null* nodes we are willing to go further and thus eventually find a label. But, the accuracy doesn't increase significantly after depth=3.

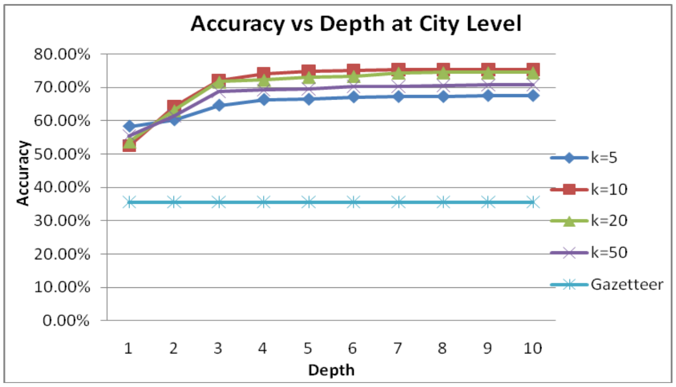


Figure 5.2. Accuracy vs Depth at the city level for TweetHood

Second, for a major portion, choosing k=10 gives us the highest accuracy as compared to the other values of k. The baseline gazetteer-based approach has a fairly low accuracy of 35.6% compared to our approach.

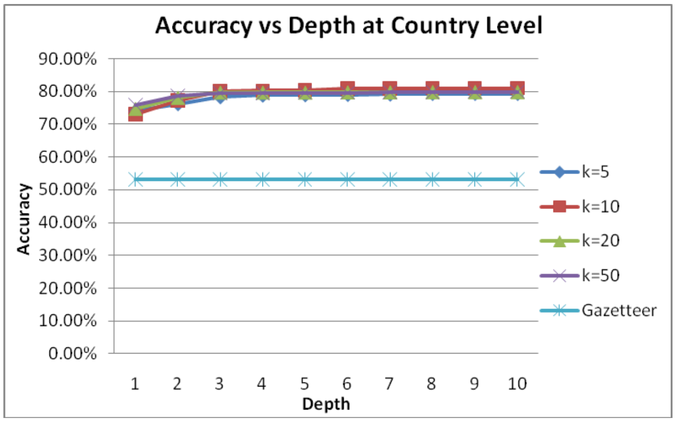


Figure 5.3. Accuracy vs Depth at country level for TweetHood

Next, we study the effect of increasing the depth on country level location identification for the Agglomerative clustering (described in chapter 8) on Fuzzy *k*-closest Friends. The observations are very similar to the city level identification i.e. for depth greater than 3 the accuracy saturates. But here, the choice of k does not affect the accuracy as significantly as it did for the city level identification. And understandably, the accuracy for country level is higher than for the city level, and at k = 10, depth = 3, it is found to be 80.1%.

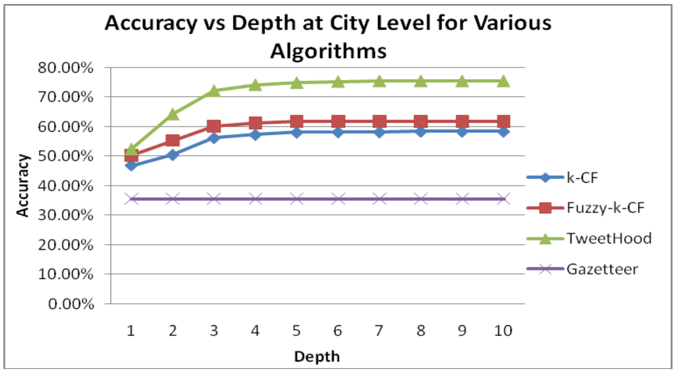


Figure 5.4. Accuracy vs Depth for various algorithms compared to TweetHood

Figure 5.4 shows the comparison of various algorithms proposed by us on the city level location identification. It is important to note here that on the basis of previous experiments, we conclude that k=10 is the optimal value for the future experiments. The key observations to make here are that the introduction of agglomeration of concepts actually brings about a great improvement in the accuracy because in some cases just choosing the maximum value does not produce the correct result; the proximity of concepts and the threshold have to be taken into account.

5.4.3 Experiment Type 2: Time Complexity

Now, we discuss the average running time for determination of the location of a single user. First, we compare the execution time for the various algorithms as a function of depth. As expected, the time increases exponentially with increasing depth.

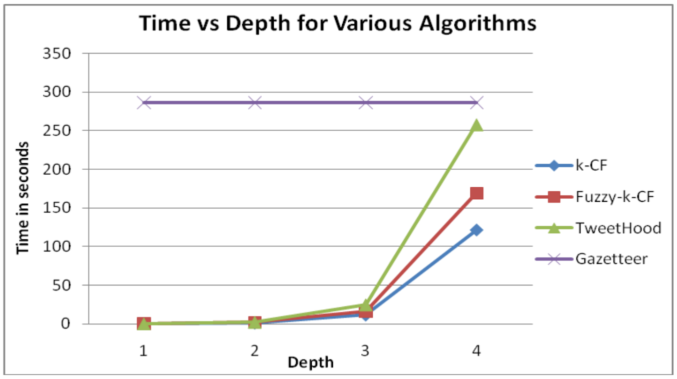


Figure 5.5. Time vs Depth for various algorithms compared to TweetHood

The other observation we make is that the time complexity increases as we go from *k*-closest friends to fuzzy *k*-closest friends to agglomerative fuzzy *k*-closest friends. This happens because of the increased overhead in the calculations and additional iterations performed to choose the cluster of concepts. But even then, for depth less than 4, the time is less than that for the baseline gazetteer approach in which the searching of gazetteer proves to be expensive on time.

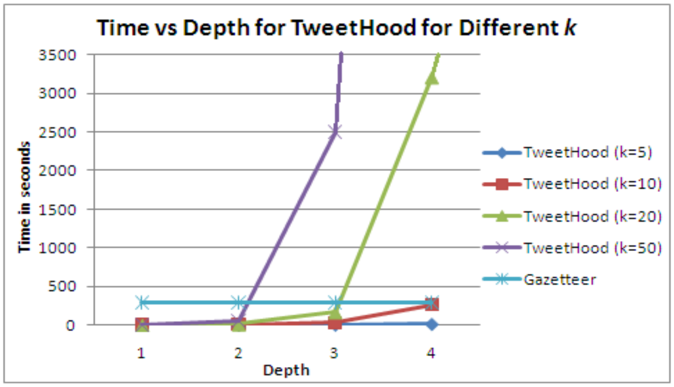


Figure 5.6. Time vs Depth for different values of k

Finally, we discuss the effect of increasing k on the time complexity of the algorithm. The increase is still exponential, but with the greater value of k, the greater is the slope. In fact, we have just shown that even for $depth = 4$, the graph for $k = 50$ becomes too large to be considered for practical use.

CHAPTER 6

TWEECALIZATION: LOCATION MINING USING SEMI SUPERVISED LEARNING*

Graph related approaches are the methods that rely on the social graph of the user while deciding on the location of the user. As observed earlier, the location data of users on social networks is a rather scarce resource and only available to a small portion of the users. This creates a need for a methodology that makes use of both labeled and unlabeled data for training. In this case, the location concept serves the purpose of class label. Therefore, our problem is a classic example for the application of semi-supervised learning algorithms.

In this chapter, we propose a semi-supervised learning method for label propagation based on the algorithm proposed by Zhu and Ghahramani (Zhu & Ghahramani, 2002) surveyed in (Bengio, 2006) with strong theoretical foundation, where labeled data act like sources that push out labels through unlabeled data.

Before we begin explaining the algorithm, we briefly describe the theoretical framework that lies beneath the label propagation and how it is different from the k-nearest neighbor approach. The labeled propagation algorithm is based on transductive learning. In this environment, the dataset is divided into two sets. One is the training set, consisting of the labeled data. On the basis of this labeled data, we try to predict the class for the second set, called the test or

* © 2012 IEEE. Reprinted, with permission, from Satyen Abrol, Latifur Khan, Bhavani Thuraisingham, Tweecalization: Efficient and intelligent location mining in twitter using semi-supervised learning, 2012 8th International Conference on Collaborative Computing: Networking, Applications and Worksharing (CollaborateCom), October 2012.

validation data consisting of unlabeled data. On the other hand, the k-nearest neighbor (k-NN) approach is based on the inductive learning in which, based on the training set, we try to determine a prediction function that attempts to determine the class for the test set correctly. The major disadvantage with k-NN approach is that in certain cases, predicting the model based on the test set becomes a difficult task. For example, in our case if we try to determine the number of neighbors we need to consider for optimal accuracy based on some users (from training data), this approach may not always produce the best results for other users. Hence, finding a value of k that works best for all instances of users seems a rather impossible task.

Chapelle et al. (Bengio, 2006) propose something called the "semi-supervised smoothness assumption". It states that if two points x_1 and x_2 in a high-density region are close, then so should be the corresponding outputs y_1 and y_1. This assumption implies that if two points are linked by a path of high density (e.g., if they belong to the same cluster), then their outputs are likely to be close. If, on the other hand, they are separated by a low-density region, then their outputs need not be close.

We divide the dataset into two parts. The first part consists of the labeled data (U_1, L_1)… (U_l, L_l) of the form (user, location) where $\{L_1…L_l\}$ ε $\{C_1…C_p\}$ (C_k is a location concept as discussed previously). The second part of dataset has the unlabeled data (U_{l+1}, L_{l+1})… (U_{l+u}, L_{l+u}). The pair (U_{l+u}, L_{l+u}) corresponds to the user whose location is to be determined.

Algorithm 5: Label Propagation (User, depth)

Input: User and the depth of the graph

Output: Location vector of the User

```
Compute the friends of User for maximum depth
Calculate similarity weight matrix W
Calculate the diagonal matrix D
Initialize $L^{(0)}$
Until $L^{(t)}$ converges
        $L^{(t)} = D^{-1} . W. L^{(t-1)}$
        $L_l^{(t)} = L_l^{(t-1)}$
Return $L_l^{(\infty)}[n+1]$
```

First, we need to construct a weight matrix W of dimensions $(n+1) \times (n+1)$ where W_{ij} is the measure of similarity between the two users U_i and U_j.

6.1 Trustworthiness and Similarity Measure

Just like any other machine learning technique, in label propagation also, the single most important thing is the way we define similarity (or distance) between two data points or, in this case, users. All the existing graph-based techniques, including (Abrol & Khan, 2010) and (Backstrom, Sun, & Marlow, 2010), either build a probabilistic model or simply look at the location of the friends to predict the location. In other words, these techniques are un-intelligent and have the common flaw that not all friends are equally credible when suggesting locations for the primary user. We introduce the notion of trustworthiness for two specific reasons. First, we want to differentiate between various friends when propagating the labels to the central user and second, to implicitly take into account the social phenomenon of migration and thus provide for a simple yet intelligent way of defining similarity between users.

Trustworthiness (TW) is defined as the fraction of friends which have the same label as the user himself. So, if a user, John Smith, mentions his location to be Dallas, Texas and 15 out of his 20 friends are from Dallas, we say that the trustworthiness of John is 15/20=0.75. It is worthwhile to note here that users who have lived all their lives at a single city will have a large percentage of their friends from the same city and hence will have a high trustworthiness value. On the other hand, someone who has lived in several places will have a social graph consisting of people from all over and hence such a user should have little say when propagating labels to users with unknown locations. For users without a location, TW is zero.

Friendship Similarity among two people is a subjective term and we can implement it in several ways including number of common friends, semantic relatedness between the activities (verbs) of the two users collected from the messages posted by each one of them, etc. Based on the experiments we conducted, we adopted the number of common friends as the optimum choice because of the low time complexity and better accuracy. We first calculate the common friends between users U_i and U_j and assign it as CF.

$$CF_{ij} = Common\_Friends(U_i, U_j) \tag{1}$$

The similarity between two users, SIM_{ij}, is a function of Trustworthiness and Friendship Similarity and can be represented as

$$SIM_{ij} = \alpha \times Max\{TW(U_i), TW\left(U_j\right)\} + (1 - \alpha) \times CF_{ij} \tag{2}$$

where TW is the individual trustworthiness of the two users and α is an arbitrary constant whose value is between 0 and 1. Typically, α is chosen to be around 0.7 for trustworthiness measure to have the decisive say in the final similarity measure.

Next, we use theGaussian distribution function to calculate the weight W_{ij}. If the number of events is very large, then the Gaussian distribution function may be used to describe physical events. The Gaussian distribution is a continuous function which approximates the exact binomial distribution of events. Since the number of common friends can vary a lot, we use the Gaussian distribution. The Gaussian distribution shown is normalized so that the sum over all values of CF gives a probability of 1.

$$W_{ij} = e^{\frac{SIM^2}{2\sigma^2}} \quad (3)$$

But, there are certain special cases we need to take care of. Spammers and celebrities tend to be misleading while predicting the location of a user. The algorithm has zero tolerance towards spammers. A spammer is typically identified by the high ratio of the number of users he or she is following and the number of users following him or her back. We define the Spam Ratio (Ω_{ij}) of two users U_i and U_j as

$$\Omega_{ij} = \max\left\{\frac{\text{Following}(U_i)}{\text{Followers}(U_i)}, \frac{\text{Following}(U_j)}{\text{Followers}(U_j)}\right\} \quad (4)$$

And if Ω_{ij} is found to be greater than a threshold $N_{spammer}$, either of the two users is a spammer and set W_{ij} as 0, to isolate the spammer.

Finally, we would like to control the influence of celebrities in deciding the location of the user because of previously discussed problems. But, it is also important to note here that in certain cases the celebrities the user is following are our best bet in guessing the user’s location.

If Followers(U_j) is greater than the threshold $N_{celebrity}$ then U_j is identified as a celebrity and the existing similarity it has with any user U_i gets abbreviated by a factor β, which is a function of number of followers of U_j and increases monotonically with the number of followers.

$$W_{ij} = \beta(U_i) \times W_{ij} \tag{5}$$

It is important to note here that the similarity weight matrix W is symmetric in nature for all i and j except if U_i is a celebrity. In such a case, the weight W_{ij} will be much less than the calculated value, as mentioned before.

Another data structure that we define is the (n+1) × (n+1) diagonal matrix D, used for normalization

$$D_{ii} = \sum_{j=1}^{n+1} W_{ij} \tag{6}$$

And finally we define the Location Label matrix L of dimensions (n+1) × p, where p is the number of distinct location concepts. Initialize L(0) as

$$L_{ij}^{(0)} = 1; if\ at\ j, L_i = concept\ class\ of\ U_i$$

$$0; otherwise \tag{7}$$

Thus, initially, the bottom u rows consist of only zeroes. After all the matrices have been initialized, we begin to iterate. Thus at step t of the iteration,

$$L^{(t)} = D^{-1}.W.L^{(t-1)} \tag{8}$$

$$L_l^{(t)} = L_l^{(t-1)} // \ Clamp\ the\ labeled\ data \tag{9}$$

At each step of the iteration, all unlabeled users receive a location contribution from their respective neighbors, proportional to the normalized similarity weight of the existing edge between the two. In this algorithm, we ensure that the labeled vertices are clamped to the users and do not change. It can be easily shown here that as the number of iterations, t, becomes large, L converges to a definite value (α approaches zero).

$$\alpha = L^{(t)} - L^{(t-1)} = (D^{-1}.W)^{(t)}.L^{(0)} - (D^{-1}.W)^{(t-1)}.L^{(0)} \qquad (10)$$

$$\alpha = (D^{-1}.W)^{(t-1)}.L^{(0)}.[D^{-1}.W - I] \qquad (11)$$

Because the matrix $D^{-1}W$ is a square matrix, each of whose rows consists of non-negative real numbers, with each row summing to 1, it follows that as $t \rightarrow \infty$, $(D^{-1}W)^{(t-1)} \rightarrow 0$, and hence L converges to a fixed value. The worst case running time of the algorithm is $O(n^3)$.

Now we discuss the impact of increasing the depth on accuracy and running time of the algorithm. By increasing the depth, we include the friends of friends of the user also in our set of data points. The direct advantage of this is that we have more labeled data points in our set thereby having a positive impact on the accuracy. Next, inclusion of more data points (users) leads to discovery of implicit 'friendship' relationships between users that may not be specified otherwise. The only disadvantage that is associated with increasing the depth is the increase in the running time of the algorithm.

In the next section, we evaluate the quality of the algorithms mentioned in the previous sections and describe how Tweecalization outperforms the other approaches.

6.2 Experiments and Results

6.2.1 Data

For the experiments, we randomly choose 1000 users from different countries and cities who explicitly mention their location and treat it as ground truth. It is important to note here, for uniformity, we ensure that each has at least 10 friends so that *k*-closest friends approach used in

Tweethood can be applied. Figure 6.1 shows the friend distribution for the dataset of 1000 users. We see that almost 45% of the users have 20 to 100 people as their friends.

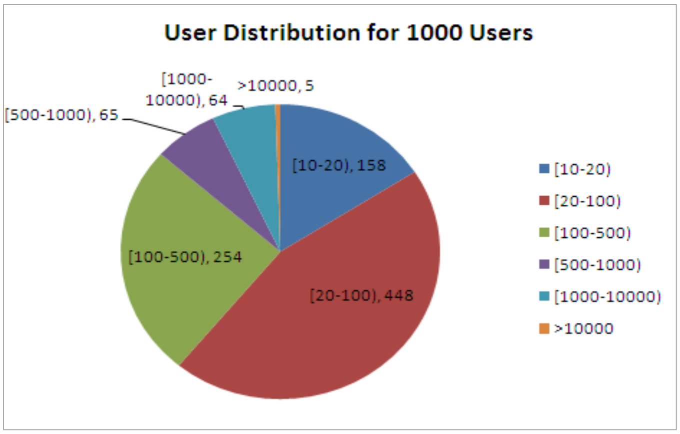


Figure 6.1.The user distribution for the data set.

Second, all processes are run offline, i.e., we store all the relevant information about the user like location, friend count, friends ids, etc. on the local machine and then run the algorithm. Hence the entire process is done offline, barring the geo-coding process, which is used to convert the explicitly mentioned locations to a standard format.

6.2.2 Evaluation Method

Our evaluation is designed with the following goals in mind. First, we aim to compare the accuracy of different approaches both at the city as well as the country level and show the effectiveness of Tweecalization in comparison to Tweethood and gazetteer based location mining technique. Second, we want to show the tradeoff between accuracy and time as a function of depth. Finally, we show how running time increases for difference algorithms with increasing depth. For all experiments, we choose the gazetteer based approach discussed in the previous sections as the baseline.

6.2.3 Experiment Type 1: Accuracy vs. Depth

For these set of experiments, the Y axis represents the accuracy in percentage and the X axis shows the depth.

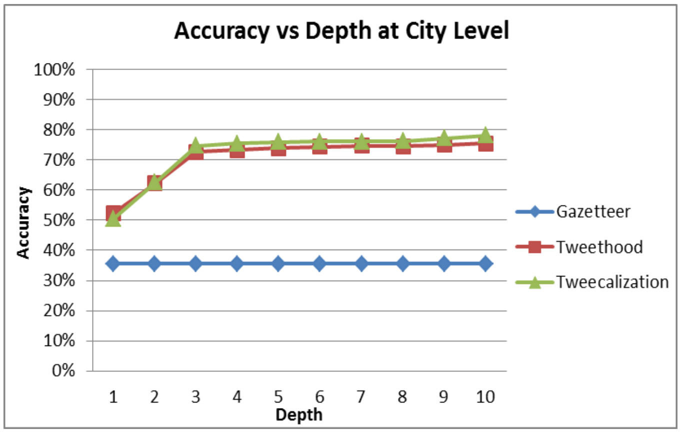


Figure 6.2. Accuracy vs Depth for various algorithms compared to Tweecalization

Figure 6.2 shows the accuracy as a function of the depth for the city level location identification for the Agglomerative clustering (described in Chapter 8) on Label Propagation (Tweecalization), compared to Agglomerative clustering on Fuzzy k-closest Friends (Tweethood). We make two key observations. First, with the increasing depth, the accuracy increases monotonically for both algorithms. As mentioned earlier, the reason for this is that by increasing depth in Tweecalization, we ensure that we are adding more labeled data to our training set. Secondly, adding more data points leads to identification of new associations between nodes, that is, we can find new friendships that may not be otherwise specified by the user himself or herself. On the other hand, for Tweethood this is obvious because for *null* nodes, we are willing to go further and thus eventually find a label. The second key observation we make for this experiment is that the accuracy doesn't increase significantly after depth=3 for both algorithms. On further analysis we find that the possibility of an implicit friendship existing between a user and node decreases with increasing depth of the graph and hence in such cases the increasing depth has little effect on the label propagation algorithm.

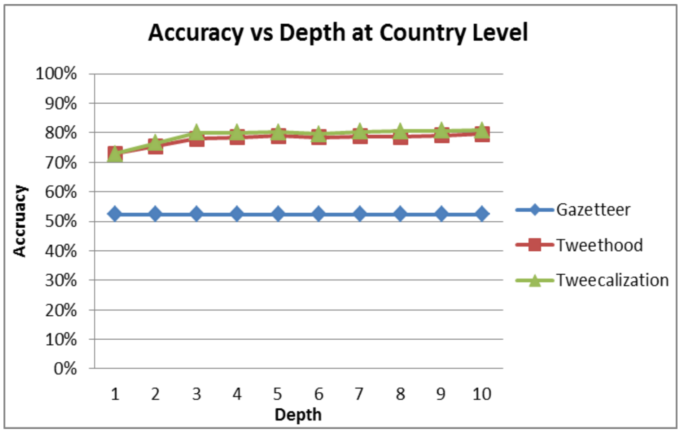


Figure 6.3. Accuracy vs. Depth at country level for Tweecalization

For depth less than 4, the accuracy value increases linearly with depth and is recorded to be 75.5% for Tweecalization at d=3. The baseline gazetteer based approach has a fairly low accuracy of 35.6% compared to our approach.

Next, we study the effect of increasing the depth on country level location identification for the two algorithms. Figure 6.3 shows the Accuracy vs. Depth comparison for different algorithms. The observations are very similar to the city level identification, i.e., for depth greater than 4 the accuracy saturates. The accuracy for Tweecalization at depth=4 is reported to be 80.10% compared to 78.4% for Tweethood. And understandably, the accuracy for country level is higher than for the city level, because in certain cases the algorithm chooses the incorrect city, even though the country for both is the same.

6.2.4 Experiment Type 2: Time Complexity

For this set of experiments, the Y axis represents the time in seconds for various algorithms and the X axis shows the depth.

Figure 6.4 shows the average running time for various algorithms for determination of the location of a single user as a function of depth. The key observations to make here are that for Tweethood, the time increases exponentially with increasing depth. Tweecalization, on the other hand, shows much better scalability because of a running time that's cubic in the size of friends. The increase in running time for Tweecalization is so insignificant in comparison to Tweethood that it appears as a straight line close to the X axis. At depth=4 the average running time recorded for Tweethood was 258.19 seconds as compared to 0.624 seconds for Tweecalization. The average running time for the content based approach is found to be 286.23 seconds. But for depth less than 4, both Tweethood and Tweecalization outperform the traditional gazetteer based location mining technique. This highlights the major contribution of Tweecalization, which is increased scalability with increasing depth for higher accuracy.

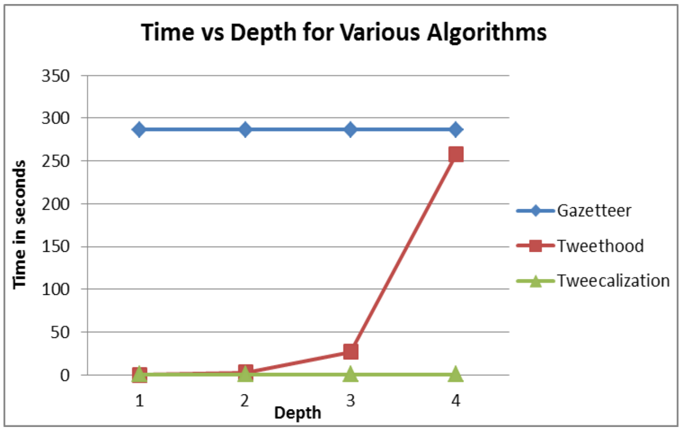


Figure 6.4. Time vs Depth for various algorithms compared to Tweecalization

CHAPTER 7

TWEEQUE: IDENTIFYING SOCIAL CLIQUES FOR LOCATION MINING*

7.1 Effect of Migration

Now we come to our second hypothesis which focuses on an important aspect of the social life in the present world. People are constantly on the move, changing homes, going from one city to another.

In this chapter we shall discuss some experiments and studies which show that a significant percentage of people move every year and it becomes necessary to do temporal analysis to be able to predict the user's current location correctly.

The first set of experiments is performed on data collected by U.S. Census Bureau (Geographical Mobility/Migration, 2009), a series of tables that describe the movement of people in the United States. The tables include data on why people moved, types of moves and the distance moved.

Figure 7.1 shows the findings regarding the migration trend in the past 5 years in US reported by the U.S. Census Bureau for people aged over 1 year moving from one county to another. We observe the migration rate varies between 4% and 6%. This means 12 to 17 million people of the total people surveyed change counties every year. And that is a significant number to be ignored.

* © 2012 ASE. Reprinted, with permission, from Satyen Abrol, Latifur Khan, Bhavani Thuraisingham, Tweelocal: Identifying Social Cliques for Intelligent Location Mining, ASE Human Journal 1, no. 3 (2012): 116-1292012.

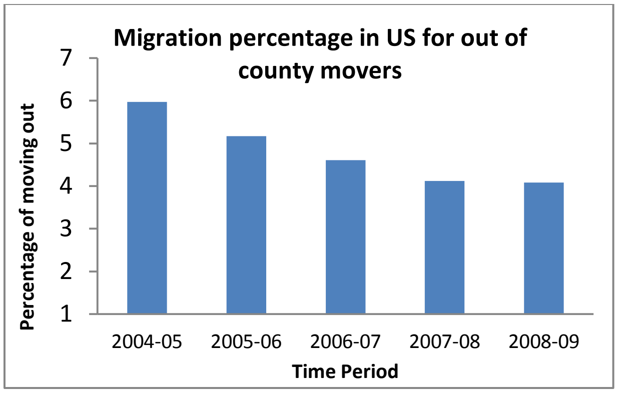


Figure 7.1. Fraction of people in the US that move out of counties every year.

To understand the long term or cumulative effect of this migration especially for online social network users, we collected demographic information including age, hometown, and current location for over 300,000 public profiles on Facebook for users with hometown in United States. Figure 7.2 shows the distribution of users based on age who have their current location the same as their hometown. It is interesting to note that only 28% to 37% users are living in their hometown. The rest of all the users have shown some form of migration, leaving their hometown.

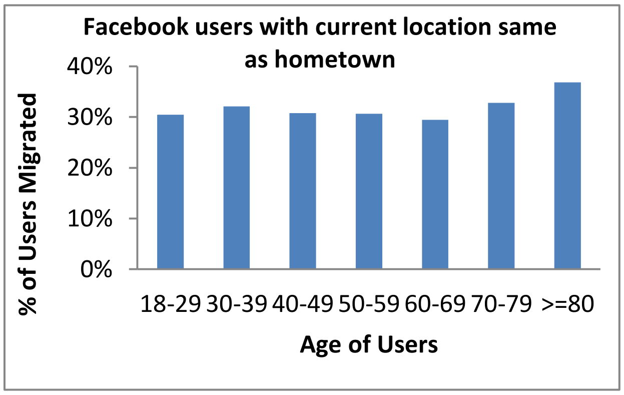


Figure 7.2. Percentage of Facebook users with current location same as their hometown.

Next, we try to link the migration effect to the users on Twitter using data from the U.S. census for the year 2008-09 and the Twitter age demographics studied by Pingdom (Report: Social network demographics in 2012, 2012).

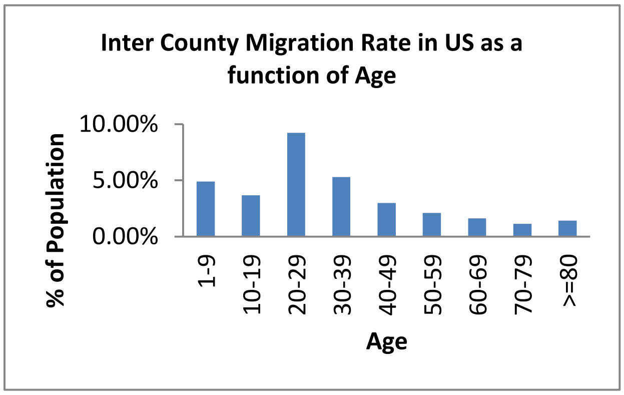


Figure 7.3. Inter-county migration rate in the US as a function of age.

First, we study the migration rate as a function of age, dividing the age groups in buckets of 10 years. There are two key observations that we make from the graph in Figure 7.3. First, we see a distinguishably high migration rate of over 9% for users in the age groups from 20 to 29 years. This is consistent with our intuition, that after completion of high school, people have a tendency to move out of their places for college or jobs. The second observation is that the migration rate decreases with increasing age. This is also intuitive, since as we grow older there are increased chances of employment stability and people with families preferring to settle down. The second part in linking is the study of demographics. Figure 7.4 shows the graph for the age distribution for Twitter users as surveyed by Pingdom (Report: Social network demographics in 2012, 2012). The interesting observation is that 25-34 year-olds make up a third of the Twitter population. Based on these two observations we conclude that Twitter users have a high tendency to migrate.

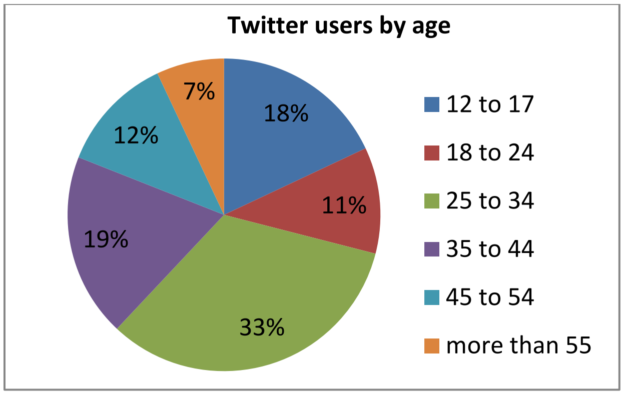


Figure 7.4. Distribution of Twitter users according to age.

To summarize this section, we make two key observations from Facebook data indicating that 63% to 72% are in a different city than their hometowns. Second, by doing age based analysis of U.S. Census data, we found that a high percentage of users between 20 and 34 years have done an inter-county migration. Thus, geographical migration is a very important factor to be taken into consideration by any algorithm which aims to predict the current location of the user successfully.

7.2 Temporal Data Mining

That leaves us with some important questions as to how do we know from a bunch of locations which one is the most current location of the user? How do we perform temporal analysis of friendships? The first half of the next section discusses how we can indirectly infer the most current location of a user and the second half describes the algorithm that helps us

Doing temporal analysis would have been much easier, if we had a timestamp attached to each friendship to indicate when it was formed in real world. Then we would have just looked at the most recent friends to determine the current location. But, unfortunately, that doesn’t happen so we have to come up with a way of inferring the time the friendship was created. To do that, we make two very simple social science observations.

7.2.1 Observation 1: Apart From Friendship, What Else Links Members of a Social Clique?

We begin by making a very simple observation. Man is a social animal and wherever he goes he has a strong tendency to form new friendships. And friendship seldom occurs alone; it's usually in groups known as cliques in social networking theory. Let us start by giving a definition of a clique. A clique is an inclusive group of people who share interests, views, purposes, patterns of behavior, or ethnicity. In social network theory, as well as in graph theory, a clique is a subset of individuals in which every person is connected to every other person. For example, I have a clique consisting of friends I made at school, John has a group at the office where mostly everyone is friends amongst themselves. An interesting observation to make here is that an individual may be part of several cliques, e.g. a reference group formed while he or she was in high school, one formed in college, another one after he started working in a company and so on. Apart from friendship, what is the attribute that links members of a clique? It is their individual locations. All members of a clique were or are at a particular geographical location at a particular instant of time like college, school, a company, etc.

7.2.2 Observation 2: Over Time, People Migrate

The second observation is based on the study from the previous section that, over the course of time, people have a tendency to migrate. In other words, over time the locations of members of a clique will change.

Based on these two social science observations, we propose a new social science theory. We hypothesize that if we can divide the social graph of a particular user into cliques as defined above and check for location-based purity of the cliques we can accurately separate out his or her current location from other locations. Amongst the different groups formed for a user, due to migration studied in the previous section, the most current group will show the maximum purity. Migration is our latent time factor, as with passing time the probability of people migrating increases. So, what happens if a user doesn't migrate, but his or her friends move? A scenario in which the user doesn't move but his or her friends show signs of migration is rare, but nonetheless, we shall have new people moving in and as the user will not lead a lonely life, new groups will be formed with high percentage of location-based purity.

Let's try to understand the intuition behind it using an example. John Smith did his schooling in Dallas and then moved to Austin for college and got a job in, say, Seattle. Now, if we divide John's friends into groups, we expect to find groups of friends formed in school, college and at work. But if we look at the locations of the users in the school group, then we shall find that due to the prominent long term effects of migration, most the school friends in the group would also have moved from Dallas. Similarly, after finishing college in Austin, a significant percentage of his college friends would show signs of migration owing to job relocation and family reasons. But because his friendship at work in Seattle is very new, the possibility of migration decrease and the chances that all the members of the group are in the same physical location increase. And we are likely to observe a pure group where most of the users have their location as Seattle.

7.2.3 Social Clique Identification

Now, that we have proposed our social theory, in this subsection, we address the problem of identifying all the social cliques of a user, U, as defined in the previous section. We construct the entire set of a user's friends as graph $G = (V, E)$ with each friend represented as a node in the graph. Two users who are friends with each other are connected by an edge. Now, the goal is to partition the graph into k non-overlapping social cliques represented by $\pi = C_1, C_2, \dots, C_k$.

Finding all the cliques in a graph is an NP-complete problem. The Bron–Kerbosch algorithm (Bron & Kerbosch, 1973) is a recursive backtracking procedure of Bron & Kerbosch (1973) that augments a candidate clique by considering one vertex at a time, either adding it to the candidate clique or to a set of excluded vertices that cannot be in the clique but must have some non-neighbor in the eventual clique. Variants of this algorithm can be shown to have worst-case running time of $O(3^{n/3})$. Since the running time is infeasible for practical applications where locations for millions of users have to be determined, we need to come up with something that is at least polynomial in running time.

We reformulate the problem to a graph partition problem. Graph partition focuses on determining a partition of the friends such that the cut (the total number of edges between two disjoint sets of nodes) is minimized. Even though the cut minimization can be solved efficiently, the outcome is partitions consisting of single nodes. Thus, we employ an often used variant, called the Normalized Cut, which is defined as

$$Normalized\ Cut\ (\pi) = \sum_{i=1}^{k} \frac{Cut\ (C_i, \bar{C_i})}{Vol\ (C_i)} \qquad (1)$$

where $\overline{C_i}$ is the complement of the partition C_i and $Vol(C_i)$ is the volume of a set of vertices C_i is the total weight of the edges incident to it:

$$Vol(C_i) = \sum_{x \in C_i, y \in V} w(x, y) \tag{2}$$

In order to obtain an optimal cut, the goal is to minimize the objective function specified in equation 1, so as to minimize the number of edges between partitions (numerator), while the denominator ensures that we do not end up with single node partitions.

Computing a cut that minimizes the equation in question is an NP-hard problem. We employ the Shi–Malik algorithm introduced by Jianbo Shi and Jitendra Malik (Shi & Malik, 2000) commonly used for image segmentation. We can find in polynomial time a $cut(C_i, \overline{C_i})$of small normalized weight $Ncut(C_i, \overline{C_i})$ using this algorithm.

Let us now describe the Ncut algorithm. Let D be an N × N diagonal matrix with d on its diagonal, W be an N × N symmetrical matrix with $W(i, j) = w_{ij}$.

After some algebraic manipulations (Shi & Malik, 2000), we get:

$$\min_{(C_i, \overline{C_i})} Ncut(C_i, \overline{C_i}) = \min_y \frac{y^T(D-W)y}{y^T D y} \tag{3}$$

subject to the constraints:

- $y_i \in \{1, -b\}$, for some constant $-b$, and
- $y^t D1 = 0$

Minimizing $\frac{y^T(D-W)y}{y^T D y}$ subject to the constraints above is NP-hard. It is important to note here that the expression on the right side in equation 3 is the Rayleigh quotient (Shi & Malik, 2000). To make the problem tractable, we relax the constraints on y, and allow it to take just real values.

The relaxed problem has the same solution as the generalized eigenvalue problem for the second smallest generalized eigenvalue,

$$(D - W)x = \lambda Dx \qquad (4)$$

Algorithm 6: Social Clique (G (V, E))

Input: Graph $G = (V, E)$, for a user U where V denotes friends of a user and E represents friendship between them.

Output: Social Cliques, $\pi = C_1, C_2, \dots, C_k$

```
1:  Given a weighted graph G=(V,E) , compute the weight of each edge, and construct the adjacency matrix W and diagonal matrix, D.
2:  Define the unnormalized graph Laplacian matrix as $L = D - W$.
3:  Solve $L.x = \lambda D.X$ for eigenvectors with the smallest eigenvalues.
4:  Use the eigenvector with the second smallest eigenvalue to bipartition the graph.
5:  Decide if the current partition should be subdivided and recursively repartition the segmented parts if necessary.
```

Algorithm 6 outlines the steps involved in partitioning the user's friends' graph $G = (V, E)$ into social cliques, represented by $\pi = C_1, C_2, \dots, C_k$, as defined earlier. In step 1 of the algorithm, we compute the diagonal matrix as described earlier with

$$d_i = \sum_{j=1}^{n} w_{ij} \qquad (5)$$

Next, we determine the un-normalized Laplacian matrix for the graph,

$$L = D - W \qquad (6)$$

In step 3, we solve the eigenproblem $Lx = \lambda Dx$ and choose the eigenvector with the second smallest eigenvalue to bipartition the graph.

We repeat the iterations involving steps 1 through 4 until we reach a point where no more partitions are necessary. But, how do we decide that? For answering that question, we need to first define weight of the edge between vertices.

Defining Weight: To ensure that we capture the phenomenon of social cliques, we have to be very careful as to how we define the weight of the edge between two users. For our work, we define the weight between two users *i* and *j* as

$$w(i,j) = w_{edge}(i,j) + \alpha \times w_{mutf}(i,j) \tag{7}$$

where w_{edge} is positive if *i* and *j* are friends and is less than 0 otherwise. The presence of w_{edge} controls the membership of each cluster to ensure that it consists of only users who are friends amongst themselves. If two users are not friends, then we penalize the weight between them, often causing the score to become less than zero.

w_{mutf} is the number of mutual friends that *i* and *j* share. α is an arbitrary constant whose value depends on the number of friends i and j have and lies between 0 and 1. The presence of w_{mutf}, in the overall similarity, guarantees that friends who are closer (have more mutual friends) have higher probability of staying in the same clique.

It is important to note that the contribution of w_{edge} to the overall similarity score is significantly larger than that of the w_{mutf}. This is done in order to ensure that the formation of each cluster is consistent with the definition of a social clique.

Let us try to answer our earlier question, “When do we stop?” In our case, we iterate till we reach a point, where the similarity measure of the nearest user clusters is negative. It can be easily shown that the complexity of the algorithm is $O(n^3)$.

Purity-based Voting Algorithm: Once we have obtained clusters which are consistent with the definition of social cliques, we have to decide on the current location of the user. As mentioned previously, we check for purity of the individual clusters to determine the current location.

Before we begin explaining the algorithm, let us first define a location concept.

Location Concept: A location concept L of a user U is the location of the user in the format {City} X/ {State} Y/ {Country} Z. And for each location depending on the level of detail, either of X, Y or/and Z can be null.

We propose a purity-based voting algorithm to determine the final location. The idea is that each cluster casts its vote on what the current location should be. First, each cluster decides which location it is going to vote in favor of. This is computed by doing a simple majority of all the locations inside the cluster.

Algorithm 7: Purity Voting (π)

Input: $\pi = C_1, C_2, \ldots, C_k$, group of all clusters with location concepts

Output: Vector (L, S), concepts and score vector

```
1:  For each cluster, $C_i \in \pi$
2:          $Location(C_i) = Simple\_Majority(C_i)$
3:          $Purity\_Vote(C_i) = \frac{|U_{max}|}{|C_i|}$
4:  Aggregate $(Location(C_i), Purity\_Vote(C_i))$
```

```
Boost ($Location(C_i), Purity\_Vote(C_i)$)
Return $Max\_Location(Final\_Location(L, S))$
```

And the power of the vote for each cluster is dependent on the purity of the cluster and the number of members in the cluster. In other words for each cluster we calculate purity, $Purity(C_i)$, defined as

$$Purity\_Vote(C_i) = \frac{|U_{max}|}{|C_i|} \tag{8}$$

where $U_{max} = U_i$, such that, $U_i \in C_i\ AND\ Location(U_i) = Max\_Location(C_i)$.

After we have calculated $Purity\_Vote(C_i)$ for each of the clusters, we have a list of location concepts, each of which is supported by a cluster. It is important to note here that several cliques may support a single location concept. Intuitively, when a user moves to a location, we can expect a user to belong to more than one social clique (probably one from work and another consisting of his friends).

Next, we perform aggregation of the locations to obtain unique locations. Finally, we perform the boosting of the concepts in which a more specific concept is boosted by a more general concept. That is, the state concepts boost all the city concepts in which the city belongs to that state. Similarly, the country level concepts boost the state and city level concepts.

7.3 Experiments and Results

7.3.1 Data

For the experiments, we randomly choose 10K users from all different countries and cities who explicitly mention their location. But to the algorithms, we do not mention the same. Figure 7.5

shows the friend distribution for the dataset of 10K users. We see that almost 45% of the users have 20 to 100 people as their friends.

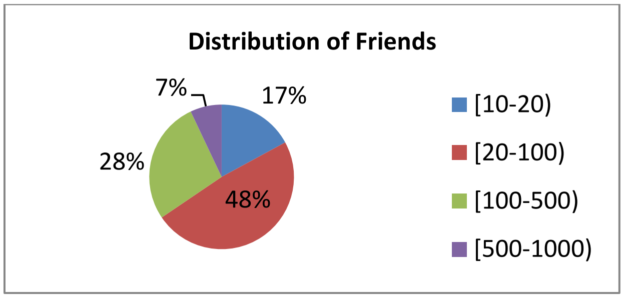


Figure 7.5.(a) User distribution for the data set according to number of friends

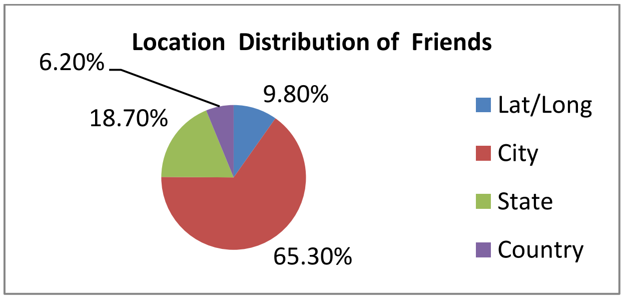


Figure 7.5.(b) Distribution of users according to granularity of location specified by them.

Second, all processes are run offline i.e. we store all the relevant information about the user like location, friend count, friends ids, etc., on the local machine and then run the algorithm. Hence the entire process is done offline, barring the geo-coding process, which is used to convert the explicitly mentioned locations to a standard format.

7.3.2 Social Clique Identification

Before we begin evaluating our location prediction approach, we first need to assess the correctness of our algorithm to form social cliques.

In order to do so, we handpicked a group of 1000 known Twitter users, and performed graph partitioning to form social cliques for each one of them. We then asked annotators to manually look into each group and verify the correctness of the group. The annotators made use of other resources such as the user's other social networking pages (Facebook, LinkedIn, etc.) to determine where the friend met the user and whether the cliques actually made sense. The users chosen by us are from a wide range of demographics including men, women, young and old, and people from different countries and cultures.

The way we evaluated the algorithm was by looking at each partition and then identifying the number of data points (friends) that the annotator thought did not belong to that particular partition. Table 7.1 shows the results of the experiments. The graph partitioning algorithm is found to have a very promising accuracy and hence can be used to obtain social cliques.

Table 7.1. Social Clique Evaluation

Total Users	Average Number of Clusters per User	Average Size of Cluster	Accuracy
1000	15	7	88.32%

7.3.3 Location Prediction

Now that we have established the correctness of the social clique formation algorithm, we would like to evaluate the location prediction algorithm.

Table 7.2 shows the results of the experiments we performed. The algorithm is able to correctly predict the current city of the user with an accuracy of 76.3% as compared to 72.1% for Tweethood and 75.5% for Tweecalization. The average size of a city group is 1.82, meaning that after the threshold is reached and the agglomeration of location concepts stops, the average location concept contains on an average 2 city concepts.

Table 7.2. Accuracy Comparison for Tweeque

	City Level	Country Level
Content Based Approach	35.6%	52.3%
Tweethood	72.1%	80.1%
Tweecalization	75.5%	80.1%
Tweelocal	76.3%	84.9%

The accuracy for the algorithm at country level is 84.9% and is much higher than 52.3% for the content based approach and 80.1% for both Tweethood and Tweecalization.

Next, we study the impact of the number of friends of any user has on the accuracy of the algorithm. Figure 7.4 shows the variation of error rate as a function of number of friends.

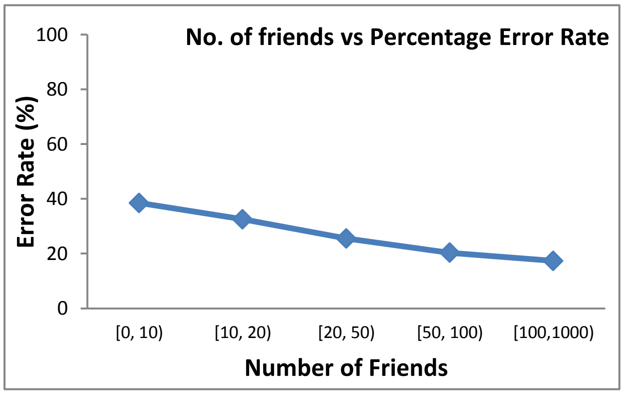


Figure 7.6. Error rate for Tweeque as a function of the number of friends of the user.

It is interesting to observe that, in general, the error rate decreases with the increase in the number of friends. The presence of more friends means that we have more data for a particular user, which works well for the algorithm, allowing it to form clusters that actually conform to the definition of social cliques.

CHAPTER 8

AGGLOMERATIVE HIERARCHICAL CLUSTERING

The three location prediction algorithms described in Chapters 5, 6 and 7, each return location concepts each associated with a score. We could just stop at this point and choose the location concept with the maximum score. But we are missing a crucial aspect of locations.

Up to this point we have given little emphasis to the geospatial proximity of the different concepts. That is, we were treating the concepts purely as labels, with no mutual relatedness. Since the concepts are actual geographical cities, we agglomerate the closely located cities and suburbs in an effort to improve the confidence and thus the accuracy of the system.

At this point we introduce something called the Location Confidence Threshold (LCT). The idea behind LCT is to ensure that when the algorithm reports the possible locations, it does so with some minimum level of confidence. LCT depends on the user itself. The LCT increases with the increasing number of friends for the user, because more friends imply more labeled data. Let us consider that we have p concepts each associated with its respective probability.

Initially, we have all concepts present individually as $\{L_1\}, \{L_2\}, \dots, \{L_p\}$. If any concept has a value greater than the LCT, then the program returns that concept as the location and terminates. Otherwise, at the next step we construct a matrix in which the number in the *i*-th row *j*-th column is an objective function Θ of the distances and cumulative scores between the *i*-th and *j*-th concepts.

$$\Theta_{\mathrm{ij}} = \frac{e^{\frac{S}{T}}}{d(i,j)} \tag{1}$$

where $S = S_i + S_j$, the combined score of concept clusters $\{L_i\}$ and $\{L_j\}$, is the geographic distance between the two clusters and T is a constant with $0<\mathrm{T}<1$.

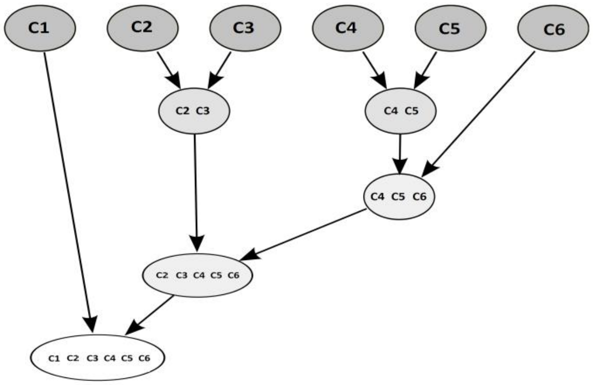


Figure 8.1. Illustration to show the agglomerative hierarchical clustering

At the first step of agglomeration, we combine two concepts with the highest value of the objective function, Θ, and check if the new concept cluster has a combined score greater than the LCT. If not, then we continue the process, constructing the matrix again, but this time some of the concepts are replaced by concept clusters. And we proceed to choose the two concepts clusters that have the maximum value of the objective function Θ. The mean geographic distance between a concept cluster A and a concept cluster B can be defined as

$$d_{AB} = \frac{1}{|A||B|} \sum_{x\varepsilon A} \sum_{x\varepsilon B} d(x,y) \tag{2}$$

Thus at each step of the agglomeration, we choose the two concept clusters with maximum value of the objective function Θ. If the score of the combined bag of concepts crosses the LCT, we return the bag of concepts as the possible location vector and terminate.

To understand how agglomerative clustering basically works, consider a scenario in which the location prediction algorithm returns an array of location concepts including (Los Angeles, 0.34), (Long Beach, 0.05), (Irvine, 0.17), and a lot of other concepts. Suppose the LCT for the algorithm to return a cluster of concepts is 0.5. Then, if we simply combine location concepts based on just proximity, then initially Los Angeles and Long Beach will get combined (Long Beach is closer to Los Angeles than Irvine), but since their combined score is not sufficient, in the next iteration Irvine also gets added to the cluster. And the final cluster that is returned is {Los Angeles, Long Beach, Irvine} with a combined score of 0.56. On the other hand if we use agglomerative clustering with an objective function mentioned previously, Los Angeles and Irvine are combined to yield a location cluster of {Los Angeles, Irvine}, which has a combined score greater than the LCT and is hence returned as the output. Thus, by using agglomerative clustering we end up being more specific by returning two concepts instead of three, at a small loss of confidence.

CHAPTER 9

UNDERSTANDING NEWS QUERIES WITH GEO-CONTENT USING TWITTER*

9.1 Application of Location Mining and Social Networks for Improving Web Search

In this chapter, as an application of our location mining work, we demonstrate the development of a system that focuses on understanding the intent of a user search query. TWinner examines the application of social media in improving the quality of web search and predicting whether the user is looking for news or not. We go one step beyond the previous research by mining social media data, assigning weights to them and determining keywords that can be added to the search query to act as pointers to the existing search engine algorithms suggesting to it that the user is looking for news.

Since location is an important part of the system as we shall show later, for the system to work efficiently, it is important that the location of the Twitter users and the location mentioned in the tweet be determined accurately.

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9.2 Determining News Intent

In this section we give a detailed description of the process that we undertake to understand the intent of the user query.

9.2.1 Identification of Location

In the first step we attempt to geo-tag the query to a location with certain confidence. For this, we can use any of the systems described in MapIt (Abrol & Khan, 2009), which uses a gazetteer-based mining algorithm to determine the location present in the text of the message.

9.2.2 Frequency – Population Ratio

Once the location mentioned in the query has been identified explicitly, the next step is to assign a news intent confidence to the query.

Coming back to the Fort Hood query, once we are able to identify Fort Hood as a unique location, our next task is to identify the intent of the user. Intuition tells us that if something has happened at a place, the likelihood of people talking about it on Twitter will increase manifolds. To understand this concept, we define an index called the Frequency - Population Ratio (FPR) for each geographical location. FPR is defined as

$$FPR = \alpha \times N_t + \beta \quad (1)$$

where α is the population density factor, N_t is the number of tweets per minute at that instant and β is the location type constant. The constant α is used taking into consideration the fact that the location of a Twitter user also affects the user's interest in the news. Hassan et al. (Hassan, Jones, & Diaz, 2009) in their experiments found out that users from areas with high population density are more interested in current news. We extended these findings to ascertain that people in higher population density areas are more likely to tweet about news. Figure 9.1 shows how the percentage of news-related tweets is affected by the population density of the region. The horizontal axis represents the population density in number of persons per sq. miles and the y axis represents the percentage of total tweets that contain news.

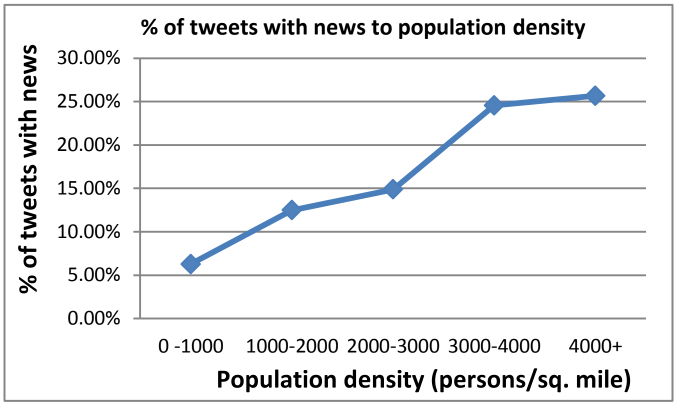


Figure 9.1. Percentage of news messages versus the population density of user's location in persons per square miles

The other observation made is that the percentage of news tweets is greatly affected by the location type. For this, we collected a sample of 10k Twitter messages having location, and classified them into pre-determined location types.

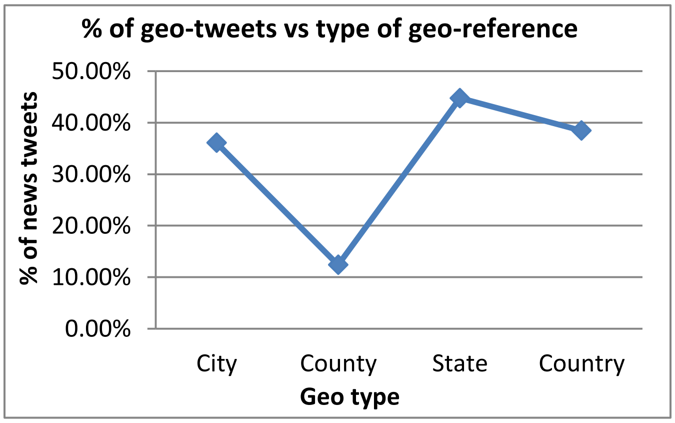


Figure 9.2. Percentage of tweets corresponding to type of geo-reference them.

Figure 9.2 shows the outcome of the experiment. We determine that state or country names are more likely to appear in Twitter messages rather than the city names. For each geo-location, we chose the value of the constants alpha and beta in such a way that the Frequency- Population ratio for each geo-location is a constant independent of the type and the population density.

Table 9.1. Some sample locations, and the corresponding estimated alpha and beta values and the Frequency Population Ratio (FPR)

Example of Location	**Value of Alpha**	**Value of Beta**	**Frequency Population Ratio (FPR)**
Fort Hood (City)	1.21	2.6315	2.8267
Los Angeles (City)	0.02	2.6315	2.8677
Collin (County)	0.749	8.1506	2.8519
Texas (State)	0.0045	2.2702	2.7790
North Dakota (State)	0.233	2.2702	2.8088
Australia (Country)	0.104	2.5771	2.9051

Table 9.1. shows some sample geo-locations, the chosen values of alpha and beta and the resulting FPR ratio for weekdays based on a one week time period.

It is very important to note here that FPR is a constant on regular days when the geo-location is not in the news or is not a popular topic on Twitter. But in events such as the Fort Hood incident, the FPR increases by manifolds. We make use of this feature to determine whether a geo-location is in news or not.

An evident drawback of this approach is that while considering the FPR, we are not taking into account the geographical relatedness of features. For example, if the user enters Tehran and is looking for Iran elections, while calculating the FPR, in addition to the Twitter messages for 'Tehran' we need to consider messages containing keywords 'Iran' and 'Asia' as well. Therefore, we modify our earlier definition for FPR to

$$FPR = \sum \mu_i \times (\alpha \times N_t + \beta) \qquad (2)$$

where the constant μ_i accounts for the fact that each geo-location related to the primary search query contributes differently. That is, the contribution of Twitter messages with 'Fort Hood' (primary search location) will be more than that of messages with 'Texas' or 'United States of America'.

Now, since we know that FPR for a location is a constant value or lies in a very narrow range in the absence of news making events, by calculating the FPR for a particular location at any given instance of time and by checking its value, we can determine to a level of certainty whether the area is in the news or not. And if the calculated FPR exceeds the values shown in Table 9.1 by a significant margin, then we can be confident of the news intent of the user.

For example, the calculated value of an average FPR for 'Fort Hood' during the week of 5th to 12th November was as high as 1820.7610 which is seemingly higher than the usual 2.8267, indicating that people were talking about Fort Hood on Twitter. And we take that as a pointer that the place is in news.

9.3 Assigning Weights to Tweets

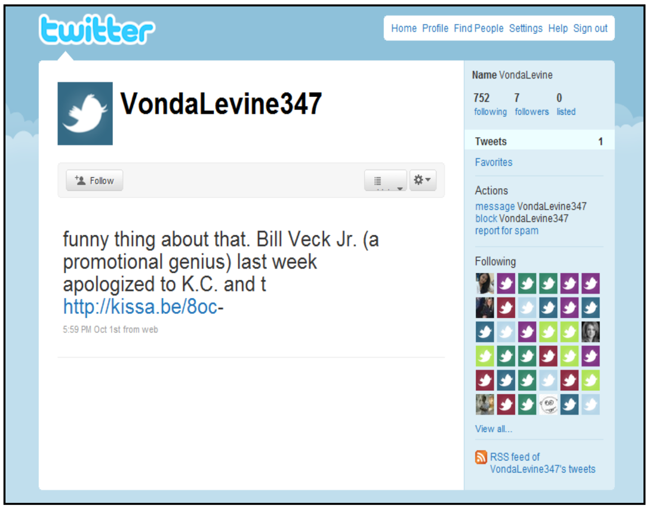
Once we have determined to a certain confidence level the news intent of the user query, the next step is to add certain keywords to the query which act as pointers to the current search engine algorithm telling it that the user is looking for news.

To begin with we collect all Twitter messages posted in the last 24 hours containing a reference to either the geo-location (e.g. Fort Hood) or the concepts that subsume it (e.g. Texas, United States of America, etc.). We then assign weights to each Twitter message based on the likelihood of its accuracy in conveying the news. In the following subsections, we describe the various factors that might affect the possibility of a Twitter message having news content.

9.3.1 Detecting Spam Messages

On close observation of the Twitter messages for popular topics, it was noticed that some of the Twitter messages are actually spam messages, where the user has just used the popular keywords so that his or her message reaches out to the people who are looking at this trending topic. In other words, a significant percentage of the Twitter messages are actually spam and carry little or no relevant information. It is thus important to recognize such messages and give lower weight to them. In this section we briefly describe our method of identifying whether a message is spam or not.

The methodology we use is based on analyzing the social network of the user posting the message. The social network of a user on Twitter is defined by two factors, one, the people he or she is following and the other people following him or her. We hypothesize that the ratio of the number of followers to the number of people he or she is following is very small. The second observation is that a spammer rarely addresses his or her messages to specific people, that is, he or she will rarely reply to messages, re-tweet other messages, etc. Figure 9.3 shows the profile of a typical spammer. Note that he or she is following 752 people and is just being followed by 7 people.



VondaLevine347

Name VondaLevine

752	7	0
following	followers	listed

funny thing about that. Bill Veck Jr. (a promotional genius) last week apologized to K.C. and t http://kissa.be/8oc-

5:59 PM Oct 1st from web

Figure 9.3. Profile of a typical spammer

Based on these two hypotheses, we come up with a formula that tags to a certain level of confidence whether the message is spam or not. The spam confidence Z_i is defined as

$$Z_i = \frac{1}{\frac{N_p}{N_q} + (\lambda \times N_r)} \qquad (3)$$

where N_p and N_q are the number of followers and number of people the user is following respectively. μ is an arbitrary constant and N_r is the ratio of number of tweets containing a reply to the total number of tweets.

It is important to note here the higher the value of the spam confidence, Z_i, the greater is the probability of the message being spam and therefore its contribution to the total weight is lowered.

9.3.2 On Basis of User Location

In this section we describe the experiments that we conducted to understand the relationship between Twitter news messages and the location of the user. We performed experiments on two different samples of data each comprising of 10 thousand tweets, one for tweets about ‘Fort Hood’ and the other on tweets for ‘Iran’. We grouped the tweets according to the proximity between the topic and the user location. The results of the experiment on Fort Hood are shown in Figure 9.4.

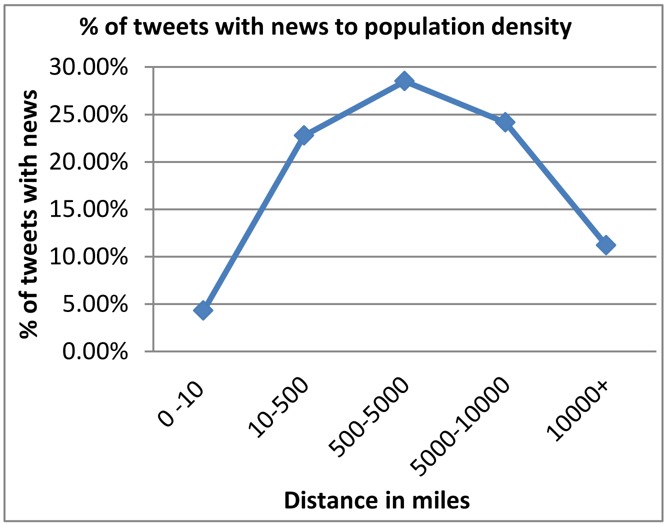
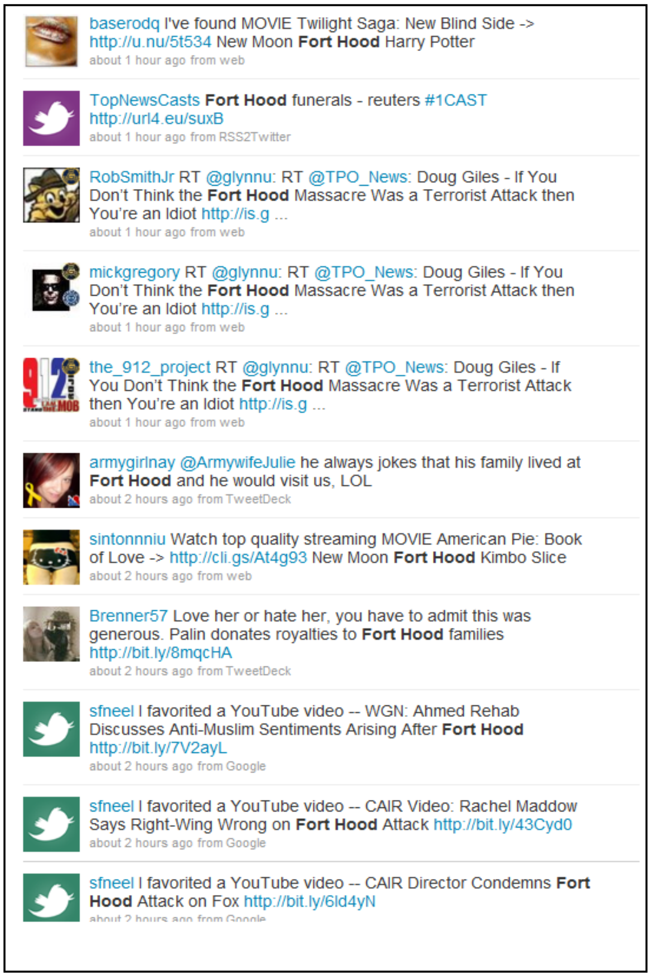


Figure 9.4. Relationship between number of tweets to the distance between the Twitter user and query location

It can be interpreted from the findings that people located in the same state, same country and also neighboring countries are more likely to talk about a news event as compared to the people located immediately next to the location (within a ten mile radius) or very far from it (different continent). We use these experiments as the baseline and use the inferences to assign weights for messages on future topics.

9.3.3 Using Hyperlinks Mentioned in Tweets

An interesting observation that we make from our experiments is that 30-50% of the general Twitter messages contain a hyperlink to an external website and for news Twitter messages this percentage increases to 70-80%. Closer analysis indicates that firstly, a lot of popular news websites tweet regularly and secondly, mostly, people follow a fixed template of writing a short message followed by a link to the actual news article. Figure 9.5 shows the screenshot for a recent Twitter search for 'Fort Hood'.



baserodq I've found MOVIE Twilight Saga: New Blind Side -> http://u.nu/5t534 New Moon **Fort Hood** Harry Potter
about 1 hour ago from web

TopNewsCasts **Fort Hood** funerals - reuters #1CAST http://url4.eu/suxB
about 1 hour ago from RSS2Twitter

RobSmithJr RT @glynnu: RT @TPO_News: Doug Giles - If You Don't Think the **Fort Hood** Massacre Was a Terrorist Attack then You're an Idiot http://is.g ...
about 1 hour ago from web

mickgregory RT @glynnu: RT @TPO_News: Doug Giles - If You Don't Think the **Fort Hood** Massacre Was a Terrorist Attack then You're an Idiot http://is.g ...
about 1 hour ago from web

the_912_project RT @glynnu: RT @TPO_News: Doug Giles - If You Don't Think the **Fort Hood** Massacre Was a Terrorist Attack then You're an Idiot http://is.g ...
about 1 hour ago from web

armygirlnay @ArmywifeJulie he always jokes that his family lived at **Fort Hood** and he would visit us, LOL
about 2 hours ago from TweetDeck

sintonnniu Watch top quality streaming MOVIE American Pie: Book of Love -> http://cli.gs/At4g93 New Moon **Fort Hood** Kimbo Slice
about 2 hours ago from web

Brenner57 Love her or hate her, you have to admit this was generous. Palin donates royalties to **Fort Hood** families http://bit.ly/8mqcHA
about 2 hours ago from TweetDeck

sfneel I favorited a YouTube video -- WGN: Ahmed Rehab Discusses Anti-Muslim Sentiments Arising After **Fort Hood** http://bit.ly/7V2ayL
about 2 hours ago from Google

sfneel I favorited a YouTube video -- CAIR Video: Rachel Maddow Says Right-Wing Wrong on **Fort Hood** Attack http://bit.ly/43Cyd0
about 2 hours ago from Google

sfneel I favorited a YouTube video -- CAIR Director Condemns **Fort Hood** Attack on Fox http://bit.ly/6ld4yN
about 2 hours ago from Google

Figure 9.5. Results of a Twitter search for 'Fort Hood'. Note the high percentage of messages with a hyperlink embedded in them.

So we make use of this pointer in the Twitter message for extra information and crawl the links to analyze the content. Hence, in addition to the previously mentioned two strategies, the weight for the message is also affected by the content of the website mentioned in the message. A weight, which is a function of the factors such as the type of site (news, spam, blog etc.), the currency of the site, etc., is assigned to each message.

9.4 Semantic Similarity

Now that we have assigned the weights to each Twitter message, it becomes essential for us to summarize them into a couple of most meaningful keywords. A naïve approach to do this would be to simply take the keywords carrying the maximum weights and modify the query with them. But one disadvantage of this approach would be that it would not take into account the semantic similarity of the keywords involved, for example, 'shooting' and 'killing' are treated as two separate keywords, in spite of their semantic proximity. In this section we describe a process that in the first step reassigns weights to the keywords on the basis of semantic relatedness and in the second step picks k keywords that are semantically dissimilar but have maximum combined weight.

As mentioned earlier any two words are rarely independent and are semantically related to each other, for example, 'shooting', 'killing' and 'murder' are semantically very similar words. To calculate the same, we use the New York Times corpus that contains 1.8 million articles. The semantic similarity, S_{xy}, of two words x and y is defined as

$$S_{xy} = \frac{\max\{\log f(x), \log f(y)\} - \log f(x\,,y)\}}{\log M - \min\{\log f(x), \log f(y)\}} \tag{4}$$

where M is the total number of articles searched in New York Times Corpus; f(x) and f(y) are the number of articles for search terms x and y, respectively; and f(x, y) is the number of articles on which both x and y occur.

Now we reassign the weight to the i^{th} keyword on the basis of the following formula:

$$W_i^* = W_i + \sum(S_{ij} \times W_j) \tag{5}$$

where W_i^* is the new weight of the keyword, W_i is the weight without semantic similarity, S_{ij} is the semantic similarity derived from formula and $W_j$is the initial weight of the other words being considered.

After all the n keywords are reassigned a weight, we go to our next step that aims at identifying k keywords that are semantically dissimilar but together contribute maximum weight. In other words, choose words $W_1, W_2, \dots, W_k$ such that

1: $S_{pq} < S_{Threshold}$, the similarity between any two words, p and q, belonging to the set k is less than a threshold, and

2: $W_1 + W_2 + \cdots + W_k$ is maximum for all groups satisfying condition (1).

It can be easily shown that the complexity of the above described method is exponential in *n*. We thus briefly describe three techniques to approximately come up with the *k* keywords.

First, we applied the greedy algorithm approach. For this, we arrange all the words in decreasing order of their weights. We start with the keyword with the maximum weight that is W_1, put it in the basket and start traversing the array of words. Next, we define an objective function by

$$\Theta_i = \frac{W_i}{E_i} \tag{6}$$

where E_i is the sum of semantic similarity of word *i* with all the words in the basket, and W_i is its own weight. Hence at each step of the algorithm we choose a word that maximizes the objective function (Θ).

The second approach is the hill climbing approach. We choose a set of *k* random words that satisfy the condition (1) mentioned above. Next, we randomly select a word and check if it satisfies the condition of semantic similarity threshold with all the *k* words. If its weight is more than the weight of the lightest word, we replace the two. We keep repeating the process until the random word selected does not satisfy the condition.

And our final method is that of simulated annealing. The advantage of simulated annealing as compared to hill climbing is that it does not get stuck on local minima. It takes into consideration the neighborhood as well and decides its progress on the basis of an objective function.

Amongst the three methods described above, simulated annealing produces the most accurate results, but in general is slower than the other two. The running time of these methods heavily depends on the value of *k*. And since for our approach *k* is a very small number (usually 2), we can safely adopt simulated annealing to obtain the bag of *k* words.

These *k* keywords derived from reassigning the weights after taking semantic similarity into account are treated as special words that act as pointers, making the news intent of the query evident to the current search engine algorithm.

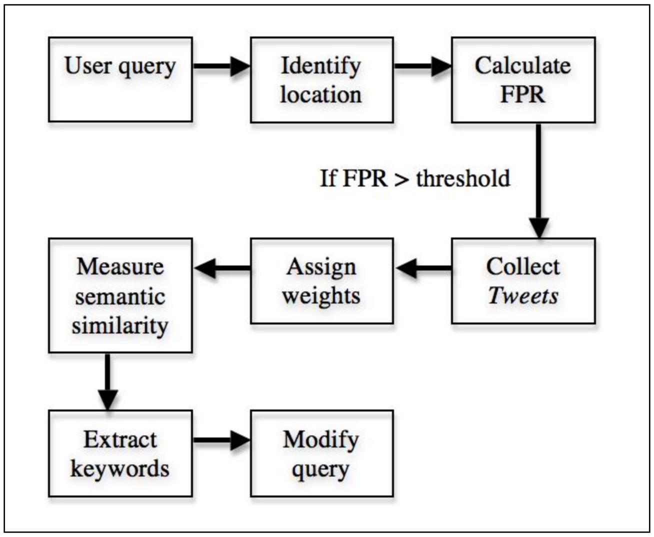
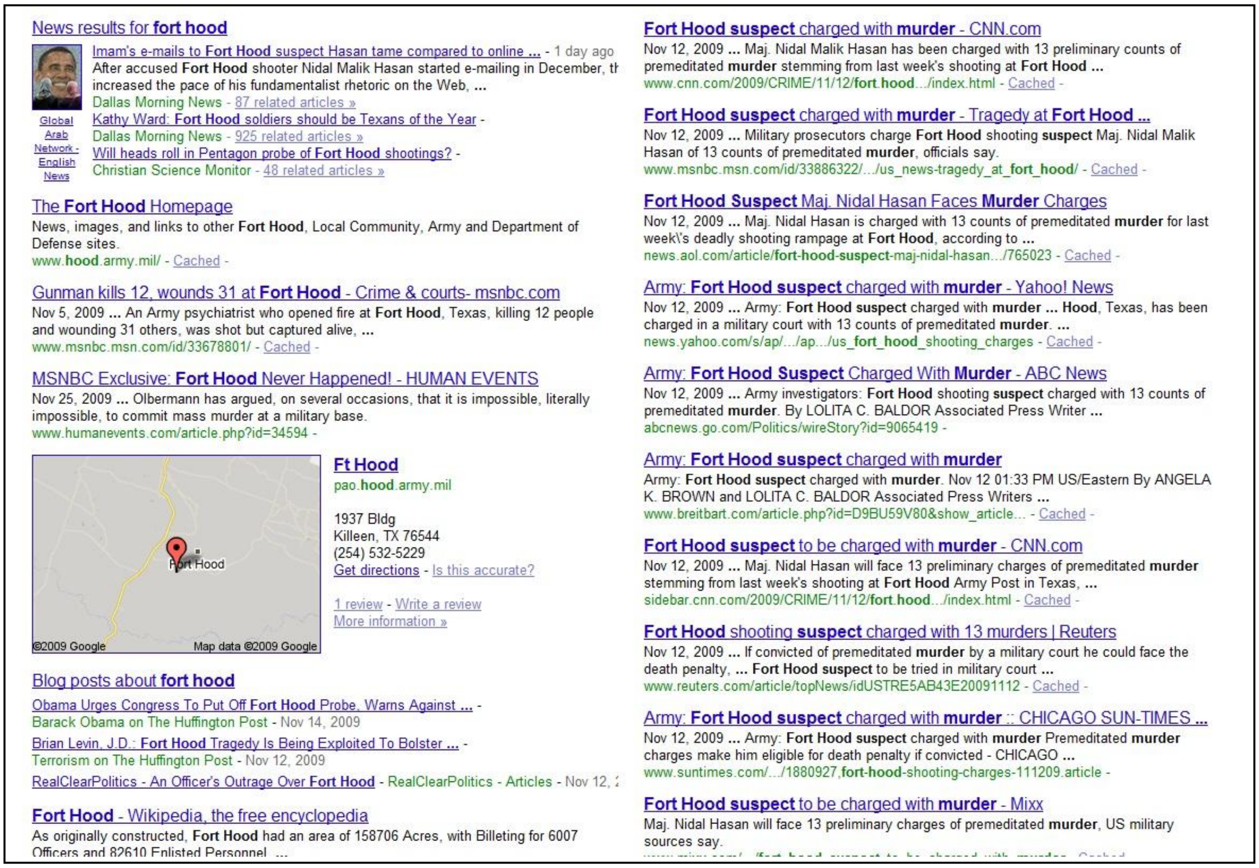


Figure 9.6. Architecture of news intent system TWinner

9.5 Experiments And Results

To see the validity of our hypothesis, we performed experiments to determine two words ($k = 2$) to enhance two queries which returned confidence values of ~ 1 indicating news intent. The first experiment was conducted to enhance the search query "Fort Hood" entered by a user on 12th November 2009. For this, we collected over 10k Twitter messages for 12th November having the keywords 'Fort Hood' or 'Texas' in them, and used our approach to determine the keywords. After using our methods and assigning weights to the messages the keywords 'murder' and 'suspect' were selected by the algorithm to have the cumulative weights. We added these keywords to the search query and observed the impact they had on the results returned by the search engine. The difference on the results is shown in Fig 9.7.

In a similar fashion we conducted an experiment to enhance the query for 'Russia'. We chose all the Twitter messages containing the keyword 'Russia' and applied the algorithm to them. The algorithm returned the two words 'night' and 'explosion', but it was interesting to note here that two other sets of words ‘club’ and ‘explosion’, also had very similar collective weight. In such a scenario, the algorithm chooses all three words ‘night’, ‘club’ and ‘explosion’ to enhance the query.



News results for fort hood
Imam's e-mails to Fort Hood suspect Hasan tame compared to online ... - 1 day ago
After accused Fort Hood shooter Nidal Malik Hasan started e-mailing in December, tł increased the pace of his fundamentalist rhetoric on the Web, ...
Dallas Morning News - 87 related articles »
Global Arab Network - English News
Kathy Ward: Fort Hood soldiers should be Texans of the Year -
Dallas Morning News - 925 related articles »
Will heads roll in Pentagon probe of Fort Hood shootings? -
Christian Science Monitor - 48 related articles »

The Fort Hood Homepage
News, images, and links to other Fort Hood, Local Community, Army and Department of Defense sites.
www.hood.army.mil/ - Cached -

Gunman kills 12, wounds 31 at Fort Hood - Crime & courts- msnbc.com
Nov 5, 2009 ... An Army psychiatrist who opened fire at Fort Hood, Texas, killing 12 people and wounding 31 others, was shot but captured alive, ...
www.msnbc.msn.com/id/33678801/ - Cached -

MSNBC Exclusive: Fort Hood Never Happened! - HUMAN EVENTS
Nov 25, 2009 ... Olbermann has argued, on several occasions, that it is impossible, literally impossible, to commit mass murder at a military base.
www.humanevents.com/article.php?id=34594 -

Ft Hood
pao.hood.army.mil
1937 Bldg
Killeen, TX 76544
(254) 532-5229
Get directions - Is this accurate?
1 review - Write a review
More information »

Blog posts about fort hood
Obama Urges Congress To Put Off Fort Hood Probe, Warns Against ... -
Barack Obama on The Huffington Post - Nov 14, 2009
Brian Levin, J.D.: Fort Hood Tragedy Is Being Exploited To Bolster ... -
Terrorism on The Huffington Post - Nov 12, 2009
RealClearPolitics - An Officer's Outrage Over Fort Hood - RealClearPolitics - Articles - Nov 12, 2

Fort Hood - Wikipedia, the free encyclopedia
As originally constructed, Fort Hood had an area of 158706 Acres, with Billeting for 6007 Officers and 82610 Enlisted Personnel. ...

Fort Hood suspect charged with murder - CNN.com
Nov 12, 2009 ... Maj. Nidal Malik Hasan has been charged with 13 preliminary counts of premeditated murder stemming from last week's shooting at Fort Hood ...
www.cnn.com/2009/CRIME/11/12/fort.hood.../index.html - Cached -

Fort Hood suspect charged with murder - Tragedy at Fort Hood ...
Nov 12, 2009 ... Military prosecutors charge Fort Hood shooting suspect Maj. Nidal Malik Hasan of 13 counts of premeditated murder, officials say.
www.msnbc.msn.com/id/33886322/.../us_news-tragedy_at_fort_hood/ - Cached -

Fort Hood Suspect Maj. Nidal Hasan Faces Murder Charges
Nov 12, 2009 ... Maj. Nidal Hasan is charged with 13 counts of premeditated murder for last week\'s deadly shooting rampage at Fort Hood, according to ...
news.aol.com/article/fort-hood-suspect-maj-nidal-hasan.../765023 - Cached -

Army: Fort Hood suspect charged with murder - Yahoo! News
Nov 12, 2009 ... Army: Fort Hood suspect charged with murder ... Hood, Texas, has been charged in a military court with 13 counts of premeditated murder. ...
news.yahoo.com/s/ap/.../ap.../us_fort_hood_shooting_charges - Cached -

Army: Fort Hood Suspect Charged With Murder - ABC News
Nov 12, 2009 ... Army investigators: Fort Hood shooting suspect charged with 13 counts of premeditated murder. By LOLITA C. BALDOR Associated Press Writer ...
abcnews.go.com/Politics/wireStory?id=9065419 -

Army: Fort Hood suspect charged with murder
Army: Fort Hood suspect charged with murder. Nov 12 01:33 PM US/Eastern By ANGELA K. BROWN and LOLITA C. BALDOR Associated Press Writers ...
www.breitbart.com/article.php?id=D9BU59V80&show_article... - Cached -

Fort Hood suspect to be charged with murder - CNN.com
Nov 12, 2009 ... Maj. Nidal Hasan will face 13 preliminary charges of premeditated murder stemming from last week's shooting at Fort Hood Army Post in Texas, ...
sidebar.cnn.com/2009/CRIME/11/12/fort.hood.../index.html - Cached -

Fort Hood shooting suspect charged with 13 murders | Reuters
Nov 12, 2009 ... If convicted of premeditated murder by a military court he could face the death penalty, ... Fort Hood suspect to be tried in military court ...
www.reuters.com/article/topNews/idUSTRE5AB43E20091112 - Cached -

Army: Fort Hood suspect charged with murder :: CHICAGO SUN-TIMES ...
Nov 12, 2009 ... Army: Fort Hood suspect charged with murder Premeditated murder charges make him eligible for death penalty if convicted - CHICAGO ...
www.suntimes.com/.../1880927,fort-hood-shooting-charges-111209.article -

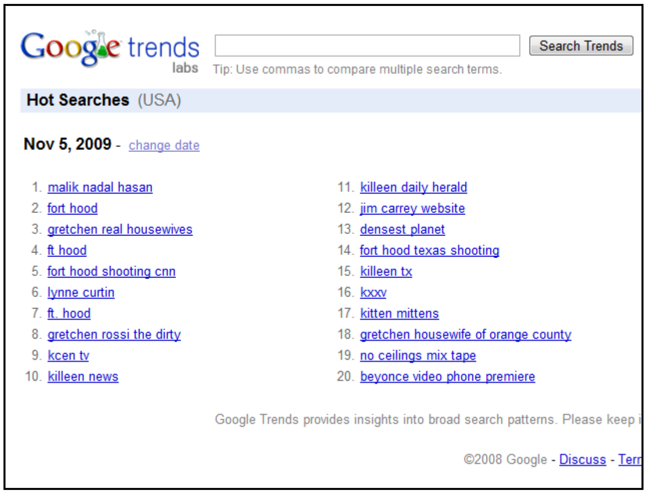
Fort Hood suspect to be charged with murder - Mixx
Maj. Nidal Hasan will face 13 preliminary charges of premeditated murder, US military sources say.

Figure 9.7. Contrast in search results produced by using original query and after adding keywords obtained by TWinner.

It can be observed that without using TWinner, the search engine is not sure about the news intent of the user. As a result, it displays results that constitute a short news caption, the homepage of Fort Hood, the maps version, Wikipedia articles, etc. On the right side in Figure 9.7 is an enhanced version of the query obtained after TWinner extracted the keywords ‘murder’ and ‘suspect’. The impact on the content of results is clearly visible. Majority of the search results are news-oriented and are also in accordance with the date the user issued the query, that is, 12th November (The Twitter dataset was also collected for 12th November).

9.6 Time Complexity

One of the apparent concerns raised by the methodology adopted could be the real time application to search queries. We would like to point out the fact that the process described earlier does not need to be repeated for each query, but instead the search engine can do it on a periodic basis and cache the special keywords corresponding to a particular keyword. And in times of situations like the Ft. Hood shootings in November 2009, ‘Fort Hood’ would become a top searched query. The Google search trends (Google Trends, 2009) for 5th November support our assumption as shown in Fig 9.8.



Hot Searches (USA)

Nov 5, 2009 -

1. malik nadal hasan
2. fort hood
3. gretchen real housewives
4. ft hood
5. fort hood shooting cnn
6. lynne curtin
7. ft. hood
8. gretchen rossi the dirty
9. kcen tv
10. killeen news
11. killeen daily herald
12. jim carrey website
13. densest planet
14. fort hood texas shooting
15. killeen tx
16. kxxv
17. kitten mittens
18. gretchen housewife of orange county
19. no ceilings mix tape
20. beyonce video phone premiere

Google Trends provides insights into broad search patterns. Please keep i

©2008 Google - Discuss - Terr

Figure 9.8. Google Search Trends for 5th November 2009.

CHAPTER 10

CONCLUSIONS AND FUTURE WORK

In this chapter we summarize the three location mining algorithms, Tweethood, Tweecalization and Tweeque, and the application, TWinner, described in the previous chapters. And later, we give directions to possible extensions to those approaches.

10.1 Conclusion

In this dissertation, we have made an important contribution in the field of identifying the current location of a user using the social graph of the user. The dissertation describes in detail three techniques for location mining from the social graph of the user and each one is based on strong theoretical machine learning. We demonstrate how the problem of identification of location of a user can be mapped to a data mining problem. We conduct a variety of experiments to show the validity of our approach and how it outperforms previous approaches and the traditional content based text mining approach in accuracy.

As an application of our work, we developed an application, TWinner, to demonstrate the application of location-based social media in improving the quality of web search and predicting whether the user is looking for news or not.

10.1.1 Challenges in Location Mining

Location is a very important attribute of the user profile, but experiments conducted by us revealed that only 14.3% users actually reveal their location on Twitter. And even among those who share their locations, there are some who provide invalid geographical information, incorrect locations which may actually exist, multiple locations, or just state or country level locations. Hence, explicitly mentioned locations are rare and untrustworthy.

Next, we looked at the various methods of determining the location of a given user. The first obvious choice is that of utilizing the user's IP information to obtain a location using large gazetteers. But, this approach has its drawbacks such as giving wrong locations, giving broad geographic locations, etc. Also, it is only Twitter which has access to the user's IP address and we want to look at prediction techniques which can be used by person.

In the remainder of Chapter 3, we discussed the challenges faced in mining the location of the user either from the messages or the social graph of the user. Content-based location mining is inaccurate primarily because the existing approaches do not work well on Twitter's noisy and unstructured data. Other issues with location mining from text include presence of multiple classes and ambiguity (Geo/Geo and Geo/Non-Neo).

Mining location from the social graph is also not an easy task in itself. The fact that only a small percentage of users reveal their locations makes the presence of labeled data scarce. Other challenges include the presence of spammers and celebrities. And finally, the absence of date/time information makes it difficult to account for migration and separate out the most recent location from previous locations.

10.1.2 Geospatial Proximity and Friendship

In Chapter 4, we studied the relationship between geospatial proximity of two users and the probability of friendship. We conducted experiments on a large number of users, whose location was known, and re-enforced the fact that the likelihood of friendship with a person decreases with distance, even for Twitter users. In fact, the relationship follows power law having a curve of the form $\mathrm{a}(\mathrm{x}+\mathrm{b})^{-c}$ with exponent of -0.87 and for distances greater than 1000 miles becomes a straight line.

10.1.3 Tweethood: *k*-Closest Friends with Variable Depth

The first approach we propose is based on the commonly used *k* nearest neighbor algorithm. It looks at locations of the *k*-closest friends of a user and decides on the basis of that. We show the evolution of the algorithm, starting from a simple majority approach, going on to the *k*-nearest neighbor approach and finally suggesting the fuzzy *k*-nearest neighbor approach which maintains the location as a vector with associated probabilities. Each of these algorithms takes as input a variable called depth, which allows us to go further into the graph of a friend of the user, if his or her (the friend's) location is not known. The presence of variable depth increases the number of labeled data at the cost of running time. The experiments conducted by us show the efficacy of the approach. With increasing depth, as expected, the accuracy increases, but saturates for depth>3.

These findings can be attributed to the phenomenon of "Six degrees of separation" (Wikipedia) (Newman, Barabasi, & Watts, 2011). Six degrees of separation is the idea that everyone is six or fewer steps away, by way of introduction, from any other person in the world, so that a chain of "a friend of a friend" statements can be made to connect any two people in a maximum of six steps. It was originally set out by Frigyes Karinthy (Karinthy, 1929) and popularized by a play written by John Guare (Art). A 2007 study by Jure Leskovec and Eric Horvitz examined a data set of instant messages composed of 30 billion conversations among 240 million people. They found the average path length among Microsoft Messenger users to be 6.6 (Leskovec & Horvitz, 2008). This research has been extended to social networks also. Facebook's data team released two papers in November 2011 which document that amongst all Facebook users at the time of research (721 million users with 69 billion friendship links), there is an average distance of 4.74 (Ugander, Karrer, Backstrom, & Marlow, 2011). For Twitter, two studies were conducted. The first, by social media monitoring firm Sysomos, studied 5.2 billion relationships and determined that the average distance on Twitter is 4.67 (Cheng A. , 2010). The other research shows that the average distance for 1500 users on Twitter is 3.435 (Bakhshandeh, Samadi, Azimifar, & Schaeffer, 2011). Hence, to conclude, for depth greater than 4, no new data points (labels) are added to the experiments and, hence, the accuracy of the algorithm saturates. We choose the values k=10, d=3 for TweetHood because of its optimal combination of accuracy and time complexity. We are able to correctly identify the location of the user at the city level with an accuracy of 60.1% and concept of group of cities with 72.1%. The accuracy for country level identification is reported to be 80.1%.

10.1.4 Tweecalization: Location Mining using Semi-supervised Learning

Since only a small fraction of users explicitly provide a location (labeled data), the problem of determining the location of users (unlabeled data) based on the social network is a classic example of a scenario where the semi-supervised learning algorithm fits in. Our second location mining algorithm, Tweecalization, demonstrates how the problem of identification of the location of a user can be efficiently solved using label propagation algorithm.

For any machine learning technique, it is very important how we define the weight between data points (users). Previous graph-based approaches (Abrol & Khan, 2010) (Backstrom, Sun, & Marlow, 2010) either build a probabilistic model or simply look at the location of the friends to predict the location. In other words, these techniques are un-intelligent and have the common flaw that not all friends are equally credible when suggesting locations for the primary user. In Chapter 6, we introduced the notion of trustworthiness for two specific reasons. First, we want to differentiate between various friends when propagating the labels to the central user and second, to implicitly take into account the social phenomenon of migration and thus provide for a simple yet intelligent way of defining similarity between users.

The system performs better than the traditional gazetteer based approach (Abrol & Khan, MapIt: Smarter Searches Using Location Driven Knowledge Discovery And Mining, 2009) and Tweethood (Abrol & Khan, 2010), in respect to both time and accuracy and is thus suited for the real-time applications. We choose the values d=4 for Tweecalization because of its optimal combination of accuracy and time complexity. We are able to correctly identify the location of the user at the city level with an accuracy of 75.5% after using agglomerative clustering. The accuracy for country level identification is reported to be as high as 80.10%.

10.1.5 Tweeque: Identifying Social Cliques for Intelligent Location Mining

In Chapter 7, we presented Tweeque, a spatio-temporal mining algorithm that predicts the most current location of the user purely on the basis of his or her social network. The algorithm goes beyond the previous approaches by understanding the social phenomenon of migration. The algorithm then performs graph partitioning for identifying social groups thus allowing us to implicitly consider time as a factor for prediction of a user’s most current city location.

Our detailed experiments on understanding the importance of geographical migration reveal that a significant number (4 to 6 million) of people in the United States move out of their counties each year. Next, experiments on over 300,000 public Facebook profiles show that only one third of the users have their current location the same as their hometown. This leads us to the conclusion that social migration is too important of a phenomenon to be ignored.

Doing temporal analysis would have been much easier, if we had a timestamp attached to each friendship to indicate when it was formed in real world and we would have just looked at the most recent friends to determine the current location. But, unfortunately, that doesn’t happen. So we came up with a way of inferring the time the friendship was created. To do that, we made two very simple social science observations. In our first observation, we claim that if we can divide the friends of a user into social cliques (such as high school friends), then all members of a clique were or are at a particular geographical location at a particular instance of time like college, school, a company, etc. And the second observation, states that over time people have a tendency to migrate from one location to other. Based on these two social science observations, we propose a new social science theory. We hypothesize that if we can divide the social graph of a particular user into cliques as defined above and check for location-based purity of the cliques, we can accurately separate out his or her current location from other locations.

To identify social cliques with a complexity that is polynomial in time, we use a graph partitioning algorithm (Shi & Malik, 2000), used previously for image segmentation. The algorithm then performs graph partitioning for identifying social groups of the user. We then perform purity-based voting in each such group. The group which has the maximum purity points to the most current location of the user.

The extensive experiments conducted by us show the validity of the approach. Tweeque achieves an accuracy of 76.3% at the city level and 84.9% at the country level, which outperforms the traditional content-based technique and previous social graph-based approaches, Tweethood and Tweecalization.

10.1.6 Agglomerative Clustering

Each of the three algorithms described above returns a location vector, which consists of a series of geographical locations, each associated with a confidence value. In Chapter 8, we proposed the use of agglomerative hierarchical clustering to make the output of the algorithm more meaningful. Clustering allows us to group locations which are very close to each other, thereby increasing the confidence at a minimal loss of location precision. For example, instead of returning just Dallas, Texas as the predicted location of the user, the algorithm may return {Dallas, Plano, Richardson} as the final location group, since Plano and Richardson are suburbs of Dallas.

10.1.7 TWinner: Understanding News Queries With Geo-Content Using Twitter

In Chapter 9, we discussed the development of an application called TWinner which focuses on identifying the intent of a user on search engines. Amongst the various categories of search queries, a major portion is constituted by those having news intent. Seeing the tremendous growth of social media users, the spatial-temporal nature of the media can prove to be a very useful tool to improve the search quality. TWinner combines location-based social media in improving the quality of web search and predicting whether the user is looking for news or not. It actually goes one step beyond the previous research by mining Twitter messages, assigning weights to them and determining keywords that can be added to the search query to act as pointers to the existing search engine algorithms suggesting to it that the user is looking for news.

10.2 Future Work

We discuss several extensions to our proposed work for location mining and possible applications.

10.2.1 Combining Content- and Graph-based Methods

We would like to investigate the effectiveness of combining the content-based (Hecht, Hong, Suh, & Chi, 2011) (Cheng, Caverlee, & Lee, You are where you tweet: a content-based approach to geo-locating twitter users, 2010) (Abrol & Khan, 2009) and the graph-based methods for location mining. Both techniques have their individual strengths and weaknesses as discussed in Chapter 3 of the dissertation. An intelligent technique to combine the two approaches would result in an algorithm that is much more accurate and also confident in returning the location. A clear advantage the content-based approach would provide is the ability to perform better temporal analysis (since all tweets are associated with timestamps).

10.2.2 Improving Scalability using Cloud Computing

A major concern is the running time of the algorithm. Since Twitter has millions of active users, it becomes a necessity to have scalable algorithms that can determine locations in fraction of a second. For this, we would like to utilize cloud computing. We propose using either the Apache Hadoop framework (Hadoop, Apache Hadoop, 2013) (Hadoop, Apache Hadoop Documentation, 2013) (Husain, Khan, Kantarcioglu, & Thuraisingham, 2010) or Twitter Storm framework (Storm, 2013) (Marz, 2011) which is designed specially by Twitter for streaming data. The use of a distributed framework would result in the partitioning of the social graph of a user allowing for parallel processing of friends and, hence, better scalability.

10.2.3 Micro-level Location Identification

The current research in location mining focuses primarily on determining the city level home location of a user. Foursquare is a location-based social network and is the focus of some current research (Cheng, Caverlee, Lee, & Sui, 2011) (Noulas, Scellato, Mascolo, & Pontil, 2011) (Masud, Al-Khateeb, Khan, Aggarwal, & Han, 2012)

There has been no prior work at identifying specific places like coffee shops, restaurants, etc., that a user may be talking about or visiting. In the future we would like to explore algorithms that can identify these points of interests (POIs). We propose to use crowd-sourced databases such as the Foursquare Venues Database (Foursquare, 2013). The database has over 50 million venues from all over the world (Jeffries, 2012) and is hence by far the most comprehensive database for POIs.

The identification of specific places that a user talks about can be further used to identify the comfort zone(s) of the user. This has several applications that include better target marketing and also better emergency preparedness and response.

10.2.4 Location-based Sentiment Mining

There has been some prior work done for mining the user sentiment from the language used in the Twitter messages (Go, Bhayani, & Huang, 2010) (Barbosa & Feng, 2010) (Kouloumpis, Wilson, & Moore, 2011) (Saif, He, & Alan, 2012). But, there are very few or no tools that perform location-based sentiment analysis. The presence of such a tool holds great potential and can be used by corporations for targeted marketing and/or by government agencies for security analysis and threat detection.

Also, determination of location can help us in designing better sentiment mining algorithms and improving accuracy. For this, we propose the introduction of "location-based bias" to the existing algorithms. The proposed technique would introduce a location-based bias in the score for calculation of the final score. For example, if we know that Texas is pro-Republican then we introduce a positive bias to a tweet from a Texas resident about Republicans.

10.2.5 Effect of Location on Psychological Behavior

There has been some prior work on predicting the psychological state of a person based on the messages he or she posts (Chung & Pennebaker, 2008). Another application that we can build would help us analyze the effect of location on the psychological behavior of people over time. For example, if there is an earthquake in Los Angeles on a particular day, what effect does it have on the behavior of people living in first, the Los Angeles area, and second the remaining cities of US?

APPENDIX

MAPIT: LOCATION MINING FROM UNSTRUCTURED TEXT

In this appendix we discuss the content based approach developed by us (Abrol & Khan, 2009) to identify the location of a user on Twitter. It is important to understand here that a location concept is typically of the format {City} A/ {State} B/ {Country} C. And for each location depending on the level of detail, either of A, B or/and C can be null.

To determine the location from mining the messages, we devise a score-based identification and disambiguation method Location_Identification. Before running the actual algorithm, we perform preprocessing of data, which involves removal of all those words from the messages that are not references to geographic locations. For this, we use the CRF Tagger, which is an open source Part of Speech (POS) tagger for English with an accuracy of close to 97% and a tagging speed of 500 sentences per second (Phan, 2006). The CRF tagger identifies all the proper nouns from the text and terms them as keywords $\{K_1, K_2, \dots, K_n\}$. In the next step, the TIGER (Topologically Integrated Geographic Encoding and Referencing system) (TIGER/Line® Shapefiles and TIGER/Line Files, 2008) dataset is searched for identifying the city names from amongst them. The TIGER dataset is an open source gazetteer consisting of topological records and shape files with coordinates for cities, counties, zip codes, street segments, etc., for the entire US.

Algorithm: Location_Identification (UM)

Input: *UM*: All Messages of User

Output: *Vector (C, S)*: Concepts and Score vector

```
For each keyword, $K_i$    //Phase 1
    For each $C_j \in K_i$//$C_j$ - Street Concept
        For each $T_f \in C_j$
            $type = Type(T_f)$
            If ($T_f$ occurs in $UM$) then $S_{C_j} = S_{C_j} + S_{type}$
For each keyword, $K_i$    //Phase 2
    For each $C_j \in K_i$//$C_j$ - Street Concept
        For each $T_f \in C_j \; AND \; T_s \in C_l$
            If $\left(T_f = T_s\right) AND \; (C_j = C_l)$
                $type = Type(T_f)$
                $S_{C_j} = S_{C_j} + S_{type}$
Return $(C, S)$
```

The algorithm describes the gazetteer based algorithm. We search the TIGER gazetteer (TIGER/Line® Shapefiles and TIGER/Line Files, 2008) for the concepts $\{C_1, C_2, \ldots, C_n\}$ pertaining to each keyword. Now our goal for each keyword would be to pick out the right concept amongst the list, in other words disambiguate the location. For this, we use a weight-based disambiguation method. In Phase 1, we assign the weight to each concept based on the occurrence of its terms in the text. Specific concepts are assigned a greater weight as compared to the more general ones. In Phase 2, we check for correlation between concepts, in which one concept subsumes the other. In that case, the more specific concept gets the boosting from the more general concept. If a more specific concept C_i is part of another C_j then the weight of C_j is added to that of C_i.

Let us try to understand this by looking at an example. City carries 15 points, state 10 and a country name carries 5 points. For the keyword "Dallas", consider the concept of {City} Dallas/ {State} Texas/ {Country} USA. The concept gets 15 points because Dallas is a city name, and it gets an additional 10 points if Texas is also mentioned in the text. In Phase 2, we consider the relation between two keywords. Considering the previous example, if {Dallas, Texas} are the keywords appearing in the text, then amongst the various concepts listed for "Dallas" would be {City} Dallas/{State} Texas/{Country} USA and one of the concepts for "Texas" would be {State} Texas/ {Country} USA. Now, in Phase 2 we check for such correlated concepts, in which one concept subsumes the other. In that case, the more specific concept gets the boosting from the more general concept. Here, the above mentioned Texas concept boosts up the more specific Dallas concept. After the two phases are complete, we re-order the concepts in descending order of their weights. Next, each concept is assigned a probability depending on their individual weights.

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