Location Prediction in Social Media Based on Tie Strength

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ABSTRACT

We propose a novel network-based approach for location estimation in social media that integrates evidence of the *social tie strength* between users for improved location estimation. Concretely, we propose a location estimator – FriendlyLocation – that leverages the relationship between the strength of the tie between a pair of users, and the distance between the pair. Based on an examination of over 100 million geo-encoded tweets and 73 million Twitter user profiles, we identify several factors such as the number of followers and how the users interact that can strongly reveal the distance between a pair of users. We use these factors to train a decision tree to distinguish between pairs of users who are likely to live nearby and pairs of users who are likely to live in different areas. We use the results of this decision tree as the input to a maximum likelihood estimator to predict a user's location. We find that this proposed method significantly improves the results of location estimation relative to a state-of-the-art technique. Our system reduces the average error distance for 80% of Twitter users from 40 miles to 21 miles using only information from the user's friends and friends-of-friends, which has great significance for augmenting traditional social media and enriching location-based services with more refined and accurate location estimates.

Categories and Subject Descriptors

H.2.8 [**Database Applications**]: Data Mining

Keywords

location prediction, spatial data mining, Twitter

1. INTRODUCTION

Location-based social media is widespread, with the adoption of voluntary user-based location sharing via "check-in" services like Foursquare, geo-tagged posts on Twitter, and photos shared on Flickr and Instagram. These services allow users to annotate their activities with a location field, ranging from a broad descriptor like "New York" or "USA" to an extremely granular latitude/longitude pair derived from the GPS capabilities of modern smartphones. Millions of users have already adopted these location sharing services, providing an unprecedented *geographical perspective* on the trails and connections among millions of social media users.

By investigating the interplay between geography and social media, both researchers and practitioners are enabling new applications that leverage location. Location information is increasingly incorporated into social media for providing localized content, location-aware recommendations, and other geo-spatial enabled services. For example, researchers have begun investigating techniques to cluster users based on their revealed geographic patterns [15], automatically deriving location-based social networks, and improving friend suggestion based on geographic proximity [4], [17], [3]. Localized social media activity – like Twitter discussions about a recent city council vote – can be automatically detected and directed to interested parties. Crowds of co-located people can be identified and related support services can be directed toward them – in the case of a fire or emergency, resources may be more smartly targeted to the affected regions.

Tempering this excitement, however is a key challenge: how to derive high-quality location estimates for users in social media. Many users choose not to reveal their location, while others may reveal their location only using noisy or overly general descriptors (e.g., " New York"). To tackle this challenge, one of the most popular location estimation methods is *network-based estimation*, in which a user's location is derived from the known location properties of other users nearby in the social network (e.g,. if most of my direct friends are in San Francisco, then perhaps I am as well) [5], [11]. One of the best known network-based approaches was introduced by Facebook researchers Backstrom et al. [1] in a comprehensive study over 2.9 million Facebook users. This Facebook study analyzed users who had posted a home street address and found that as distance increases, the probability of friendship decreases. Building on this observational study of Facebook users, they showed how the street addresses of a user's friends could be used to predict a user's location within 25 miles 57% of the time.

While an encouraging first step, this Facebook approach may encounter difficulties in location estimation when applied more broadly to other social media services:

- *Multiple (often imprecise) location granularities.* First, many users in social media reveal broad, imprecise locations (e.g., at the city or state level), while others provide fine-grained latitude-longitude information. In particular, users are less likely to post precise locations such as street addresses on public websites such as Twitter. How

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can these multiple location granularities be integrated to account for uncertainty at different levels?

- *Varying social ties.* Second, not all relationships in social media are the same. Some ties are stronger than others, and presumably some ties are more revealing of a user's location. How does this variable tie strength nature impact location estimation?
- *Conflicting purposes.* Finally, many social systems serve different purposes. Twitter, for example, is both a social network connecting friends (which may tend to be local) as well as a news media (supporting global dissemination) [10]. What is the appropriate balance between these conflicting purposes for location estimation?

To address these challenges, we propose a novel network-based approach for location estimation that integrates evidence of the *social tie strength* between users for improved location estimation, naturally incorporates uncertainty across multiple location granularities, and can distinguish between users of the system that operate at cross-purposes. We investigate this approach through an examination of over 100 million geo-encoded tweets and 73 million user profiles collected from Twitter. Concretely, we propose a location estimator – FriendlyLocation – and investigate the relationship between the strength of the tie between a pair of users and the distance between the pair. Based on this investigation, we identify several factors such as number of followers and how the users interact that can strongly reveal the distance between a pair of users, and use these factors to train a tree classifier to predict the distance between a pair of connected users. We use the results of this classifier as the input to a maximum likelihood estimator to predict a user's location. We find that this proposed method significantly improves the results of location estimation relative to the Facebook technique. FriendlyLocation improves the average error distance for 80% of Twitter users from 41 miles to 21 miles which has great significance for augmenting traditional social media and enriching location-based services with more refined and accurate location estimates.

2. RELATED WORK

The study of geographical properties of online social media users has drawn intensive attention in recent years. Characterizing network properties in relation to local geography has been studied in [18]. Lindqvist [12] analyzed how and why people use location sharing services, and discussed the privacy issues related to location sharing services. User behavior with regard to the location field in Twitter user profiles has been studied in [9].

Scellato et al. [16] used data from three location based social networks to investigate the relationship between distance and location, and they showed that connections are not purely caused by geographical or social factors. They investigated two random models where they shuffle the user locations and another where they shuffled the social connections and investigated what happened to the user location. They showed that if a user has more connections, then their friends tend to be further away. They also found that longer connections are equally likely to be part of a social triangle as shorter connections.

Several researchers in recent years have looked into predicting user locations in a social network based on the social graph. In the largest-to-date study on this subject, Facebook researchers analyzed the physical distance between Facebook users' social relations and utilized the locations of a user's friends' to predict the user's geographical location [1]. Davis et al. [5] investigated a system that predicted location by taking a vote among the locations of the user's friends and picking the most popular location.

An alternative to network-based approaches is *content-based*, in which a the content associated with a user either explicitly reveals location information (e.g,. mentioning a local attraction like Disneyland) or implicitly does so (e.g., by inferring subtle local linguistic cues to estimate a user's location). Cheng et al. [2] proposed a content-based system for locating users on Twitter. They found words that are highly concentrated in specific regions and built a model to calculate the probability that a user lives at a location. Eisenstein et al. [6] proposed a functionally similar system based on a latent variable model that predicted a user's location based on the words in their tweets. Recently, Li et al. [11] proposed a system to integrate both network and content-based estimation via a unified discriminative influence model which combined locations that a Twitter user mentioned with the locations of the user's followers.

In recent work [14], the authors look at users who post at least 100 geo-located tweets a month in NYC and LA. They reconstruct the social graph from co-occurring geo-located tweets and used dynamic Bayesian networks to predict where a user was at a particular moment in time.

Finally, Cranshaw et al. [4] tackled the inverse of the problem we are investigating: they predicted the existence of a social network tie given precise location information from laptops and cell phones. They used a collection of features of when users are co-located. Together, these efforts have begun to lay a foundation for the study geo-social media.

3. LOCATION ESTIMATION INCORPORATING TIE STRENGTH

In this section, we build a model for the probability that a user, who we refer to as the target user, lives at a specific location given the approximate location of his friends and followers. Every user on Twitter has a set of people that they interact with, which we refer to as their contacts. This includes the user's friends, followers, and people they mention in tweets (i.e., people the user speaks to). Many of these contacts share their locations. We define L^c to be the set of known locations of the contacts of a user. Given a target user, our goal is to estimate the location l of the user provided only with some imperfect information about the location of that user's social network, L^c. We first describe the baseline Facebook model for location estimation, identify several limitations of applying it more widely, and then describe the proposed FriendlyLocation approach that integrates tie strength for augmented location estimation.

3.1 Baseline: The Facebook Model

The Facebook model developed by Backstrom et al. [1] begins with a striking observation: that the probability of friendship is roughly inversely proportional to distance. Specifically, by examining the ratio of actual edges in the social graph at a particular distance to the total number of possible edges at that distance (i.e., the probability of friendship), they find a curve of the form $a(b+x)^{-c}$, with an exponent close to $c = -1$.

With the empirically observed probability of friendship, they can estimate the likelihood that a user lives at a location l using both L^c, the set of locations of the user's friends with known locations, and L^s, all 2.9 million known locations of Facebook users. Then, the Facebook model estimates the likelihood of location l as:

$$\text{Facebook}(l, L^c) = \prod_{l^c \in L^c} \frac{\text{p}(|l - l^c|)}{1 - \text{p}(|l - l^c|)} \prod_{l^s \in L^s} 1 - \text{p}(|l - l^s|)$$

where p is the probability of friendship given an input distance (which again, can be derived empirically). The first product in the formula combines the probabilities from a user's friends. Locations near a user's friends will have a higher probability because p is roughly inversely proportional to distance. The last product in the likelihood formula is only a function of the location l_i^c and the locations of the strangers; it does not depend on any other information about the target user's contacts. For convenience, we refer to this as pStgrs:

$$\text{pStgrs}(l) = \prod_{l^s \in L^s} 1 - p(|l - l^s|)$$

As suggested in [1], this can be pre-computed for every location. Major cities have the lowest probability for pStgrs, and remote areas have the highest probability. It may seem counter-intuitive that areas with low population density have a higher probability, but consider this example: if someone has ten friends in New York City and ten friends in a small town in upstate New York, they are more likely to live in the small town, and just happen to know people in the big city.

The Facebook model naturally aggregates the locations of a user's friends, and gives the probability that a user lives at a given location. They then calculate this probability at each of the locations of the user's friends. The location with the highest probability is often the center of the cluster of the user's friends. However, directly applying this approach to other non-Facebook domains may encounter difficulties. First, the Facebook empirical study focused only on the continental US, meaning that distances between contacts were naturally limited to around 1,000 miles. When investigating global friendships (as on Twitter or on the rest of Facebook), there is considerable noise introduced in the 1,000–10,000 mile range due to the distribution of land and oceans on the surface of the earth. Second, the Facebook dataset had street addresses for approximately 2.9 million Americans, and they used the friendships between users with street addresses to do the calculation. Since information on Facebook is usually only shared with a user's friends, people are more willing to divulge their home addresses. On most other social media websites, the location is publicly shared. In practice, many users in social media reveal broad, imprecise locations (e.g., at the city or state level), while others provide fine-grained latitude-longitude information. Third, the strength of connection between users necessarily varies, so capturing this variation is important. Encouragingly, Gilbert [7] have shown how the strength of a tie can be predicted by interaction patterns. Finally, many social systems serve different purposes. Twitter, for example, is both a social network connecting friends (which may tend to be local) as well as a news media (supporting global dissemination) [10].

3.2 FriendlyLocation: Incorporating Tie Strength

A common theme of these challenges is that the quality of the geographic information conveyed by a relationship in social media varies. Some edges may convey strong evidence of the location of a user. For example, intuitively the many

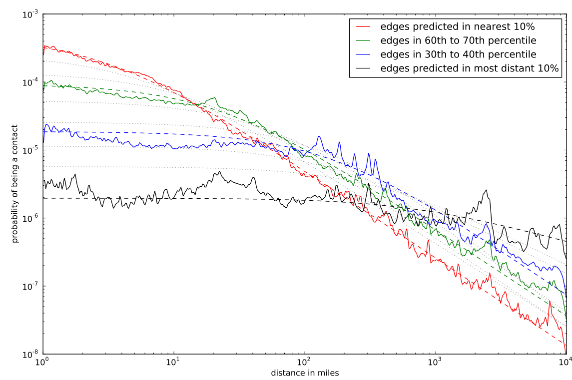


Figure 1: After splitting edges into quantiles based on their predicted distance, each quantile was fit to a curve. Here are four of the ten curves and their curves of best fit. The other six curves of best fit are shown as faint dotted lines.

edges between a user with an unknown location and his coworkers (for whom we know their location) should contribute strongly to the likelihood that the user is nearby those coworkers. In contrast, links between a user with an unknown location and with a news service (e.g., CNN) should contribute little discriminating power to estimating the location of the user.

The challenge here is to separate the best contacts, who are likely to be nearby, from bad contacts who are likely to be far away. Simply encoding our intuitions about who should make a good contact is a starting point, but could miss many non-obvious relationships: for example, there may exist a pair of users who are good friends, communicate with each other, have many friends in common, and yet still live on opposite sides of the globe.

Hence, we propose to assess the relative quality of each edge from a target user to his contacts, so that edges conveying strong location information are weighed more than others. This could be looked at as a classification problem where we want to classify edges as local or non-local, but the problem is there is a smooth continuum from local to non-local, and semi-local friends can be useful for location prediction. As a result, we model this as a regression problem, and we propose improving the Facebook system by adding in information from a decision tree. Concretely, suppose we have a single edge from a user to one of his contacts. We propose to assign this edge to a quantile based on its estimated "goodness" as determined by the decision tree. The tree regressor will sort out the best contacts and the worst contacts for location prediction.

Before going into the details of using the tree regressor, we introduce some notation:

- L^t denotes the locations of every target user
- L^s denotes the locations of every contact
- D^a is the set of actual distances from target users to contacts
- D^p is the set of goodness values returned by the decision tree
- $n = |D^a| = |D^p|$ is the number of edges
- m is the number of quantiles

Label	Size	Description	Data obtained
Target Users	249,584	Users who posted at least 3 geo-located tweets	Location from GPS coordinates, user ids of friends and followers, and text of tweets.
Geocoded Users	894,617	Users who posted at least 3 geo-located tweets and had a location the geocoder could parse, but not selected as target users	Location from GPS coordinates and geocoded location from user profile
Located Contacts	10 million	25 contacts of target users with locations, randomly selected	Geocoded location from profile, user ids of friends and followers, and text of tweets
Leafs	71 million	100 contacts of target users, randomly selected	user profile (some of these users have a geocoded profile)

Table 1: Four different sets of users and the data we obtained about them

Our crawler discovered millions of edges between target users and their contacts. We ran the decision tree regressor on these edges to create a set of tuples (d_i^a, d_i^p) for $d_i^a \in D^a$ and $d_i^p \in D^p$ where d_i^a is the actual distance from target to contact, and d_i^p is the value predicted by the decision tree. Although the values returned by the regression tree are also distances, we only use them as a measurement of quality.

Suppose we construct a set of m quantiles, representing edges with different predicted goodness. Let the boundaries for these quantiles be $\{q_0, \ldots, q_m\}$, where:[1]

$$q_j = \begin{cases} D^p_{(1+\lfloor \frac{jn}{m} \rfloor)}, & j < m \\ \infty & j = m \end{cases}$$

The quantile for a specific distance d_i^p can be found by comparing it to the boundaries:

$$\text{qntl}(d_i^p) = \max_{j \in \{0,\ldots,m\}} \{j : d_i^p < q_j\}$$

We use this to find actEdges, which is the number of edges that belong to quantile j and have a distance of d miles from the target to the contact:

$$\text{actEdges}(j, d) = |\{i \in \{1, \ldots, n\} : d = d_i^a \wedge j = \text{qntl}(d_i^p)\}|$$

We will compare this to the number of edges that could have possibly existed by looking at the Cartesian product of all the target users (L^t) and all of the contacts (L^s). We define stgrEdges to be the number of edges that could have existed at a distance d:

$$\text{stgrEdges}(d) = |\{(l^t, l^s) : l^t \in L^t \wedge l^s \in L^s \wedge d = |l_t - l_s|\}|$$

Just like they did in the Facebook paper, we can compare actEdges (the number of edges that actually existed in a specific quantile) with stgrEdges (the number of edges that might have existed) to find the probability that a contact in a quantile j lives d miles from the target user:

$$\text{p}^*(j, d) = \frac{\text{actEdges}(j, d)}{\text{stgrEdges}(d)}$$

For each of the quantiles, we can fit this probability to the curve from [1]:

$$\text{p}^*(j, d) = a_j(b_j + d)^{-c_j}$$

We can combine this improved model into the existing estimator by replacing the probability of being a contact based purely on distance (p) to the probability based on the regression tree (p^*). We now have a formula for predicting the best location given L, the set of locations of the contacts, and P, the set of predicted distances to the same contacts:

$$FL(l, L, P) = \left(\prod_{l_k^c \in L, p_k \in P} \frac{\text{p}^*(\text{qntl}(p_k), |l - l_k^c|)}{(1 - p(|l - l_k^c|))} \right) \text{pStgrs}(l)$$

We choose to split into ten quantiles, which gave us ten different curves for the probability that a certain type of contact exists between a pair of users. Four of the ten curves from one of the folds from the five-fold evaluation and their lines of best fit are shown in Figure 1. The best contacts are orders of magnitude more likely to live near a target user than the worst contacts. If the predictions from the tree regressor were ignored, and users were placed into one group instead of ten equal groups, this would reduce to the model for friendship and distance presented in [1]. We choose ten because it was large enough to distinguish between the curves. Larger numbers of quantiles give no benefit since the curves we are fitting are so noisy as can be seen in Figure 1.

4. FACTORS IMPACTING THE DISTANCE TO A CONTACT

In the previous section, we formalized the location estimation problem incorporating evidence of tie strength. But what factors actually impact the distance to a contact? In this section, we empirically examine a large sample from Twitter, totaling 100 million geo-encoded tweets and 73 million user profiles. Based on this sample, we examine the following properties to study how various types of edges correlated with proximity, including (i) friendship relationships, (ii) friend and follower counts, (iii) conversations between users, (iv) if the account is public or private, (v) edges in social triangles, (vi) distances from a contact to their contacts, and (vii) granularity of locations.

4.1 Data Collection from Twitter

To investigate how social relation and geographical distance between the relations correlate, we sample a dataset from Twitter. Our analysis and prediction is based on data collected from Twitter during May, June, and July of 2012.

We built a crawler to find these contacts for users who used Twitter's Location Feature to disclose their location. The crawler sampled over one hundred million geo-coded tweets by monitoring Twitter's public streaming API for all of May 2012. We kept the tweets from the users who posted at least three tweets, which left us with 1,758,101 Twitter users. For each of these users with geo-coded tweets, we used the median latitude and median longitude of the locations of the user's tweets as an approximation of her home location. Some Twitter accounts, such as accounts that posted jobs, would move around faster than a human could

[1]The notation used for order statistic may need some explanation. $X_{(n)}$ is the n^{th} element in the set X when sorted in increasing order, so $X_{(2)}$ means the second smallest element in X.

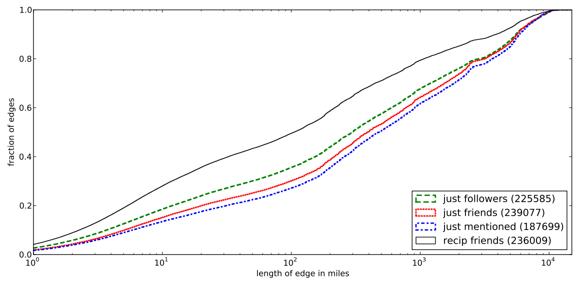


Figure 2: CDF of distance from target users to users they have some contact with. Reciprocal friends tend to be closer than other types of friendships.

possibly move. To account for this, the crawler calculated the distance between each tweet and the user's home location. The crawler ignored users if the median distance from their tweets to their home location was greater than 50 miles. This only removed 3.4% of the geo-located users. We also removed an additional 2.9% of the geo-located users who did not have any contacts with locations we could decode, which left us with 1.6 million Twitter users with a known location. We randomly selected 249,584 of these users for analysis and experimentation. [2] We refer to these users as the target users. Almost all of the experiments in this paper are based on these target users.

Users who post geo-located tweets are not entirely representative of the average Twitter user. In particular, they are less concerned about their privacy and have a precise location. We only use information obtained from the contacts, and not the geo-located users themselves in our prediction. There are some Twitter accounts, such as large organizations, who do not have a single location. In practice, a location prediction system would need to identify users who do not have a location.

For all of the target users, our crawler used Twitter's API to download the users' 100 most recent tweets, a list of friend ids, and a list of follower ids. We also collected the user profiles for a sample of users who were two steps away from the target users on Twitter's social graph. In the end, we collected just over 73 million Twitter user profiles. Table 1 shows a summary of the data obtained from Twitter. This data was used to do the analysis in the rest of this section.

4.2 Factor 1: What type of contact is closest?

We first consider the type of contact and its impact on distance by dividing all contacts into one of four disjoint sets:

Reciprocal Friend: The target user follows this user and is followed back.

Just Friend: The target user follows this user and is not followed back.

Just Follower: The target user is followed by this user, but does not follow them.

Just Mentioned: The users do not follow each other, but the target user mentioned the other user in a tweet.

[2]We originally selected 250,000 users, but had to remove 416 of them. These users had contacts with locations, but none of their contacts had meaningful locations.

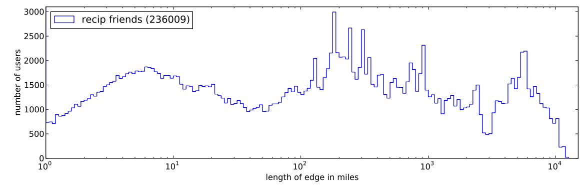


Figure 3: Histogram of distance to reciprocal friends.

Figure 2 shows the cumulative distribution function(CDF) of the distance between a target user and several types of contacts. Distance is plotted on a logarithmic scale to show both local and global effects. On a logarithmic scale, the contacts are fairly evenly distributed from being nearby to being on the opposite side of the world.

In general, we observe that reciprocal friends are the closest, followed by followers, friends, and finally users who are just mentioned. 38% of reciprocal friends live within 25 miles while only 18% of users who are just mentioned live within that radius. While it may seem that since being followed by someone and following someone should be identical, they are not. Celebrity and news accounts on Twitter often have large numbers of followers, but they normally do not follow a large number of users. Since the target user is selected randomly, they are usually an average user and not a celebrity. If they follow someone, it might be a celebrity; however, if someone follows them, it is probably someone who knows them.

What is the distribution of contacts? To further analyze the distribution of contacts, we show in Figure 3 a logarithmically-scaled histogram of the distances between various types of contacts. All four types of contacts follow roughly the same distribution: one peak around 10 miles from people who live nearby, and several other peaks between 100 and 10,000 miles. Since the contacts often list the name of their town, there is a small distance between the geocoded location of the town and the location of the target user's tweets. There aren't as many contacts in the 30 to 150 mile range, but then after 150 miles, peaks start appearing for major cities. One reasonable explanation for this is that Twitter is not just a social network; it is also a news distribution network as described in [10]. This distribution suggests that users have two types of contacts: people who they met in real life, and people who they met online or know about via mainstream media.

Most previous location prediction work has focused on doing predicting locations in the continental U.S. In the first figure from [13], McGee et al. observe a bimodal distribution in distances between American Twitter users with strong peaks at 10 miles and 2500 miles. When looking at this similar set of data on a global scale, we find more chaos in the distribution of contacts at distances greater than 200 miles.

4.3 Factor 2: Does the number of friends and followers a person have affect how close they are?

The second factor we consider is the number of friends and followers of a contact. We took each of the reciprocal friendships that we looked at in Figure 2 and put them into five log-scaled bins based on the number of friends or followers that the contact had. Figure 4 shows the result of this procedure.

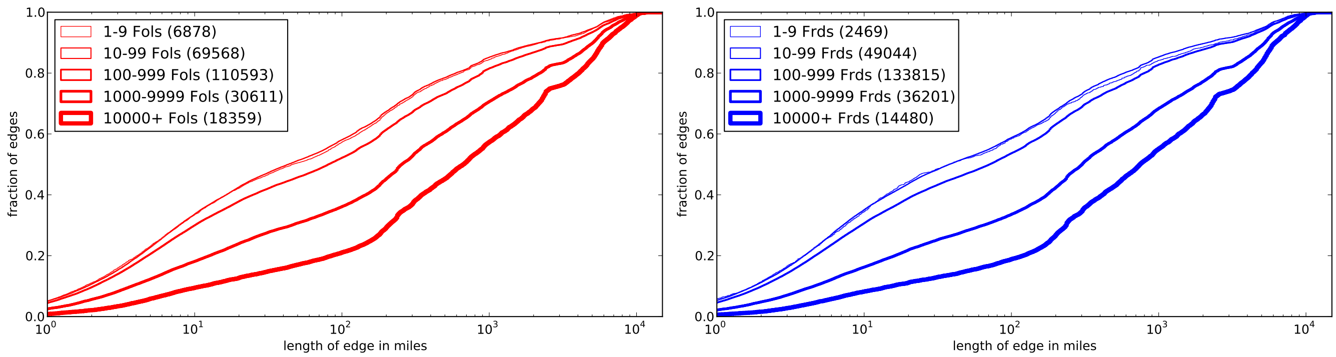


Figure 4: A comparison between number of followers and proximity—people who have more friends or followers tend to be further away.

In general, people who are more promiscuous followers and friends are less likely to live nearby. This makes sense because it is easy to meet 15 Twitter users in real life, but very few people know 1000 Twitter users who live in the same town. Contacts with 10–99 followers were within 25 miles of their geo-located friend 45% of the time while contacts with 1000–9999 followers were nearby only 26% of the time. There was a similar result in the number of friends: the proportion of local contacts went from 46% down to 23%.

Mainstream media and celebrity accounts such as the New York Times and Lady Gaga have millions of followers while normal users rarely have more than a few hundred. Follower count and friend count are good ways to distinguish celebrity and news accounts which are useless for location prediction.

4.4 Factor 3: Are users closer to people they communicate with?

We look at the 100 most recent tweets for the targets and one of their contacts for each type of their contacts. The edges are divided into groups based on whether the target user mentioned the contact and whether the contact mentioned the target user. For each of the groups, we calculate the percentage of contacts who live within 25 miles of the targets and the number of edges in that group. This is shown in Table 2. Since contacts who were just mentioned were mentioned by the target user by definition, the contact mentions and both ignore table cells are empty.

In almost every case, increased communication increases the probability that two users live near each other. There is one exception: when an average user mentions someone they follow who does not follow them back, it has no effect—in both cases the contact is local 25% of the time. In other words, if a random user mentions a celebrity who does not bother to reply, they probably do not live in the same area. On the other hand, in the rare event that someone who is just a friend replies to their follower, then the probability that they live near each other is much higher—it goes from 21% to 42%.

The weakest type of contact is users who were just mentioned, but never replied to. If the person is mentioned, then 36% of users with no friend/follow relationship who have a conversation live within 25 miles. This is approximately equal to the 35% of reciprocal friends who ignore each other and live within 25 miles. Unsurprisingly, the strongest type of connection is reciprocal friends who communicate. One challenge to using communication patterns as a source of information for location prediction is that the communication patterns that are correlated with proximity are rare.

	Public		Private	
	local	count	local	count
Recip Friend	37%	211136	41%	24873
Just Follower	25%	204417	31%	21168
Just Friend	21%	233849	39%	5228
Just Mentioned	18%	183368	35%	4331

Table 3: Comparison between public accounts and private accounts on Twitter. Private accounts tend to be closer.

4.5 Factor 4: Are users closer to private accounts?

Like many social networks, Twitter allows users to control the privacy settings on their account. The specifics differ from network to network, but in Twitter's case a user can make their account private which means followers have to get permission to follow the account. There are demographic differences between public and protected accounts. For example, Gilbert [8] demonstrates that rural users are more likely to make their accounts private than public accounts. In the case of protected accounts on Twitter, basic information about their profile such as their location and the number of friends and followers is public, but their friends list, followers list, and the text of their tweets is private, and not available for analysis.

As seen in Table 3, the most dramatic difference between private and public occurs if a user follows a protected account. Since users generally only allow people they know to follow a protected account, this brings the users almost as close together as if they were reciprocal friends. On the other hand, if a protected account follows the target user, they are only slightly more likely to be nearby.

4.6 Factor 5: If two of your friends live near each other, does that increase the chance they live near you?

We now turn our attention to triangles of users. Finding useful relationships between the edges of a social triangle is tricky because the three distances depend on each other. Unfortunately, it is fairly simple to show using the triangle inequality theorem that if two users are 1000 miles apart, then the third member of the triangle has to be at least 500

	both mention		target mentions		contact mentions		both ignore		overall	
	local	count	local	count	local	count	local	count	local	count
recip friend	42%	28067	50%	17903	45%	21066	35%	168973	38%	236009
just follower	40%	2001	47%	792	40%	5958	25%	216834	25%	225585
just friend	21%	23314	40%	910	42%	1884	21%	212969	21%	239007
just mentioned	18%	182978	36%	4721		0		0	18%	187699

Table 2: If target users interact with their contacts, then they are more likely to live nearby.

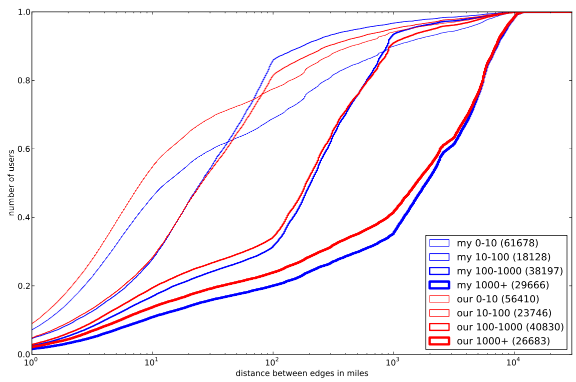
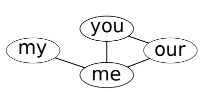


Figure 5: Comparison between distance to a mutual friend, labeled "our", and someone who is not a mutual friend, labeled "my". If two contacts are mutual friends and live near each other, a target user is more likely to live near them than two contacts who live nearby but are not mutual friends.

miles from one of the other two. Since this isn't a useful result, we designed a more complex experiment to analyze the relationship between the sides of the triangle. A script searched for a specific pattern in the social network of the target user's reciprocal friends: two people who were friends with each other and a third person who had no connection with the other two:



To help label the four users, we describe this social graph from the perspective of the target user:

- "me" is the target user
- "you" is the contact who is reciprocal friends with "me"
- "my" has no relationship with "you" and is reciprocal friends with "me"
- "our" is reciprocal friends with both "me" and "you"

We found this pattern for 147,669 of the target users. If a user had multiple instances of this pattern, it picked one of them randomly so that particular users would not bias the results. Figure 5 shows a comparison between distances to the "my" users and the "our" users. For each of the "my" users and the "our" users, we put them into one of four logarithmically scaled bins based on their distance from the "you" user. Then we plot the CDF for the distance from the target to the "my" and "our" users. This allows us to investigate the effect of mutual friendship on distance. We report one very simple result: if two of your friends are close (within 10 miles), then whether they know each other or not strongly affects how close you are to them. If they are farther apart, it doesn't matter.

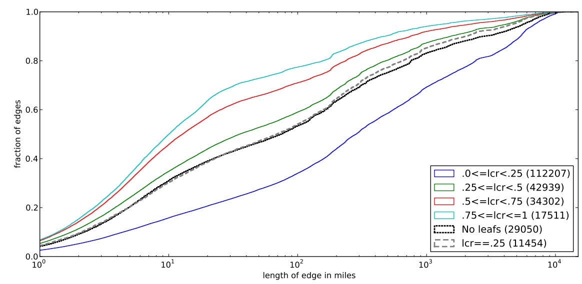


Figure 6: The colored lines show the distance to contacts split into groups based on the proportion of the contact's friends and followers who live near the contact. The dotted line shows the distance to contacts who have no locatable contacts. Contacts who have a high proportion of nearby leafs are much more likely to live near the target user.

4.7 Factor 6: Are some users closer to all of their friends and followers?

In the previous sections we only looked at the contacts of the target users. In this section we will go two steps out on the social graph and investigate the friends-of-friends. We want to know if some users are more localized than others, so we compare contacts with lots of local contacts to contacts with mostly distant contacts. **Local Contact Ratio**(LCR) is the fraction of a user's contacts who live near the user. For a contact at location l^c and a set of their contacts' locations L, we formally define LCR as follows:

$$LCR(l^c, L) = \frac{|\{l_i \in L : |l_i - l^c| < 25\}|}{|L|}$$

We picked a cutoff distance of 25 miles to distinguish between local and non-local contacts. 25 miles is about the distance where the bulk of local users ends as seen in Figure 4. The distance cutoff is somewhat arbitrary, but it doesn't seem to matter much in practice since we are really trying to distinguish between contacts who are hundreds of miles away and contacts who live in the same town. Around one in ten contacts did not have any contacts with a location from the contacts we looked at—they were treated as a separate group.

In [11], the authors model the probability distribution of user's followers using a Gaussian distribution, and use this to build a location prediction system. There are many other ways to analyze the leafs: average distance to the leafs, median distance to the leafs, fitting the distances to a curve such as a Gaussian. We are looking at location prediction anywhere in the world, which means contacts may be 10,000 miles away, and a location 10,000 miles away is nearly as bad as a location 1000 miles away, so average is obviously not useful. The disadvantage to using the median is more subtle. As seen in Figure 2, the median distance to a contact is often in the 100–1000 mile range, and only about a third of contacts are actually local. This means that median distance to leafs does a reasonable job of separating the worst contacts from the average contacts, but local contact ratio does a better job of identifying the very best contacts.

Figure 6 is a graph of the distance to reciprocal friends split into bins based on the local contact ratio of the contact. The figure shows that some users are much more local than other users. For example, a local newspaper may have thousands of followers and few friends, but the people who follow a newspaper are generally local. According to the other factors we looked at, the newspaper is a bad predictor of location, but in reality it is a great predictor.

Of the factors we have investigated, this is the one that is most strongly correlated with distance—in the next section we will see that local contact ratio ends up at the top of a decision tree to separate local contacts from non-local contacts. One problem with this technique is that it is somewhat expensive to deal with the large number of profiles two steps out on the social graph. Our crawler originally looked at 100 leafs per contact because Twitter's API will return up to 100 profiles at a time, but fetching and saving all those profiles is slow. The percentage of contacts within 25 miles with a good LCR based on 10 leafs, 20 leafs, and 100 leafs was 53%, 55%, and 58%, respectively. All of these are noticeably closer than reciprocal friends who are within 25 miles 38% of the time, but it wasn't worth the expense of obtaining 100 leafs for each contact. We used LCR based on only 10 friends when evaluating the FriendlyLocation system.

4.8 Factor 7: Are some locations better than others?

The location field on a user's profile is just a text field that asks the user to respond to "Where in the world are you?". Responses include neighborhood names, state names, country names, and even jokes and nonsense. We use Gisgraphy to geocode this free-form text to a location using the GeoNames database.

Since some locations are significantly more useful than others, we needed a way to evaluate the quality of a location. The geocoding users are the 894,617 users who posted geo-located tweets, were not selected as target users, and also filled in the the free-response location field with something that the geocoder is able to decode. We can compare the results of the geocoder to the location of the geo-located tweets for these users to quantify how accurate the geocoder is for certain types of locations. We define the **location error** to be the great circle distance between a user's home location (from their tweets) and the location returned from the geocoder. The location error for a user can vary from less than a mile to over ten thousand miles. We calculated the location error for each of geocoding users, and grouped the users by their location. For the 17,370 locations that had at least three geocoding users, we calculated the median location error (MLE) for that location. All the users who were at locations with only one or two users were grouped according to the type of location returned by the geocoder. We calculated the median error for each location type. The median is more appropriate than the average or standard deviation because those metrics are strongly affected by large outliers. This gives us a method to estimate the quality of a coordinate returned by Gisgraphy.

Figure 7 shows the distance from target users to their reciprocal friends after being divided into three groups based on MLE. Contacts with a low MLE provide relatively high-

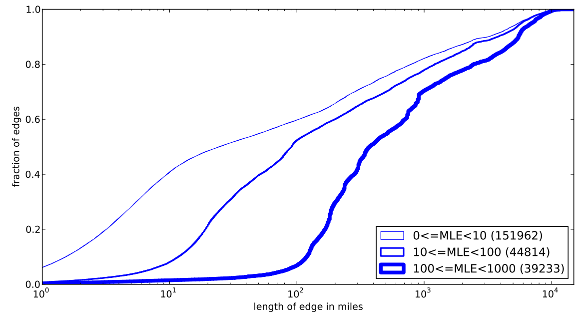


Figure 7: Reciprocal friends divided into groups based on the median location error(MLE) of their location. Contacts who report a location with a low MLE usually live near their contact, while contacts with a high MLE generally live in the same region.

quality location information—50% of reciprocal friends with a MLE less than 10 live within 25 miles of the target user. Contacts with locations with a MLE greater than 1000 were ignored for all of the experiments in this paper, since these locations were almost always nonsense values that happen to decode to an actual location.

4.9 Summary

Based on this large-scale analysis of Twitter, we conclude the following:

- Reciprocal friendships tend to be physically closer than contacts with less strong relationships such as someone who is just a follower.
- Contacts who mention or are mentioned by the target user on Twitter tend to be located nearby.
- Protected accounts tend to be closer, but we provide less additional information for assessing their relative quality.
- Contacts with lots of friends and followers tend to be further away (since, in many cases these contacts correspond to celebrities or news organizations).
- Some accounts, such as a local newspaper, may have lots of users from the same area. These accounts can be identified by looking at a small number of their contacts.
- Contacts with more precise locations are more useful for location prediction.

5. BUILDING AND EVALUATING FRIENDLYLOCATION

In this section, we integrate the observations from our study of the factors that impact distance into the FriendlyLocation location estimator. While there are many options for mapping from input factors to tie strength, we adopt a decision tree regressor based on the CART algorithm (classification and regression trees) to distinguish the best edges from the worst.[3] A decision tree regressor works similar to the well-known decision tree classifier, except that it produces real numbers as output instead of discrete classes. During training, the training data is recursively split based

[3] Since most of the input features are correlated and either binary or non-linear, linear regression is unlikely to work well. In addition, the data is dense and low-dimensional, so support vector machines do not work well.

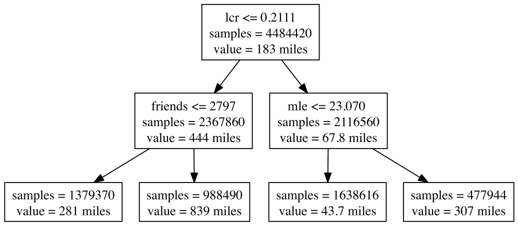


Figure 8: The top three levels of the decision tree. Samples is the number of edges used to train that node of the tree, and value is the geometric average distance from a target to a contact for that node. This tree will predict a distance of 839 miles for a contact with a local contact ratio of .2 and 2800 friends. It will predict a much-closer distance of 43.7 miles for a user with a local contact ratio of .5 and a median location error of 10 miles.

on the input variable with the most predictive power to build a binary tree. Each of the internal nodes of this tree have a cutoff for one of the input variables, and the leaves of the tree have a predicted value.

Setup. Since the distances between users varied by several orders of magnitude, we trained the regressor to predict the log of the distance. The tree regressor was configured to not split leafs with fewer than 1000 data points to prevent overfitting. The top three levels of a decision tree are shown in Figure 8. The predictor does not do a great job of predicting the actual distance to a contact; there's simply too much noise. However, it does do an excellent job of separating the closest pairs of users from the most distant pairs as we will show in the next section.

We evaluate the system against a baseline implementation, and we investigate several modifications to the system. We use five-fold cross validation on the target users to evaluate the system. We evaluated the FriendlyLocation system against the 249,584 target users.

For each of the folds, we ran the tree classifier and generated a new set of curves for p^* from the training data. We did not recalculate pStgrs or the probability as a function of distance used for the baseline, since these are fairly independent of the selected set of users.

Metrics. We evaluate the system against the metrics used in previous works: accuracy at 25 miles (ACC) which was used in [1] and average error distance (AED) proposed in [2] and extended in [11]. Following the notational conventions from [11], we define ACC and AED for a set of users $u \in U$ with $\mathrm{Err}(u)$ as the distance between a target user's home location and the predicted location.

Accuracy is the fraction of users who live within 25 miles of their predicted location:

$$\mathrm{ACC}(U) = \frac{|\{u \in U : \mathrm{Err}(u) \leq 25\}|}{|U|}$$

Average error distance (reported as AED@100%) is as follows:

$$\mathrm{AED}(U) = \frac{\sum_{u \in U} \mathrm{Err}(u)}{|U|}$$

Since AED may be affected by outliers, we also report the AED at other percentiles, following [11].

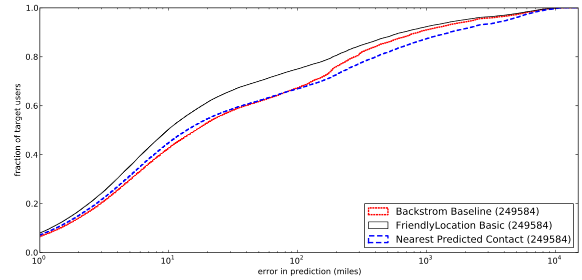


Figure 9: FriendlyLocation against several baseline systems.

Model	aed@60	aed@80	aed@100	acc@25
Baseline	8.41±.038	40.8±.20	426±3.9	55.7%±.09%
Nearest	7.73±.117	50.3±.39	594±9.3	56.5%±.22%
FriendLoc−Strangers	5.79±.028	25.2±.18	377±4.3	62.4%±.09%
FriendLoc−Leafs	5.36±.011	22.1±.12	367±4.0	63.6%±.12%
FriendLoc Basic	5.35±.008	21.4±.12	364±3.2	63.9%±.05%

Table 4: Results of our location prediction system when compared to a baseline. The value after the ± is the standard deviation from the five-fold cross-validation.

5.1 Evaluating FriendlyLocation

We investigate several implementations of the FriendlyLocation system along with two baseline systems, which we will discuss in upcoming sections:

Baseline This is based on the maximum likelihood estimator presented in [1]. Some changes to the system had to be made to make it work on Twitter's directed graph. (Facebook friendships are always reciprocal.)

Nearest Contact This predictor chooses the location of the contact that the tree regressor picks as the closest contact.

FriendlyLocation Basic This is the system described in the previous section with only information from the locations of contacts.

FriendlyLocation - Strangers This is the system described in the previous section without pStgrs.

FriendlyLocation - Leafs This is the system described in the previous section without the locations of the leafs and tweets from the contacts.

Table 4 shows our system compared to a baseline implementation. As seen in the table our basic FriendlyLocation system predicts the location within 25 miles 63.9% of the time. Our basic system preforms significantly better than the baseline implementations. The results are more impressive when you look at it in terms of average error distance. The baseline system has an average error distance of 40.8 for the best 80% of predictions, and our basic system has an average error distance of 21.4. This means that our system is better at making good estimates better than it is at making bad estimates good. Unfortunately, when the predictor is wrong, it can be very wrong. As seen in Figure 9, around a tenth of the predictions are worse than 1000 miles for all of the predictors. Some of this inaccuracy may be caused by inaccurate training data, but there is no real way to know.

5.2 Ignoring Strangers

Calculating pStgrs is very expensive. It only has to be computed once, but if you wanted to do location prediction on a different social network, it would need to be recomputed. We investigate the FriendlyLocation system without this information, by running prediction without multiplying by pStgrs when calculating the overall probability for each location:

$$\prod_{l_k^c \in L, p_k \in P} \mathrm{p}^*(\mathrm{qntl}(p_k), |l - l_k^c|)$$

As seen in Table 4, removing this information results in a slightly worse prediction. There is a trade-off to be made here, and it may not be worth the time it takes to calculate pStgrs.

5.3 Prediction Using Only Contacts

Local Contact Ratio was the top node in the tree classifier for all 5 decision trees, which means it was the most important feature for classification. However, getting information about the leafs is by far the most expensive part of the crawling and predicting process. If we don't crawl the leafs, we also do not need to download the friends and followers of the contacts to find the leafs, which makes the process well over an order of magnitude faster. We re-ran the tree regressor, curve fitting, and prediction using only information from the target users friends, followers, and tweets and the profiles of the contacts. The accuracy for FriendLoc−Leafs at 25 miles was 63.6% which is not quite as good as the basic version of FriendLoc at 63.9% accuracy, but they are still very close. Prediction using only contacts takes only four calls to Twitter's API instead of the approximately 80 API calls it takes to do the basic version of FriendlyLocation.

6. CONCLUSION

In this paper, we have demonstrated that some features of relationships are correlated with physical proximity. For example, users with lots of followers tend to be distant, while users who mention each other tend to be closer. In general, users with stronger ties tend to be local. We used this to accurately predict the locations of users on a social media website.

There are two general directions that the future work on this research could go: improving the results of the prediction and using the predicted locations to build systems. One way to improve this predictor is to combine tie strength and the social graph with other factors such as the words users choose to use as described by Cheng et al.[2]. It could be useful for the predictor to return not just a location, but an estimate of the quality of the prediction. The system described in this thesis only considered users who have a well-defined location. FriendlyLocation could be modified to identify users who do not have meaningful locations such as people who constantly travel and accounts that represent large organizations.

Finally, high-quality geographic information opens up new avenues for research and software engineering. Location prediction will allow websites to provide hyper-local content and services. For example, the distance between a pair of users could be considered when suggesting new friends on a social network and websites will be able to give users more accurate, localized search results.

The idea that started our research into location prediction was community crowd detection. With geographic location of users, we can cluster users and find local conversations. These conversations can be analyzed to understand local political and social events. Location prediction will allow us to create a more clear picture of the conversations in a community.

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