Assessing Connectivity Bias in the Twitter Network

Adam Bates and Lara Letaw
Department of Computer & Information Science
University of Oregon
{amb,zephron}@cs.uoregon.edu

Abstract—**Over the past few years Twitter has been at the forefront of the online social networking phenomenon. Twitter experienced a growth rate of almost 1400% between February 2008 and February 2009 [1]. This surge in popularity has legitimized Twitter as a channel for communities to interact within the United States and across the globe. Still in its nascent stages, there is much that is unknown about the nature of interaction and influence within the Twitter network.**

This paper presents a detailed analysis of the nature of the relationships that exist between users within an online social network. We have collected a complete subgraph of the Twitter network that contains tens of millions of users and hundred of millions of those users' relationships. We profile this subgraph and explore its strengths and limitations by comparing it to a random sample of Twitter users. We then characterize the connectivity of our dataset based on the user attributes associated with each Twitter account. We use these results to identify a number of bias patterns that can be observed between different user groups. It is our belief that these observations shed new light on the nature of the global community's Twitter usage.

Keywords— **Online social network, Twitter, Measurement, Overlay topology**

I. Introduction

Twitter is a microblogging and social networking servive that allows its users to send short, one-to-many messages called *tweets*. Like many online social networks, users can opt-in to viewing other users' messages by *following* them, creating a customized content stream. The act of following is an implicit endorsement of another user on the network. It can be inferred that the user being followed is of interest to another user on the network. These interactions constitute a networked system through which users connect and messages propagate.

In order to gain a better understanding of Twitter, it is necessary to investigate the nature of this network. This information can be used when considering design decisions or allocating resources within Twitter or other future social networks. While Twitter's innovativion lies in the manner in which it distributes messages, a great deal of this profiling must take place at the user-level network.

Twitter, like many other online social networks, present a novel opportunity to study interactions between people. Through them, it becomes possible to easily aggregate the activities of millions. The simple and open structure of the Twitter network is particularly well-suited for this purpose. As each user account is associated with a variety of attributes, there a variety of methods to approach this task. The work we present here establishes a framework for further analysis.

There are many commonly held intuitions regarding influence that can be proved, disproved or quantified through analysis of Twitter. For example, it is a commonly held belief that activity in states such as California and New York is of a higher culturally relevance than the activity in other states. As each user account is associated with a location field, it is possible to use the Twitter network to measure the influence of these allegedly trend-setting states. Other, subtler biases can also be identified and evalued in the same manner.

A defining aspect of Twitter that lends itself to research is that all activity defaults to public. Each user's messages are visible unless they explicitly change their privacy setting. Although tweets can be protected, all other information associated with an account is visible to all. Using this publicly available connectivity information, it is possible to make broad assessments of connectivity within the Twitter community.

Given the massive size and continued growth of Twitter, capturing a complete snapshot of the network is an increasingly unrealistic endeavor. To make matters worse, Twitter imposes prohibitive rate limitations on access to many of its network measurement resources. It is therefore necessary to obtain a representative and meaningful sampling of the network before analysis can begin.

One possible option is to take a random sample of a small percentage of Twitter accounts and activity. Inspection of this random sample's attributes would lead to a representative view, but not necessarily a meaningful one. The users of greatest interest are small in number and some of their attributes will have extreme values. A random sample is not likely to capture these users' impact on the network.

It is also possible to conduct a biased sampling. Here, interesting users with extreme user attribute values are specifically targetted for measurement. If good metrics are used to assess influence, this will ensure that important user accounts are not crowded out by unimportant ones. Of course, this leads to data that is less representative than a random sampling. There is a natural trade-off between these two goals.

Our approach finds a healthy compromise between these competing priorities by starting with a biased sample and then performing a multi-hop crawl across a small piece of the network to conduct further sampling. This crawl creates a snapshot of a part of Twitter that is acceptably representative while simultaneously ensuring that rare users are acceptably prominent. We establish that our snapshot is sufficiently representative by comparing its profile to the profile of a true random sample.

Analysis of our results shows a number of influence patterns across various attributes in our Twitter subgraph. These influence patterns take the form of bias measured between different groupings of users following one another. We explain these patterns in detail and discuss how these attribute relationships may speak to the general use of Twitter.

The rest of this paper is organized as follows. We outline our data collection process in section II. In section III, we present our method for evaluating connectivity bias within the Twitter network. Analysis of our results is contained in section IV. We review some of the related work in section V. Section VI concludes the paper.

II. DATA COLLECTION

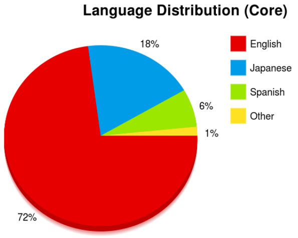


Fig. 1. For the core set, the percentage users who have marked Japanese as their Twitter language is more than four times that of the random set.

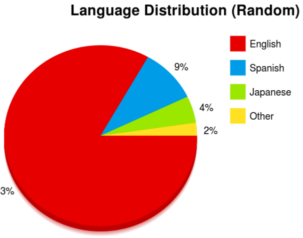


Fig. 2. English, Spanish, and Japanese are the top languages for both the connected and the random user sets.

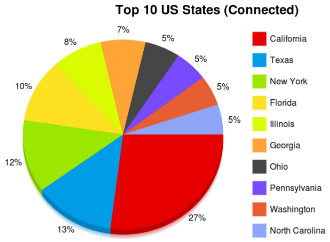


Fig. 3.

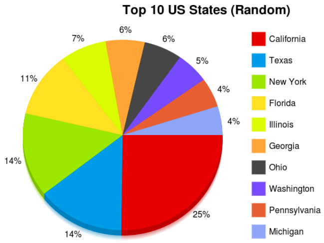


Fig. 4.

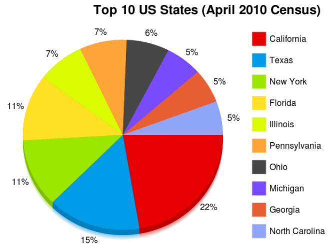


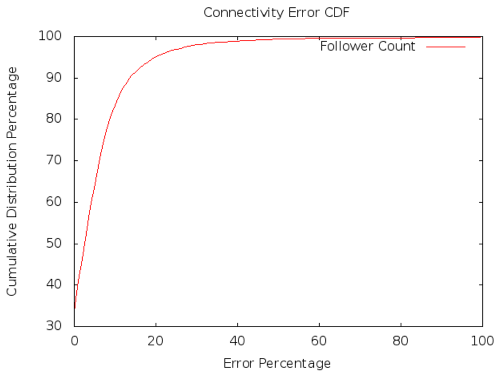
Fig. 5. The distribution of U.S. states for both the random and the connected datasets aligns well with the population census data.

At the start of our work we inherited a large dataset from Rejaie *et all* that was created through a biased sampling of the Twitter network. The dataset contained partial connectivity information for 242,275 potentially influential users. Due to limitations of the Twitter REST API at the time of collection, the connectivity data was incomplete. Additionally, the dataset did not include the associated attribute information for each user because it was not germaine to Rejaie's previous work. This dataset needed to be completed before beginning our analysis.

Our goal was to characterize the relationships in a completed section of the Twitter network. It was first necessary to determine if a large, complete subgraph existed within this dataset. A collection of smaller subgraphs would not be sufficient as they would be less likely to capture the impact of rare influential users. By performing a series of reconstructions of the graphs in the dataset we were able to discover a single subgraph of 215,606 sampled users. Including the next hop information for these sampled users, the subgraph included 16 million unique user accounts.

The inherited dataset was not originaly intended to measure the extreme connectivity degrees of rare users. As a result, the friend and follower information for each user in the subgraph were truncated at 1,000 connections apiece. This truncation was due to the prohibitive rate limiting of of the Twitter API, which made it infeasible to collect the complete connectivity information for these users in real time. Over the course of several weeks we were able to restore this missing information, growing our subgraph to the inclusion of over 30 million unique users. Several months passed between these two collection phases. The potential error that this introduced is explored below.

Simultaneously, we needed to collect the user attribute information for the tens of millions of users in our subgraph. Completing this task via the Twitter API was difficult due to the connectivity restoration process, and it was not our wish to violate Twitter's terms of service by launching API calls from dozens of hosts. Fortunately, we were able to find an alternate method of collecting user attribute information. Twit-



ter provides XML dumps of user information through their primary website. These calls are not subject to API rate limites, presumably for the benefit of mobile applications that may issue frequent user lookups. Using this service, we were able to collect the necessary information without violating the Twitter API ToS.

A. *Measuring Error*

Because our user attribute information was collected in less than a month, we have assumed that no significant error is present. It is not possible to capture a realtime snapshot of user attributes in the Twitter network, so we have no method of comparing collected attributes to actual attributes. Our intuition here is that most user attributes are not subject to frequent change. The exception to this is connectivity, which is explored below. For our purposes, the collected user attribute information can be accepted as accurate.

In contrast, connectivity information for our subgraph was collected in two different phases between September 2010 and February 2011. It would be foolish to assume that significant change did not occur in the network over this time. It was therefore necessary to confirm that the temporally disparate collection phases did not introduce error to our network measurements. To do this, we compared our snapshot of connectivity for each user to the stated connectivity in each user's attributes.

Figures **??** confirms that we have captured an accurate view of connectivity in our piece of the Twitter network. 90% of users have a follower count error of less than 15%. Most users that exhibit a non-negligible error percentage are of a very low degree, and are therefore not of high significance in our subgraph. High degree users exhibited the lowest error rate because their connectivity information was collected most recently. This holds true for friend count as well. It is our belief that our connectivity error is sufficiently low that are results are meaningful.

B. *Profiling*

Our set of Twitter users was created by first discovering the IDs of approximately 250,000 users that met a certain time-in-system threshold, and then querying the Twitter API for all users connected to that initial core. Since user connectivity is central to our study, this allowed us to quickly acquire a subgraph in which every node was usable. However, since this collection method was not random, the distribution of attributes across our dataset could be different than that which we would observe by choosing random users. These differences are important to examine because they may indicate ways that our dataset is not generalizable to the entire Twitter universe.

To quantify these potential discrepancies, we performed attribute profiling for both our connected subgraph and a set of 1.5 million randomly-selected users. We calculated the percentages of users falling into each attribute grouping for each set and then compared the two profiles. We also contrasted the profiles of the core users in our subgraph to the other connected, next-hop users.

B.1 Boolean Attributes

Two of the attributes we examined were true/false values: protected and geo-enabled. Below is a table of percentages of users who enabled each attribute, for the core, connected, and random data sets.

Attribute	**Core**	**Connected**	**Random**
Protected	3.6	12.3	8.3
Geo-Enabled	24.5	15.8	6.7
Verified	0.1	0.0	0.0
Contributors Enabled	0.0	0.0	0.0
Show All Inline Media	7.9	6.3	1.6
URL	49.7	26.7	10.2
Is Translator	0.0	0.0	0.0

Attribute distribution percentages for three data sets.

We found that our core users were less than half as likely to be protected, and more than three times more likely to allow the inclusion of GPS information in their tweets than the random users. The percentage of geo-enabled users in the connected subgraph is inbetween that of core and random, which indicates that the original user selection could have carried over to the first-hop connections to some extent. Interestingly, the subgraph users are more likely than either of the other sets to be protected. This may be because users who are connected to the initial group, which we would characterize as more “established", are more experienced than the average random user, as random users likely include many people who have signed up but have not made much use of their accounts. The random set could, for example, include users who are not connected to anyone else.

B.2 Language

Users have seven choices for the language attribute. Choice of language affects the text of the Twitter interface, but does not translate tweets. It is unclear whether the language changes based on the location (IP address) of the user, or if English is default for everyone. We find that, in comparison to the random set, the connected and core users are substantially more likely to be configured for using Japanese (Figures 1, 2). This could indicate that the filtering techniques used to gather our original set of users was more likely to pick up Japanese users.

Language	**Core**	**Connected**	**Random**
English	72.9	78.3	83.2
Spanish	6.8	12.1	9.7
Japanese	18.7	7.6	4.8
French	0.5	0.8	1.2
German	0.7	0.7	0.7
Italian	0.3	0.4	0.5
Korean	0.1	0.1	0.0

Language distribution percentages for three data sets.

B.3 Location

We examined data for the ten U.S. states with the greatest number of associated users. Distribution of locations was similar between the connected and random sets, and also aligned fairly well with population data (Figures 3, 4, 5). For the states that appear in all three data sets, all percentages are within 5% of each other, and most are differ by no more than 2%. Also, the top five states are the same and in the same order.

C. Approaching Attribute Analysis

C.1 Location

The location attribute field has no enforced format, apart from length. That is, users can type in essentially any text for their location. From a small random sample and manual examination of this attribute field, we estimate that approximately 50% of users provide location text that can be matched to at least one city, state/region, or country. We also find that almost 90% of users who match one city will match more than one city. Since we want our analyses to be by specific location, we need to address these ambiguities.

Given that there are hundreds of thousands of cities in the world, we decided to start our location analyses with U.S. states because of their familiarity to the authors. Our approach is to filter users based on exact matches with a precompiled list of U.S. cities in the standard *San Francisco, CA* or *San Francisco, California* format. If a user matches one of these locations exactly, the user cannot exactly match a different location. For the top 100 most populous cities, we try to match the city name itself, without the state, with the intuition that, for example, users from *San Francisco* would not find it necessary to specify their state.

We find that 8% of connected users and 5% of random users are successfully matched to a state.

III. METHODOLOGY

A. Approaching Attribute Analysis

Although each user account is associated with 33 publicly available attributes, only a few of these were of any interest for our purposes. 10 of the attributes are profile display settings, which were not considered. Another 6 are user identifiers such as name and ID and are not of any use to network-level analysis. We initially identified 14 potential attributes of interest. Further description of these attributes is available in appendix VI.

After selecting attributes for consideration, we identified appropriate groupings for each attribute. The format of the considered attributes took one of three forms. These formats informed the manner in which they were grouped. Many of the attributes had a finite number of options, such as a boolean value for *Protected* or one of seven options for *Language*. A group was assigned for each possible value of these attributes.

The next field format was that of a continuous integer range, such as *Follower Count* or *Status Count*. For these, groups took the form of a range of values. It was important to create groups in such a manner that rare, high values user were clearly visible in the results. It was also important that the large population of low value users were represented. To accomplished this, we increased the range of our groupings logarithmically.

The final and most challenging format took the form a free text field. Free text fields are used by the *Bio*, *URL* and *Location* attributes. Of these, only *Location* was considered in our study. After parsing this field for identifiable locations on a variety of scales, it was decided that groupings by U.S. state would be the most impactful. Of these, results for the top ten most popular states are included in this paper.

Paragraph: Mention the simple random survey of records that was performed, the percentage of users with no entry, the percentage of users with an indecipherable entry, etc.

After identifying discrete groupings for each attribute it became possible to enumerate all possible attribute relationships within our dataset. Each edge in our subgraph represents a relationship between two Twitter users, each with a group assignment for each attribute. We created a unique identifier for all possible relationships for each attribute. We then processed our dataset by assigning these identifiers and counting their frequency.

B. Measuring Bias

Through data processing we obtained a set of values A_{XY}, representing the actual count of each possible attribute relationship *X follows Y*. However, this value alone is insufficient for measuring network bias. It does not consider the frequency of users of attribute X or Y. It also does not consider the total number of outgoing edges from X, X_{out} ,or incoming edges to Y, Y_{in}. Before network bias can be determined it is necessary to normalize A_{XY} against the value one would expect in a randomized, bias-free version of the graph. This

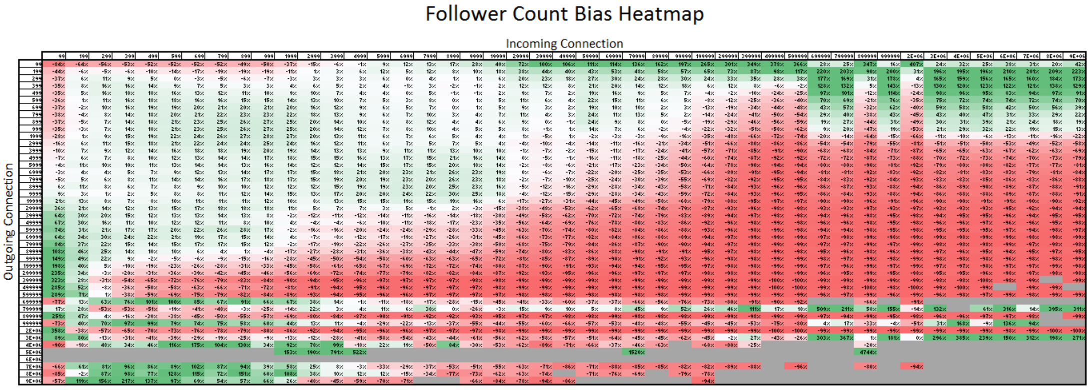


Fig. 6. A connectivity bias chart for number of followers in logarithmically increasing groupings.

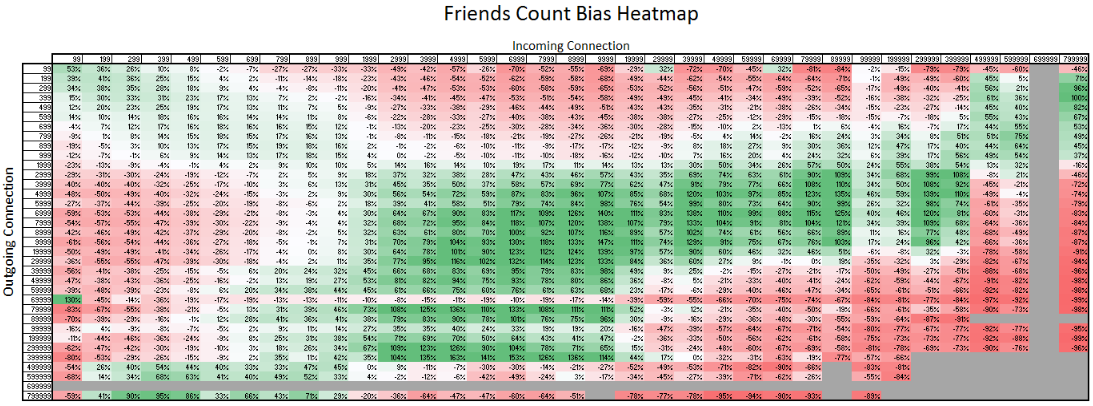


Fig. 7. A connectivity bias chart for number of friends in logarithmically increasing groupings.

value is given by:

$$R_{XY} = \frac{X_{out} * Y_{in}}{\sum_{x,y,z} u}$$

where X_{out} is the number of outgoing edges from X, Y_{out} is the number of incoming edges to Y, and $\sum_{x,y,z} u$ is the sum of all edges for all attribute values in the network. For our Twitter network, R_{XY} is consistent when considered from both the incoming and outgoing edge perspective because of following fact:

$$\sum_{x,y,z} u_{out} = \sum_{x,y,z} u_{in}$$

Given A_{XY} and R_{XY}, the bias for the relationship *X follows Y* is given by:

$$B_{XY} = \frac{A_{XY} - R_{XY}}{R_{XY}}$$

A positive B_{XY} indicates that group X is biased towards following group Y. A negative B_{XY} indicates that group X is biased against following group Y. If $[B_{XY}]$ is very nearly zero, no bias is observed. If $[B_{XY}] > 1$ then the relationship *X follows Y* is biased to the point that it is several times more frequent or infrequent than would be expected in a randomized graph.

IV. ANALYSIS

Our results are visualized for each attribute in figures throughout this paper. These figures can be interpretted as follows: the groupings that are orderd by row are following the groupings that are ordered by column. To read the bias for a particular relationship in these charts, find the desired row grouping and move right across the page. Negative bias relationships are shaded red, and indicate that a row group has a bias against following a particular column group. Positive bias relationships are shaded green, and indicate that a row group is biased in favor of following a particular column group. The shade color increases with the strength of the bias. Relationships that were not contained in our dataset are represented by gray-shaded empty squares. For the sake of readability, the strength of shading is adjusted across different figures. The strength of observed biases across different attributes is evaluated in IV-A

Figure 6, a visualization of bias across follower count groupings, reveals a number of interesting facets of our Twitter subgraph. One important feature is the values on the diagonal line moving from the top left to botthom right corner of the graph. This line marks a group's affinity towards follow-

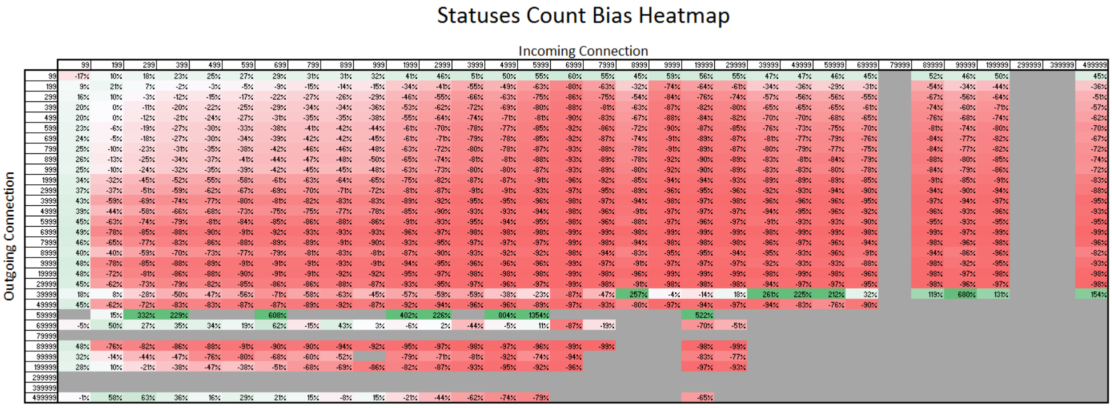


Fig. 8. A connectivity bias chart for number of status updates in logarithmically increasing groupings.

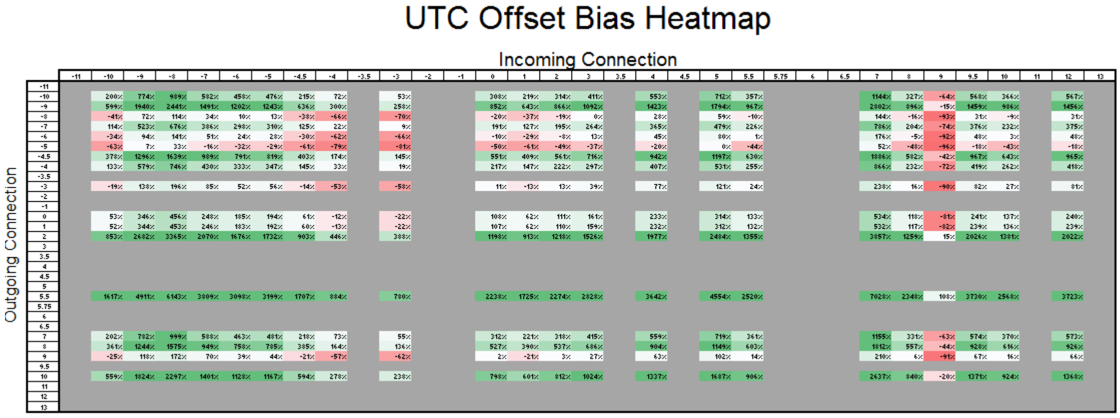


Fig. 9. A connectivity bias chart for Coordinated Universal Time (UTC) offset.

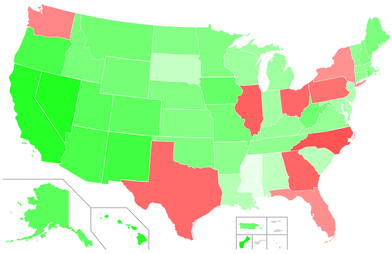


Fig. 10. Followers of California

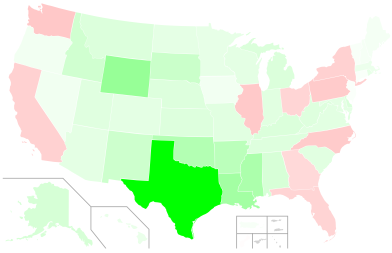


Fig. 11. Followers of Texas

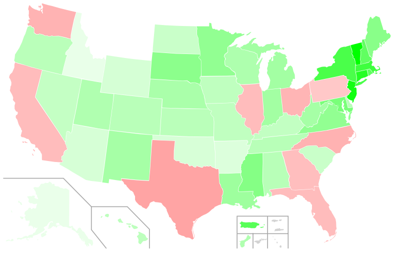


Fig. 12. Followers of New York

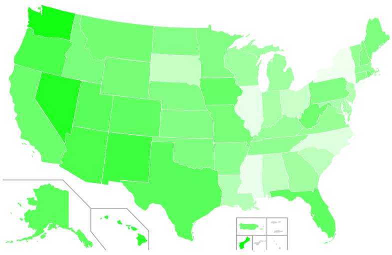


Fig. 13. Followers of Florida

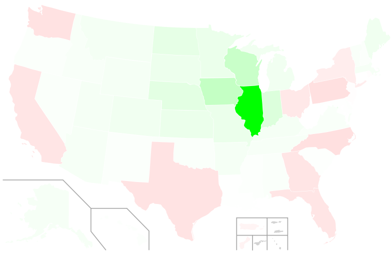


Fig. 14. Followers of Illinois

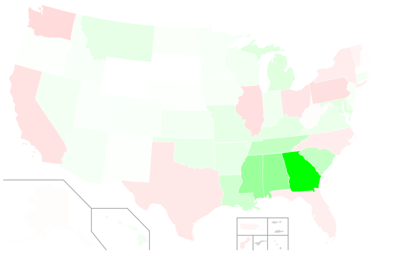


Fig. 15. Followers of Georgia

ing itself, and will be referred to often in this section. Here, we observe that our groupings are either neutral or subtly positively biased in favor of following their own group until a very high degree is reached. The other exception to this trend

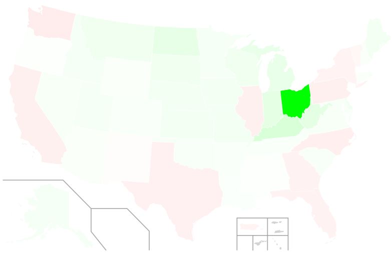


Fig. 16. Followers of Ohio

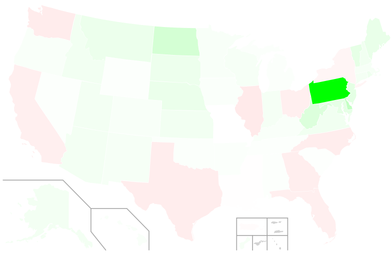


Fig. 17. Followers of Pennsylvania

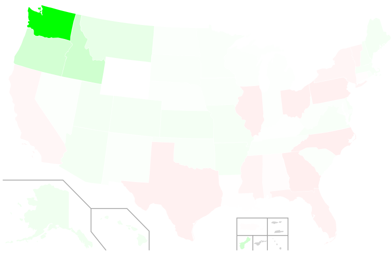


Fig. 18. Followers of Washington

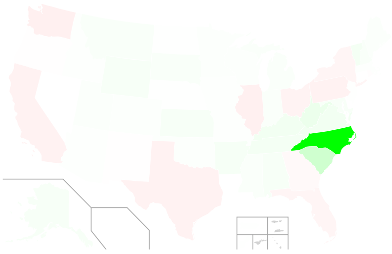


Fig. 19. Followers of North Carolina

is at the lowest follower count level, where the group is biased against following itself. Across our results for the quantitative attributes it can be observed that users of extremely low degree exhibit unique behavior.

Figure 7, a visualization of bias for the friend count attribute, contains much of the same trends that are observed in Figure 6. A moderate bias towards following users of a similar friend count is clearly visible here along the chart's diagonal. This bias grows stronger once the grouping being followed reaches a degree of greater than 2000, at which point there is extremely strong bias in favor of following users from these groups. Unlike with follower count, low degree users follow eachother at a frequency above that which would be expected in an unbiased network.

Figure 8 displays bias patterns for user groupings by status count. Our intuition here was that users would be that likely to connect to user accounts with different degrees of status count. This intuition is at least partially confirmed in the graph – low degree users are moderately biased towards following those with a high status count degree. Those with a moderate-to-high status count are strongly biased against following others of a moderate-to-high status count. This could be explained by businesses and professionals who use their twitter accounts to send frequent messages, but who follow very few people.

Figure 9 displays attribute relationships for users in different parts of the world by their offset from coordinated universal time. While, UTC Offset generally refers to a longitudinal slice of the globe, certain offsets are used exclusively by certain countries or regions. We observe that the strongest positive bias in this chart is at UTC Offset +5.5 following UTC Offset -8. These two offsets correspond to user accounts in India and Sri Lanka following user accounts in Pacific Standard Time. All groupings displayed varying degrees of bias against following user accounts at UTC Offset +9, which corresponds to the time zone in Japan and North and South Korea. However, many of these groupings are not very well supported by our dataset. We do not perform any further analysis on UTC offset.

Figures 10-19 show connectivity bias for the top 10 U.S. states, within the set of edges going to or coming from those states. In general, states show a tendancy towards following themselves, and are followed by bordering states. In the case of California, all states except the remaining top 9 are biased toward following California. The mostly consistent bias against followers from the top 10 states is likely due to their being central to this analysis.

Figure IV displays connectivity bias based on the number of Twitter lists tha a user appears on. Lists are a way to organize and separate different message streams, and our intuition here was that there would be a bias towards following users that appear more frequently on lists. As it turns out, this trend is only present when considering users of a low listed count degree. Groupings of users that appear on over 100 lists display a consistent and considerable bias against following other high degree listed count users.

Figure 22 displays connectivity bias based on whether or not a user's messages are protected. The only considerable bias displayed in this chart is that users with protected accounts are biased against following one another. Figure 23 displays significant positive bias for all relationships featuring non-geoenabled user groupings as well as a negative bias for *Geoenabled follows Geoenabled*.

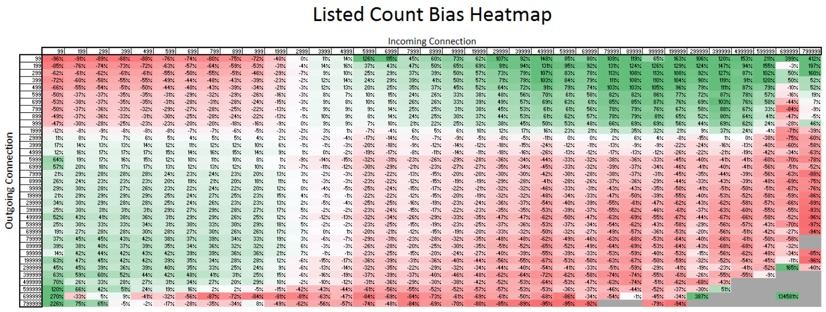
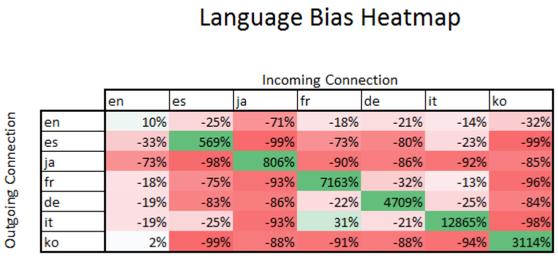
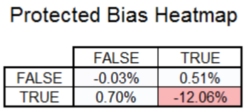


Fig. 20. A connectivity bias chart for number of lists a user appears on in logarithmically increasing groupings.



	en	es	ja	fr	de	it	ko
en	10%	-25%	-71%	-18%	-21%	-14%	-32%
es	-33%	569%	-99%	-73%	-80%	-23%	-99%
ja	-73%	-98%	806%	-90%	-86%	-92%	-85%
fr	-18%	-75%	-93%	7163%	-32%	-13%	-96%
de	-19%	-83%	-86%	-22%	4709%	-25%	-84%
it	-19%	-25%	-93%	31%	-21%	12865%	-98%
ko	2%	-99%	-88%	-91%	-88%	-94%	3114%

Fig. 21. A connectivity bias chart for users by language setting.



	FALSE	TRUE
FALSE	-0.03%	0.51%
TRUE	0.70%	-12.06%

Fig. 22. A connectivity bias chart for whether or not the user's account is protected.

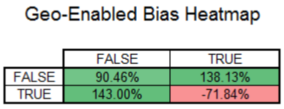
A. *Comparing Bias Across Different Attributes*

While analyizing each attribute, we indentified several recurring bias patterns through which the attributes can be compared. Each attribute can be described by its behavior across these bias patterns. Across all attributes, we observed *group follows itself* and *group follows others* patterns. There are additional patterns for attributes of continuous range – *low degree follows low degree*, *high degree follows high degree*, *low degree follows high degree*, and *high degree follows low degree*.

We have characterized the strength of each of these bias patterns across all attributes. For the sake of brevity, these have been summarized as a table in appendix . Rather than mathematically define each bias pattern, we have decided to keep our identifications loose and use our visualizations as a guide. The transition 'low degree' and 'high degree' is clear in the visual aids; the included table serves only as guide to compare the relative strengths of patterns in different attributes.

V. RELATED WORK

Our analysis of Twitter is informed by the previous work of Rejaie *et all* on the characterization of overlays in P2P file-sharing systems. Their analysis of the Gnutella network discovered a bias in peer connectivity based on age in the system, creating an onion-like overlay in which the longest active peers formed the center of the network [2]. Our work borrows this concept of connectivity bias and applies it to the wide variety of attributes present in the Twitter system. The challenges in system characterization vary between P2P networks and online social networks. One example of this is volatility of the network. Twitter's structure is much more stable than Gnutella's, although it is still difficult to acquire an accurate snapshot of the network due to Twitter's rate limits on access to network measurement tools.



	FALSE	TRUE
FALSE	90.46%	138.13%
TRUE	143.00%	-71.84%

Fig. 23. A connectivity bias chart for whether or not the user's account is geo-enabled to include location information with each tweet.

One of Twitter's core functions is the analysis of individual messages to determine trending topics. As such, Twitter is capable of acting a cultural barometer. A variety of studies have attempted to answer the question of how information spreads within the Twitter network. Investigations have included spam, the meme life cycle, and news discovery and explanation.

A variety of Twitter-related work has been conducted over the past several years. The majority of this work focuses on the analysis and propagation of individual messages as they spread through the network. Many have characterized the nature of spam on Twitter [3] [4] [5]. Cheng *et al* have used tweets to attempt to geo-locate users based on the content of their messages [6]. Others have attemped to aggregate message feeds in order to discover real world events [7] [8]. Lerman and Ghosh have studied Digg and Twitter to measure news items' lifespan and speed within social networks [9]. Sadikov and Martinez have conducted similar work, chosing instead to focus on URL and tag propagation [10].

It is only reasonable that message-level analysis has captured the attention of the research community. After all, the novelty of modern social networks is largely that they are a new medium for the spread of information. For many purposes,

however, message-level analysis does not tell the whole story. Twitter is a networked system of users exchanging information. Message-level work has frequently relied on predictive message filtering or spotting trending phrases. This is not perfectly suited for the task of broadly assessing the state of the network. Instead, we ask a much simpler question – what type of people are different users choosing to listen to?
For this, we have turned to user-level analysis. When a user choses to opt-in to another user's tweet stream, this says much more about influence than the propagation of individual messages. This idea of influence through followers is a truth that rests at the very core of Twitter, one that can be plainly seen by visiting any user's page and making note of the prominently displayed *Follower* and *Following* counts. Here, we taken this fundemental concept and cross-reference it with various user attributes in an attempt to make more general claims about the nature of influence in the Twitter network.

VI. CONCLUSION

In this paper we have presented a detailed analysis of a large subgraph of the Twitter network. We have identified a number of influence patterns across different attributes within the twitter network. Our work is unique in that it provides a method of tracking information flow without being dependant on access to individual messages. There are a number of pitfalls to message analysis that our work avoids. It is our belief that a combination of both methods of Twitter network analysis are necessary in order to gain a complete perspective on the way this tool is used.

Future work – ideas to consider regarding future projects that could come of our work?

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APPENDIX

User Attributes Below are the user attributes we plan to examine in our analyses. In reference to number of baskets, *varied* means we will experiment with different numbers of baskets.

Attribute	**Description**	**# of Baskets (Core)**	**# of Baskets (All)**	**Values**
Location	User-reported geographic location.	3481	3481	U.S. state code
Protected	If true, only approved followers may see the user's tweets	2	2	true, false
Followers Count	Number of users who track this user's tweets	2116	2116	integer
Friends Count	Number of users this user follows	2116	2116	integer
Account age	Difference between account creation date and current date	169	169	time
Geo-Enabled	GPS meta data is included on tweets	2	2	true, false
Verified	Twitter has verified the identity of the user, currently used for Twitter partners and advertisers	2	2	true, false
Statuses Count	Number of tweets	2116	2116	integer
Language	User's chosen language	7	7	en, de, it, es, ja, fr, ko
Contributors Enabled	If enabled, multiple users can tweet from this account	2	2	true, false
Listed Count	Number of lists that include this account	2116	2116	integer
Show All Inline Media	Display photos and videos of other users, not just friends	2	2	true, false
URL	This user posted a URL	2	2	true, false
Is Translator	User has signed up to translate other people's tweets	2	2	true, false

APPENDIX

Bias Comparisons Across Attributes

Bias Pattern	**Attribute**	**Direction**	**Strength**	**Comments**
Group follows Itself	Followers Count	Positive	Weak	
	Friends Count	Positive	Moderate	
	Statuses Count	Negative	Moderate	
	Listed Count	Negative	Moderate	
	System Age	Positive	Moderate	Increases with age
	Language	Positive	Strong	For non-english users
	State	Positive	Strong	
	Protected	Negative	Weak	
	Geo-Enabled			Not observed
Group follows Others	Followers Count	Positive	Strong	
	Friends Count	Negative	Moderate	
	Statuses Count	Positive	Moderate	
	Listed Count	Positive	Moderate	
	System Age			Not observed
	Language	Negative	Moderate	
	State	Positive	Strong	
	Protected			Not observed
	Geo-Enabled	Positive	Strong	
Low Deg. follows Low Deg.	Followers Count	Negative	Moderate	Very low degree
	Friends Count	Positive	Moderate	
	Statuses Count	Negative	Weak	Very low degree
	Listed Count	Negative	Moderate	Very low degree
	System Age			Not observed
High Deg. follows High Deg.	Followers Count	Negative	Mod. Strong	
	Friends Count	Negative	Moderate	
	Statuses Count	Negative	Mod. Strong	
	Listed Count	Negative	Moderate	
	System Age	Positive	Strong	Strongest Observed
Low Deg. follows High Deg.	Followers Count	Positive	Strong	
	Friends Count	Negative	Moderate	
	Statuses Count	Positive	Moderate	
	Listed Count	Positive	Strong	
	System Age			Not observed
High Deg. follows Low Deg.	Followers Count	Positive	Strong	
	Friends Count	Negative	Moderate	
	Statuses Count	Positive	Weak	
	Listed Count	Positive	Moderate	
	System Age			Not observed