Moving Beyond the Twitter Follow Graph

Giambattista Amati[1], Simone Angelini[1], Marco Bianchi[1],
Gianmarco Fusco[2], Giorgio Gambosi[3], Giancarlo Gaudino[2],
Giuseppe Marcone[1], Gianluca Rossi[3] and Paola Vocca[4]

[1]*Fondazione Ugo Bordoni, Rome, Italy*

[2]*Istituto Superiore delle Comunicazioni e delle Tecnologie dell'Informazione (MiSE-ISCOM), Rome, Italy*

[3]*University of Rome Tor Vergata, Rome, Italy*

[4]*University of Tuscia, Viterbo, Italy*

Keywords: Social Network Analysis, Twitter Graph.

Abstract: The study of the topological properties of graphs derived from social network platforms has a great importance both from the social and from the information point of view; furthermore, it has a big impact on designing new applications and in improving already existing services. Surprisingly, the research community seems to have mainly focused its efforts just on studying the most intuitive and explicit graphs, such as the follower graph of the Twitter platform, or the Facebook friends' graph: consequently, a lot of valuable information is still hidden and it is waiting to be explored and exploited. In this paper we introduce a new type of graph modeling behavior of Twitter users: the mention graph. Then we show how to easily build instances of this graphs starting from the Twitter stream, and we report the results of an experimentation aimed to compare the proposed graph with other graphs already analyzed in the literature, by using some standard social network analysis metrics.

1 INTRODUCTION

Twitter is a widespread micro-blogging platform which allows different user behaviors: posting tweets (*tweeting*), following other users, replying to tweets, mentioning users, labelling tweets (*hashtagging*), forwarding tweets generated by other users (*retweeting*), etc.

Each of these operations can be used to build a graph modeling relationships between users, or between user and contents. The study of the topological properties of these graphs is of fundamental importance to evaluate the structure and to predict the evolution of the Twitter network both from the social and from the information point of view. Additionally, understanding these graphs is important to improve current systems and to design new applications of online social networks.

The most natural and intuitive graph is the *follow graph* (Myers et al., 2014; Kwak et al., 2010), obtained by modeling the *following* relationship existing between the Twitter users. This graph has been already studied to quantitatively gauge the Twitter network (Kwak et al., 2010); to investigate the role of Twitter as a social or information network (Myers et al., 2014); to identify authoritative user accounts (Java et al., 2007; Weng et al., 2010). In (Bild et al., 2015) the authors introduce and analyze the *retweet graph*, better encoding true interest and trust relationships among users than the follow graph, and useful for detecting spammers.

Also other kind of graphs have been considered in the literature: for example in (Wang et al., 2011) the authors introduce the *hashtag graph* where the vertex set is a set of hashtags and an undirected link between two hashtags exists if they co-occur in at least one tweet. This Twitter representation model is used to derive a sentiment classification of the tweets. In (Yamaguchi et al., 2010) the authors introduce the *user-tweet graph*. In a user-tweet graph the nodes correspond to user accounts and tweets, and edges represents both the follow relation and the retweet relationship. In contrast with the follow graph which is static, this graph is reconstructed whenever a new

Amati, G., Angelini, S., Bianchi, M., Fusco, G., Gambosi, G., Gaudino, G., Marcone, G., Rossi, G. and Vocca, P..
Moving Beyond the Twitter Follow Graph.
In *Proceedings of the 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2015) - Volume 1: KDIR*, pages 612-619
ISBN: 978-989-758-158-8

retweet occurs. The user-tweet-graph is used to identify authoritative users. The same model is used in (Arxiden, 2013) to measure users influence in terms of users activities.

Surprisingly, the research community seems to have not yet taken into consideration many other kind of graphs that can be easily built and analyzed just by elaborating a flow of tweets. Some of these graphs can be extremely interesting both for research and applicative purpose.

In this paper we introduce a new type of graph: the *mention graph*. This graph, presented in Section 2, can be used to improve the identification of authoritative accounts, to discover active and dynamic communities, or to assign weights to the follow relationships.

In order to verify the overall structure of our graph, we built an instance of the mention graph and we performed a series of quantitative analysis that are in general used in network analysis (Myers et al., 2014): the degree distributions, connected components, path length distributions; clustering coefficients.

For further information we also built and analyzed an instance of the retweet graph in order to compare our results with those presented in (Bild et al., 2015).

The analysis performed shows that the mention graph is sound, that is the values obtained are in line with the expected values and are similar to the same values for the follow graph as shown in (Myers et al., 2014).

The paper is organized as follows: in Section 2 we briefly describe our graph model; in Section 3 we report about our experimentation. Finally, in Section 4 we conclude the work.

2 GRAPH MODELS

We model interactions between Twitter users by defining the *mention graph*.

In the mention graph each node represents a Twitter account. A directed edge between two nodes *a* and *b* exists if the account *a* mentions the account *b* in at least one tweet. To record multiple citations, we label the edge with a list of timestamps corresponding to each mention, allowing the filtering of edges on the basis of a temporal parameters. As a design choice, mentions contained into retweets and replies are ignored.

It is worth to note, with respect to the follow graph, the mention graph:

- *captures the information spreading on the network*. The follow relationship tends to better represent the social ties between users, since users most likely follow another user on a social basis. On the counter part, the mention relationship better represents the information spreading on the network.
- *furthers a deep qualitative analysis of the follow graph itself*. For instance, comparing the follow and the mention graphs we quantitatively evaluate the actual strength of the follow relationship.
- *is easier to be built and updated*. Since all information needed is derivable just parsing tweets, the graph building process is not affected by the rate limitations of the Twitter Search API.

In order to compare our mention graph with the retweet graph presented in (Bild et al., 2015), we also built an instance of this last kind of graph as follows: in the *retweets graph* two nodes, *a* and *b*, are connected by a direct edge if *a* has retweeted at least one tweet of *b*. Similarly to the mention graph, timestamps of the different retweets between the same user accounts are stored in a list labeling the corresponding directed edge, while retweets of retweets are ignored by design.

3 EXPERIMENTATION

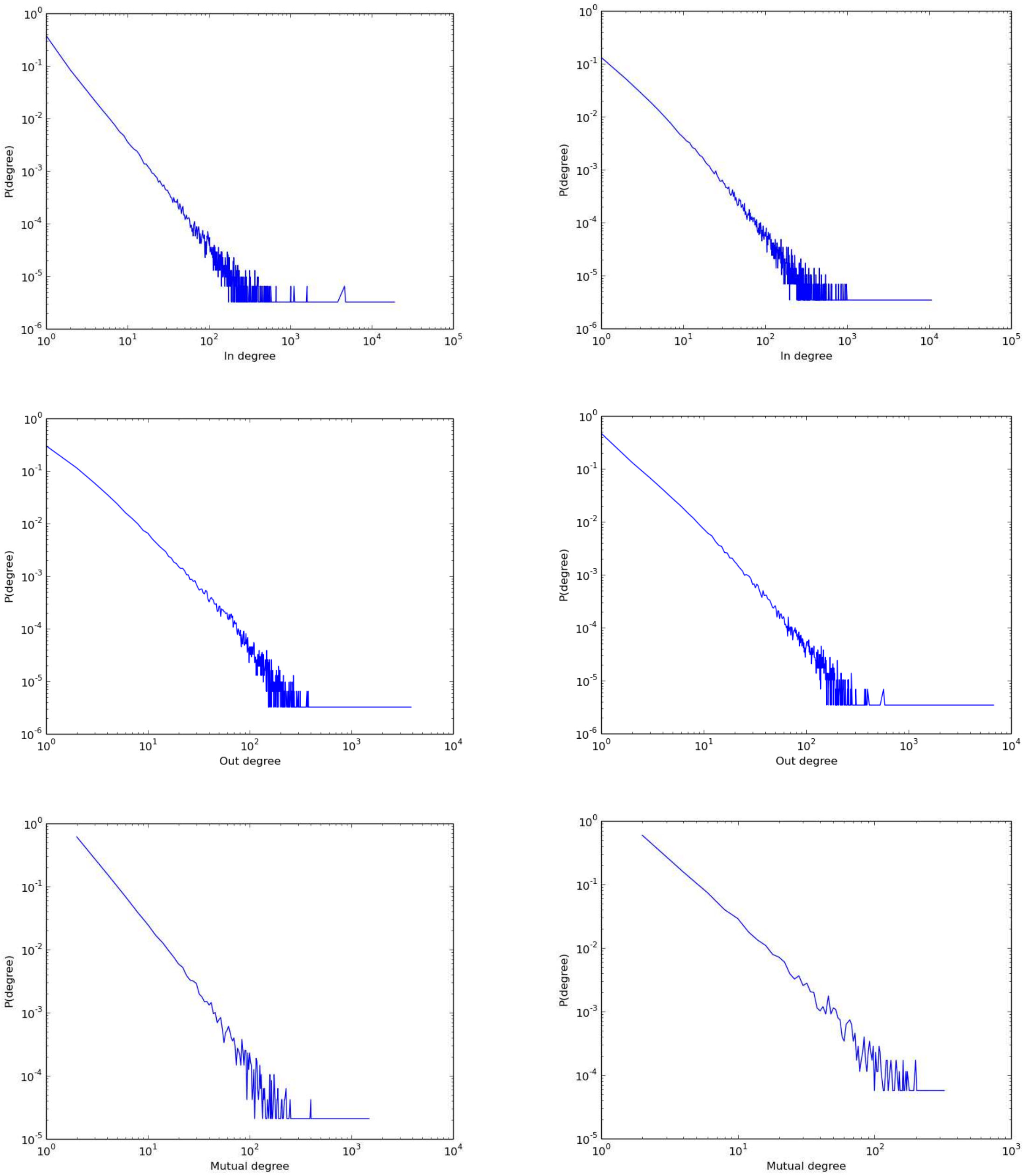
3.1 Building Graph Instances

We perform network analysis of the new mention and retweet graphs using a Twitter collection that was built by monitoring the activities of the Italian Public Administrations on Twitter. More precisely, the collection was obtained selecting a list of about 400 Italian seed keywords (e.g. with all Italian ministers, agencies, etc.) and 5000 Twitter authoritative accounts. These accounts were selected by starting from a few dozens of seed accounts, such as the official accounts of the Prime Minister (@Palazzo_Chigi) and the Ministers (@Viminale, @MinisteroDifesa etc.), and completing the list with the inclusion of their following accounts with the highest number of followers. We have also restricted the tweets to the Italian language.

In the period from the 7th May to the 23rd May 2015 we collected about 5,604,779 tweets, containing 469,359 users, 991,589 mentions and 1,041,955 retweets.

3.2 Analysis

We present a preliminary analysis of some topological features of mention and retweet graphs. In particular we use the degree distribution, connected compo-



(a) (b)

Figure 1: The in-degree, out-degree and mutual-degree distribution of the mention graph (a), of the retweet graph (b).

nents, clustering coefficient, two-hop neighborhood, path-length distribution measures, that are in general used in network analysis (Myers et al., 2014).

We also consider the undirected *mutual* graphs, for each of these two graphs (mention, retweet): an edge between x and y of the mutual graph exists when both (x,y) and (y,x) are edges of the original graph.

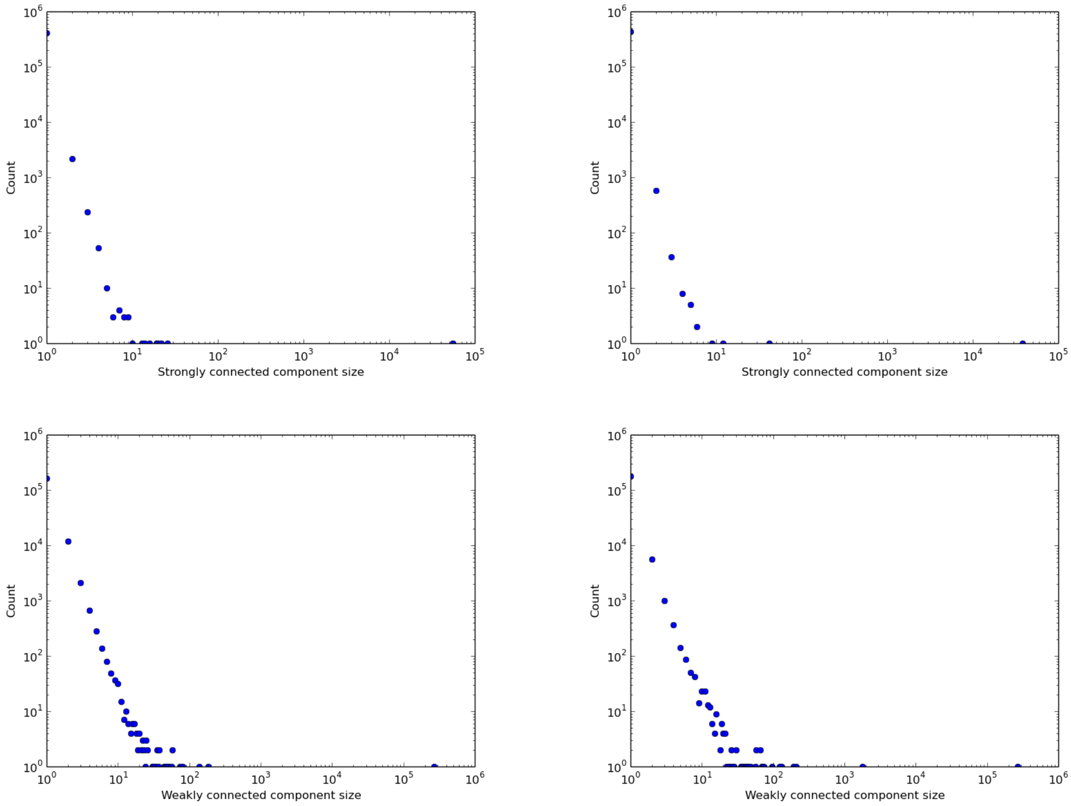
Table 1 shows how the size of mutual graphs are affected by the topological properties of the generating graphs.

Degree Distributions. We here consider the in-degree, out-degree and mutual-degree distributions. The degree distribution provides the ratio of vertices that have a specific number of links (in-links, out-links, mutual-links). These distributions are shown in Figure 1. The Kolmogorov-Smirnov test shows that the fitting of the degree distributions with the power law is statistically significant at 99% level of confidence.

Comparing the mention and retweet graphs of Fig-

Table 1: Edges and Nodes Size of graphs: the percentage refers to the rate of edges or nodes number falling into the mutual graph with respect to their generating graphs.

	Mention	Mention mutual	Retweet	Retweet mutual
Vertices	309,807	47,631 (6.50%)	289,895	17,551 (6.05%)
Edges	991,589	141,244 (14.24%)	1,041,955	53,262 (5.11%)



(a) (b)

Figure 2: The connected component size distribution of the mention graph (a), of the retweet graph (b).

ure 1 with the follow graph of (Myers et al., 2014) we observe a smaller power law coefficient of the follow graphs ($\alpha = 1.35$ 1.28 and 1.39 for in, out and mutual respectively) than that of mention or retweet graphs as shown on Table 2. This difference shows that the rate of most mentioned or retweeted accounts within a topic-driven Twitter flow of information is smaller than the rate of accounts with highest number of followers. Differently from the retweet graph of a Gardenhose sample of Twitter (Bild et al., 2015) (a 10% random sample of the entire flow of Twitter in a given period of time) we did not find a two-tailed fitting model with two power-law distributions. The decision to have selected the most authoritative accounts and a set of relevant keywords could explain this discrepancy as a sampling bias. Similarly, the constraint imposed by Twitter that an account cannot follow more than 2000 accounts, unless one does not already possess an equally number of followers, may be another bias explanation equally possible.

Connected Components. Figure 2 illustrates the distribution of the strongly and weakly connected component size. We remind that, differently from the strong connectivity, the weak connectivity ignores the direction of the edges.

Figure 2 shows some similarity with the Twitter follow graph (Myers et al., 2014). We remind that when considering all vertices with at least one edge (either in or out), the largest weakly connected component of the follow graph contains almost all vertices (99.94%) and that in both weakly and strongly connectivity there is a very large component containing almost all vertices. Differently from follow graphs one can observe that there is a single very large component that squeezes the size of all other con-

Table 2: Power law coefficients for the mention and retweet graphs. The D_c are the critical values of the Kolmogorov-Smirnov test. The distance D for the mention and retweet graphs at the confidence level of 99% are below their critical values.

Mention				
Degree	Power Coefficient α	KS Distance D	D_c	Max degree
In	1.511	0.021	0.071	19066
Out	1.518	0.030	0.089	3856
Mutual	1.471	0.051	0.138	1490
Retweet				
Degree	Power Coefficient α	KS Distance D	D_c	Max degree
In	1.541	0.026	0.066	10661
Out	1.469	0.030	0.091	6745
Mutual	1.515	0.065	0.171	324

Table 3: The average distance in the considered graphs.

	Mention	Mention mutual	Retweet	Retweet mutual
Average distance	6.62	6.25	6.28	7.08

nected components only with the weakly connectivity of retweet and mention graphs.

The largest strongly connected component contains only 17.56% of accounts for the retweet graphs and 17.86% for the mention graph against the 68.7% of the follow graphs of (Myers et al., 2014).

On the other hand, the largest weakly connected component contains only 92.18% of accounts for the retweet graphs and 86.86% for the mention graph similarly to the 91.2% of the follow graphs (Myers et al., 2014).

The explanation of this discrepancy is that some vertices are mentioned or retweeted by many accounts so that when one ignores directions the connectivity increases significantly.

Path-length Distributions. Figure 3 shows the path-length distribution of the examined graphs and Table 3 shows the average distance between the vertices. These data contrast with the ones reported in (Myers et al., 2014) and (Bild et al., 2015) where the values are 4.17 for the follow graph, 4.05 for the mutual follow graph, and 4.8 for the retweet graph. It is important to note that in our case, although the graph is of several orders of magnitude smaller of the two considered in those papers, and is very sparse (in our case the average degree is 3 and their is 10) our graphs show the ”small-world” property typical of the social networks.

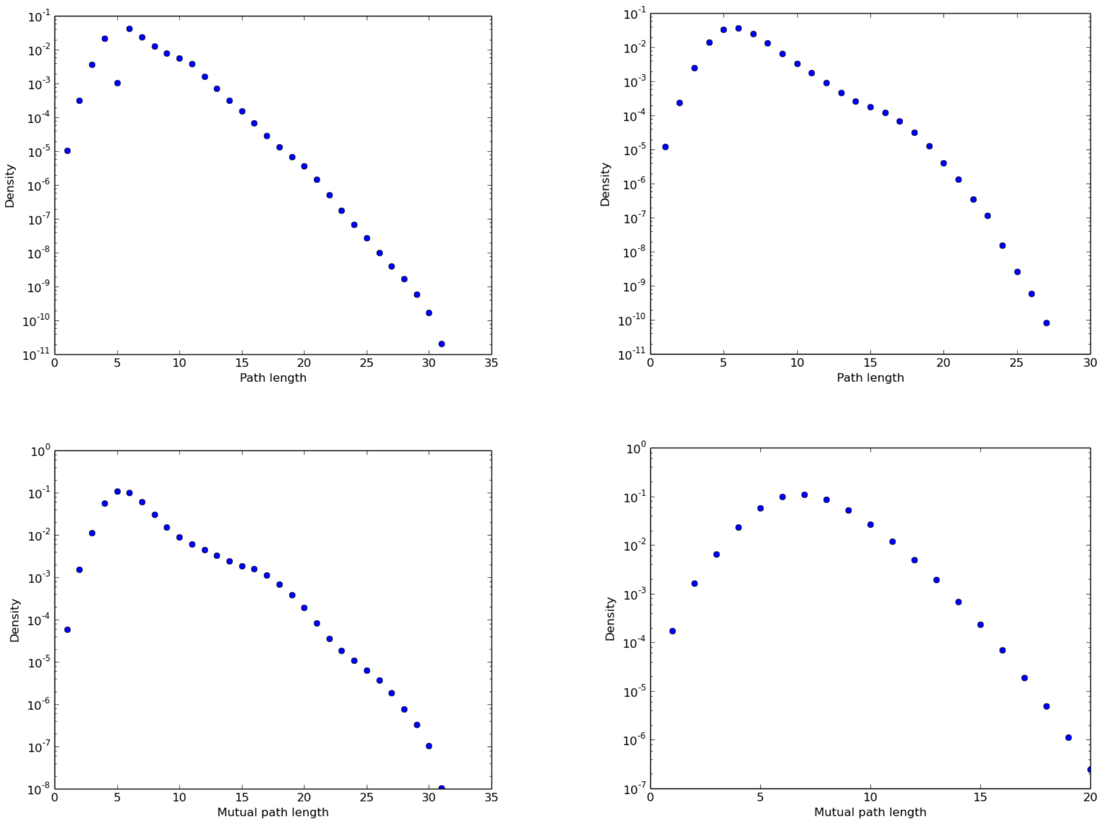
Clustering Coefficient. The clustering coefficient in a network measures the fraction of vertices whose neighbors are themselves neighbors: social networks have an high clustering coefficient (Watts and Strogatz, 1998). In our case, this metric is significant just in the case of the mutual graphs. In Figure 4 it is represented the average clustering coefficient of vertices as a function of the mutual degrees.

The irregularity of the diagram from values of mutual degrees around 100 and beyond is due to the low number of vertices with that degree. This makes the average statistically insignificant.

Two-hop Neighborhoods. This is the set of vertices that are neighbors of a vertex's neighbors; we consider both in-and out-neighbors. This is an important feature in a communication network because indicates how a vertex is a potential information collector or disseminator of information (depending on whether we are considering incoming or outcoming edges).

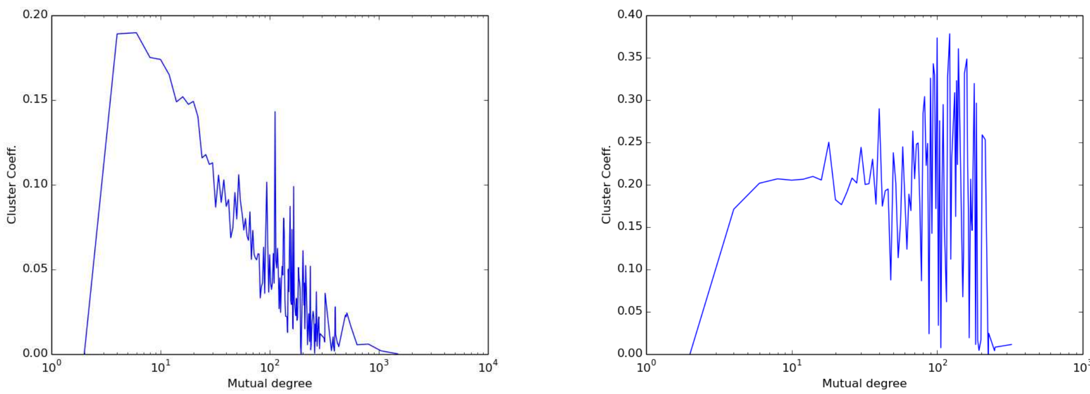
In the charts in Figure 5 are shown the size of the two hop neighborhoods as a function of the size of the in- and out-neighborhood. “Unique” and “not unique” refer to whether a node in the two-hop neighborhood is counted one or as many times as it appears in the neighborhood of the neighbors. Finally, k^2 indicates the size of the two-hop neighborhood in the case all neighbors of a node have the same degree of the node.

If the sizes of the two-hop neighborhoods are greater than k^2 the network shows high information spreading. The analysis of Figure 5 reveals that the curves representing the two-hop neighborhood sizes cross k^2 much earlier than in the follow graph (Myers et al., 2014). However, in our case, the number of nodes with two-hop neighborhood sizes less than k^2 is very small (because is small the number of nodes having tens of neighborhoods); therefore we conclude that mention and retweet graphs have high information spreading.



(a) (b)

Figure 3: The path length distribution of the mention graph (a) and the retweet graph (b).

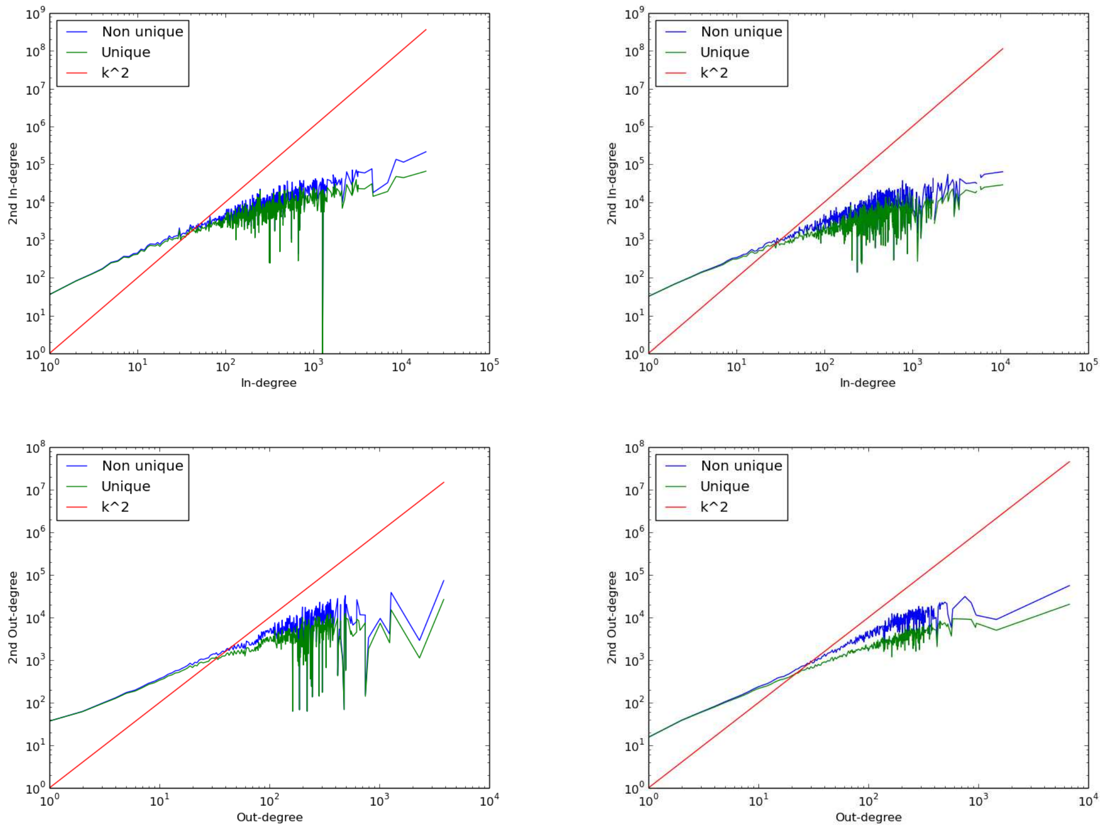


(a) (b)

Figure 4: The average clustering coefficient of vertices as a function of the mutual degree (a) in the mention graph and (b) in the retweet graph.

4 CONCLUSIONS

In this paper we presented a new graph modeling the Twitter user behavior: the mention graph. We used well-known social networks analysis metrics for comparing the mention graph with both the follow and the retweet graphs. The path-length distribution results show that, although the mention graphs considered in this paper is of several orders of magnitude smaller than the ones studied in (Bild et al., 2015) and in (Myers et al., 2014), it still has the "small-world" property of the social networks.



(a) (b)

Figure 5: The size of the two-hop neighborhoods of the mutual degree (a) in the mention graph and (b) in the retweet graph.

Finally, the two-hop neighborhoods analysis shows that, compared to the follow graph, the mention and the retweet graphs have a higher information spreading.

Hence, the mention graph represents a promising approach for performing typical qualitative analysis such as sentiment analysis, authoritative users, community detection.

ACKNOWLEDGEMENTS

This work has been carried out in the MiSE-ISCOM laboratories within a long-term research agreement between FUB and ISCOM.

REFERENCES

Arxiden, A. (2013). Analysis of users' influence based on activity and quality of tweets for specific topics in micro-blog. *Journal of Computational Information Systems*, 9(20):8127–8137.

Bild, D. R., Liu, Y., Dick, R. P., Mao, Z. M., and Wallach, D. S. (2015). Aggregate characterization of user behavior in twitter and analysis of the retweet graph. *ACM Trans. Internet Technol.*, 15(1):4:1–4:24.

Java, A., Song, X., Finin, T., and Tseng, B. (2007). Why we twitter: Understanding microblogging usage and communities. In *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis*, WebKDD/SNA-KDD '07, pages 56–65, New York, NY, USA. ACM.

Kwak, H., Lee, C., Park, H., and Moon, S. (2010). What is twitter, a social network or a news media? In *Proceedings of the 19th International Conference on World Wide Web*, WWW '10, pages 591–600, New York, NY, USA. ACM.

Myers, S. A., Sharma, A., Gupta, P., and Lin, J. (2014). Information network or social network?: The structure of the twitter follow graph. In *Proceedings of the Companion Publication of the 23rd International Conference on World Wide Web Companion*, WWW Companion '14, pages 493–498, Republic and Canton of Geneva, Switzerland. International World Wide Web Conferences Steering Committee.

Wang, X., Wei, F., Liu, X., Zhou, M., and Zhang, M. (2011). Topic sentiment analysis in twitter: A graph-based hashtag sentiment classification approach. In *Pro-*

ceedings of the 20th ACM International Conference on Information and Knowledge Management, CIKM '11, pages 1031–1040, New York, NY, USA. ACM.

Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of'small-world'networks. *Nature*, 393(6684):409–10.

Weng, J., Lim, E.-P., Jiang, J., and He, Q. (2010). Twitterrank: Finding topic-sensitive influential twitterers. In *Proceedings of the Third ACM International Conference on Web Search and Data Mining*, WSDM '10, pages 261–270, New York, NY, USA. ACM.

Yamaguchi, Y., Takahashi, T., Amagasa, T., and Kitagawa, H. (2010). Turank: Twitter user ranking based on user-tweet graph analysis. In *Proceedings of the 11th International Conference on Web Information Systems Engineering*, WISE'10, pages 240–253, Berlin, Heidelberg. Springer-Verlag.