Applying an Influence Measurement Framework to Large Social Network

Khaled Almgren, Jeongkyu Lee
Department of Computer Science and Engineering
University of Bridgeport, Bridgeport
CT 06604, USA
kalmgren@my.bridgeport.edu, jelee@bridgeport.edu

ABSTRACT: *Predicting influential users is one of the important research problems on social network analysis. It helps to understand many complicated phenomena including information dissemination. It can be employed in many real world applications such as viral marketing. Influential users can influence social network users using their attributes, strategic locations or expertises. In this paper, we tackle this problem by proposing a novel hybrid framework that is used to predict influential users on social network. In this framework, we integrate users' attributes and their strategic location to measure influence. We apply several centrality analysis algorithms to find user's strategic locations, while we adapt a real world attribute measure that is used by Flickr based on users' attributes. We employ our framework to a large dataset crawled from real world social network, i.e., Digg. We evaluate the proposed framework in term of correlation. We further show that the proposed framework outperforms other measurements*

Keywords: Social Network Analysis, Influence Measurements, Predicting Influential Users, Centrality Analysis, Flickr

Received: 25 November 2015, Revised 29 December 2015, Accepted 4 January 2016

1. Introduction

One of the most widely discussed topics in social network analysis is the influence measurement. Influence is defined as "*change in an individual's thoughts, feelings, attitudes or behaviors that result from interaction with another individual or a group* [22]." This topic has been long approached by sociologists because it can explain many phenomena including decision making and information spread [10]. Katz, a famous sociologist, measuring influence can be related to three major values: finding the personification of certain values, competence, and situation in a strategic social location [11]. The first value is about people's personal characteristics, the second value is related to people's knowledge and experiences, where the third value is represented by people's social locations in a group or organization [11].

Recently, social networks provided a promising platform to study social phenomena such as influence in social networks because of the huge size and convenient access method. For example, Flickr has more than 92 million users as of 2014 [26], while Twitter has about 288 million active users as of 2015 [27]. Moreover, social networks provide their own APIs which can provide users with easy access, such as Flickr API [1] and Twitter API [2]. Because of the availability of huge amount of data, measuring influence on social networks can be used for predicting influential people.

Influential users on social networks are users who attract many people to react to their published contents using social networks activities including tweets on Twitter, and photos on Flickr. Influential users can be employed in many useful applications including viral marketing, recommendations systems, and expert search engines [1, 6, 8, 13, 14, 15, 16, 21, 23, 24, 25].

However, predicting the influential users on social networks encounters several challenges. First, current measurements do not consider all the characteristics of social networks and not feasible to all social networks. To approach this problem, we consider two aspects of social networks i.e., user's structural location in a network and attributes. The second problem is the absence of ground truth data [5]. To address this issue, Gosh and Lerman propose an empirical measurement of influence that can be used as ground truth. They state that the average number of votes can estimate the users' influence effectively. They show the statistical significance of their measure using the URN model. We adopt their approach to a large dataset crawled from a real social network, i.e., Digg, to evaluate our measurement [7].

In this paper, we propose a hybrid framework to predict influential users. This framework integrates:

(1) Users' structural location in a network, and

(2) Users' attributes.

The structural location in a network can be computed using centrality analysis. Centrality analysis is used to find important nodes on social networks based on its structure of social network. There are several centrality analysis algorithms including in-degree centrality, weighted in-degree centrality, eigenvector centrality, and pagerank centrality [30]. These four algorithms are discussed in details in Sec. 4. On the other hand, users' attributes on social networks such as users activeness should be counted for measuring influence because users' attribute is one of the three influence types of Katz communication model [11].

In order to improve the performance of influence measurement, we employ different centrality analysis algorithms for our measurement, and integrate it with users' attributes to predict influential users. In addition, we apply locations-based influence measurements and attribute-based influence measurements to show the superiority of the proposed framework. For the attribute-based influence measurements, we adopt Flickr's contribution measurement,i.e., number of uploads. Flickr ranks users in groups by the number of shared photos. This measurement represents how much active users are. Suppose that users A and B post five and four photos, respectively. User A will be ranked higher than user B. Therefore, we can define the problem of social influence as follows:

Social Influence: For any social network, called *SN* that is represented as a graph G (V, E) of V vertices and E edges that can be weighted and directed, given a set of connected users $V_n = \{v1, \dots, V_n\}$ who can post multiple posts $p \in P$, and can be characterized by a set of given attributes $\{att_1, \dots, att_n\}$, and perform multiple social interactions $z \in Z$, where Z is a set of social interaction shown as edges $E_n = \{e_1; : : : ; e_n\}$, predict a user i who will influence users j to perform further social interaction Z.

An overview of our framework is shown in Figure 1. The framework includes three modules: (i) user location module, (ii) user attribute module, and (iii) hybrid integration module. The main contributions are listed below:

(1) We propose a hybrid framework to predict influential users that considers users' structural network location, and users' attributes,

[1] https://www.flickr.com/services/api/

[2] https://dev.twitter.com

(2) We employ different centrality analysis algorithms to evaluate our framework, and

(3) We apply our framework to a real world social network, i.e., Digg.

The remainder of the paper is organized as follows. We review the related work and categorize them according to the influence measurement in Section 3. In Section 3, we present the influence model. We propose our framework and discuss the location-based influence measurements and the attribute-based influence measurement in Section 4. In Section 5, we discuss our experimental setup and results. We conclude in Section 6.

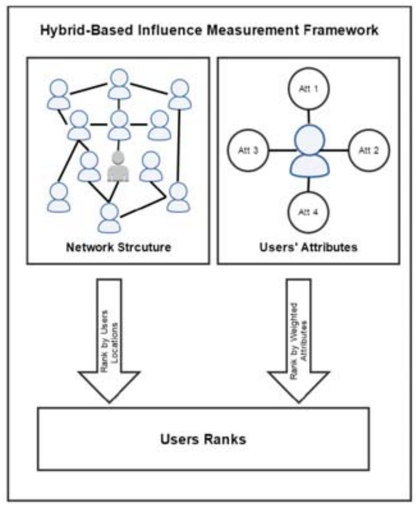

Figure 1. Overview of the proposed framework

2. Related Works

In this section, we classify the measurements to three categories: location-based influence measurements, attribute-based influence measurements, and hybrid-based influence measurements. In location-based influence measurements, influence is measured by users' location on social networks. In attribute-based influence measurement, users' attributes are used to quantify influence such as user activeness. We integrate these two measurements and propose a hybrid-based influence measurement, influence is measured using both users' locations and attributes.

2.1 Location-Based Influence Measurements

Location-based influence measurements, influence considers the structural location of users on social networks [30]. The measurements consider social networks context, content, or both [3]. Most of the existing measurements are computed using centrality analysis algorithms, such as in-degree centrality that is based on the number of direct numbers [6, 13, 25, 28, 19, 17, 18, 31, 3, 20, 7].

2.2 Attribute-Based Influence Measurements

In attribute-based influence measurements, influence is measured based on users attributes, such as activeness which is represented by the number of posts. These measurements rely mostly on the users' content. Flickr rank users based on the number of uploaded photos in a group[3], this can represent how active users are. In addition, there are few papers who proposed attribute-based influence measurements [1, 6, 12].

2.3 Hybrid-Based Influence Measurements

In hybrid-based influence measurements, influence is measured by integrating both users' locations and attributes. From out best of knowledge, there has been one attempt to propose this type of measurements. Yi et al. [29] proposed an integrated

[3]https://www.flickr.com/groups/2749529@N22/

measurement that is based on both users' attributes and location. They quantify users' attributes using analytical hierarchy and integrate it with Pagerank [29]. Furthermore, their algorithm relies on pagerank to compute the users' locations. However, there are many ways to compute the locations of users.

In this paper, we look at the big picture and consider different centrality analysis algorithms for computing users' locations in a network. Moreover, we compare our framework with a real-world attribute-based influence measurement, i.e., Flickr contribution measurement, as well as different location-based influence measurements. Our goal is to propose a framework that considers all the characteristics of social networks. Therefore, we propose a new framework that can integrate several locations-based influence measurements and attribute-based influence measurements.

3. Graph-Based Influence Model

In this section, we discuss how influence on social networks is modeled using a graph. In a graph G(V;E), we can represent users in social networks as nodes V , and interactions as edges E. Edges can be either directed or undirected, and either weighted or unweighed depending on the characteristics of social networks. For example, retweet on Twitter is directed while friendship on Facebook is undirected. In a graph, influence flows between users through edges. A graph can be denoted using adjacency matrix or adjacency list[2]. [9] shows that social networks can be sparse networks. Therefore, it is more efficient in terms of time and space to use adjacency lists.

In adjacency lists, only node that points to other nodes are stored in row cells. For example, suppose that there are three nodes a, b and c where a points to b and c ,and b points to c. Therefore, in the first row, we can have a, b and c, in the second row, we have b and c, and in the third row, we have only c. This example shows how space is utilized effectively as shown in Figure 2. In this paper, we sort the adjacency list using MergeSort [2].

4. Hybrid Framework For Influence Measurement

In this section, we discuss our proposed work, i.e., hybrid framework for influence measurement. As mentioned in Section 1, the framework consists of user location module, user attribute module, and hybrid integration module. In the user location module, we compute the influence of users based on their structural locations of social networks. In the user attribute module, we measure influence using users' attribute values. In the integration module, we integrate both users' location and attribute in measuring their influence.

4.1 User Location Module

In this module, the structural location of users on social network is considered. We measure users' social influence by their structural locations in a network, which is called ULM. To analyze the importance of nodes based on their locations on social networks, we employ centrality analysis. Centrality analysis utilizes the structure of social networks [30]. However, there are different ways to compute the importance of nodes. For example, in-degree centrality uses the number of direct neighbors as the importance. We implement four centrality analysis algorithms to consider different ways of looking at the structure of social networks including pagerank centrality, eigenvector centrality, in-degree centrality, and weighted in-degree centrality. In the subsections, we discuss each centrality analysis algorithm. Figure 4 shows an overview of the user location module using four centrality analysis algorithms. ULM can be computed using any of the following centrality analysis algorithms.

(1) Eigenvector Centrality: Eigenvector centrality, i.e., C_e is the first centrality analysis algorithm that considers the depth of networks [30]. In eigenvector centrality, the importance of nodes are determined by their neighbors importance. It is computed using the following equation.

$$C_e(v_i) = \frac{1}{\lambda}\sum_{j=1}^{n} AC_e(v_i) \quad (1)$$

,where A is the adjacency matrix and λ is a constant representing the largest eigenvalue.

(2) Pagerank Centrality: Pagerank, i.e., C_p is a variation of eigenvector centrality [30]. However, eigenvector centrality encounter some problems. For example, the centrality of nodes is passed to all neighboring nodes, which can make them have the same centralities. This is not efficient because not all the nodes linked to popular nodes are necessarily popular. In pagerank, the importance of nodes that is passed to neighboring nodes are divided by the number of neighboring nodes. For example, a node is important if it is being pointed by nodes that are also being pointed at by many other nodes. Pagerank is computed using the following equation [30].

$$C_p(v_i) = \beta(I - \times AD^{-1}C_p(v_i)^{-1} \times 1) \tag{2}$$

, where β is an attenuation constant, and α is a constant used to avoid zero centralities. I is the identity matrix, A is the adjacency matrix, and D^{-1} is the reverse of diagonal matrix of degrees.

(3) In-degree Centrality: In-degree centrality, i.e., C_{din} considers the number of direct neighbors as measure of importance [30]. The idea behind this algorithm is that people with many friends can be considered as important users. In-degree can computed using the following equation.

$$C_{d_{in}} = d_i^{(in)} \tag{3}$$

, where $d_i^{(in)}$ is the number of direct neighbors for node i.

(4) Weighted in-degree centrality: Weighted in-degree centrality, i.e., Cd_{win} is a variation of in-degree centrality that considers the interaction strength between every two nodes [3]. Therefore, a user who receives many interactions from many neighbors is considered as an important user. This algorithm uses the fact that users who have many strong relationships with many friends are considered as important. It is computed by considering the weighted incoming edges $d_i^{w(in)}$ for every node i.

$$Cd_{win} = d_i^{w(in)} \tag{4}$$

, where $d_i^{w(in)}$ represents the weighted incoming edges for i.

4.2 User Attribute Module

In this module, attributes are used to measure their influence such as activeness. We use weights to consider the importance of each attribute, i.e., $\{w_1, \ldots, w_n\}$, where $\sum_{i=0}^{n} w_i = 1$. Each w_i will be assigned to each attribute att_i. Equation (5) is used to compute the influence using the user attribute module, i.e., UAM, to rank users based on their attributes.

$$UAM = \sum_{i=0}^{n} att_i \times w_i \tag{5}$$

Figure 3 describes the overview of the user attribute module using Flickr contribution measurement.

4.3 Hybrid Integration Module

In this module, we integrate the previous two modules: user location and user attribute modules. We compute a user's influence based on his/her attributes and locations on social networks, called *HIM*. We use a parameter τ to controls the relative importance between the two measurements. As shown in Equation 6, *HIM* is computed by integrating two modules, i.e., *UAM* and *ULM*.

$$HIM = \tau \times UAM + (1 - \tau) \times ULM \tag{6}$$

5. Experiments

In order to evaluate the proposed framework, we select four location-based influence measurements and one real-world attributebased influence measurements. Then, we apply them to a real-world social network, i.e., Digg. In order to evaluate the proposed framework, we perform the correlation analysis between each measurement and the ground truth data. In the experiment, we will apply different values of τ for the proposed framework to decide the optimal τ value.

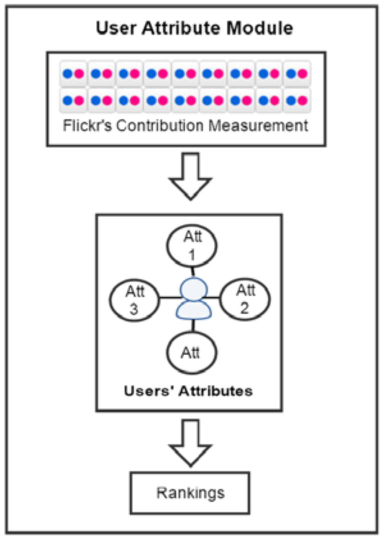

Figure 3. Overview of user attribute module

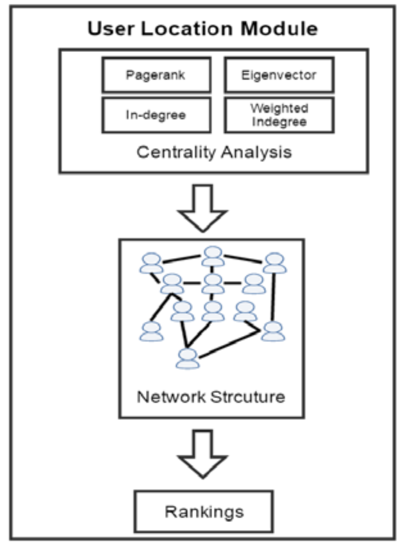

Figure 4. Overview of user location module

5.1 Experimental Setup

For the dataset, we used a real-world dataset to assess the framework introduced in this paper. The dataset is crawled from Digg and is provided by [7]. Digg is a social network that allows users to become popular by sharing stories. Users can interact with each other by voting on stories. The dataset contains 139,409 users and 1,534,314 edges representing votes. Among of these users, 474 users have shared 3,553 stories. The Digg's dataset Characteristics is shown in Table 1.

Number of Nodes	Number of Edges	Number of Photos	Number of Contributing	Number of Candidate Influential Users
139409	1534314	3553	474	74

Table 1. Digg's dataset Characteristics

We create the ground truth using the statistical influence measurement [7]. The ground truth data is computed using the average fan votes. The fan votes basically represent the directed interactions between the users. Therefore, we apply this measure to the dataset to evaluate and assess the influence measurements. Only users who share at least 10 posts and have at least 10 followers are considered as candidate of influential users. The dataset has 74 candidates and the ground truth rank is referred to as *Emp*.

For the evaluation of our framework, we perform the correlation analysis for several influence measurements with the ground truth to see how much the result of each measurement is similar. We further divide our experiment into three subsections: location-based influence measurements, attribute-based influence measurements, and hybrid-based influence measurements. We use Pearson's Correlation *Coefficient*(r) to correlate the measurement with the ground truth. Pearson's Correlation Coefficient measures the linear dependency between two variables to measure how much they are similar to each other [30]. It is computed using the following equation

$$r_{A,B} = \frac{\sum_{i=0}^{n}(a_i b_i) - n\bar{A}\bar{B}}{n\sigma_A\sigma_B} \quad (7)$$

, where A and B are the two variables. A and B represent the rankings of influence measurement and the ground truth respectively.

5.2 Results

Figure 5 shows the experimental results. For locations-based influence measurements, we have applied four centrality analysis algorithms introduced in Section 4 to the dataset to measure users' influence. The correlation between C_e with $\alpha = 0.05$ and *Emp*, i.e., ground truth, is 0.66. The correlation of C_p and *Emp* is $r = 0.7$. C_{din} is less correlated with *Emp* with $r = 0.66$. Cd_{win} is the most correlated with *Emp* with $r = 0.82$. Although the attribute-based influence measurement can consider many users' attributes in measuring influence, we only consider one attribute because we have adopted Flickr's contribution ranking scheme. Flickr ranks users in every group based on the number of posts P that users upload. This can show how much active users are on social networks [4]. Therefore, the selected attribute in this measurement is considered as activeness. Since we only have on attribute, we assign the maximum weight to the attribute, i.e., $w_1 = 1$. This measurement is correlated with *Emp* with $r = 0.89$. Its correlation with *Emp* is higher than an other location-based influence measurements.

For the proposed framework, we integrate each of the centrality analysis algorithm with the attribute-based influence measurement, and then correlated them with *Emp*. To optimize the correlation between the hybrid measurements and *Emp*, we applied different values of τ as shown in Figure 6. For the comparison purpose, we select the optimal τ values. The optimal τ values for C_e, C_{in}, C_{win} and C_p are 0.005, 0.0005, 0.005, and 0.0005, respectively as shown in Table 2. For the correlation between the hybrid measurements and ground truth data, hybrid C_e is correlated with *Emp* with $r = 0.903$. Hybrid C_p has a correlation with *Emp* of 0.904. Hybrid C_{win} has a correlation with *Emp* of 0.901 while the correlation for C_{in} and *Emp* decreases to 0.89. Among these measurements, the hybrid C_p is the most correlated measurement with the ground-truth.

Since the hybrid measurements act differently using different τ values, we apply different τ values ranging from 0. 0005 to 0. 9 to the hybrid measurements. We find that hybrid C_p starts with 0:9 and then slightly increase to 0. 904 and then slightly decrease to 0:8 when τ values are between 0:0005 and 0:05. However, hybrid C_p starts to decrease more after that. This shows that hybrid C_p performs better when the attribute-based influence measurements is more important than the location-based influence measurement. For hybrid C_e, we find that the correlation stays within the same range for all the τ values which shows that attribute-based influence measurements is as important as location-based influence measurements. Hybrid C_{win} starts with high correlation with *Emp* and then starts to decrease. This shows that the attribute-based influence measurements is more important than the location-based influence measurements. Hybrid C_{in} also starts with high correlation with *Emp* and then dramatically decrease, which shows that attribute-based influence measurements is much much more important than the location-based influence measurements.

Hybrid Measurement	τ values
C_e	0.005
C_{in}	0.0005
C_p	0.005
C_{win}	0.0005

Table 2. Optimal τ values for each hybrid measurement

For the comparison of all the measurements, Hybrid C_p is the most correlated measurement. This occurs because it considers the strength of interactions between influential users and other users, and the importance of followers. Hybrid C_{win} is the second most correlated, since C_{win} is based on the interactions strength only. Hybrid C_e is the third most correlated since it considers the importance of followers only. Hybrid C_{in} is the next correlated measurement, followed by the attribute-based influence measurement. The locations-based influence measurements are the least correlated measurements with *Emp*. C_{win} is the sixth most correlated measurement with Emp followed by C_e. C_p comes after them. The least correlated measurement is C_{in}. The results show that integrating both users' locations and attributes outperforms location-based and attribute-based influence measurements. In general attribute-based influence measurement is better than location-based influence measurement. However, the importance of location-based and attribute-based influence measurements are different from each centrality analysis algorithm. We can conclude that hybrid-based influence measurements is better than single-based influence measurements and users' attributes are more important than their structural locations in a network in term of correlation.

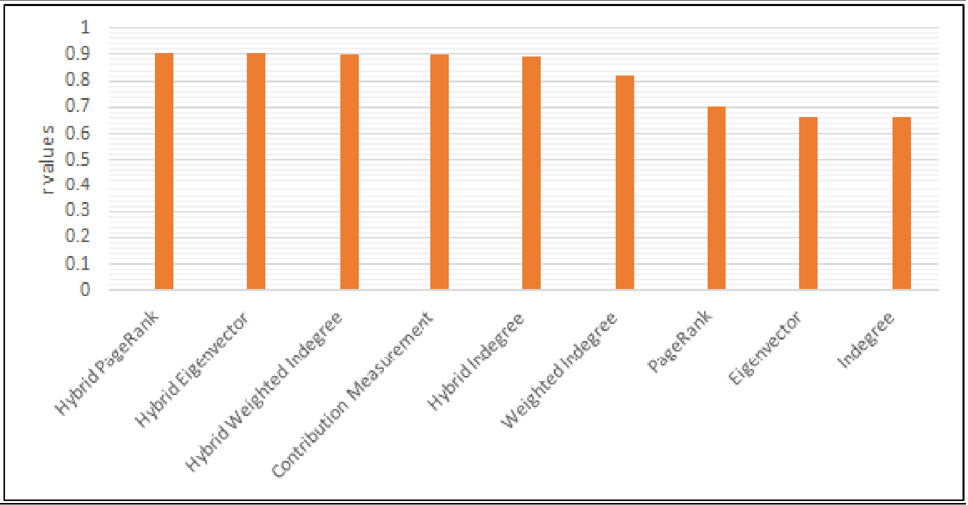

Figure 5. Correlation results between influence measurements and the ground-truth

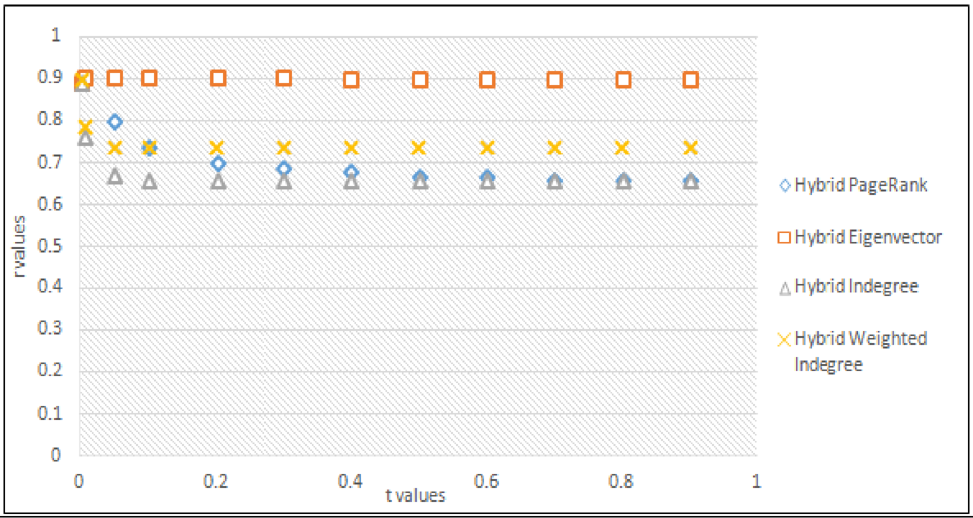

Figure 6. Different "values applied to hybrid influence measurements

6. Conclusion

We apply a novel hybrid influence measurements to predict influential users on a large dataset crawled from a real-world social network, i.e., Digg. The hybrid measurements integrate both users' structural network locations and their attributes. The framework is comprised of three modules: integration module, location-based module, and attribute-based module. In the location-based module, influence is measured using the structural location in a network while in attribute-based module, influence is measured using users' attributes. In the integration module, we integrate both users' locations and attributes. We compared the influence measurements with the ground truth in term of correlation. Our results show that hybrid-based measurements outperform other influence measurements. For our future work, we wish to add a third module that can compute users experiences through their published posts. We are confident that the addition of this module can be applied to real-world applications such as expert search engine.

References

[1] Aggarwal, C. C. (2011). An introduction to social network data analytics (1-15). Springer US.

[2] Aho, A. V., Hopcroft, J. E. (1974). Design Analysis of Computer Algorithms. Pearson Education India.

[3] Almgren, K., Lee, J. (2015). Who Influences Whom: Content-based Approach for Predicting Influential Users in Social Networks: *International Conference on Advances in Big Data Analytics* (ABDA), 89-99, Las Vegas, USA

[4] Anger, I., Kittl, C. (2011). Measuring influence on Twitter. *In*: Proceedings of the 11th *International Conference on Knowledge Management and Knowledge Technologies,* (31). ACM. Chicago

[5] Bakshy, E., Hofman, J. M., Mason, W. A., Watts, D. J. (2011). Everyone's an influencer: quantifying influence on twitter. *In: Proceedings of the fourth ACM international conference on Web search and data mining*, (65-74). ACM.

[6] Cha, M., Haddadi, H., Benevenuto, F., Gummadi, P. K. (2010). Measuring User Influence in Twitter: *The Million Follower Fallacy. ICWSM*, 10, 10-17.

[7] Ghosh, R., Lerman, K. (2010). Predicting influential users in online social networks. arXiv preprint arXiv:1005.4882.

[8] Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology,* 1360-1380

[9] Huberman, B. A., Romero, D. M., Wu, F. (2008). Social networks that matter: Twitter under the microscope. Available at SSRN 1313405.

[10] Katz, E., Lazarsfeld, P. F. (1955). Personal Influence, The part played by people in the flow of mass communications. *Transaction Publishers*.

[11] Katz, E. (1957). The two-step flow of communication: An up-to-date report on an hypothesis. Public opinion quarterly, 21 (1), 61-78.

[12] Leavitt, A., Burchard, E., Fisher, D., Gilbert, S. (2009). The influentials: New approaches for analyzing influence on twitter. *Web Ecology Project*, 4 (2), 1-18

[13] Lee, C., Kwak, H., Lee, C., Park, H., Moon, S. (2010). What is Twitter, a social network or a news media?. In: Proceedings of the 19th international conference on World wide web (591-600). ACM

[14] Lee, C., Kwak, H., Park, H., & Moon, S. (2010, April). Finding influentials based on the temporal order of information adoption in twitter. *In*: Proceedings of the 19th international conference on World wide web (1137-1138). ACM.

[15] Li, H, Cui, JT, Ma, JF. (2015). Social influence study in online networks: A three-level review. *Journal of Computer Science and Technology* 30 (1): 184-199 January.

[16] Li, J., Peng, W., Li, T., Sun, T. (2013). Social network user influence dynamics prediction. *In Web Technologies and Applications* (310-322). Springer Berlin Heidelberg.

[17] Li, X., Cheng, S., Chen, W., Jiang, F. (2013). Novel user influence measurement based on user interaction in microblog. *In*: Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (615-619). ACM.

[18] Liao, Q., Wang, W., Han, Y., Zhang, Q. (2013). Analyzing the influential people in Sina Weibo dataset. In Global Communications Conference (GLOBECOM), 2013 IEEE (3066-3071).

[19] LÃij, L., Zhang, Y. C., Yeung, C. H., Zhou, T. (2011). Leaders in social networks, the delicious case. PloS one, 6(6), e21202.

[20] Maharani, W., Gozali, A. A. (2014, October). Degree centrality and eigenvector centrality in twitter. In Telecommunication Systems Services and Applications (TSSA), 2014 8th International Conference on (1-5).

[21] Probst, F., Grosswiele, D. K. L., Pfleger, D. K. R. (2013). Who will lead and who will follow: *Identifying Influential Users in Online Social Networks. Business & Information Systems Engineering*, 5 (3), 179-193

[22] Rashotte, L. (2007). Social influence. *The blackwell encyclopedia of social psychology*, 9, 562-563.

[23] Reilly, C. F., Salinas, D., Leon, D. D. (2014). Ranking Users Based on Influence in a Directional Social Network. *In Computational Science and Computational Intelligence* (CSCI), 2014 International Conference on (2, 237-240).

[24] Sang, J., Xu, C. (2013). Social influence analysis and application on multimedia sharing websites. ACM Transactions on Multimedia Computing, *Communications, and Applications* (TOMCCAP), 9 (1), 53.

[25] Sun, B., Ng, V. T. (2013). Identifying influential users by their postings in social networks. In Ubiquitous Social Media

Analysis (128-151). Springer Berlin Heidelberg.

[26] Techcrunch. (2014). Flickr At 10: 1M Photos Shared Per Day, 170 Increase Since Making 1TB Free.Retrieved from http://techcrunch.com/2014/02/10/flickr-at-10-1m-photos-shared-per-day-170-increase-since-making- 1tb-free

[27] Twitter. (2015). Twitter usage. Retrieved from https://about.twitter.com/company

[28] Weng, J., Lim, E. P., Jiang, J., He, Q. (2010, February). Twitterrank: finding topic-sensitive influential twitterers. *In Proceedings of the third ACM international conference on Web search and data mining* (261-270). ACM.

[29] Yi, X., Han, Y., Wang, X. (2013). The Evaluation of Online Social NetworkâØA´ Zs Nodes Influence Based on UseraAZs Attribute and Behavior. *In: Frontiers in Internet Technologies* (9-20). Springer Berlin Heidelberg.

[30] Zafarani, R., Abbasi, M. A., Liu, H. (2014). Social media mining: an introduction. Cambridge University Press.

[31] Zhang, Y., Mo, J., He, T. (2012, October). User influence analysis on micro blog. In Cloud Computing and Intelligent Systems (CCIS), 2012 IEEE 2nd International Conference on (3, 1474-1478).