Evaluating Twitter Influence Ranking with System Theory

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Abstract: A considerable part of social network analysis literature is dedicated to determining which individuals are to be considered as influential in particular social settings. Most established algorithms, such as Freeman and Katz-Bonacich centrality metrics, place emphasis on various structural properties of the social graph. Although this makes centrality metrics generic enough to be applied in virtually any setting, they are oblivious to the functionality of the underlying social network. This paper examines five social influence metrics designed especially for Twitter and their implementation in a Java client retrieving network information from a Neo4j server. Additionally, a sceheme is proposed for evaluating the performance of an influence ranking based on estimating the exponent of a Zipf model fitted to the ranking score.

1 INTRODUCTION

Social media constitute a mainstay of the connected age. Recently, Twitter has emerged among them as one of the most popular microblogging platforms, where on a daily basis a vast amount of information, including tweets and hashtags, is posted by the users of the platform to the public or to selected circles of their contacts.

Their advent made feasible the application of both traditional and innovative social network analysis methods in previously prohibitive magnitude for cornerstone problems such as social coherence, social graph clustering, expansion potential, or information flow (Russell, 2013)(Leskovec et al., 2014)(Leskovec, 2011). Currently, social influence ranking has been recognized as an important research topic. Existing influence metrics rely heavily on structural properties of the social graph, such as the number of shortest paths through a given vertex. Although these structural metrics are well defined and can be applied to literally every social graph, they ignore the array of functions each social network performs.

Graph databases such as Neo4j provide production grade front- or back-end social graph storage. Moreover, they offer graph analytics such as link prediction, shortest paths, clustering coefficient, and minimum spanning trees, bolstering the potential of graph tools such as NetworkX, machine learning frameworks such as Graphlab, and distribiuted processing systems such as Spark (Robinson et al., 2013)(Onofrio Panzarino, 2014).

The primary contribution of this work is threefold. Five Tweeter-specific metrics capturing essential online behavior characteristics have been developed. Additionally, a methodology for evaluating influence metrics based on concepts from system theory is proposed. Finally, the aforementioned metrics have been implemented in Java over Neo4j through the Cypher API.

The rest of this paper is structured as follows. Section 2 summarizes the influence ranking literature. Implementation aspects are described in section 3. Twitter-specific functional metrics are outlined in section 4. Section 5 discusses the experimental results and the metric evaluation methodology, while section 6 explores future research directions.

Table 1: Symbols used in this paper.

Symbol	Meaning
$\triangleq$	Equality by definition
$\{x_1,\ldots,x_n\}$	Set containing elements $x_1,\ldots,x_n$
$\lvert S\rvert$	Cardinality of set S
τ_{S_1,S_2}	Tanimoto coefficient of sets S_1 and S_2
t_k	k-th Twitter user (used as shorthand)
μ	Twitter user influence metric
μ_k	Influence score of t_k assigned by μ
$\mu^1 \succ \mu^2$	Metric μ^1 outperforms μ^2
$\mu^1 \succeq \mu^2$	Metric μ^1 is at least as good as μ^2

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2 RELATED WORK

Social network analysis scientific literature abounds with influence rankings or metrics (Kempe et al., 2003). Although ranking classification is not always clear, distinct metric design methodologies can be broadly classified to structural and functional, while the former can be further subdivided to combinatorial and spectral. Structural metrics are more versatile than functional ones, since the former are network-independent. On the contrary, the latter are network-specific but they tend to reveal more information about the underlying network.

Combinatorial rankings compute the influence score based on basic graph properties. Prominent metrics of this category are the degree metric, namely the neighborhood size of a given vertex, and the Newman-Girvan centrality, a function of the graph shortest paths (Leskovec et al., 2014). Combinatorial rankings may as well be expressed in the linear algebra domain through the graph adjacency matrix. One such example is the Katz centrality (Katz, 1953).

Spectral rankings derive the influence score directly or indirectly through the spectral decomposition of the graph adjacency matrix. Eigenvalues and eigenvectors play an important role in metrics such as PageRank (Leskovec et al., 2014) or eigenvector centrality (Drakopoulos et al., 2015).

On the contrary, functional metrics are associated with particular aspects of a given social network performs. TwitterRank (Weng et al., 2010) and TunkRank (TunkRank, 2015) are two PageRank extensions which take into account user similarity and retweet probability respectively. In (Bakshy et al., 2011) the most influential users are also the most cost-effective ones, where the cost is defined in terms of overall communication complexity. In (Mehta et al., 2012) influence is expressed in terms of a sophisticated metric incorporating structural and functional elements. In (Pal and Counts, 2011) the problem of finding the most influential authors for a given topic in Twitter are selected from a Gaussian Mixture Model. A similar problem in Yahoo! Answers was addressed in (Bouguessa et al., 2008), where ranking is done as a mixture of gamma distributions.

Finally, authors in (Rogers and Beal, 1957) move along a different reasoning beyond the structural and functional divisive line, presenting influence in terms of an intuition stemming from the current technological evolution, which eventually led to the successful spread of online social media. Quoting (Cha et al., 2010), influence is

> "[...] the ability of a person to influence the thoughts or actions of others."

3 SYSTEM ARCHITECTURE

Figure 1 illustrates the components of the system developed to address the needs of this work as well as the information flow between them. The three main functions are to retrieve the social graph through the social media crawler, to store it in the Neo4j server, and to query this graph through its Java client.

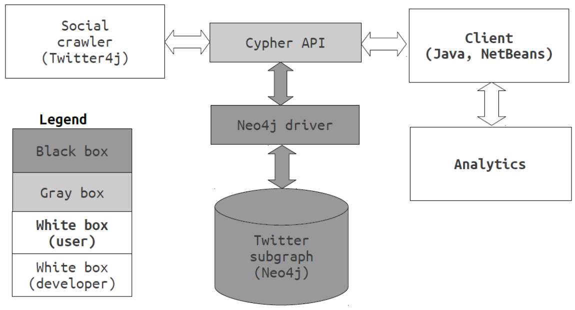


Figure 1: System architecture.

The social crawler, described in (Kafeza et al., 2014), has been programmed in Twitter4j to collect im JSON format data such as tweets, retweets, and hashtags. It communicates with the Neo4j server through the Cypher API, a Java interface extended by Neo4j to Java clients, in order to populate the graph database. The crawler is inaccessible from the client. The Neo4j version is 2.2.5, the latest available version at the beginning of system development. It communicates both with the Twitter crawler and the client. The expressive power of Cypher, its declarative query language, reduces relatively complex graph queries to simple patterns modifiable dynamically by the Java client. Since only the API is visible by the client, it is listed as a grey box, while the graph database proper as a black box. On the end user side, the client has been developed in Java using the libraries available in NetBeans for interfacing with Neo4j.

The need for new database approaches, besides the relational one, was highlighted with the advent of Web 2.0, which is dominated by high velocity, unstructured or semistructured and high order data. Neo4j, a NoSQL graph database, stores data physically as a graph.

Property 1. *Neo4j is schemaless (Robinson et al., 2013).*

This is a fundamental NoSQL characteristic which yields design flexibility but also imposes additional design and administration burdens.

Property 2. *The relational ACID operational requirements have been replaced by the three BASE requirements (Robinson et al., 2013)(Onofrio Panzarino, 2014).*

The BASE set is less strict than the ACID one, providing implementation flexibility and ease of maintenance at the expense of data consistency. Despite the latter, a NoSQL database can be in practice successfully tailored to the local operational demands.

Property 3. *The property graph model is the primary conceptual data model supported by Neo4j and offered to a high level user typically through the Cypher querying language (Drakopoulos et al., 2015)(Kontopoulos and Drakopoulos, 2014).*

Property 4. *Neo4j fully supports for both vertices and edges the CRUD set of operations, namely **C**reate, **R**ead, **U**pdate, and **D**elete.*

Neo4j supports Cypher, a declarative, ASCII art, and pattern based query language for handling conceptual graphs. Cypher possesses suitable syntax to concisely express CRUD operations. For instance, a vertex can be inserted with the command

```
create <pattern>
```

Similarly, a vertex can be removed with the command

```
delete <pattern>
```

Deleting a vertex leads to the deletion of all of its in- and out-bound edges.

The basic structure of a Cypher query is:

```
match <pattern>
[with [<pattern>]]
where [<constraints>]
return <expression> [as <expression>]
```

4 INFLUENCE RANKING

This section reviews five Twitter influence metrics and describes the corresponding Cypher queries. The social media crawler has been programmed to traverse Twitter starting from the account of a major higher educational institution in order to collect the following six features for each anonymized Twitter user t_k as in (Kafeza et al., 2014),(Kanavos et al., 2014a),(Kanavos et al., 2014b): Tweets (T_k), retweets (R_k), conversations (C_k), followers (F_k), hashtags (H_k), and tweet frequency (Q_k). The last is computed based on tweet tiemstamps.

In Neo4j, a Twitter subgraph has been created based on the collected data. Each user has been placed in a vertex with the command:

```
create (n:user {'tweets': x,
                'retweets': x,
                'conversations': x,
                'followers': x,
                'frequency': x,
                'hashtags': x})
```

where x denotes a value computed elsewhere in the source code. The above Cypher command creates a vertex n of type user along with a set of associated key-value pairs. This makes the conceptual graph homogeneous in the sense that each vertex has the same number of key-value pairs. Moreover, there are no missing values. Therefore, an implicit schema does exist for the vertices of the particular Twitter graph, but this need not to be the case generally.

In a similar manner, if a user u follows another user v, then an edge with the FOLLOWS tag (and FOLLOWEDBY) is created:

```
create ((u)-[:FOLLOWS]->(v),
        (v)-[:FOLLOWEDBY]->(u))
```

Notice that the inverse relationship has also been established in a similar manner. Although this is by no means necessary, finding the number of Followers that a given user has, facilitates subsequent analysis.

Based on the above attributes, a range of categories for influential Twitter users can be constructed depending on their online activity as in (Kafeza et al., 2013).

Atomic conversational users have a high number of tweets and retweets. The rationale is that active users either generate or relay a significant amount of information and they are therefore consulted by a large number of users. The following query changes the vertex type of the top x conversational users, marking them as such.

```
match (n:user)
with n, n.tweets + n.retweets as sum
order by sum desc
limit x
set n:conversational
```

Subsequently, the vertices marked as conversational are returned along with the sum of tweets and retweets.

```
match (n:conversational)
return n, id(n), n.tweets, n.retweets,
    n.tweets + n.retweets as sum
order by sum desc
```

The atomic conversational metric is denoted by μ^C.

Atomic multisystemic users, denoted by μ^M, have a high number of hashtags in their tweets and retweets. These type of users are probably proficient in a broad range of topics and they are a likely point of advice for other users.

```
match (n:user)
with n
order by n.hashtags desc
limit x
set n:multisystemic
```

Subsequently, the users marked as multisystemic are returned along with the number of corresponding hashtags.

```
match (n:multisystemic)
return n, id(n), n.hastags as h
order by h desc
```

Atomic energetic users, denoted by μ_E, have a high number of Tweets over a specified time interval. This behavior pattern likely indicates a user knowledgeable of or at least one strongly opinionated about a particular topic. Thus, users curious to know about this topic or, correspondingly, like minded users may choose to consider this user an authority.

```
match (n:user)
return n, n.tweets
order by n.tweets desc
```

Notice that the above command retrieves the users sorted in descending order according to the total number of their Tweets as well as their corresponding number of Tweets they have posted. The time each Tweet was posted as well as the time resolution determining which user is atomic energetic takes place elsewhere in the source code. The actual time resolution was three days, which is a reasonably enough time to post a tweet, read a reply, and in following to post a new tweet.

Atomic popular users, denoted by μ_P, have a high number of followers. Although popularity, in Twitter terms, does not necessarily translate to actual popularity, highly followed users can be expected to at least be read by other Twitter users, exerting thus an at least limited amount of influence. The number of users who connect to a given user through an edge can be identified by

```
match (n:user {'name':x})
    <-[:FOLLOWS]-(u)
return n, count(distinct u)
    as followers
order by followers desc
limit x
```

or by the quicker query

```
match (n:user
    {'name':x}-[:FOLLOWEDBY]->(u))
return n, count(distinct u)
    as followers
order by followers desc
limit x
```

Atomic influential users, denoted by μ^I, combine in a sense the above notions as their overall influence score I_k is computed as in (Kafeza et al., 2013):

$$\mu_k^I \triangleq T_k R_k C_k \log_{10}(1+F_k) Q_k H_k \tag{1}$$

The number of followers F_k is in base 10 logarithm for avoiding outliers. In addition, F_k is incremented by 1 so as to avoid a minus infinity metric when a user has no followers. The following Cypher command returns these statistics for a given user

```
match (n:user)
with n
return n, n.tweets, n.retweets,
    n.hashtags
```

Also, the number of followers has been computed for each user. For each user its score was computed according to (1) and was stored as a new property named overall to the appropriate vertex. Having computed this property, the following command returns the top influential users according to (1) and changes their type to influential:

```
match (n:user)
with n
order by n.overall desc
limit x
set n:influential
```

5 RESULTS

5.1 Twitter Subgraph Synopsis

Definition 1. *A Twitter egg is an account with no followers.*

Definition 2. *A star is a bipartite graph where the one parition is a singleton. Moreover, the vertex of this singleton is connected to all remaining vertices.*

The Twitter subgraph was collected in a time interval of two months (September and October of 2015). Its properties are stated in table 2. The first column has fundamental graph structure properties such as the number of edges and triangles, whereas the second column has Twitter specific properties such as the average tweet length and the average number of followers. Note that the vertices are accounts and the directed edges represent “following” relationships.

There is only a small fraction of eggs and stars. Specifically, there are 31 stars are comprised of 148

Table 2: Twitter subgraph properties.

Property	Value	Property	Value
Vertices	6561	Hashtags	417
Edges	35422	Tweets	18221
Triangles	213	Retweets	7221
Squares	72	Avg.following	2.11
Stars	31	Avg. followers	4.61
Components	32	Eggs	117
Diameter	9	Avg. tweet	102.8

Table 3: Influential Twitter subgraph accounts breakdown.

Account type	Instances
Official university account	1
Official school accounts	8
Official department accounts	22
Faculty member accounts	46
Student leader accounts	23
Organization accounts	20
Total	120

vertices, namely the 117 eggs plus the 31 central vertices. By the very definition of the egonet, its diameter equals 2. The remaining 6413 vertices belong to a single, large component which is densely connected since its diameter equals 9. These structural characteristics indicate an active social network.

This is corroborated in the functional level by the large number of hashtags, indicative of topic variations, and by the numerous and lengthy tweets. The daily tweet and retweet traffic as shown in figure 2 has variations and bursts, signifying an active online community. Notice that in figure 2 the tweets and the retweets are expressed as percentages of the raw total number of tweets and retweets respectively.

The Tweeter crawler began its search from the official account of a prominent university and it was programmed to contain its search strictly within education topics. As a result, table 2 consists of only eductional accounts - see also table 3. Although users from more than one domain would yield a more realistic subgraph, the selection of a single topic facilitates the analysis.

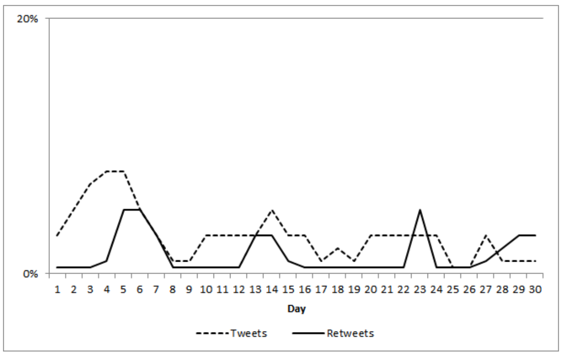


Figure 2: Tweets and retweets per day.

In order to gain a deeper insight of the behavior of Twitter analytics, the ranking scores are shown in figures 2, 3, and 4. Initially there are more tweets than retweets, but eventually retweets rise to an almost steady fraction of tweets. Also, there are interleaving periods where retweets are anticorrelated with tweets and periods where retweets are correlated with twewets.

Concerning figure 3, conversational ranking scree values are a bit higher than the influential ones, though they both tend to have percentages equal to 1% after rank 60. For the conversational ranking scree plot, the two major percentage decreases take place for rank ranges starting from 5 to 35 and from 45 until 65. For the influential ranking scree plot, there are also two decreases but smoother than in conversational one; the first starts from rank equal to 1 until 5 and the second from 10 to 50.

On the other hand, regarding figure 4, user ranking logscree plots, for both conversational and influential scores, seem to have almost the same behavior. More concretely, conversational values are bigger until rank 60, while influential values are by little bigger for the next 10 ranks. Then all the remaining ranks have percentages equal to 1%.

A secondary finding is that accounts who regularly tweet usually have more influence than ones who mostly retweet, although there are many exceptions to that rule. This is expected as accounts who post new tweets can be considered as potential influencers. Also, retweeting typically adds more status to the poster of the original tweet than to its retransmitter. The exception to the rule seems to be users who selectively retweet about specific topics, acting in this way as information hubs for these particular topics.

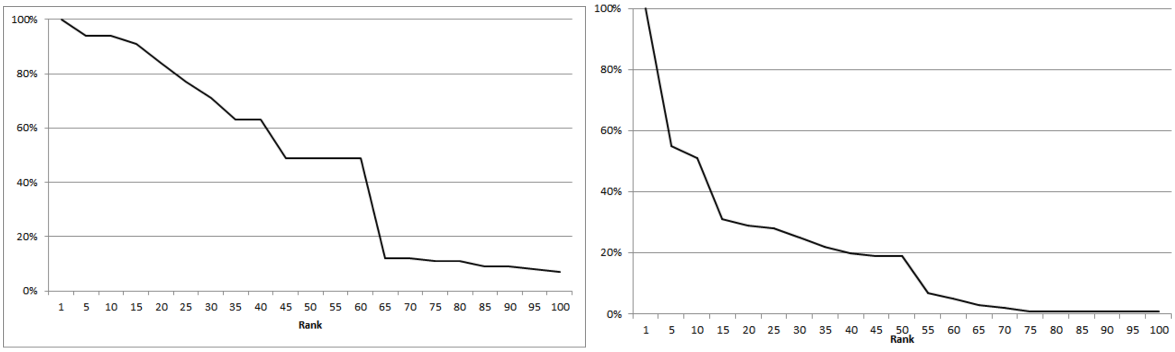
5.2 System Based Analysis

Definition 3. *Assume a (multi)set $S = \{x_1, \ldots, x_n\}$ is partitioned into b distinct subsets $S_k, 1 \leq k \leq b$ such that*

$$\sum_{k=1}^{b} |S_k| = |S|$$

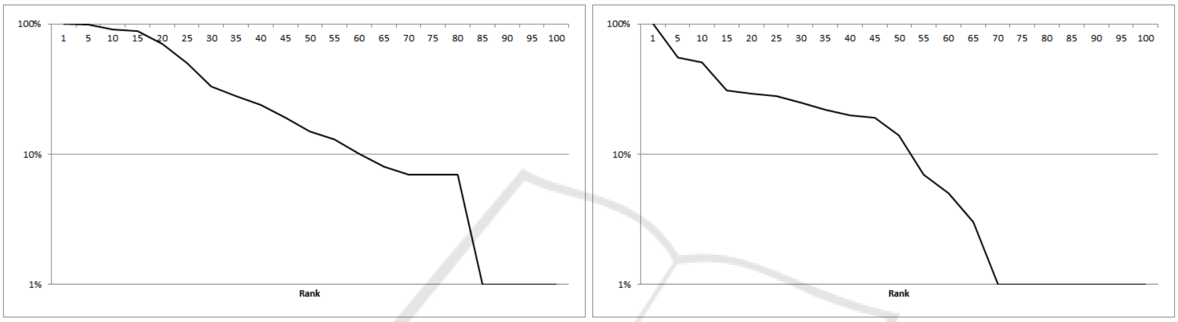
where identical elements of S are placed on the same S_k. The plot of $|S_k|$ versus their ranking is termed the scree plot of S. When the logarithm of $|S_k|$ is used instead, then the plot is called the logscree plot.

Definition 4. *Assume a fixed set T of influence metric evaluation tests. Metric μ^1 outperforms μ^2 with respect to T if and only if μ^1 achieves strictly better evaluation scores than μ^2 in each test of T. This case is denoted as $\mu^1 \succ \mu^2$.*



(a) Conversational (b) Influential

Figure 3: Atomic conversational and influential ranking scree plots.



(a) Conversational (b) Influential

Figure 4: Atomic conversational and influential ranking logscree plots.

Definition 5. *Assume a fixed set T of influence metric evaluation tests. Metric μ^1 is at least as good as μ^2 with respect to T if and only if μ^1 achieves*

- *strictly better evaluation score than μ^2 in at least one test of T*
- *the same evaluation score with μ^2 in the remaining tests*

This case is denoted as $\mu^1 \succeq \mu^2$.

This section outlines a method for evaluate rankings based concepts from system theory. The analysis relies on the following properties:

Property 5. *Rankings in large, scale free graphs tend to exhibit behavior which can be modelled by a Zipf equation which has the form*

$$|S_k| = \alpha_0 k^{-\gamma_0}, \quad \alpha_0, \gamma_0 > 0, \sum_{k=1}^{b} |S_k| = |S| \qquad (2)$$

where $|S_k|$ is the cardinality of the k-th subset of S.

In this case, the data has been partitioned to $b = \sqrt{|S|}$ bins. This choice yields unbiased estimators with reasonable error bounds while keeping low the computational complexity.

Property 6. *For most large systems γ_0 belongs to the continuous interval $[2,3]$.*

Taking logarithms of both sides linearizes (2) yielding

$$\begin{bmatrix} \ln|S_1| \\ \ln|S_2| \\ \ln|S_3| \\ \vdots \\ \ln|S_b| \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\ln 2 & 1 \\ -\ln 2 & 1 \\ \vdots & \vdots \\ -\ln b & 1 \end{bmatrix} \begin{bmatrix} \gamma_0 \\ \ln\alpha_0 \end{bmatrix} \qquad (3)$$

The normal equations for (3) are:

$$\begin{bmatrix} -\sum_{k=1}^{b} \ln|S_k| \ln k \\ \sum_{k=1}^{b} \ln|S_k| \end{bmatrix} = \begin{bmatrix} \sum_{k=1}^{b} \ln^2 k & -\sum_{k=1}^{b} \ln k \\ -\sum_{k=1}^{b} \ln k & b \end{bmatrix} \begin{bmatrix} \gamma_0 \\ \ln\alpha_0 \end{bmatrix} \qquad (4)$$

The least squares estimation $\hat{\gamma}_{LS}$ of γ_0 under this model is

$$\hat{\gamma}_{LS} = -\frac{b\left(\sum_{k=1}^{b} \ln|S_k| \ln k\right) - \left(\sum_{k=1}^{b} \ln|S_k|\right)\left(\sum_{k=1}^{b} \ln k\right)}{b\left(\sum_{k=1}^{b} \ln^2 k\right) - \left(\sum_{k=1}^{b} \ln k\right)^2} \qquad (5)$$

For each influence metric of section 4, a Zipf model has been fitted using the least squares approach which was just described. Table 4 shows the values of $\hat{\gamma}_{LS}$ for each case. Observe that the exponent estimated for the atomic influence metric is the closest to the exponent continuous range $[2,3]$, which is the interval most exponents associated with aspects of large, real world social graphs typically belong to (Leskovec, 2011).

Table 4: $\hat{\gamma}_{LS}$ for each influence metric.

	μ^C	μ^M	μ^E	μ^P	μ^I
$\hat{\gamma}_{LS}$	1.41	1.78	1.65	1.61	1.91

At this point two questions arise. The first is which of the five influence metrics reveals more information regarding user online activity and thus identifies influential individuals in a better way. The second question is, once a baseline ranking is established, how the others compare with it.

The first question has been addressed by a domain expert, who established a ground truth ranking μ^*. Table 3 contains a complete ranking according to the domain expert, whereas table 5 shows the percentage of influential users listed in each of the ten percentiles of the rankings returned by each of the five metrics.

Table 5: Percentage of influential users.

μ^*	μ^C	μ^M	μ^E	μ^P	μ^I
50	10	22	11	32	26
50	11	7	11	7	52
0	9	33	9	8	19
0	5	28	7	7	6
0	10	10	8	6	7
0	12	10	12	19	0
0	28	0	25	5	0
0	10	0	10	6	0
0	9	0	10	0	0
0	11	0	7	0	0

Atomic conversational and atomic energetic tend to exhibit similar patterns. Moreover, they yield the worst list as the influential users are scattered almost uniformly across the percentiles. On the other hand, the atomic influential has the best performance. This was expected since μ^I combines multiplicatively five features in a nonnegative scalar, whereas the other four rankings rely on a single feature.

Table 6 contains the Tanimoto coefficients between the five influence metrics of section 4. Through the five sets of ranking results, the similarity of each influence metric is approximated by the Tanimoto coefficient defined for any two sets S_1 and S_2 as:

$$\tau_{S_1,S_2} \triangleq \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} = \frac{|S_1 \cap S_2|}{|S_1| + |S_2| - |S_1 \cap S_2|} \tag{6}$$

There are many dissimilarities each ranking has from the baseline μ^I. It is remarkable that each of the remaining rankings differs in its own way. For instance, out of the 25 most atomic influential users, only 6 have been deemed as important, 4 were both atomic conversational and multisystemic and 2 were atomic popular.

Table 6: Tanimoto coefficient between metrics.

$\tau_{\cdot,\cdot}$	μ^C	μ^M	μ^E	μ^P	μ^I
μ^C	1	0.523	0.400	0.511	0.340
μ^M	0.523	1	0.017	0.194	0.403
μ^E	0.400	0.017	1	0.701	0.192
μ^P	0.511	0.194	0.701	1	0.210
μ^I	0.340	0.403	0.192	0.210	1

From the above, the following metric ordering can be inferred:

$$\mu^I \succ \mu^M \succ \mu^C \succ \mu^P \succeq \mu^E \tag{7}$$

Concluding, as a general remark regarding influence metrics, it should be noted that social graphs contain information of inherently high order, in the sense that for a spectrum of queries, a considerable number of edges should be visited in order to obtain meaningful information. This can be at least partly attributed to the distributed and connection oriented nature of a graph. User influence metrics are not an exception to this rule as influence can be in a certain sense diffused through tweets, retweets and user references. Therefore, a significant Twitter user can influence the opinion of its neighbors but also the opinions of their neighbors (e.g. followers of followers). Thus, influence metrics should take into account higher order phenomena, if meaningful results are to be obtained.

6 CONCLUSIONS AND FUTURE WORK

Twitter influence ranking has been cast in a multidisciplinary way. Five Twitter-specific functional influence metrics have been implemented in Java using the NetBeans libraries for interfacing with a Neo4j server through the Cypher API. Also, an evaluation methodology for the influence metrics based on systems theory is proposed.

Within the immediate scope of this work, research can be conducted towards developing advanced functional rankings or hybrid structrural-functional rankings. The same analysis proposed in this paper should be applied to Twitter subgraphs consisting of accounts from multiple domains. Finally, research should include the development of rankings integrating the concepts of reputation and trustworthiness in social media.

At this point, the authors would like to publicly express their gratitude to the sociology expert for setting the ground truth regarding the influential Twitter accounts of the graph of table 2.

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