Social Network Influence Ranking via Embedding Network Interactions for User Recommendation

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ABSTRACT

Within social networks user influence may be modelled based on user interactions. Further, it is typical to recommend users to others. What is the role of user influence in user recommendation? In this paper, we first propose to use a node embedding approach to integrate many types of interaction into embedded spaces where we then define a novel closeness measure to quantify the closeness of users based on interactions. We then propose a new influence ranking algorithm based on PageRank by incorporating the closeness measure into the ranking mechanism. We evaluate our algorithm, EIRank, using a dataset collected from Twitter. Our experimental results show that our algorithm measures user influence better by way of a user recommendation task, where our algorithm outperforms TwitterRank across a range of experimental network settings.

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1 INTRODUCTION

Due to the pervasiveness and scale of digital social networks, there has been significant interest in understanding the mechanisms of their formation and growth, for example, in understanding the role of social influence in online social networks [10]. Many social networks permit non-reciprocal connections, whereby it is not uncommon for a user to be non-reciprocally connected to a vast number of other users [6, 10]. This affords that user with the potential to write communications that are received by large swathes of people. Social influence is a crucial factor in many aspects of life and society, which motivates the study of the quantification of influence, as well as understanding how this influence diffuses through (social) networks [2].

In this paper, we will consider, without loss of generality, the social network Twitter. One common way of measuring influence between two users is by observing the likelihood that one user reads the other's tweets [13]. On the other hand, interaction information has been shown to be an important indicator of influence among users [5, 12]. On Twitter, these interactions may include mentioning another user, liking a tweet, retweeting a tweet or replying to a tweet. These could be considered as strong indicators of influence as they explicitly represent the reaction of users to tweets. For example, the retweet interaction can be considered as the intent of users to amplify or further diffuse the original tweet, thus potentially increasing the influence of the original tweet. Each of these different types of interaction on Twitter contain useful information that can be utilized to better measure the influence of users. Once user influence has been modelled, it may be used for tasks such as user recommendation.

In this paper, we study how we can assign influence values to users in a social network. We are particularly interested in how the integration of interaction information into an influence measure can lead to a better measure of influence. In particular, we incorporate the embedded interaction information into a PageRank-like [8] algorithm and show how this leads to a better method for measuring social influence. Inspired by recent success in node embedding in graphs, we embed the nodes of different interaction graphs into embedded spaces and define a closeness measure which measures how close users are within the embedded spaces. Using this measure, we can assign transition probabilities between users in a social network, allowing us to model the propagation of influence through the network using a PageRank-like approach to assign an influence value to each user.

We make four main contributions in this paper. First, we propose an approach for embedding different types of interaction graphs into embedded spaces such that different types of interaction information can be integrated and collectively represented. Second, we define a novel measure of closeness in the embedded spaces to measure how close users on a network are in terms of their interaction. Third, we integrate this into a PageRank-like algorithm to rank users based on both their connections and interactions. Finally, we conduct an experimental evaluation on Twitter, comparing our proposed EIRank method with PageRank, node2vec [4] and TwitterRank [13].

2 RELATED WORK

Measuring social influence can be broadly divided into two categories based on the methods used. The first category typically utilize centrality measures which use the topological structure of the social network [1] to capture the positions and connectivity

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of users. The second category of methods are based on ranking algorithms [8, 10], which measure the influence of each user in a network based on how they are connected other users in the network. It is a challenging task for classic centrality algorithms to quantify every user's influence, especially on large networks.

TwitterRank [13] is a social influence ranking algorithm, which uses topic similarity between two users' tweets. The core idea of TwitterRank is that interest in similar topics, as well as connectivity, are important in measuring influence. However, TwitterRank ignores the interactions between users, which we argue, relative to interest in the same topic, is a more important signal of influence.

Truetop [15] utilizes *mentions*, *replies* and *retweets* to build a graph where the edge weights represent the number of interactions, to calculate the PageRank values. RetweetRank and MentionRank [14] extend PageRank on Twitter retweet and mention graphs directly to measure every user's influence. Their idea is that a user's influence value will increase if the user interacts with an influential user. In [1], the authors use centrality measures on a dynamic retweet graph to detect the influential nodes. One drawback of these methods is that while they never considered using all available interaction information, more importantly, they also did not effectively combine the interaction information along with the connection information.

There is recent work which predicts social influence with deep learning. DeepInf [9] defines social influence as the probability that a user's neighbours are influenced to show the same social behaviour after the user. For instance, their method can predict the probability that a user's friend will retweet the same tweet that the user previously retweeted. While related, this work differs from ours in that it is not concerned with the direct measurement and ranking of user influence on a social network.

3 PRELIMINARY

We will use Twitter as a running example of the social network under study.

3.1 Twitter Networks

DEFINITION 1. *A graph $G = (V, E)$ consists of a set of nodes V and a set of edges E, where $E \subseteq V \times V$. Two nodes p, q are adjacent $iff(p, q) \in E$. If (p, q) is ordered, the graph is directed, otherwise it is undirected. A weighted graph is a graph in which a weight is assigned to each edge and can be represented as $G = (V, E, W)$, where W is a set of weights.*

In the most general sense, a Twitter network can be represented by a graph $G = (V, E)$, where V represents Twitter users and E is the set of directed edges representing how the nodes are connected.

DEFINITION 2. *A* following *graph is a directed graph $G_{following} = (V, E_{following})$ which represents the users and the* following *relationships among them. There is an edge $(p, q) \in E_{following}$, if user p has followed by q.*

We consider that there is at least one form of interaction between users on the network. For example, on Twitter, this may be a retweet, reply, favourite or mention.

DEFINITION 3. *An interaction graph is a weighted graph $G_{i_n} = (V_{i_n}, E_{i_n}, W_{i_n})$ where the interaction type n represents one of the four interactions. There is an edge $(p, q) \in E_{i_n}$ with weight w, if user p has interacted with user q for w times.*

3.2 node2vec

node2vec [4] learns a feature representation for nodes in a graph. This algorithm extends the Skip-gram model [7] into the graph domain in order to model the conditional likelihood of each node and its neighborhood. For each node in the graph, the objective function maximizes the probability of observing neighborhood nodes in the feature representation. The objective function has two conditions. The first condition is that when a source node is given, the probability of observing a neighborhood node is independent of any other neighborhood node. The second condition is that, for each neighbourhood node of a source node, the source node is also one of its neighbourhood nodes.

3.3 PageRank

PageRank [8] was first proposed as a web page ranking algorithm which can quantify the importance of web pages based on the links between them. PageRank assigns an initial PageRank (*PR*) value to each node which is usually $1/N$, where N is the total number of nodes. The *PR* value is the probability of a node being visited. As the calculation of *PR* is a Markov process, the *PR* value becomes stable after a number of iterations. The *PR* value of a node is calculated as follows:

$$PR(p_i) = \alpha \sum_{p_j \in M_{p_i}} \frac{PR(p_j)}{L(p_j)} + \frac{(1-\alpha)}{N} \tag{1}$$

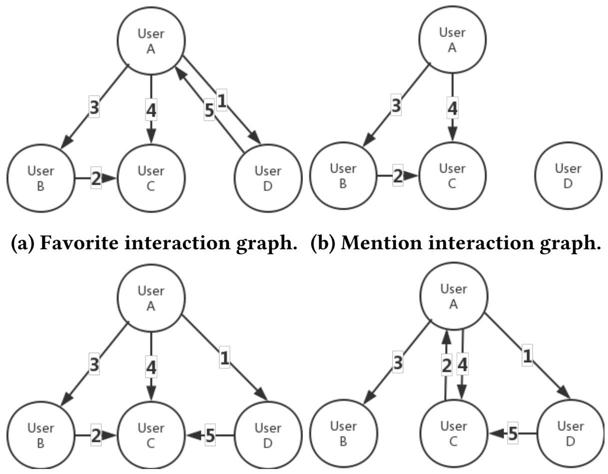
where M_{p_i} is the set of nodes which are incident to node p_i, $L(p_j)$ is the number of nodes which node p_j is incident to, and α is the damping factor.

4 SOCIAL NETWORK INFLUENCE RANKING

In this section, we describe our approach, EIRank, which measures how close users are within the embedded space of their interactions and then uses a PageRank-like method to diffuse and rank their influence.

4.1 Influence

Our definition of influence is based on the following intuition; if a user is both followed and interacted with by many users, then we consider this user to be influential. Inspired by PageRank, if a user with a high influence value follows another user, the influence value of the user being followed will increase accordingly (e.g. by $1/m$ if the influential user follows m users). This follows the PageRank assumption that each *following* relationship has equal strength. Our core idea is that if a user follows another user with active interactions then the user's contribution to another user's influence value should be higher than the default contribution of $1/m$. Thus, we define a closeness measurement to quantify how close a pair of users are, with a closer relationship causing an increase in the contribution of influence. More specifically, the closeness measurement is defined based on the extent of different types of interaction between users.



(a) Favorite interaction graph. (b) Mention interaction graph.

(c) Reply interaction graph. (d) Retweet interaction graph.

Figure 1: Examples of four interaction graphs, where the weights represent the frequency of interactions between users.

4.2 Closeness Measurement

The level of influence between users depends on how close their relationship is, i.e., the closer the relationship, the greater the mutual influence. According to Sun et al. [11], the strength of social influence depends on the relationship between people in the network. Intuitively, the premise of an interaction (between a pair of users) is that by interacting with a tweet, the user has not only read it, but also elicited strong enough feelings to, for example, retweet or like it. Therefore, we can better calculate the strength of relationships between users by effectively utilizing the available interactions, examples of which are shown in Figure 1.

The weight of edges in interaction graphs is a simple method of representing how close a pair of nodes are, but it is less able to measure the relationship between unconnected nodes. Therefore, we propose to use a node embedding method, node2vec, to map the graph nodes to a vector space where the relationship between embedded nodes can be easily calculated.

We consider four vector spaces $S = \{favorite, mention, reply, retweet\}$ which are the mappings of the four interaction graphs shown in Figure 1 by node2vec. For each node, the representation in each vector space is a d-dimensional vector. After embedding, there is a set of d-dimensional vectors: $Vec_{favorite}$, $Vec_{mention}$, Vec_{reply} and $Vec_{retweet}$. A common method to measure the closeness in a vector space is the Euclidean distance:

$$dist(p, q) = \sqrt{\sum_{i=1}^{d} (q_i - p_i)^2} \tag{2}$$

where $p = (p_1, p_2, \ldots, p_d)$ and $q = (q_1, q_2, \ldots, q_d)$ are two d-dimensional vectors. An embedded space may not contain every user, i.e., when a user does not have any form of interaction, such as the user D in Figure 1(b). We account for this in our closeness measure over all (the four) embeddings for a single user as follows:

$$c_i(p, q) = \begin{cases} \frac{1}{dist(p,q)}, & if\ p, q \in Vec_i, i \in S \\ 0 & , otherwise \end{cases} \tag{3}$$

With the accumulated closeness between two users defined as:

$$C(p, q) = \sum_{i=1}^{|Vec|} w_i c_i(p, q) \tag{4}$$

where w_i is the weight of this interaction type. $C(p, q)$ calculates how close a pair of users are, where the higher the $C(p, q)$ value is, the closer the pair are, and the greater the likelihood that user q has influenced user p.

4.3 EIRank

In order to calculate the influence of users on Twitter, we propose a PageRank-like algorithm. In our setting, given a pair of users p and q, where q follows p, q's contribution to p's influence value is calculated as q's influence value divided by the number of q's outgoing edges. In addition, because a user q may have different degrees of closeness to each of its followees, the extent of influence q contributing to each of its followees is different.

Algorithm 1 The Ranking Algorithm via Embedding Interactions (EIRank)

Input: Graph $G_{following}$, interaction graphs set G_i
Output: *EIRank* for each node

for all G_{i_n} in G_i **do**
  Vec_{i_n} = node2vec(G_{i_n})
end for
Calculate the distance as Eq. (2)
Calculate closeness between each pair of users as Eq. (3,4)
Calculate transition probability on each edge as Eq. (5)
Initialize influence value of each node as $EIRank(v_i) = 1/N$
for $iter = 1$ to max_iter **do**
  for all nodes in $G_{following}$ **do**
    Calculate $EIRank(v_i)$ as Eq. (6)
  end for
  $\delta = \sum_{i=1}^{N} |EIRank_{iter}(v_i) - EIRank_{iter-1}(v_i)|$
  if converged(δ) **then**
    break
  end if
end for
return *EIRank* for each node

As described in Algorithm 1, EIRank computes the influence values of users as follows: EIRank visits each user with a transition probability by following an appropriate edge in $G_{following}$. In order to utilize both the interaction graphs and our closeness measure, we improve the calculation of the transition probabilities of the PageRank model as follows. The transition probability from user v_j to v_i is defined as:

$$Pt(v_j, v_i) = \frac{C(v_j, v_i)}{\sum_{v_j\ follows\ v_k} C(v_j, v_k)} \tag{5}$$

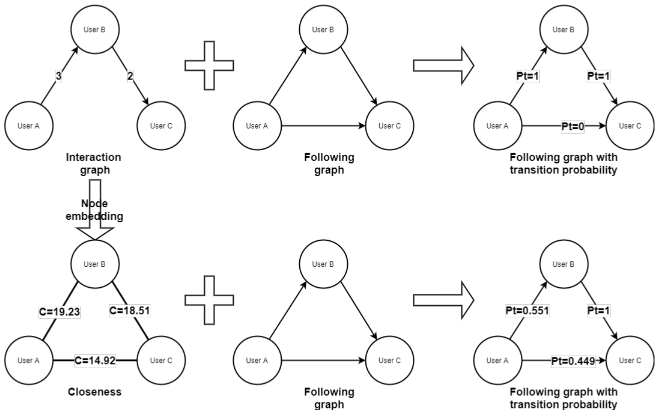


Figure 2: Example of the advantage of our method of deriving transition probabilities from the closeness measure.

With the transition probability, the influence value can be calculated as:

$$EIRank(v_i) = \alpha \sum_{V_j \in M_{V_i}} EIRank(v_j) \times Pt(v_j, v_i) + (1 - \alpha)/N \quad (6)$$

where M_{v_i} represents the set of nodes that are incident to node v_i, α is the damping factor between 0 and 1 to prevent the random walk following the loop edges and getting stuck in sinks, and N is the total number of users in the $G_{following}$. Through an iterative approach, the algorithm propagates the influence along the edges of the graph to reach a stable state. The *EIRank* value at convergence is the influence value of each user in $G_{following}$.

Compared with merely using the interaction frequency on the *following* graph, the transition probability calculated with our closeness measurement better reflects influence propagation. As can be seen in Fig. 2, if we just integrate the frequency of interactions into $G_{following}$, the transition probability from user A to user C is 0, even though there is a *following* relationship from A to B and B to C. However, with our proposed method, the transition probability from A to C after embedding is 0.449, which is more reasonable than 0.

5 EXPERIMENTAL RESULTS

In this section we demonstrate the performance of our method for social network influence ranking, via a proxy user recommendation task, with both an ablation study and a comparison with the well-known TwitterRank algorithm.

5.1 Data Collection and Preprocessing

Using the Twitter API, we collected data[1] as follows. We seeded our collection with the 100 users who have the most Twitter followers[2]. We then collected their followers (and associated metadata), resulting in a dataset of 14,709 Twitter users. To build interaction graphs, for each user we collected up to 500 of their most recent tweets and favourite tweets, collecting 9,232,343 tweets in total. The statistics of each graph are shown in Table 1.

[1]The data was captured from May to August 2019.
[2]https://friendorfollow.com/twitter/most-followers/

	Num Nodes	Num Edges	Density	Avg Degree
$G_{following}$	14,708	1,077,400	0.0050	73
$G_{favorite}$	13,891	291,834	0.0015	21
$G_{mention}$	14,082	266,120	0.0013	19
G_{reply}	13,098	68,172	$3.97{*}10^{-4}$	5
$G_{retweet}$	11,770	67,128	$4.84{*}10^{-4}$	6

Table 1: Statistics for each network.

5.2 User Recommendation

We evaluate the performance of our proposed influence ranking algorithm via a standard recommendation task, in this case, recommending users to follow on Twitter. While there are many factors that may be involved in a user's decision to follow another user on Twitter, we are interested in understanding the role of influence in this process. Therefore, we make the assumption that a Twitter user will choose to follow the most influential user of *the potential options*. In our experiments, we will create a list of 11 users, with 1 of them being the ground truth user, along with 10 other unconnected nodes randomly selected from the entire *following* network. Our method will rank the influence of each user, and choose the user with the highest influence as the one to follow.

We use the existing *following* graph as the ground truth, and our methodology is as follows. We choose existing *following* relationships among Twitter users by using the sampling strategy d, stated below. For each *following* relationship, let s_o and s_f be the *followee* and *follower* respectively. We randomly choose 10 Twitter users (denoted as s_1 to s_{10}) who have no direct connection to s_f, and remove the true edge between s_f and s_o. Thus, out of the possible 11 options (the 10 unconnected Twitter users and the true followee s_o), our assumption is that s_o shall be ranked the 1st in the ranked list L of recommended users to follow. That is, s_o should have the highest influence. We quantify the performance of the recommendation rankings as $L(s_o)$, where $L(s_o)$ is the rank of s_o in L.

To gain a better understanding of the performance of different network configurations and settings, we use different sampling strategies to select different sampling sets for selecting *following* relationships and evaluate the algorithms' performance when dealing with different contexts of *following* relationships. In total, we have designed four sampling strategies.

- d_1: Randomly sample N existing *following* relationships from the entire $G_{following}$ graph.
- d_2: Select the top 10% of users who have the most followers and randomly sample N existing *following* relationships among them.
- d_3: Select the bottom 10% of users who have the least followers and randomly sample N existing *following* relationships among them.
- d_4 : To measure the performance in individual communities in the network, we choose the top five largest communities and sample N existing *following* relationships from each of them. The statistics of these five communities are shown in Table 2.

In each case, we retrain our model with the true edge removed and we set N to 30. In settings d_2 and d_3 and d_4 we select the true relationship, s_f and s_o, from the subset, and 10 test nodes from the entire graph.

To further understand our method, we perform an ablation studying using only PageRank (PR) [8] and only node2vec (NR). Further, we compare our algorithm with the well-known TwitterRank (TR) [13] algorithm, which uses an alternative method to calculate influence. In our experiments, w_i in Eq.(4) is set to 1, the damping factor α in Eq.(6) and in PageRank is set to 0.85. For node2vec, we set the dimensions and context size to 64, walk length to 30, walks per node to 200, and return parameter and in-out parameter to 1.

	Com 1	Com 2	Com 3	Com 4	Com 5
Num Nodes	2601	1710	1501	1272	952
Num Edges	206256	78657	47198	46939	17780
Avg Degree	79	46	31	37	19
Density	0.030	0.027	0.021	0.029	0.020

Table 2: Community statistics for d_4.

5.3 Results

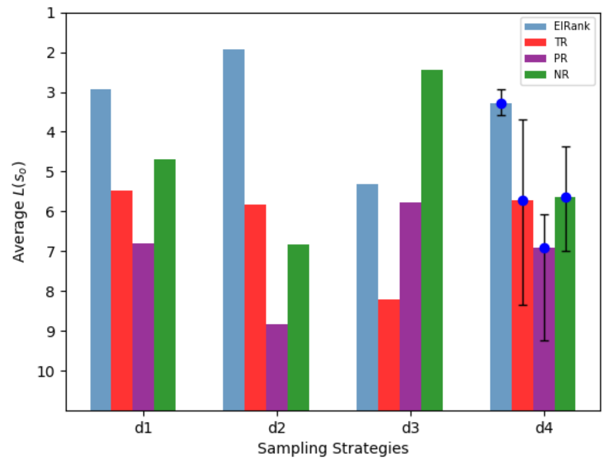
Fig. 3a shows the results of each approach with different strategies. As can be seen from the results, in all scenarios studied, our proposed algorithm EIRank performs better than TwitterRank (TR), as it on average ranks the true follower higher on the list. We further evaluate our algorithm on the individual components of our approach, namely PageRank (PR) and node2vec (NR), in which our proposed method shows the best performance in three of the four experiments.

In experiment d_1 we did not induce specific properties of the network, such as selecting only users with the most or least followers, but merely used the complete network as collected by us. In this scenario, our proposed approach EIRank achieves the best performance, on average ranking the true follower of the user in the third position in the list.

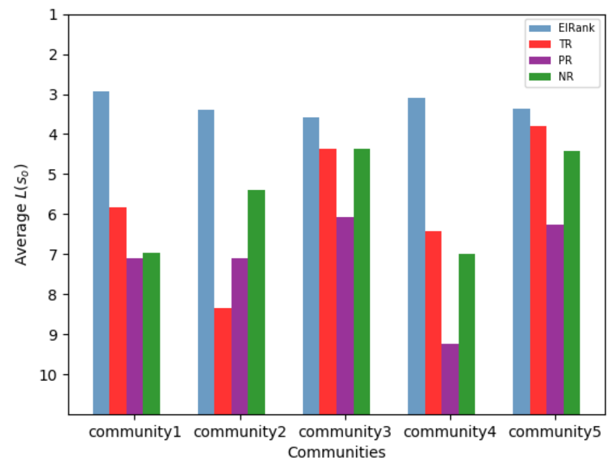
In scenario d_2, where we sample from the top 10% of users in terms of followers, we see that our method performs even better, with the true node having an average position of 2 in the ranked list. As we sampled the true edge, s_f and s_o, from the top 10% of users in terms of followers, and the rest of the test nodes from the entire graph, this improvement can be explained by users with more influence tending to have more followers. TwitterRank performs similarly to before, while both PR and NR have considerable performance degradation. We believe that our method performs well in the scenario involving the top 10% of users because it properly models the diffusion of influence. For example, given a user with a large number of followers who non-reciprocally interact with them, our method properly assigns high influence values to that user, but not the followers. In contrast, NR may embed the popular user and their interacting follower close, highlighting how our algorithm can lead to superior performance.

For scenario d_3, node2vec (NR) outperforms all the other algorithms. We calculated the percentage of friendship relationships (mutual following relationship) within the d_3 graph, which is 66%, while the rate in the entire graph is 25.8%. We believe that in this case, when another user follows a user who has few followers, they are likely to be friends in real life. Therefore, the mechanism behind this action is not influence and thus not captured by our method. That is, social network ranking of influence for user recommendation appears to perform poorly for the bottom percentile of users in terms of follower counts. node2vec performs well as it does not consider influence.

For scenario d_4, we show the average result based on ranking influence within communities, discovered by Louvain [3], rather than the entire graph. Here it is clear that our method performs the best on average across all communities, with the highest ranking for the true user, as well as the smallest standard deviation. If we look closer into each community, as shown in Fig. 3b, EIRank has consistently the highest performance across all communities.

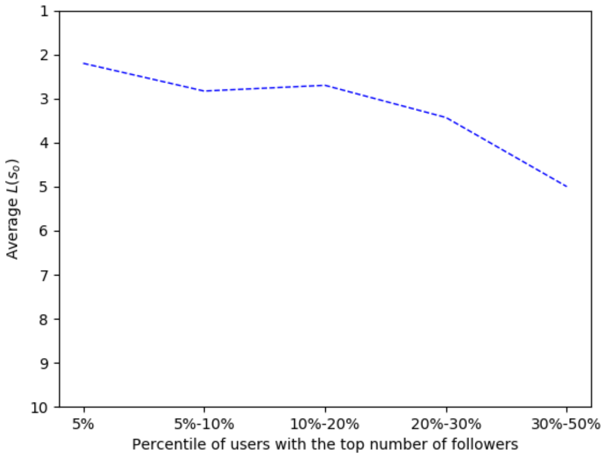


(a) Performance of each method across each sampling strategy.

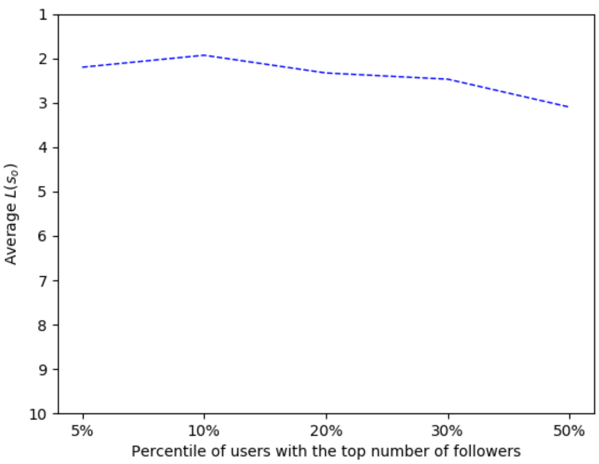


(b) Performance of each method when applied to the extracted communities.

Figure 3: Performance comparison of our method compared to TwitterRank (TR) and the ablated baselines (PR, NR). The higher the bar height, the better the performance. Sampling strategy d_4 in Figure 3a contains error bars calculated from the 5 communities in Figure 3b.



(a) Strategy 1.



(b) Strategy 2.

Figure 4: Performance of our method when applied to different network samples based on percentiles of follower counts.

Finally, in order to have a more precise understanding of performance at more specific percentile intervals of follower counts, we will conduct a final study across a range of percentiles. We select 30 existing *following* relationships from network configurations where we sample from the top 5%, 5% − 10%, 10% − 20%, 20% − 30% and 30% − 50% percentile of all the follower counts of the users, respectively. We also conduct a similar experiment by sampling from the top 5%, 10%, 20%, 30% and 50% percentile of follower counts.

As can be seen from Fig. 4, the performance of EIRank decreases when we sample relationships from the users with less followers. As $L(s_o)$ is the ranked position of s_o in terms of influence, it Fig. 4 shows that influence becomes more difficult to measure when considering users with less followers. As we consider a global influence measure, the further we move from the more influential users in the network, the more difficult it is for us to accurately model influence for user recommendation.

6 CONCLUSION

This paper proposed a new social network influence ranking method based on embedded interaction networks, and studied this influence ranking within the application of user recommendation on Twitter. We first proposed a method for calculating how close nodes are based on the embedded interaction networks. We then proposed a PageRank-like method that utilizes the closeness method to model transition probabilities that capture influence propagation on a social network. Evaluating our social network influence ranking method in the context of user recommendation on Twitter, we studied the ranking of the true followee across a range of experimental settings. By selecting the user with the highest influence as the recommended user to follow, our experimental results show that influence ranking for user recommendation typically performs well, but is more challenging in the lower follower percentiles of the social network. However, across all percentiles, and within extracted communities, our method outperforms TwitterRank, a popular method for social network influence ranking.

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