

Identification of Most Influential Spreaders in Twitter Social Network using Modified K Core Decomposition in Distributed Environment

ABSTRACT

A clear and well-documented L^AT_EX document is presented as an article formatted for publication by ACM in a conference proceedings or journal publication. Based on the “acmart” document class, this article presents and explains many of the common variations, as well as many of the formatting elements an author may use in the preparation of the documentation of their work.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

KEYWORDS

datasets, neural networks, gaze detection, text tagging

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1 INTRODUCTION

Modified K Core NayeemSocial Networks have gained remarkable popularity in the past few decades. A huge number of people are using social networking sites like Facebook, Twitter, Google+, LinkedIn etc. The heavy reliance on social networking sites causes them to generate massive data. Online social networks play a major role in the diffusion of information [4]. Since social network has great influence on society, the recent focus is on extracting valuable information from this huge amount of data. Events, issues, interests etc. happen and evolve very quickly in social networks and their capture, understanding, visualization, and prediction are becoming critical expectations from both end-users and researchers. Therefore researchers in recent years have developed a variety of techniques and models to capture information diffusion in online social networks, analyze it, extract knowledge from it and predict it [1, 15].

Micro-blogging is an emerging form of communication. One of the most notable micro-blogging services is *Twitter*. It allows *twitterers* to publish tweets (with a limit of 140 characters). *Twitter*

employs a social-networking model called “following”, in which each *twitterer* is allowed to choose who she wants to follow without seeking any permission. Conversely, she may also be followed by others without granting permission first. In one instance of “following” relationship, the *twitterer* whose updates are being followed is called the “friend”, while the one who is following is called the “follower”. *Twitter* has gained huge popularity since the first day that it was launched [41]. It has also drawn increasing interests from research community [9]. Many analysis have been done on the dataset of twitter including identification of the most influential spreader [47, 55]. We discuss the state-of-art in details in the next section.

Information diffusion is a vast research domain and has attracted research interests from many fields, such as physics, biology, etc. The diffusion of innovation over a network is one of the original reasons for studying networks and the spread of disease among a population has been studied for centuries [3, 21, 24]. The knowledge of the spreading pathways through the network of social interactions is crucial for developing efficient methods to either hinder spreading in the case of diseases, or accelerate diffusing in the case of information dissemination. The information diffusion model is based on three fundamental questions: (i) *Which pieces of information diffuse the most*, (ii) *How, why and through which paths information is diffusing*, and will be diffused in the future, (iii) *Which members of the network play important roles in the spreading process?*

In this paper we are mainly focusing on the third question. Identifying the most influential spreaders in a network is critical for ensuring efficient diffusion of information, which allows to control the outbreak of any kind of epidemic [10, 49], utilize the limited resources to optimize the information propagation [20], successful e-commercial advertisements [30, 36], optimize the use of limited resources to facilitate information propagation [8] etc. In large social network graph the nodes having the largest degree are often considered as the most influential spreader [48]. However, recent studies have shown that the most connected people are not the most influential spreader. Kitsak et al. [25] showed that the best spreaders are not necessarily the most connected people in the network. They found that the most efficient spreaders are those located within the core of the network as identified by the *k*-core decomposition analysis [53]. Moreover, many centrality measures have been proposed to identify the most influential spreaders on a social network. All these metrics are mainly of two kinds: global and local metrics. Local metrics like degree centrality and K-core decomposition are of simple complexity but are less effective i.e. they fail to find the most influential spreaders accurately since of omitting the global structure of the network. Global metrics such as betweenness centrality and closeness centrality perform well in the identification of the influential nodes. However, these global

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measures incur high computational complexity which make them infeasible to use in case of large graph [18, 44]. The state-of-the-art of different methods of finding most significant nodes in a network has been discussed in the paper of Lü et al. [35] reviewed the state of the art of different proposed methods and approaches dealing with detection of vital nodes in complex networks. Moreover, available methods are compared based on the different nature of the network.

Liu et al. [33] provided an improved method of using k-shell decomposition by removing the redundant links which have a low diffusion significance. Another improved method of k-shell decomposition was proposed by Wang et al. [54] who used k-shell iteration factor to evaluate the influence capability of a node. They used the iteration information of k-shell decomposition to distinguish among the nodes with the same maximum k-shell value.

Node of the existing methods take the user info into consideration while identifying the most influential spreaders which obviously play vital role for information spreading. On top of that, with the ubiquitous use of social network, social networks are producing large amount of data. The higher the number of nodes and their friend-follower relationship data is available, the more the graph becomes suitable to identify the real most influential spreaders. However, we need special kind of

We propose a variant of *k*-core decomposition which is distributed and also incorporates the node information. Summarizing, our main contributions are:

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2 TECHNICAL BACKGROUND

2.1 Formal Definition of Twitter Social Network

The users of Twitter form a social network with their friend-follower relationship. There are several approaches to define any network formally. However, the mostly used and flexible definition can be formalized using the graph theory. That means the social network is conceptualized as a graph, i.e. a set of vertices (or nodes) representing the users of the social network and a set of edges (directed or undirected) representing social relationship between the incident vertices (users). In case of Twitter social media, we define the following two graphs:

- **Friend-Follower graph:** which is created from the relationship between the users. In this graph, a vertex represents a user and there exists a directed edge from vertex u to vertex v if and only if the user represented by v is a follower of the user represented by u . This also implies that the user represented by u is a friend of the user represented by v . For simplicity, in several cases, these directed edges may be considered as undirected. Figure 1 shows a sample friend-follower graph of twitter social network. Here every node is labeled with the name of the user along with the twitter screen name. The bidirectional edges are shown in bold edges and they implies that the users represented by the incident vertices are following one another.
- **Tweet Graph:** which is created from the retweets. In this graph, a vertex represents a user and there exists an edge

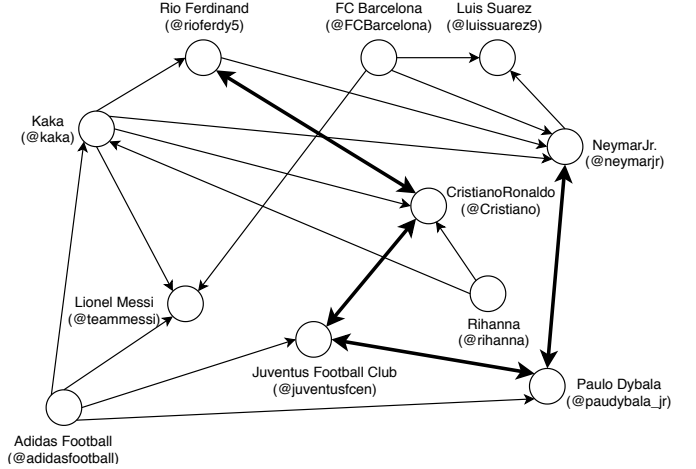


Figure 1: sample Friend-Follower Graph of Twitter Social Network

between two vertices if and only if one user retweets at least one of the other user's tweets. The edge should be directed to the retweeter from the user of the original tweet. For simplicity we may consider the edges as undirected.

2.2 Centrality Measurement

In graph theory, centrality is a term to describe importance of individual vertex within a graph or a network. The concept of centrality was first developed with an intention of doing social network analysis and there has been a lot of research works carried out in this topic for network analysis mainly to answer the question, "Which vertices are the most influential in a graph?" There are several centrality measures which are very popular in graph analysis. These measures can be categorized in two types: local and global metrics. In this section, we briefly describe various local and global centrality metrics that are available to find the influential nodes from a graph network.

2.2.1 Local Centrality Measures. In general, local centrality measures use only the features of an individual node through the partial information around it. The number of neighbors (degree of a node) plays the main role in such local methods and they work better mainly for undirected networks. There are mainly two local centrality measures and they are described below:

- **Degree Centrality:** Degree Centrality is the simplest centrality measure which assume that the node with the maximum neighbors possess the maximum influence on the network. The degree of the node v_i signifies the total number of edges incident to it i.e. the number of neighbors. Assume that, a graph $G(V, E)$ where V is a set of n nodes and E is the edge set, is represented by an $n \times n$ adjacency matrix $A = \{a_{ij}\}$, that is $\{a_{ij}\} = 1$ if nodes v_i and v_j are connected and 0 otherwise. If the degree of node v_i is denoted by d_i , then the degree centrality of node v_i is:

$$DC(v_i) = \frac{d_i}{n-1} \quad (1)$$

Here $n - 1$ is the largest possible degree in G and it is used as the numerator of the formula for normalization.

The most important side of using degree centrality to find the most influential spreader on a network is its simplicity and low computational complexity. However, in most of the cases this measure fails to identify the most influential spreaders accurately. However, there are several use cases where degree centrality can provide surprisingly good performance such as with very small spreading rate, degree centrality is a better metric to identify the spreading influences of nodes than other well-known centrality metrics [26, 32].

- **K Core Decomposition:** Degree centrality only considers the number of the adjacent neighbors in order to assess the influence of a node in the network. However, Kitsak et al. [25] identified that the location of a node in a network has a more significant aspect in evaluating its spreading influence. Nodes located at the core of a network are more likely to have a higher influence rate than those located at the periphery. Therefore, they suggested that core value of a node is a better metric in finding most influential spreaders and the core value can be obtained by using the k-core (aka k-shell) decomposition [16] of the networks.

The k -shell method starts by removing all nodes having degree 1. The process is repeated until there is no node of degree 1 exists in the network. These pruned nodes are assigned into the 1-shell. After assigning the 1-shell, all nodes with residual degree 2 are recursively removed and the 2-shell are created. This procedure continues as the residual degree increases until all nodes in the nodes have been assigned to one of the shells. The nodes with high k -shell value tend to locate in the center of the network and the spreading starting from each of these nodes are likely to widely cover the network. In this way all nodes are assigned a k (sometimes refereed to as k_s) value. Figure ?? presents a sample network and the k_s value for the nodes by this algorithm. The algorithm is very simple and robust.

However, k core decomposition method has a tendency to assign the same k_s value to multiple nodes in case of large networks. Therefore, the hypothesis of declaring the node(s) of the largest k_s value i.e. the node(s) of the innermost shell to be the most influential results in a good number of nodes with the same spreadability and that may not be the desired outcome in many cases. However, the simplicity and lower computational complexity make this metric very useful to find the most influential nodes on a network and in this paper, we extend this idea and propose a modified k core decomposition method that can accurately find the most influential spreaders on a social network with very lower computational complexity.

2.2.2 Global Centrality Measures. Global centrality measures consider the whole network during its computation. There exists many different types of global centrality measures and each of them addresses slightly different properties of the network and the nodes in order to compute the centrality value. Two mostly used global centrality measures are closeness and betweenness centralities and they are described briefly below:

- **Closeness Centrality:** As the name suggests, closeness centrality measures how close a node is from all other nodes in a network. In case of a connected graph, the normalized closeness centrality of a node is the average length of the shortest path between the node and all other nodes in the network. Let d_{ij} be the length of shortest path between node v_i and v_j , n be the number of nodes of the network, then the average shortest distance of node v_i will be [52],

$$Avg_i = \frac{1}{n-1} \sum_{i \neq j} d_{ij} \quad (2)$$

Since the centrality measure is intended to find the most closer nodes, the closeness centrality of node v_i is inversely proportional to the average shortest distance, Avg_i and can be defined as,

$$CC(v_i) = \frac{n-1}{\sum_{i \neq j} d_{ij}} \quad (3)$$

However, this equation will not be suitable to use in case disconnected graph where some node may be unreachable from the considering node v_i . Wasserman and Faust [45] proposed an improved formula for graphs with more than one connected component. The result is "a ratio of the fraction of nodes in the network which are reachable, to the average distance" from the reachable nodes. Let n_r be the number of reachable nodes in the network from node v_i , then the modified formula of measuring closeness centrality is,

$$CC(v_i) = \frac{n_1-1}{n-1} \frac{n_1-1}{\sum_{i \neq j} d_{ij}} \quad (4)$$

- **Betweenness Centrality:** Betweenness centrality determines how many times a node falls along the shortest path between two different nodes i.e. acts as a bridge between those two nodes. Linton Freeman [19] introduces this measure for quantifying the control of a human on the communication between other humans in a social network. For starting node v_s and destination node v_t and the input node v_i that holds the condition $v_s \neq v_t \neq v_i$, let n_{st}^i be 1 if node v_i lies on the shortest path between v_s and v_t ; and 0 otherwise. So the betweenness centrality is defined as:

$$BC(v_i) = \sum_{st} n_{st}^i \quad (5)$$

However, there can be more than one shortest path between v_s and v_t and that will count for centrality measure more than once. Thus, if total number of shortest paths between v_s and v_t is g_{st} , the updated equation for finding betweenness centrality of node v_i will be,

$$BC(v_i) = \sum_{st} \frac{n_{st}^i}{g_{st}} \quad (6)$$

2.3 Susceptible-Infected-Recovered (SIR) Model

The SIR model is one of the simplest compartmental models in epidemiology. In an SIR model, every mode of a network can be at one of the following three states:

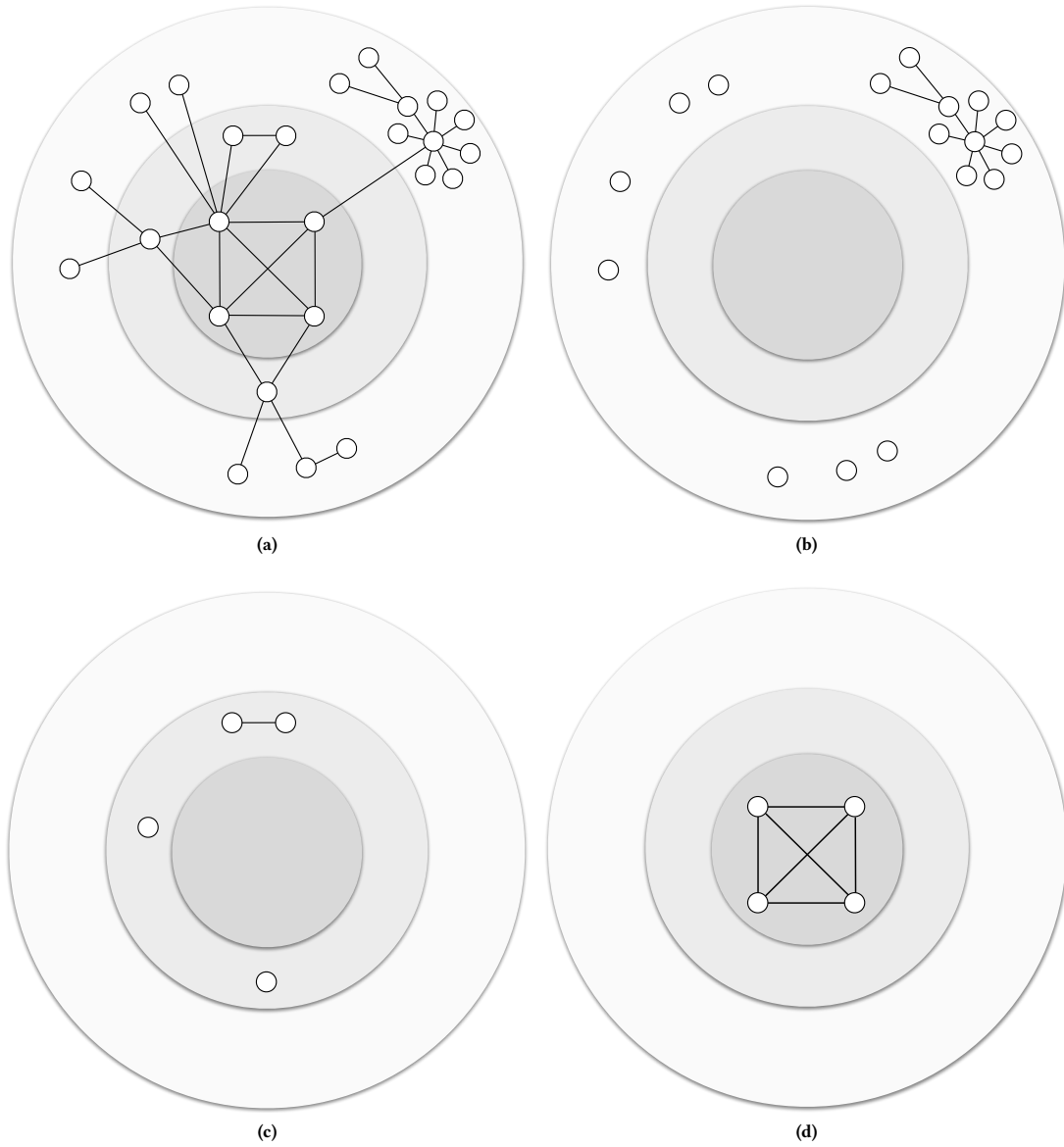


Figure 2: A sample network with k_s value of the nodes

- **S (Susceptible):** These denotes those people who have not been infected with the disease yet. However, they are not immune to it and therefore they are under threat of being infected with the disease in the future.
- **I (Infected):** These are people who have already been infected with the disease. Moreover, the infected people can transmit the disease to the susceptible neighbors with a probability of β .
- **R (Recovered):** These people have been recovered from the disease with a probability of γ and are immune now. Therefore, they are no longer under any threat to be infected with the disease in future.

The SIR model runs the simulation of disease diffusion based on the topology of the network and the probability parameters β and γ . The simulation stops when the network has no more infected nodes. This SIR model is capable of finding the most influential spreaders based on their spreadability.

3 RELATED WORK

An online social network (OSN) results from the use of a social network site (SNS) that allows the users to publish messages and connect to other users which result in creating social relationships. An OSN is formally represented by a graph, where nodes are users and edges are relationships that can be either directed or undirected.

In this graph the nodes play an important role to disseminate information. Finding the most influential spreader in an OSN has caught attention of the researchers. Recently more and more attentions have been paid to microscopically study the *spreadability* for each node. The knowledge of node *spreadability* is crucial for developing efficient methods to either decelerate spreading in the case of diseases, or speed up spreading in the case of information flow. Moreover, it can be helpful for identifying the initial spreader of certain disease or information.

Though the most connected nodes (hubs) and the nodes with high betweenness centrality are commonly believed to be the most influential spreaders in networks, the k -core (also called k -shell) method is found to perform better in identifying the best individual spreaders [6, 25]. Basically, the principle of the k -core decomposition is to assign a core index k_s to each node such that nodes with the lowest values are located at the periphery of the network while nodes with the highest values are located in the center of the network. We shall discuss the details about the algorithm shortly.

Cataldi et al. [7] proposed to use the well known PageRank algorithm [46] to assess the distribution of influence throughout the network. The *PageRank* value of a given node is proportional to the probability of visiting that node in a random walk of the social network, where the set of states of the random walk is the set of nodes. Both the methods only exploit the topology of the network, and ignore other important properties, such as nodes' features and the way they process information. Lü et al. [37] proposed the *LeaderRank* algorithm to identify influential spreaders in directed networks, which is a simple variant of *PageRank*, namely a so-called ground node connected with every other node by a bidirectional link is introduced into the original network, and then the standard random walk process is applied to dig out influential spreaders. Li et al. [31] further improved the *LeaderRank* by allowing nodes with more fans get more scores from the ground node. With almost the same converging speed (we have checked by simulations), this so-called *WeightedLeaderRank* performs better than *LeaderRank*.

Romero et al. [51] develop a graph-based approach similar to the well known HITS algorithm, IP (i.e. *Influence-Passivity*), that assigns a relative *influence* and a *passivity* score to every users based on the ratio at which they forward information. However, no individual can be a universal influencer, and influential members of the network tend to be influential only in one or some specific domains of knowledge. Therefore, Palet al. [47] developed a non-graph based, topic-sensitive method. To do so, they define a set of nodal and topical features for characterizing the network members. Using probabilistic clustering over this feature space, they rank nodes with a within-cluster ranking procedure to identify the most influential and authoritative people for a given topic. Weng et al. [55] also develop a topic-sensitive version of the *PageRank* algorithm dedicated to Twitter, *TwitterRank*. They presented the phenomenon of *homophily* in a community of Twitter. By making use of this phenomenon, a PageRank-like algorithm, called *TwitterRank*, is proposed to measure the topic-sensitive influence of the *twitterers*.

All these methods described are summarized in Table 1. We can see that none of the above approach is distributed. Most famous

approach for finding influential spreader is the k -core decomposition which considers only the network topology. We propose a distributed variant of the algorithm which also considers user info like no. of followers, no. of friends, whether the user is verified etc.

Table 1: Summary of influential spreaders identification methods

Algorithm	Network Topology	User Info	Topic Info	Distributed
k -core decomposition	Y			
PageRank	Y			
Topic-sensitive PageRank	Y		Y	
IP		Y		
Topical Authorities		Y	Y	

4 OUR PROPOSED MODIFIED K CORE DECOMPOSITION METHOD

4.1 Distributed K Core Decomposition

Centralized algorithms for the k -core decomposition already exist [5]. Their algorithm is based on the recursive deletion of vertexes (and edges incident to them) of degree less than k . The algorithm makes use of *bin-sort*, and can run in $O(\max(m, n))$, which equals $O(m)$ for connected networks. However a distributed variant is very much needed because of two possible scenarios: the graph could be so large to not fit into a single host, due to memory restrictions; or its description could be inherently distributed over a collection of hosts, making it inconvenient to move each portion to a central site. Montresor et al. [42] proposed a distributed algorithm for k -shell decomposition for very large graph. Their distributed algorithm is based on the property of locality of the k -core decomposition: due to the maximality of cores, the *coreness* of node u is the largest value k such that u has at least k neighbors that belong to a k -core or a larger core. The locality property tells that the information about the *coreness* of the neighbors of a node is sufficient to compute its own *coreness*. Based on this idea, the algorithm works as follows: each node produces an estimate of its own *coreness* and communicates it to its neighbors; at the same time, it receives estimates from its neighbors and use them to recompute its own estimate; in the case of a change, the new value is sent to the neighbors and the process goes on until convergence.

5 EVALUATION METRICS

In this section, we briefly present the metrics we use to evaluate the merit our proposed ranking technique against the already established ones. In the following two sections, we present the environment we use to to run our experiments, present the datasets we use to cross check the and discuss the out

5.1 Modified Jaccard Similarity Coefficient

Jaccard similarity coefficient measures the similarity between two finite sets which is defined as the ratio of the intersection to the size of the union of the sample sets. Therefore, for two comparing sets A and B , the Jaccard similarity coefficient $J(A, B)$ is,

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (7)$$

In this paper, we intend to measure the similarity of top n items from two different rankings. Let a and b be two comparing methods and A and B are the two generated rankings respectively, A_n and B_n are subsets of A and B respectively with top n elements, then we define modified Jaccard similarity coefficient $J_m(A, B)@n$ as follows,

$$J_m(a, b)@n = \frac{|A_n \cap B_n|}{n} \quad (8)$$

We use this modified metric mainly to test the proportion of the common users in the two n sized sets of the most influential users obtained from the two comparing ranking algorithms. While comparing with a established method, the higher the overlap is, the more reliable the comparing ranking algorithm.

5.2 Rank Correlation Coefficient

In general, correlation analyses are bi-variate analyses that measure the strength of association between two variables and the direction of the relationship. In terms of the strength of relationship, the value of the correlation coefficient varies between +1 and -1. A value of ± 1 indicates that there exists a perfect degree of association between the comparing two variables. As the correlation coefficient value goes towards 0, this relationship between the two variables gets weaker. The \pm signs of the coefficient indicated the direction of the relationship; a + sign indicates a positive relationship while a - sign indicates a negative relationship.

In Section ??, we measure the correlation of the ranked list of users based on their spreadability generated by our modified K core decomposition against the rankings generated by other methods. We use two non-parametric rank correlations: Kendall's tau and Spearman's rank correlation coefficient.

5.2.1 Kendall Tau Correlation Coefficient. The Kendall tau rank correlation coefficient is used to test the similarities in the ordering of data when it is ranked by quantities. While other types of correlation coefficients use the observations as the basis of the correlation, Kendall's correlation coefficient uses pairs of observations and determines the strength of association based on the pattern on concordance and discordance between the pairs. Assume that L_1 and L_2 are the two rankings that are to be compared. Then Kendall analysis takes the following two properties into consideration:

- **Concordant:** Any pair of items (x_1, y_1) in L_1 and (x_2, y_2) in L_2 are considered as concordant if and only if they meet one of the following two conditions:
 - $(rank_in_L_1(x_1) > rank_in_L_2(x_2) \text{ and } rank_in_L_1(y_1) > rank_in_L_2(y_2))$
 - $(rank_in_L_2(x_2) > rank_in_L_1(x_1) \text{ and } rank_in_L_2(y_2) > rank_in_L_1(y_1))$
- **Discordant:** Any pair of items (x_1, y_1) in L_1 and (x_2, y_2) in L_2 are considered as discordant if and only if they meet one of the following two conditions:
 - $(rank_in_L_1(x_1) > rank_in_L_2(x_2) \text{ and } rank_in_L_1(y_1) < rank_in_L_2(y_2))$
 - $(rank_in_L_2(x_2) > rank_in_L_1(x_1) \text{ and } rank_in_L_2(y_2) < rank_in_L_1(y_1))$

$$rank_in_L_2(y_2) < rank_in_L_1(y_1))$$

Kendall Tau correlation co-efficient is denoted by τ . If L_1 and L_2 are two different rankings with n similar elements, $N(C)$ and $N(D)$ represent the number of concordant and discordant pair respectively, then τ can be calculated using the following equation:

$$\tau(L_1, L_2) = \frac{N(C) - N(D)}{\frac{1}{2}n(n-1)} \quad (9)$$

5.2.2 Spearman's Rank Correlation Co-efficient. Spearman's Rank correlation coefficient, R_s is a technique which can be used to summarize the strength and direction (negative or positive) of a relationship between two variables. The result will always be within 1 and minus 1. The closer R_s is to +1 or -1, the stronger the likely correlation. A perfect positive correlation is +1 and a perfect negative correlation is -1. Assume that L_1 and L_2 are two rankings of same n elements. For any element x , if the rankings of x in L_1 and L_2 are $rank_in_L_1(x)$ and $rank_in_L_2(x)$ respectively, then the distance of ranks, $d = rank_in_L_1(x) - rank_in_L_2(x)$. This value is squared to remove any negative values and When written in mathematical notation the Spearman Rank formula looks like this:

$$R_s = 1 - \frac{6 \sum d^2}{n^3 - n} \quad (10)$$

5.2.3 Calculating Statistical Significance using Co-efficient Values. Statistical significance is a measure of whether any research outcome are meaningful or not. In the field of hypothesis testing of statistics, the term *null hypothesis* is the default assumption that there is no association or relationship between two measured phenomena [17]. A result has statistical significance when it is very unlikely to have occurred given the null hypothesis [43]. To be specific, a significance level, α is set for the experiment which denotes the probability of the experiment rejecting the null hypothesis, given that the null hypothesis were assumed to be true [12]; and the p-value of a result, p is the probability of obtaining a result at least as extreme, given that the null hypothesis were true. The result is statistically significant, by the standards of the study, when the condition $p \leq \alpha$ holds [11, 14, 23, 27, 50]. for the evaluation of our ranking method, we set the significance level to 5%.

To measure the statistical significance of the result, we use the following formula to compute a z-value:

$$z = \frac{3 \times T \sqrt{n(n-1)}}{\sqrt{2(2N+5)}} \quad (11)$$

where T is the correlation co-efficient measured by the previously described techniques. Using the z-score, an area is found from a z-table. This area value is considered as the p -value of a result.

5.3 Normalized Discounted Cumulative Gain, NDCG

In this paper, we use Normalized Discounted Cumulative Gain, *NDCG* which is one of the widely used techniques to evaluate ranking systems. Let GT represents the weighted set of all users who generate the network. The weights are the relevance of the nodes to be selected as the most influential spreader on the network and the set GT is sorted according to this relevance value. We can

refer to these relevance values and the ranking of the nodes in this set as our ground truth.

Now let X be the ranking of nodes to be the most significant spreaders identified by any comparing method. We define cumulative gain for first m rankings in X , $CG@m$ as:

$$CG@m = \sum_{i=1}^m rel_i \quad (12)$$

Where rel_i indicated the relevance value (from ground truth) of node at rank i in X .

Discounted cumulative gain (DCG) penalizes each relevance value based on its rank in the results. Therefore, we define Discounted cumulative gain for first m rankings in X as:

$$DCG@m = \sum_{i=1}^m \frac{rel_i}{\log(i+1)} = \sum_{i=1}^m \frac{2^{rel_i} - 1}{\log(i+1)} \quad (13)$$

$IDCG$ is the DCG of the best possible results based on the ground truth. Therefore we define Ideal Discounted cumulative gain for first m rankings in GT as:

$$IDCG@m = \sum_{i=1}^m \frac{rel_i}{\log(i^{(I)} + 1)} = \sum_{i=1}^m \frac{2^{rel_i} - 1}{\log(i^{(I)} + 1)} \quad (14)$$

Where $i^{(I)}$ indicates the Ideal rank of a node in GT . $NDCG$ is obtained by dividing DCG by Ideal DCG ($IDCG$), which normalizes the gain within $[0, 1]$. Therefore $NDCG$ for first m rankings in X can be defined as,

$$NDCG@m = \frac{DCG@m}{IDCG@m} \quad (15)$$

In our evaluation section we use the metric $NDCG@m(a, b)$ as the Normalized Discounted Cumulative Gain for first m elements of a ranking generated by method a , taking the ranking generated by method b as our ground truth.

5.4 Infection Rate on SIR Model

We use two different metrics related to infection rate on SIR model to evaluate our proposed method. These metrics were introduced by Ahajjam et al. [2] and are presented below:

5.4.1 Infection Rate Function. This metric is used in order to compare different method of finding most influential spreaders by simulating the network on SIR model with some of the top spreaders as initially affected ones. At any time t , the infection rate can be defined as,

$$IR(t) = \frac{N_I(t) + N_R(t)}{n} \quad (16)$$

Where $IR(t)$ is infection rate at time t , $N_I(t)$ is number of infected nodes at time t , $N_R(t)$ is number of recovered nodes at time t and n is the total number of nodes.

5.4.2 Final Infection Rate. In order to investigate the fraction of nodes that is finally affected a metric $IR(t_{max})$ is used. When the simulation reaches a steady state, if $N_R(t_{max})$ is the number of finally recovered nodes, then this metric can be defined as,

$$IR(t_{max}) = \frac{N_R(t_{max})}{n} \quad (17)$$

6 EXPERIMENTAL SETUP

As we already have discussed, the global methods of finding most influential spreaders take large amount of time to generate the final result. Therefore, to evaluate the performance of our proposed modified K core decomposition method of finding most influential spreaders on twitter social network, we need to keep the size of the dataset considerably small. On the other hand, we run the experiments with on a distributed environment with large scaled network data which fails to run on a single computer because of memory overflow and/or take infeasible amount of time due to larger computational complexity. Consequently, we run our experiments on two different environments and they are described below:

6.1 Cross Validation on a Single Computer

Global metrics like closeness or betweenness centrality possess a very high computational complexity which makes them infeasible to apply on large datasets i.e. networks with large number of nodes and edges. Therefore, in order to cut off the time requirement during evaluating the performance of our proposed method against such global techniques with high complexity, we run all the comparing methods on network with smaller number of nodes and edges on computer with simple commodity hardware.

6.2 Large Network Analysis on Distributed Environment

A number of related works for the distributed and/or parallel processing of graph structures has been presented in the literature. One popular framework for massively parallelizing computational tasks is MapReduce [13], introduced by Google in 2004 for the parallel processing of large data-sets. While Map-Reduce can be used for processing graphs, its structure is not optimized for such tasks. This is the reason that led Google researchers to develop another framework, called Pregel [38] which is optimized for mining graphs data [20]. Apache Giraph [39, 40] is the open source version of Pregel built on top of hadoop. The main idea of Giraph is “think like a vertex”. The computation in Giraph consists of a sequence of iterations, called supersteps, during which the framework runs a user-defined function on each vertex. In this function, a node receives messages from neighbor nodes sent during the previous superstep, modifies its local state and sends messages to its neighbor nodes, to be received in the next superstep. Barrier synchronization is used, so that each superstep is separated from the next one. Individual nodes may leave the computation when they have reached the convergence to their final state. We use Apache Giraph for implementing distributed k -core decomposition algorithm as described in the previous subsection 4.1.

6.3 Methods Compared

We

6.4 Datasets Used

In order to test the performance of our proposed modified K core decomposition method of finding most influential spreaders on twitter social network, we mainly use *** real twitter datasets. Since we compare the ranking generated by our proposed method with

that of the global techniques and the global techniques take too much time to generate the results, we consider multiple subsets of the main datasets with smaller number of nodes and edges. Below we briefly describe the datasets we use for evaluating our proposed method.

- We use the dataset from [28] which was collected by crawling the entire Twitter site for 6 months in 2009. This dataset contains 41.7 million of user profiles, 1.47 billion friend-follower relationships, 4,262 trending topics, and 106 million tweets. However, due to Twitter's new Terms of Services, this dataset has removed the tweet contents. Therefore, we only generate the friend-follower graph from this dataset. Since for cross validation with global techniques of finding most influential spreaders, we make two subgraphs from this dataset with smaller number of nodes and edges and we define them as follows.
 - **Kwak_50K**: We generate a subgraph from the main dataset with 50,000 randomly selected nodes and edges connecting them in the main graph. Since at every run we select a different set of randomly selected graphs, the number of average incident edges on each node vary from 1.5 to 4. We refer this dataset to *Kwak_50K* in the upcoming sections.
 - **Kwak_100K**: Similar to the previous one, this dataset is another subgraph generated from the main one with randomly selected 100,000 nodes and their incident edges. We refer this dataset to *Kwak_100K* in the upcoming sections.
- Another twitter dataset we use is collected by Kristina Lerman [29] in the year of 2010. It is a dataset containing 736,930 users and 36,743,448 links of social relationship among them. To make it feasible to run the global metrics on this dataset, we generate a smaller dataset out of this one also with randomly selected 100,000 nodes and their incident edges and we refer to this dataset as *Lerman_100k* in our upcoming sections.
- **Twitter-Dynamic-Net**: Lou et al. [34] and Hopcroft et al. [22] collected this dataset for their research works. To collect this dataset, one of the known popular user on twitter was selected and then 10,000 of his/her followers were randomly collected. After that, these users were taken as seed users and a crawler was used to collect all followers of these users by traversing "following" relationships. The total number of users is 112,044. The crawler monitored the change of the network structure among the 112,044 users during December, 2010 and finally obtained 443,399 dynamic friend-follower relationships between them. In our evaluation section, we refer to this dataset as *Lou_Hopcroft*

One thing to be noted that, all the smaller datasets generated from the original ones are opted to be used for cross validation of the ranking generated by our proposed method. of against the established methods like

7 EXPERIMENTAL OUTCOME AND EVALUATION

7.1 Modified Jaccard Similarity Co-efficient with other Methods

We measure modified Jaccard similarity co-efficient as defined in subsection 5.1

7.2 Simulation on SIR Model

We simulate the SIR model to depict the disease diffusion based on the topology of our experimental datasets. For each method, the SIR model is simulated on the same dataset for five (5) times so that a steady result is obtained and the simulation was run for infection transition probability, $\beta = 0.1$ and recovery probability, $\gamma = 1$. We observe the simulation upto a maximum time, $t_{max} = 16$. The simulations stop when a saturation in infection spreading is achieved and Figure 3 shows the infection rate achieved with the flow of time for each of the methods on each of the datasets. Every time we select top 10 most influential spreaders identified by the comparing methods and assign them as the initially affected nodes on the SIR model. We can clearly see that the infection rate while selecting the top 10 most influential spreaders obtained by our modified k core decomposition outperforms the that of the other methods. Even though for $\beta = 0.1$, the betweenness centrality provides a better result in a very slight fraction, our method can generate the accurate result in significantly lower computational complexity than the global methods.

8 FUTURE WORK

9 ACKNOWLEDGMENT

10 CONCLUSION

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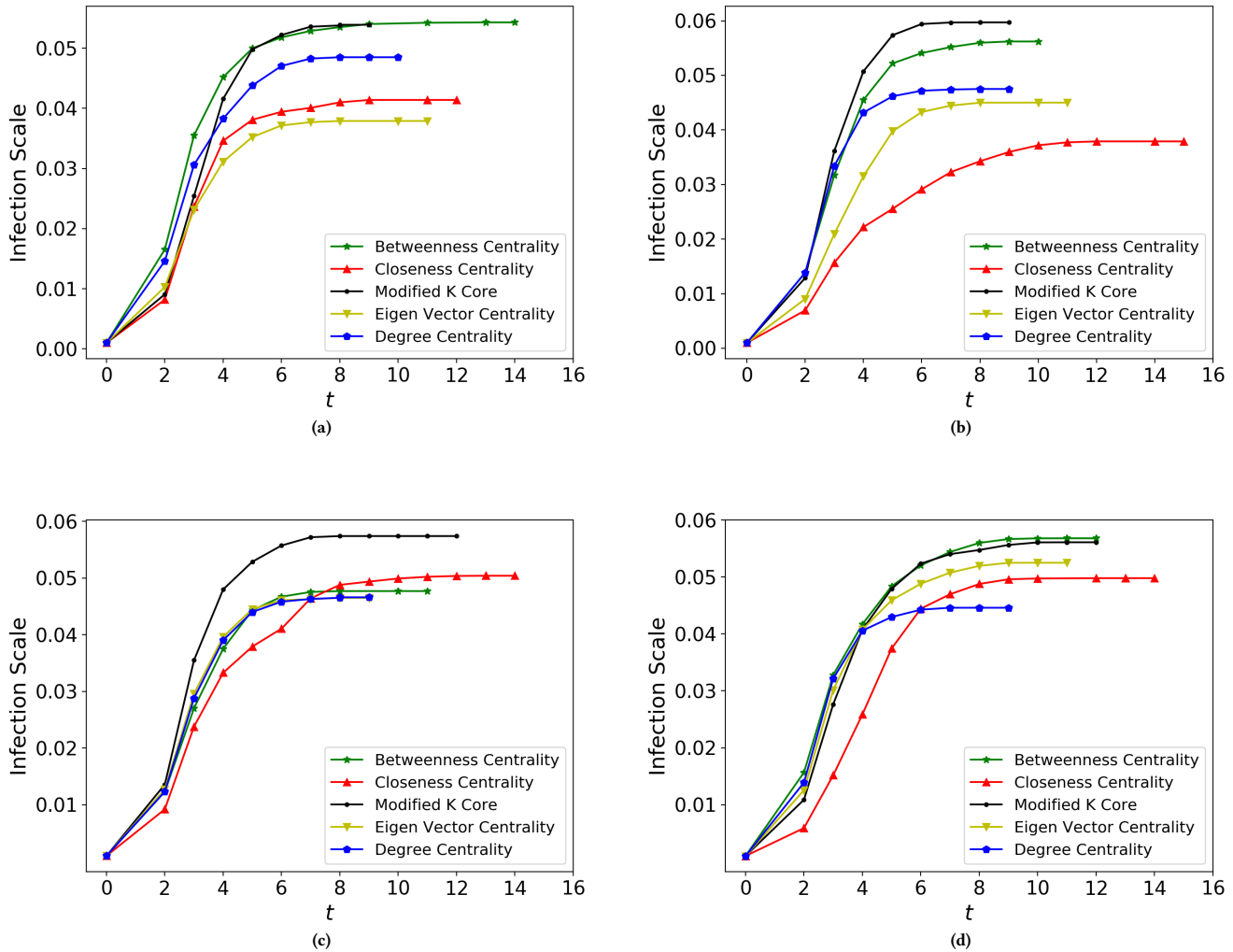


Figure 3: Simulation of SIR model on 4 datasets using each of the methods.

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