A Survey on the Role of Centrality as Seed Nodes for Information Propagation in Large Scale Network

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From the popular concept of six-degree separation, social networks are generally analyzed in the perspective of small world networks where centrality of nodes play a pivotal role in information propagation. However, working with a large dataset of a scale-free network (which follows power law) may be different due to the nature of the social graph. Moreover, the derivation of centrality may be difficult due to the computational complexity of identifying centrality measures. This study provides a comprehensive and extensive review and comparison of seven centrality measures (clustering coefficients, Node degree, K-core, Betweenness, Closeness, Eigenvector, PageRank) using four information propagation methods (Breadth First Search, Random Walk, Susceptible-Infected-Removed, Forest Fire). Five benchmark similarity measures (Tanimoto, Hamming, Dice, Sorensen, Jaccard) have been used to measure the similarity between the seed nodes identified using the centrality measures with actual source seeds derived through Google's LargeStar-SmallStar algorithm on Twitter Stream Data. MapReduce has been utilized for identifying the seed nodes based on centrality measures and for information propagation simulation. It is observed that most of the centrality measures perform well compared to the actual source in the initial stage but are saturated after a certain level of influence maximization in terms of both affected nodes and propagation level.

CCS Concepts: • **Human-centered computing** → Empirical studies in collaborative and social computing; *Social networks*; Social recommendation; • **Social and professional topics** → User characteristics;

Additional Key Words and Phrases: Large scale social network, Influence maximization, Centrality measures, Information propagation, Similarity measures

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1 INTRODUCTION

1.1 Overview

Online social networks (OSNs) act as an important medium of information propagation and influence maximization in modern society. The spread of information, and influence, through OSNs can in turn influence real-life phenomena, such as viral marketing, flash mobs, and unified protests. Information propagation and influence maximization also help in understanding public opinion, like opinion formation in Brexit [36], or U.S. presidential polls through social platforms like Facebook and Twitter. Thus, information propagation and influence maximization are the key areas of interest in recent research.

A crucial starting point for information propagation is seed node selection. The seed nodes are considered to be the source of the information. The more influential the seed node, the higher the information spread [10]. There is, however, an alternative line of thought that seed node selection is not related to information propagation in any way [17]. However, there is much research literature in support of significance of seed nodes in information spread.

Different centrality measures, such as clustering coefficients, Node degree, Betweenness, Closeness, Eigenvector, K-core, and PageRank, can be used to identify seed nodes in an OSN. Over the years, several measures of centrality have been proposed by different researchers [13]. For example, if an OSN is modeled as a graph $G(V, E)$, where V denotes the set of vertices representing the users and E denotes the edge set, then higher node degree centrality could signify higher influence. However, it can happen that it inherits the properties of local maxima where influence is confined within the local community. For such reasons, there is no universal consent on which measure is appropriate for influence maximization. Multiple information propagation methods, such as Breadth First Search, Random Walk, **Susceptible-Infected-Removed (SIR)**, and Forest Fire, have been considered to preserve generalization.

Evidence exists in the literature that centrality measure plays a major role as a seed node when a network shows the small world network phenomenon [37]. This article focuses on establishing the same for large-scale networks.

For the purpose of this work, the Twitter data stream has been considered, Twitter, which is a very popular OSN site, gives the option of opinion generation. One can generate a maximum of 280 characters (previously 140 characters) as a tweet and others can share (retweet) on that tweet information.

1.2 Contribution

In this research work, a thorough literature review and an extensive experimental study has been conducted for the derivation of the following:

- (i) Role of centrality measures as seed nodes for propagation
- (ii) Similarity between centrality measures and the true seed node from where the information is actually generated using five benchmark similarity measures (namely, Tanimoto, Hamming, Dice, Sorensen, and Jaccard)
- (iii) Comparative study between different centrality measures as the seed node of the propagation.

1.3 Organization of the Article

The rest of the article is organized as follows. Literature review and background are discussed in Section 2. Section 3 presents the problem statement and proposed approach to study the influence of centrality measures as seed nodes in the OSN. The implementation in the Spark framework

is discussed in Section 3.5. Results and analysis are presented in Section 4. Finally, the article is concluded in Section 5.

2 LITERATURE REVIEW AND BACKGROUND

OSNs are generated by nodes, representing the user in the network, and edges, representing the interaction patterns among the users [7]. Recent research depicts the fact that the topology generated from the user interaction patterns inherit centrality patterns within the network [2, 15]. A challenging motivation in network science is to find the relationship between the structure of a network, the dynamic change of the structure, and the influence of the nodes within the network, and to find contagion of information [28]. Using the structural properties of the network, the information flow in the network can be controlled [6, 23] using these methodologies.

2.1 Influence Maximization

Different controlling factors [16] are responsible for the maximization of information flow in the network [12, 38]. Due to their topological advantages, centrality nodes are generally more influential than others in the network as compared to other nodes present in the network, and it is expected that this kind of node can act as spreader in the network for maximizing the influence [34]. Arruda et al. [10], in their research work, show that K-shell decomposition can be used to identify the most influential spreaders in the network. This K-core nodes represent the core of the network and may not be the most connected nodes in the network. An earlier work by Dey et al. [31] show the effect of influential node selection on influence maximization as well. Another recent work by Chen and Teng [5] focuses on studying the connection between static properties such as node significance centrality and the dynamic influence process in an OSN.

Holthoefer and Moreno [17] claim that influential spreader identification is not possible using the same parameters for standard information propagation models, and show that spread from K-core centrality make no significant difference in information propagation. Although most researchers claim that centrality nodes can be utilized as an influential spreader, the result is not uniform. In some recent research work, it was shown that some centrality measures can distinguish nodes with better granularity, whereas for some centrality measures, the performance is poor [14]. Some researchers generate a greedy strategy to influence the maximum number of users for spreading the information [20]. In the work of Sun and Tang [33], a comparative study of different influence maximization algorithms is executed.

2.2 Network Modeling

OSNs like Facebook and Twitter generate large-scale data and exhibit the properties of scale-free networks [26]. The Erdos-Renyi random graph model [9] can be used to simulate a complex real-world network, but the dynamic nature of the real-world graph cannot be characterized through this model. The Barabasi-Albert model [1], however, follows the power law (i.e., node degree distribution follows the power law) and can be used to simulate the structure of a scale-free network. The scale-free network can be considered as a collection of small networks whose center is called a *hub*. A small world model was proposed by Watts and Strogatz [37], based on the small world criterion (stated as six-degree separation) where clustering coefficient is much more as compared to a random network with the same number of nodes. This theory stated that all nodes are connected friends of friend. Therefore diameter of the network is much less as compared to the number of nodes in the network.

2.3 Centrality Measures

Centrality measures identify nodes of importance in a given graph of the form $G(V, E)$. There are multiple centrality measures, and each one considers specific concepts and confronts the other. For example, Betweenness and Closeness centrality are derived from all possible shortest paths calculated from the network [11], ignoring existing alternative paths between them. Rusinowska et al. [32] show the effect of centrality measures on influence of nodes and propose to model this using a relation-algebraic approach. A recent work by Li [24] focuses on one particular centrality measure, namely Betweenness centrality, and its effect on the Bulletin Board Server.

2.4 Propagation Approaches

There exist several propagation models based on different diffusion models used in the network. The most popular approach is Random Walk, and its variants like Markov chain Monte Carlo Random Walk, where the walk is done from the seed node with a predefined probability. Viana et al. [35] propose a model of thermal diffusion to spread the information. There exist several probabilistic approaches for simulating the spreading of the information in the network. Zhang et al. [22] propose a new information dissemination model based on individual behavior that includes the visibility of content on a social network under constraints like time. A new context-specific framework for recommending and diffusing education resources in a social network is proposed by Neves et al. [27]. Dey et al. [30] provide a survey on different information propagation approaches in a small world network.

To increase efficiency of calculation of centrality measures for large graphs and information diffusion in large graphs, distributed and parallel implementation of classic graph theory algorithms have also been proposed in the literature. Betweenness centrality is a computationally complex centrality measure, and Jamour et al. [18] suggest a parallel algorithm for it. Jo et al. [19] provide a fast and scalable distributed implementation of the Loopy Belief Propagation method to fit the huge volume of real-world graphs.

Table 1 provides a representation of the taxonomy of recent popular work in relevant and related topics. This article focuses on combining all three aspects—that is, centrality measures, information propagation, and distributed implementation—and does a comprehensive study on influence maximization through choice of seed nodes using centrality measures using multiple information propagation models, and utilizes distributed implementation for efficiency without compromising accuracy.

3 PROPOSED SOLUTION

3.1 Problem Statement

Given a graph $G(V, E)$, $C \in \{\text{Node degree, Betweenness, Closeness, Eigenvector, clustering coefficient, K-core, PageRank}\}$ denotes set of centrality measures. For $A \in \{\text{Breadth First Search, Random Walk, Susceptible-Infected-Removed, Forest Fire}\}$, a set of information propagation algorithms, and $M \in \{\text{Tanimoto, Hamming, Dice, Sorensen, Jaccard}\}$, a set of similarity measures, a set of seed nodes S using C is derived such that the set of infected nodes I is obtained. Using $a \in A$ similarity is measured using $m \in M$ in the original set of infected nodes I_{original} with I .

3.2 Centrality Measure

For the generation of influential source of propagation, seven centrality measures (Node degree centrality, Betweenness centrality, Closeness centrality, clustering coefficient, Eigenvector centrality, K-core, and PageRank) have been considered. Properties of these centrality measures are briefly described next.

Table 1. Taxonomy of Recent Popular Work in Related Topics

Author	Description
<i>Centrality Measures and Influence</i>	
Li, 2018 [24]	Centrality analysis of OSN data
Chen & Teng, 2017 [5]	Interplay between social influence and network centrality
Grando et al. 2016 [14]	Compute vertex centrality in a complex massive social network
Arruda et al., 2014 [10]	Describe role of centrality as an influential spreader
Holthoefer & Moreno, 2012 [17]	Absence of an influential spreader in a social network
Rusinowska et al., 2011 [32]	Describe centrality and its influence
Sun & Tang, 2011 [33]	Social influence analysis
Brandes, 2008 [3]	Betweenness centrality in a complex network and computation
Newman, 2002 [28]	Describe different types of centrality measures
<i>Information Propagation Model</i>	
Neves et al., 2019 [27]	Diffusion model of information in an education network
Zhang et al., 2017 [22]	Information propagation model based on individual behavior
<i>Distributed and Parallel Implementation</i>	
Jo et al., 2018 [19]	Fast and Scalable Distributed Loopy Belief Propagation
Jamour et al., 2018 [18]	Parallel Algorithm for Incremental Betweenness Centrality on Large Graphs

3.2.1 Node Degree Centrality. The degree centrality of a node $n \in V$ is defined by $D_C(n; G) = \text{degree}(n)/(V - 1)$, where $\text{degree}(v) = |\{u \mid (v, u), (u, v) \in E\}|$. The Node degree [16] informs the number of connections formed among the nodes in the network. It is not indicative of frequency of communication and often is a local maxima with respect to the network.

3.2.2 Betweenness Centrality. The Betweenness centrality of a node $n \in V$ is defined by $\text{between}(n) = \sum_{s \neq n \neq t} \frac{\sigma_{st}(n)}{\sigma_{st}}$, where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(n)$ is the number of those that pass through n . The Betweenness centrality [16] indicates the capability of a node for faster transfer of information through the network.

3.2.3 Closeness Centrality. The closeness of a node $n \in V$ can be defined as $\text{close}(n) = \frac{1}{\sum_{v \in V} \delta(n, v)}$, where $\delta(n, v)$ is the shortest distance from n to v . The Closeness centrality [16] indicates how fast information can spread from the node to the rest of the network. Note that if any node is v is unreachable from the node n , then $\text{close}(n) = 0$. To solve this, mean harmonic distance can be used as $\frac{1}{|V|-1} \sum_{v \neq n \in V} \frac{1}{\delta(n, v)}$.

3.2.4 Clustering Coefficient. Clustering coefficient for a node $n \in V$ is defined as $\text{cluster}(n) = \frac{\lambda(n)}{\tau(n)}$, where $\lambda(n)$ represents the number of triangles and $\tau(n)$ represents the number of triples containing n . It is a measure of the degree to which nodes in a graph tend to cluster together [16].

3.2.5 K-core. A K-core of a graph G is a maximal connected subgraph of G in which all vertices have degree at least K . Equivalently, it is one of the connected components of the subgraph of G formed by repeatedly deleting all vertices of degree $< K$ [16]. In a graph $G = (V, E)$ having $|V| = n$ and $|E| = m$, a subgraph $G' = (V', E')$ formed out of G is called a K-core if and only if $\text{deg}(v) \geq K, \forall v \in V'$, and for a preassigned positive integer k , moreover G' is maximal in the sense that it cannot be augmented further without destroying the property of K-core. A node belonging to K-core but not including a $(k + 1)$ core is assigned K-core centrality K .

3.2.6 Eigenvector Centrality. Eigenvector centrality is a measure of the degree of influence of a node in a network that is calculated as a function of the influence of its neighbors. It can be formulated as $\text{eigen}(x) = 1/\lambda \sum x_t \forall t \in N(x)$ where $N(x)$ is the neighbors of x in the network and x_t is the weight of the edge (x, t) [16].

3.2.7 PageRank. PageRank [29] is a link analysis algorithm, and it assigns a numerical weighting to each node in a graph, with the purpose of measuring its relative importance within the set. The PageRank of a node $n \in V$ is defined as $prank(n) = \frac{1-d}{|V|} + d \sum_{v:(v,n) \in E} \frac{prank(v)}{| \{v:(v,u) \in E \}|}$, where d is a dampening factor.

3.3 Propagation Models

For the purpose of this research work, four propagation models have been considered: Breadth First Search, Random Walk, SIR, and Forest Fire. Details of these models are provided next.

3.3.1 Forest Fire. The Forest Fire model was first presented by Bak et al. [39], where propagation emulates the pattern a fire grows in the forest [8]. The fire is started from the seed node, and concept is that the nodes close to the affected nodes will be affected faster than other nodes. The infection will be spread in a manner similar to the fire spread in a forest extended from a single tree.

3.3.2 Breadth First Search. In Breadth First Search, propagation depends on the probabilistic searching techniques considering seed nodes as root nodes [8]. In the proposed approach, the probability is considered as 1, and therefore if a node is connected with an affected node, then for the next level the nodes will be affected through the information.

3.3.3 Random Walk. For Random Walk, propagation of the node follows a path that is randomly selected from the seed node [8]. The concept of the propagation is that if some nodes are connected with the affected nodes, the affected node will choose a node between them randomly to spread the information in the next level.

3.3.4 SIR Model. In the SIR model, a portion of the nodes is considered to be infected. The rest of the nodes are considered to be susceptible. Infected nodes can infect susceptible nodes. Infected nodes can also recover, in which case it can be labeled as recovered. Once recovered, nodes cannot go back to the susceptible state. The rate of infection is given based on a parameter *beta*, and the rate of recovery is given based on a parameter *lambda* [30].

3.4 Proposed Methodology

Information can be defined as the set of all tweets containing a particular #hashtag. But the network generated from all nodes participating in the tweet generation will have a large volume to process. Moreover, the network will be sparse in nature, which will contain a large number of unnecessary data. Therefore, we need to segregate those nodes that are actively participating in #hashtag generation.

Nodes, which signify users in a network, can be classified according to their nature of participation in the network:

- *Source*: A user who originates the information for a particular flow.
- *Propagator*: A user who does not originate the information but knows about and propagates it.
- *Stifler or Sink*: A user who knows about the information but does not propagate the information (i.e., the flow ends at a sink). This usually happens in two situations:
 - The user is unwilling to share the information.
 - The information loses its significance with time.
- *Ignorant*: A user who does not know about the information.

In broad sense, nodes can be grouped into two types of nodes: active (Source/Propagator or Spreader) or inactive (Stifler/Ignorant). For the network formation, only active nodes are considered. To study the propagation of information on Twitter data, a directed *Tweet Information Graph*

Fig. 1. Schematic Representation of Proposed Approach.

is defined with each node representing a user in the network. Nodes are active or inactive, based on whether their corresponding users are active or inactive participants. All active nodes are labeled with the timestamp of their first tweet containing the specified #hashtag. All inactive nodes are ignored. The edge set consists of connections between nodes satisfying the following:

- Both nodes are active.
- There exists a Following link between the two corresponding nodes in the Twitter User Graph.
- The followee has a lower timestamp than the follower.

Here, the followee signifies those “who are followed by the user,” and the follower signifies those “who follow the user.”

The nodes selected through different centrality measures as discussed in Section 3.2 are considered as influential nodes and considered for the source of propagation in the Tweet Information Graph. These nodes are termed as *influential seeds* in the proposed methodology. The spread of information in the Tweet Information Graph is simulated using the propagation models discussed in Section 3.3. A schematic diagram representing the proposed method is shown in Figure 1.

True seeds are generated using the Google two-phase Largestar-Smallstar algorithm, and propagation is measured using the same algorithms and the results are compared.

3.5 Distributed Implementation

OSNs produce a huge volume of data at a high velocity. Standard graph-theoretic algorithms are not sufficient for producing acceptable results with high efficiency. Thus, the MapReduce approach is chosen to handle the high volume of data. For the purpose of this research, the Spark platform has been utilized.

Table 2. Comparison Between Spark and Some of the Other Distributed Big Data Tools

<i>Spark vs. MapReduce</i>	
In-RAM computation Faster compared to MapReduce More suited for data that can fit into RAM	Required dedicated file system Slower compared to Spark Uses a two-step paradigm irrespective of size of data
<i>Spark vs. Hive</i>	
Compatible with Python, Scala, Java Independent of any framework	Mostly works with Java Uses Hadoop framework
<i>Spark vs Cassandra</i>	
Data Analysis Tool Faster computation	Database High availability and scalability

3.5.1 Spark. Spark excels in applications that exhibit cyclic dataflow models, or reuse a working set of data across multiple parallel operations, while retaining the scalability and fault tolerance of MapReduce [25]. MapReduce is a paradigm for distributed computation where Map with the input data generates another set of data in (key, data) format and distributes to different resources for computation and in reducer all results are compiled from the mapper to generate the output. In the Spark framework, both Map and Reduce can be generated in a single instance. The other alternative to Spark is Hadoop MapReduce, which is also a Big Data Analytics tool. However, Spark has some considerable advantages over Hadoop,^{1,2} such as Spark works In-Memory, whereas Hadoop requires a dedicated File System, commonly known as Hadoop File System (HDFS), which makes Spark more suitable for datasets that can be fitted into the RAM. Spark is also potentially a lot faster compared to Hadoop MapReduce. Spark also reduces complexity compared to the two-stage paradigm maintained by Hadoop MapReduce. In comparison to Hive as well, Spark has certain benefits that cannot be overlooked.³ Hive utilizes the underlying Hadoop framework. Spark is more compatible with a larger number of programming languages, such as Python and Scala. Similarly, in between Cassandra and Spark⁴ as well, Spark seems to be a better-suited option for the problem at hand. Thus, Spark has been considered for the distributed implementation of the algorithmic approach described in this article.

3.5.2 Algorithm Formulation. The graph-theoretic algorithms are all popular algorithms that have been reused here. However, these algorithms, without any adaptations, are not sufficient to process the huge volume of data produced in real-life OSNs. That is why an adaptation of the existing algorithms for the distributed implementation has been utilized for the purpose of this work. This allows the computation of computationally complex centrality measures such as Betweenness centrality possible over the whole network.

The general approach can be divided into two modules. The first module, which will be referred to as the iteration step, maps each node to its initial value and performs some filtration based on additional parameters. In the algorithmic representation 1, two filtration steps have been considered. The first filtration is applied on the complete graph. Then, for the filtered graph, each node is mapped to its initial value. The second filtration step then processes the nodes/edges based on the initial values of the nodes. During application, either or both of these filtration steps might

¹<https://www.xplenty.com/blog/apache-spark-vs-hadoop-mapreduce/>.

²<https://logz.io/blog/hadoop-vs-spark/>.

³<https://www.educba.com/apache-hive-vs-apache-spark-sql/>.

⁴<https://stackshare.io/stackups/cassandra-vs-spark>.

be present. For example, in K -core, given two nodes u and v , the iteration step first filters out all edges not containing either u or v . For each node, the out degree is then calculated. The edges are retained if the out degree of the source is greater than K .

The second module, which will be referred to as the convergence step, utilizes the iteration step until the values converge. A state of convergence can be said to have been achieved if for two consecutive iterations the results are the exact same. The convergence step accepts as input the initial graph and then calls the iteration step. The initial graph is updated with the results of the iteration step. This is repeated until a state of convergence is achieved. For example, in K -core, the convergence step continues until no new edges/nodes can be removed from the graph. A general approach is pointed out in Algorithm 1 and Algorithm 2.

ALGORITHM 1: $\text{iteration_step}(G(V, E), \text{args})$

Input :

- $G(V, E)$ —graph with vertex set V and edge set E
- args —additional parameters

Output : iteration_result —result at the end of iteration

filter $G(V, E)$ based on args

map $v \in V$ to a tuple of the form (v, i) where i is the initial value

$\text{iteration_result} \leftarrow \text{filter based on } \text{args}$

return iteration_result

ALGORITHM 2: $\text{convergence_step}(G(V, E), \text{args})$

Input :

- $G(V, E)$ —graph with vertex set V and edge set E
- args —additional parameters

Output : $\text{convergence_result}$ —result at the end of convergence

while *more iterations are possible* **do**

 | $\text{convergence_result} = \text{iteration_step}(G(V, E), \text{args})$

end

return $\text{convergence_result}$

4 EXPERIMENTAL OUTCOME

4.1 Dataset

For the purpose of this work, six datasets have been collected. The user graph is derived from the 2009 database of Kwak et al. [21].⁵ The open source dataset was collected from archive.org.⁶ A distribution diagram of collected tweets, which is in the range of a million (10^6), is shown in Figure 2. Five other hashtags were collected from Twitter data streams using a filter query using the keywords #covid, #pandemic, #quarantine, #lockdown, and #mask. All of these keywords are associated with the recent outbreak of global pandemic Covid19 and are now trending in OSNs.

⁵<https://an.kaist.ac.kr/traces/WWW2010.html>.

⁶<https://archive.org/details/twitterstream> (using the hashtag #Brexit).

Fig. 2. Twitter dataset distribution statistics.

Table 3. Similarity Measures

Jaccard(S_1, S_2)	$\frac{ S_1 \cap S_2 }{ S_1 \cup S_2 }$
Dice(S_1, S_2)	$\frac{ S_1 \cap S_2 }{ S_1 \cap S_2 + \frac{1}{2}(S_1 - S_2 + S_2 - S_1)}$
Tanimoto(S_1, S_2)	$\frac{ S_1 \cap S_2 }{ S_1 \cap S_2 + S_1 - S_2 + S_2 - S_1 }$
Sorensen(S_1, S_2)	$2 \frac{ S_1 \cap S_2 }{ S_1 + S_2 }$
Hamming(S_1, S_2)	$\frac{ S_1 \cap S_2 }{\max(S_1 , S_2)}$

The preceding datasets were chosen for several reasons. First, they aptly represent the data rate for OSNs, where a huge amount of data is generated over a short period of time. The size of the datasets also make them ideal to be processed over distributed implementation. The datasets are open source, and thus can be re-evaluated and re-used for other scopes on work and to build on this existing work. In addition, the datasets were collected over hashtags that are both relevant at the time of experimentation and on the longer run as well.

4.2 Influential Seed Selection

In this section, the success of centrality measures as influential seed detection algorithms is measured against the true seeds derived from the data. Table 3 represents five similarity measures [4] and the equations for calculating the corresponding similarity measures.

A comparison of the similarity between actual and influential seeds, with respect to different measures, for various centrality measurement algorithms is shown in Table 4 for the datasets. Here, actual seed indicates the source of actual information and influential seed indicates the node with the highest centrality value. The set of influential seeds was obtained each time by first ranking all nodes in the graph using the centrality measure, then selecting the nodes corresponding to the top 10%, 20%, and 50%, respectively. The values in the table represent the similarity values.

Table 4. Comparison of the Similarity Between Actual and Highest Centrality Seeds: D-Dice, T-Tanimoto, H-Hamming, Jaccard, and Sorensen Results Coincide with Tanimoto and Dice, Respectively

Experiment	Properties	10%			20%			50%		
		D	T	H	D	T	H	D	T	H
#Brexit	degree	0.0025	0.0029	0.0049	0.0199	0.0258	0.0390	0.1595	0.2487	0.2751
	closeness	0.0122	0.0140	0.0241	0.0447	0.0566	0.0856	0.2669	0.3809	0.4213
	betweenness	0.0144	0.0165	0.0284	0.0597	0.0745	0.1126	0.2823	0.3981	0.4403
	eigenvector	0.015	0.0145	0.0296	0.0604	0.0743	0.1085	0.29	0.3965	0.4393
	pagerank	0.0138	0.0158	0.0271	0.0491	0.0620	0.0937	0.2720	0.3866	0.4277
	clustering	0.0247	0.0279	0.0481	0.0377	0.0480	0.0726	0.2707	0.3852	0.4261
	kcore	0.0034	0.0039	0.0038	0.0207	0.0269	0.0406	0.1608	0.2504	0.2771
#covid	degree	0.3592	0.2189	0.5211	0.4639	0.302	0.6294	0.5951	0.4236	0.8212
	closeness	0.361	0.2202	0.5211	0.401	0.2508	0.5664	0.4989	0.3324	0.662
	betweenness	0.3654	0.2235	0.5352	0.4675	0.3051	0.6294	0.5949	0.4234	0.8184
	eigenvector	0.361	0.2202	0.5211	0.398	0.2484	0.5594	0.4995	0.3329	0.662
	pagerank	0.3558	0.2164	0.5211	0.4694	0.3067	0.6434	0.5243	0.3553	0.6927
	clustering	0.5231	0.3542	0.7183	0.6055	0.4342	0.8531	0.6256	0.4552	0.8939
	kcore	0.3662	0.2124	0.5211	0.4642	0.2505	0.6445	0.6161	0.4142	0.6962
#pandemic	degree	0.3462	0.2093	0.507	0.3445	0.2081	0.5035	0.3563	0.2168	0.5196
	closeness	0.3429	0.2069	0.507	0.338	0.2034	0.5035	0.3486	0.2111	0.5112
	betweenness	0.3429	0.2069	0.507	0.3462	0.2093	0.5035	0.3563	0.2168	0.5196
	eigenvector	0.3429	0.2069	0.507	0.338	0.2034	0.5035	0.3486	0.2111	0.5112
	pagerank	0.3429	0.2069	0.507	0.3429	0.2069	0.5035	0.3435	0.2073	0.5056
	clustering	0.3663	0.2242	0.5211	0.3527	0.2141	0.5105	0.3563	0.2168	0.5196
	kcore	0.3412	0.2003	0.5011	0.3132	0.2918	0.5535	0.3561	0.2504	0.5152
#quarantine	degree	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.3333	0.2	0.5
	closeness	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.3333	0.2	0.5
	betweenness	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.3333	0.2	0.5
	eigenvector	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.3333	0.2	0.5
	pagerank	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.3333	0.2	0.5
	clustering	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.3333	0.2	0.5
	kcore	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.3333	0.2	0.5
#lockdown	degree	0.3333	0.2	0.493	0.3412	0.2057	0.5035	0.3454	0.2087	0.5084
	closeness	0.3302	0.1977	0.493	0.338	0.2034	0.5035	0.3422	0.2064	0.5056
	betweenness	0.3333	0.2	0.493	0.3541	0.2151	0.5175	0.346	0.2092	0.5084
	eigenvector	0.3302	0.1977	0.493	0.3364	0.2022	0.5035	0.3422	0.2064	0.5056
	pagerank	0.3333	0.2	0.493	0.3412	0.2057	0.5035	0.3415	0.2059	0.5056
	clustering	0.3333	0.2	0.493	0.3541	0.2151	0.5175	0.3463	0.2094	0.5084
	kcore	0.3302	0.1977	0.493	0.3114	0.2007	0.5113	0.3414	0.2112	0.5204
#mask	degree	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.345	0.2085	0.5084
	closeness	0.3365	0.2023	0.493	0.3349	0.2011	0.4965	0.3358	0.2018	0.5
	betweenness	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.345	0.2085	0.5084
	eigenvector	0.3365	0.2023	0.493	0.3349	0.2011	0.4965	0.3358	0.2018	0.5
	pagerank	0.3302	0.1977	0.493	0.3318	0.1989	0.4965	0.3447	0.2082	0.5084
	clustering	0.3302	0.1977	0.493	0.3333	0.2	0.4965	0.345	0.2085	0.5084
	kcore	0.3132	0.1878	0.493	0.3318	0.1887	0.4965	0.3321	0.2111	0.5

It is interesting to note here that with an increase in the percentage of seed nodes used, the similarity between the actual seed nodes and the influential seed nodes using similarity measures also increases. This is because choosing a larger set as seed nodes increases the probability of overlap.

In Figure 3, similarity between actual and influential seeds, with respect to different seed node selection algorithms, in terms of the different similarity indexes for the keyword #Brexit have been compared. The maximum number of influential nodes for #Brexit is 4511. It is to be noted

Fig. 3. Comparison of similarity between actual and influential seeds for different centrality measures for hashtags(#) Brexit. Moving from left to right, beginning with the first row, the centrality algorithms depicted are betweenness, closeness, clustering, degree, eigenvector, pagerank, and K-core.

that in the chart, only Tanimoto, Dice, and Hamming curves are distinctively obtained. Jaccard and Sorensen curves coincide perfectly with Tanimoto and Dice, respectively. For all centrality measures, similarity indexes with actual seeds saturated in almost the same way at around 60% to 80%. For smaller sets of data, Betweenness centrality is generally most similar to the actual seeds.

Fig. 4. Comparison of Performance of Centrality Measures with True Seeds for Breadth First Search Model with keywords #Brexit, #covid, #pandemic, #lockdown, #quarantine, #mask respectively moving from left to right, beginning with the first row

4.3 Information Propagation

In this section, the effect of simulating the spread of information from the highest centrality nodes, as discussed in the previous section, is shown. For studying the level of dissemination through centrality measures as seed nodes, the simulation is carried out using Breadth First Search, Random Walk, SIR, and Forest Fire.

4.3.1 Breadth First Search. In Table 5, a comparative analysis of information propagation from different centrality nodes along with an actual seed using Breadth First Search is shown for six datasets of #Brexit, #covid, #pandemic, #quarantine, #lockdown, and #mask. The columns list the number of affected nodes after 1, 3, 5, and 10 levels or steps of propagation.

From Table 5, it can be observed that PageRank, Betweenness, and Degree are the three front-runners in maximizing information propagation. Closeness, K-core and Eigenvector centrality are also promising centrality measures for seed selection. All of these six methods are considerably better in seed selection compared to the true seed identified using the two-phase algorithm. Clustering coefficient is consistently a poor measure for seed selection, as can be seen from this table.

Figure 4 represents the performance of highest centrality measures with True Seeds as the source of propagation when propagation is simulated through Breadth First Search. It is the graphical representation of Table 5, where previous statements are represented through the compare charts for all six hashtags.

Table 5. Comparative Analysis of Information Propagation from Highest Centrality Measures as Seed Nodes Using Breadth First Search Propagation

<i>Experiment</i>	<i>Properties</i>	Level 1			Level 3			Level 5			Level 10		
		<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>
#Brexit	degree	49	30	15	924	755	501	1684	1640	1444	1874	1872	1786
	closeness	45	28	14	978	854	573	1701	1668	1597	1874	1872	1871
	betweenness	35	22	12	815	666	458	1645	1583	1379	1869	1869	1743
	eigenvector	31	23	13	813	668	500	1582	1602	1524	1892	1892	1732
	kcore	41	29	15	916	768	508	1672	1642	1668	1872	1872	1802
	pagerank	48	28	14	830	595	429	1623	1313	1279	1824	1524	1679
	clustering	4	5	9	334	376	444	1196	1294	1368	1581	1674	1730
	trueseed	22	20	12	380	450	550	1432	1322	1490	1661	1752	1782
#covid	degree	744	629	518	791	676	559	797	682	565	797	682	565
	closeness	615	355	200	669	399	224	669	399	224	669	399	224
	betweenness	743	629	507	797	683	559	797	683	559	797	683	559
	eigenvector	616	248	154	663	274	157	669	280	157	669	280	157
	kcore	641	629	615	716	668	608	772	742	768	792	772	702
	pagerank	878	661	556	922	705	593	928	711	599	928	711	599
	clustering	333	147	78	668	409	281	674	415	286	674	415	286
	trueseed	352	189	128	708	545	484	714	551	490	714	551	490
#pandemic	degree	665	569	429	757	661	516	786	690	545	790	694	549
	closeness	558	246	156	674	344	242	691	361	259	691	361	259
	betweenness	658	560	336	762	664	433	784	686	455	787	689	458
	eigenvector	503	176	93	595	245	143	624	274	168	628	278	172
	kcore	541	529	515	706	720	705	727	702	708	772	772	722
	pagerank	795	584	485	887	673	566	916	702	595	920	706	599
	clustering	300	125	68	637	372	244	675	408	278	675	408	278
	trueseed	289	157	110	636	497	448	677	536	487	678	537	488
#quarantine	degree	703	596	505	759	652	555	780	673	576	781	674	577
	closeness	575	271	154	655	339	211	659	343	214	659	343	214
	betweenness	698	591	498	778	671	576	782	675	580	782	675	580
	eigenvector	581	217	116	637	249	134	658	269	134	659	270	134
	kcore	514	509	505	516	586	518	672	642	638	762	752	725
	pagerank	834	631	552	888	684	598	909	705	619	910	706	620
	clustering	287	115	63	577	354	265	620	397	308	659	436	347
	trueseed	288	140	89	619	469	417	681	531	479	687	537	485
#lockdown	degree	665	557	417	738	630	485	748	640	495	748	640	495
	closeness	558	245	147	659	335	193	662	338	196	662	338	196
	betweenness	659	569	380	739	649	455	748	658	464	748	658	464
	eigenvector	563	225	123	636	269	141	646	279	148	646	279	148
	kcore	531	519	405	516	468	408	672	542	568	627	602	612
	pagerank	791	598	474	864	670	538	874	680	548	874	680	548
	clustering	307	137	68	564	251	127	594	259	127	602	259	127
	trueseed	304	156	105	581	429	378	604	452	401	612	460	409
#mask	degree	746	647	509	816	717	577	820	721	581	821	722	582
	closeness	637	332	189	707	387	226	711	391	230	712	392	231
	betweenness	746	645	469	816	715	537	820	719	541	821	720	542
	eigenvector	509	232	123	599	277	136	603	281	136	604	282	136
	kcore	641	529	551	761	768	708	772	752	786	762	772	712
	pagerank	876	667	567	946	735	631	950	739	635	951	740	636
	clustering	303	138	73	686	465	334	690	469	338	692	471	340
	trueseed	324	171	120	739	581	529	743	585	533	745	587	535

Figure 5 shows the comparison chart for #Brexit, and the top five centrality values are selected and denoted as C1, C2, C3, C4, and C5, respectively. Thus, the graph for C1 traces propagation starting at the node with the highest centrality, whereas the graph for C5 traces the propagation starting at the node with the fifth highest centrality. From the chart, it is evident that for true seeds, it takes three to four hops to affect 10% of the total population. As mentioned earlier, total population for #Brexit is 4511, and after six hops the information reaches its saturation level (i.e., almost

Fig. 5. Comparative graph of information propagation using Breadth First Search for hashtags(#) Brexit with seeds displaying the highest K-core Centrality (a) with True Seed (b).

50% of total data). But when the information is propagated from a seed with high betweenness centrality, it enjoys an initial head start. In Breadth First Search, one hop of all possible paths from the concerned node is checked for information propagation. Since a node with high betweenness centrality has a higher number of unique paths passing through it compared to other nodes, it therefore has higher chances of fanning out to a higher number of nodes in every step/hop. As such, 10% of the total population is affected after two hops, and the saturation point is reached within three hops.

4.3.2 Forest Fire. In Table 6, information propagation using Forest Fire for the same six datasets is represented. The columns list the number of affected nodes when considering the first (C1), second (C2), and third (C3) most favorable centrality measure, after 1, 3, 5, and 10 levels or steps of propagation. The experiments were conducted with the probability of new trees growing in the forest (p) set at 0.01 and the probability of a tree catching on fire (f) set at 0.01.

From Table 6, it is observed that PageRank, Betweenness, Eigenvector, K-core, Closeness, and Node degree centrality are all good measures for influential seed nodes. Contrary to the other propagation models, in forest fire, the performance of clustering coefficient is also considerably improved. True seed predicted using the two-phase algorithm is outperformed by all centrality measures in almost all datasets. Another important observation is that all influential seeds reach their saturation values of approximately 48% at almost the same five-hop distance.

Figure 6 represents the performance of highest centrality measures with True Seeds as the source of propagation when propagation is simulated through Forest Fire. From the figures, it can be observed that centrality measures have better performance in terms of affected nodes in comparison to true seed.

Figure 7 reflects the level of propagation for #Brexit when seed nodes are determined by the highest Closeness centrality and clustering coefficient. From the figure, it is evident that when information starts propagating the seeds derived by clustering coefficient, it reaches merely 5% of the total population, irrespective of the influential seeds—that is, it shows the same trend for all five seed nodes. Using closeness centrality as the seed node selection, 15% to 20% of the total population is reached in the second hop. For C1, more than 50% of the population is reached at saturation.

4.3.3 Random Walk. Table 7 provides the data as Table 6, corresponding to the use of the Random Walk algorithm for propagation. Hence, the structure is semantically identical. Results are tabulated at levels 10, 30, 50, and 100 for the low propagation in the network.

From Table 7, it is also evident that the saturation levels for propagation of all influential seed nodes except clustering coefficient and the original seed node are identical. The poor performance

Table 6. Comparative Analysis of Information Propagation from Different Seed Nodes Using Forest Fire Propagation

<i>Experiment</i>	<i>Properties</i>	Level 1			Level 3			Level 5			Level 10		
		<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>
#Brexit	degree	560	337	282	1879	1400	1328	2203	1926	1996	2305	2130	2095
	closeness	557	279	179	1899	1746	1598	2216	2024	1983	2324	2126	2086
	betweenness	182	285	66	1556	1340	1462	1996	1995	1966	2122	2093	2126
	eigenvector	162	193	184	1135	1616	1516	1614	2260	2520	2416	2448	2496
	kcore	181	161	126	1549	1241	1376	1983	1937	2005	2104	2162	2128
	pagerank	561	200	184	1898	1220	1553	2224	2001	2000	2317	2105	2111
	clustering	43	49	47	717	620	540	1817	1846	1761	2107	2144	2098
	trueseed	201	182	220	890	980	1123	1818	1834	1702	1889	1786	1890
#covid	degree	15	17	19	134	180	100	249	263	218	477	503	452
	closeness	18	16	9	66	121	158	199	221	275	498	480	471
	betweenness	15	15	15	105	100	78	288	276	255	413	468	573
	eigenvector	18	19	16	156	66	135	250	260	164	496	448	416
	kcore	16	18	16	145	101	130	233	255	217	471	457	422
	pagerank	20	13	13	97	92	137	271	228	215	439	519	520
	clustering	22	19	22	84	100	162	275	219	205	514	468	538
	trueseed	15	18	31	116	118	201	251	213	246	472	464	455
#pandemic	degree	16	19	14	99	98	52	219	282	252	523	521	481
	closeness	14	11	18	102	102	96	284	257	271	521	478	493
	betweenness	12	17	18	109	108	78	219	242	244	459	505	461
	eigenvector	20	17	24	113	98	73	224	320	237	504	529	489
	kcore	14	16	18	101	100	101	231	220	217	501	504	480
	pagerank	15	17	19	101	109	141	279	207	248	458	514	511
	clustering	18	22	15	130	103	129	221	275	229	518	524	479
	trueseed	14	18	18	98	105	96	256	232	266	453	549	521
#quarantine	degree	21	13	21	182	139	132	340	304	237	527	555	489
	closeness	23	17	21	116	209	203	236	293	300	503	476	510
	betweenness	18	17	14	124	183	86	308	279	244	533	525	540
	eigenvector	16	17	14	179	137	114	279	342	261	513	558	539
	kcore	15	17	14	149	169	98	277	287	261	502	500	504
	pagerank	13	18	24	152	140	171	335	296	295	561	503	453
	clustering	13	17	20	101	163	105	295	257	372	569	514	462
	trueseed	13	14	14	110	120	143	379	267	323	509	524	487
#lockdown	degree	16	13	17	141	157	175	296	294	275	469	486	449
	closeness	15	19	16	128	73	186	293	239	282	467	499	464
	betweenness	14	19	14	54	110	91	213	279	268	538	436	527
	eigenvector	20	11	15	95	164	124	221	260	288	430	481	483
	kcore	16	13	16	98	110	99	245	249	230	450	463	456
	pagerank	11	13	13	99	155	93	238	236	234	510	458	459
	clustering	15	6	18	157	143	191	256	251	344	460	480	394
	trueseed	12	19	10	98	138	171	243	287	266	339	419	501
#mask	degree	23	12	13	138	77	143	308	331	341	496	521	512
	closeness	18	15	15	170	161	99	236	253	321	521	536	530
	betweenness	14	16	18	89	94	119	247	268	234	541	518	498
	eigenvector	14	22	11	121	116	157	287	314	242	472	545	577
	kcore	18	20	14	110	108	124	265	301	241	451	519	499
	pagerank	13	16	11	136	113	106	283	239	306	524	499	474
	clustering	23	14	26	155	108	102	215	312	242	552	564	472
	trueseed	12	21	10	114	115	113	253	286	296	459	503	512

of clustering coefficient may be attributed to the fact that it confines itself to a local community within the network.

Figure 8 represents the performance of centrality measures with True Seeds as the source of propagation when propagation is simulated through Random Walk. Except #Brexit, for all other

Fig. 6. Comparison of performance of centrality measures with true seeds for the Forest Fire model with keywords #Brexit, #covid, #pandemic, #lockdown, #quarantine, and #mask respectively from top left to right, beginning with the first row.

Fig. 7. Comparative graph of information propagation using Forest Fire propagation from seed nodes for hashtags(#) Brexit highest Closeness centrality (a) and highest Clustering coefficient (b).

#, as compared to original seed, all centrality measures show better influence. For #Brexit as well, only clustering coefficient fails to achieve better performance.

In Figure 9, the extent of propagation for #Brexit is shown for the degree and PageRank seed selection strategies. Degree outperforms PageRank during the initial stages of propagation. Its results are dependent on the particular seed node selected, whereas the influence of PageRank is almost identical for the top five centrality measures.

From Figure 9, it is evident that propagation from all influential seeds are overlapping in nature, especially for PageRank centrality. The saturation level is only 20% to the total population of

Table 7. Comparative Analysis of Information Propagation from Different Seed Nodes Using Random Walk

<i>Experiment</i>	<i>Properties</i>	Level 10			Level 30			Level 50			Level 100		
		<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>
#Brexit	degree	560	337	282	1879	1400	1328	2203	1926	1996	2305	2130	2095
	closeness	557	279	179	1899	1746	1598	2216	2024	1983	2324	2126	2086
	betweenness	182	285	66	1556	1340	1462	1996	1995	1966	2122	2093	2126
	eigenvector	181	280	156	1796	1741	1489	2100	1989	2001	2254	2080	2127
	kcore	453	410	460	965	962	981	1165	1150	1167	1357	1350	1355
	pagerank	561	200	184	1898	1220	1553	2224	2001	2000	2317	2105	2111
	clustering	43	49	47	717	620	540	1817	1846	1761	2107	2144	2098
	trueseed	161	242	82	1230	1242	1122	1740	1732	1712	1901	1911	1991
#covid	degree	1114	436	210	1222	533	280	1251	576	307	1280	605	338
	closeness	1157	501	274	1256	538	283	1294	561	286	1325	580	296
	betweenness	1113	435	209	1209	529	275	1247	570	310	1279	600	337
	eigenvector	1158	501	279	1251	531	281	1293	542	281	1325	554	281
	kcore	1111	410	234	1212	531	276	1242	553	290	1299	536	280
	pagerank	1080	430	210	1161	513	275	1202	559	310	1233	587	336
	clustering	1104	433	215	1157	454	230	1171	461	236	1191	468	238
	trueseed	858	373	216	904	401	230	920	403	237	935	414	240
#pandemic	degree	1044	411	196	1180	540	262	1234	587	303	1271	626	344
	closeness	1084	452	202	1220	506	232	1264	534	248	1308	556	260
	betweenness	1046	414	204	1179	535	274	1224	587	303	1270	629	341
	eigenvector	1073	456	222	1188	505	246	1228	526	259	1276	542	268
	kcore	1056	412	203	1124	522	232	1232	567	261	1250	535	235
	pagerank	1021	409	187	1135	516	237	1176	559	282	1224	605	311
	clustering	1032	408	203	1101	446	219	1130	461	230	1159	471	239
	trueseed	741	328	188	787	350	203	807	356	208	824	361	210
#lockdown	degree	1005	414	205	1167	558	297	1227	615	341	1294	679	387
	closeness	1015	431	242	1179	507	279	1252	546	291	1303	582	299
	betweenness	1010	428	206	1185	583	300	1238	650	333	1298	705	370
	eigenvector	1010	428	243	1175	495	279	1229	527	294	1289	560	305
	kcore	1002	421	220	1165	562	281	1225	550	267	1257	550	355
	pagerank	989	407	205	1113	521	282	1167	583	328	1209	629	366
	clustering	969	373	189	1053	408	209	1086	429	222	1102	438	225
	trueseed	723	315	178	784	344	195	793	352	204	819	360	211
#quarantine	degree	1090	421	200	1192	528	263	1223	548	300	1261	587	324
	closeness	1139	491	263	1232	516	275	1273	528	283	1302	541	292
	betweenness	1090	421	200	1185	510	264	1226	556	298	1248	579	318
	eigenvector	1137	498	269	1220	514	272	1269	527	273	1299	531	273
	kcore	1099	441	260	1155	511	241	1234	554	276	1251	510	285
	pagerank	1029	412	200	1116	486	258	1146	525	286	1182	556	311
	clustering	1071	425	206	1120	453	223	1139	460	233	1151	466	234
	trueseed	755	328	183	788	343	192	797	348	194	810	353	196
#mask	degree	1073	431	202	1183	557	270	1236	575	306	1268	618	328
	closeness	1134	483	266	1248	531	279	1293	550	284	1325	561	287
	betweenness	1074	430	217	1188	538	288	1234	592	328	1269	621	359
	eigenvector	1127	492	262	1223	524	270	1256	539	273	1289	553	275
	kcore	1072	430	241	1195	542	270	1236	550	257	1271	557	257
	pagerank	1051	422	202	1165	525	265	1203	569	297	1222	598	325
	clustering	1059	407	203	1119	433	213	1137	444	218	1159	453	221
	trueseed	787	344	203	832	370	215	852	374	221	864	383	223

the network. For the simulation of propagation, Random Walk is a poor choice for a large-scale network due to the problem that slow mixing in graphs consists of a large number of communities (or mostly in networks where community structure is dominating). In such scenarios, random walk needs a large number of samples and a long period to reach the steady-state with the desired

Fig. 8. Comparison of performance of centrality measures with true seeds for the Random Walk model with keywords #Brexite, #covid, #pandemic, #lockdown, #quarantine, and #mask respectively from top left to right, beginning with the first row.

Fig. 9. Comparative graph of information propagation using Random Walk propagation from seed nodes for hashtags (#) Brexit highest Degree (a) and highest PageRank (b).

accuracy. Moreover, it tends to be limited within a close community structure and cannot spread widely.

4.3.4 SIR Model. Table 8 provides the data corresponding to the SIR model for propagation. Here, the seed nodes, either chosen using the centrality measures or the true seeds chosen using

Table 8. Comparative Analysis of Information Propagation from Different Seed Nodes Using the SIR Model

<i>Experiment</i>	<i>Properties</i>	Level 1			Level 3			Level 5			Level 10		
		<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>
#Brexit	degree	580	339	262	1697	1410	1526	2005	1728	1778	2503	2150	2073
	closeness	559	297	197	1677	1948	1576	2218	2121	1763	2520	2128	2068
	betweenness	162	278	156	1736	1430	1264	1966	1559	1696	2121	2093	2112
	eigenvector	161	260	158	1978	1941	1467	2001	1767	2100	2232	2060	2129
	kcore	451	429	415	1545	1550	1542	1962	1950	1972	2310	2300	2302
	pagerank	341	255	164	1696	1440	1335	2442	2110	2101	2173	2051	2110
	clustering	45	47	49	919	820	560	1619	1648	1981	2109	2166	2076
	trueseed	121	242	130	1200	1142	1222	1701	1702	1712	1901	1901	1992
#covid	degree	722	322	167	722	360	191	722	399	222	722	520	315
	closeness	722	322	167	722	362	193	722	402	225	722	507	313
	betweenness	722	322	166	722	362	193	722	399	224	722	515	308
	eigenvector	722	323	167	722	361	194	722	398	224	722	512	302
	kcore	722	321	166	722	360	192	722	396	223	722	509	306
	pagerank	722	323	167	722	360	193	722	402	223	722	513	309
	clustering	722	321	167	722	360	193	722	400	221	722	496	311
	trueseed	580	252	129	604	287	151	631	320	177	694	436	256
#pandemic	degree	681	305	157	681	341	180	681	381	208	681	483	298
	closeness	681	305	157	681	339	182	681	381	211	681	484	290
	betweenness	681	303	156	681	340	182	681	378	209	681	479	300
	eigenvector	681	305	157	681	338	182	681	375	211	681	481	297
	kcore	681	301	155	681	337	180	681	375	208	681	476	297
	pagerank	681	305	157	681	339	181	681	380	210	681	483	293
	clustering	681	305	157	681	342	181	681	381	209	681	476	296
	trueseed	529	228	116	564	260	135	595	296	158	680	393	229
#lockdown	degree	647	288	150	647	322	174	647	359	199	647	445	280
	closeness	647	289	150	647	321	171	647	359	199	647	458	284
	betweenness	647	289	150	647	322	173	647	360	200	647	454	282
	eigenvector	647	289	150	647	322	171	647	356	199	647	453	279
	kcore	647	287	150	647	320	170	647	354	200	647	456	279
	pagerank	647	288	150	647	323	172	647	358	199	647	452	279
	clustering	647	289	150	647	322	174	647	359	198	647	463	283
	trueseed	522	227	116	552	259	135	582	293	158	650	386	227
#quarantine	degree	685	306	158	685	343	181	685	377	210	685	482	288
	closeness	685	306	157	685	344	183	685	382	208	685	492	297
	betweenness	685	304	158	685	342	182	685	379	210	685	485	299
	eigenvector	685	306	158	685	344	183	685	377	211	685	480	293
	kcore	685	304	158	685	341	180	685	383	212	685	480	297
	pagerank	685	307	158	685	343	182	685	378	212	685	494	291
	clustering	685	307	158	685	343	183	685	380	210	685	485	295
	trueseed	535	229	117	566	259	138	604	296	161	687	402	232
#mask	degree	697	311	162	697	347	186	697	378	212	697	489	298
	closeness	697	310	162	697	342	186	697	387	214	697	500	297
	betweenness	697	309	162	697	344	185	697	385	215	697	493	295
	eigenvector	697	310	162	697	347	187	697	381	216	697	491	298
	kcore	697	310	162	697	347	185	697	381	214	697	490	296
	pagerank	697	311	162	697	343	187	697	383	213	697	489	299
	clustering	697	310	162	697	347	186	697	384	217	697	493	299
	trueseeds	544	235	120	572	264	140	596	302	166	660	410	241

the two-phase algorithm, are initially taken to be the infected nodes. All other nodes in the network are considered to be susceptible in the beginning, and no node is in the recovered state. Results are tabulated at levels 1, 3, 5, and 10. The probability of infection (β) is set at 0.2, and the proportion of infected persons recovering every unit time (λ) is set at 0.1.

Fig. 10. Comparison of performance of centrality measures with true seeds for the SIR model with keywords #Brexit, #covid, #pandemic, #lockdown, #quarantine, and #mask respectively from top left to right, beginning with the first row.

From Table 8, it can be seen that although Closeness centrality and degree centrality seem to be better than other centrality measures in the initial stages of propagation, with a higher number of hops taken in consideration, the values saturate for almost all centrality measures. Overall, clustering coefficient is the weakest method for seed selection for maximization of information propagation. It can also be noted that the true seeds of the network is almost always outperformed by all centrality measures, with clustering coefficient being the only exception.

Figure 10 represents the performance of centrality measures with True Seeds as the source of propagation when propagation is simulated through SIR. It is very clearly depicted from the graphs that for each #(hashtag), all centrality measures show better influence than true seed in terms of affected nodes.

Figure 11 represents the extent of information propagation for the top five centrality measures. It can be seen from the figure that even though initially the propagation might vary, they saturate to a similar value after five hops.

4.4 Analysis

For the experiment, six datasets of streamed tweets have been considered, one each for #Brexit, #covid, #pandemic, #quarantine, #lockdown, and #mask. From the datasets, nodes with the highest values for seven centrality measures are collected. Four information propagation models are used to simulate flow of information in the network. In Table 5, Table 6, Table 7, and Table 8, the affected nodes and levels of propagation for C1, C2, and C3 centrality values as the seed node are

Fig. 11. Comparative graph of information propagation using the SIR model for hashtag(#) Brexit with seeds displaying the highest Eigenvector Centrality (a) and Betweenness Centrality (b).

represented. For all five influential seeds (top five centrality measures), the propagation through graphs is shown in Figure 5, Figure 7, Figure 9, and Figure 11 for #Brexit. A comparative study of similarity measures between centrality measures and actual source node of the information is shown in Table 4. Comparison between centrality measures along with true seed as the source of propagation are represented in Figure 4, Figure 6, Figure 8, and Figure 10.

A few interesting observations can be made from the empirical results. The graphs to compare the similarity between influential seed nodes and actual seed nodes seem to suggest the following:

- Degree centrality, Betweenness centrality, and PageRank consistently perform well irrespective of the dataset or propagation method. However, clustering coefficient consistently performs poorly for all propagation methods and datasets except for Forest Fire. Therefore, there is an inherent handicap in clustering coefficient as influential seed selection.
- It is also evident that the choice of similarity metric used to report the results is completely unbiased. If a particular metric reports a higher value than another, it does so consistently.
- It can be seen that except for clustering coefficient, all other centrality measures perform better than true seeds detected by the two-phase algorithm in maximizing information propagation consistently irrespective of the dataset or propagation method. For forest fire, even clustering coefficient outperforms the true seeds.

The graphs to compare the extent of information propagation across different centrality nodes and different propagation algorithms seem to indicate the following:

- The differences between the extent of propagation between the n^{th} selections are more starkly visible in Breadth First, Forest Fire, and SIR propagation. This seems to suggest that the Random Walk method of propagation undermines the selection of the seed node. It is thus not particularly useful. It is noticeable that Random Walk requires a lot of steps to achieve the same degree of propagation, which further tends to even out the differences that arise from seed selection. Thus, generalizations are formulated based on the other methods.
- Regardless of the method of propagation, the trend of the graph tends to remain the same—that is, all graphs uniformly have a sigmoidal shape.
- In most of the cases, the node with highest centrality enjoys a head start in terms of the extent of propagation. However, the other top n selections asymptotically catch up in approximately six hops.
- In the cases corresponding to the true seeds, it can be noticed that top n selections sometimes perform better than the first seed. This seems to suggest that artificial seeds selection methods using centrality measures tend to work better with the propagation techniques than natural seed selection. This indicates that the methods of seed selection through centrality measures show more potential use than actually determining the true seeds.

From the experimental results, it can be seen that while in the initial stages of propagation, some centrality measure might outperform others, and some centrality measures might perform consistently well. However, after about five hops, the number of nodes reached by all centrality measures saturate to similar values. This can be partially attributed to the small world properties of OSNs.

From the experimental results, it can also be seen that for every keyword, when propagation begins with influential nodes selected from Node degree or PageRank as seed nodes, it spreads better to begin with. If propagation is initiated with an influential node derived from betweenness centrality as seed nodes, it begins slowly but shows a large number of affected nodes in the long run. Influential seeds measured by Closeness, Eigenvector, and K-core centrality exhibit consistent results in all cases. Seeds determined by clustering coefficient show the poorest results for all keywords and all simulated methods of propagation except Forest Fire.

5 CONCLUSION

A debate in information propagation theory is regarding the impact of centrality in determining seed nodes of the propagation. The main objective of this work is to thoroughly analyze the correlation between existing algorithms for seed node detection using multiple centrality measures and the flow of information in real-life social media. Finding centrality of a large network is a time- and resource-consuming problem, and although many researchers have proposed different centrality measures for scale-free networks, there is no uniform consensus about the most effective centrality measure.

The article presents comprehensive and extensive coverage on the effectiveness of different centrality measures, namely clustering coefficients, Node Degree centrality, Betweenness centrality, Closeness centrality, Eigenvector centrality, K-core centrality, and PageRank centrality for influential seed node detection. Four information propagation techniques—Breadth First Search, Random Walk, SIR, and Forest Fire—are used for simulating propagation. Seed node selection plays an important role in influence maximization, as it often offers a head start, which can determine the maximum number of affected nodes.

The proposed approach is tested on real-life Twitter data, and the algorithms are implemented on the Spark distributed computing framework. The empirical results show Betweenness centrality to be an effective seed node selecting parameter in the initial stages of propagation. In addition, degree centrality, Eigenvector, K-core, PageRank, and Closeness centrality are good choices for maximizing overall reach of information. The other centrality measure clustering coefficient has little to no effect in maximizing information propagation over the whole network in the long run.

For the propagation approaches, Random Walk suffers with the local clustering in the network. Therefore, for the approximation of the influence maximization, it is required to use modified versions of Random Walk. It can be observed that the maximum saturation level reaches approximately 20% of the total nodes, whereas for other simulations it reached almost 50% of the total population. Another important observation of the study is that in the long run, the influence of actual seeds coincides with that of centrality nodes. Therefore, centrality nodes play pivotal roles in influence maximization at the initial stages of information propagation. Whatever may be the initial seed nodes, after a certain number of hops, it reaches a threshold value and cannot spread further. In future work, an attempt to study the influential propagator to maximize information propagation in social networks will be made. An interesting observation derived from the analysis is that whatever may be the seed nodes and influence maxima, the levels are saturated within five to six hops in the network. As scale-free networks can be considered as the collection of small world networks, choosing centrality nodes as the seed node only ensures maximum propagation within the small world network.

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