A NOVEL APPROACH OF VOTERANK-BASED KNOWLEDGE GRAPH FOR IMPROVEMENT OF MULTI-ATTRIBUTES INFLUENCE NODES ON SOCIAL NETWORKS

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Abstract

Recently, measuring users and community influences on social media networks play significant roles in science and engineering. To address the problems, many researchers have investigated measuring users with these influences by dealing with huge data sets. However, it is hard to enhance the performances of these studies with multiple attributes together with these influences on social networks. This paper has presented a novel model for measuring users with these influences on a social network. In this model, the suggested algorithm combines Knowledge Graph and the learning techniques based on the vote rank mechanism to reflect user interaction activities on the social network. To validate the proposed method, the proposed method has been tested through homogeneous graph with the building knowledge graph based on user interactions together with influences in real-time. Experimental results of the proposed model using six open public data show that the proposed algorithm is an effectiveness in identifying influential nodes.

Keywords: Video surveillance, deep learning, Moving object detection

1 Introduction

The rapid growth of data coming from multiple sources will present both opportunities and challenges for researchers in data analysis [1, 2, 3, 4]. The development of the internet leads to abundant utilities and social networks such as Facebook, Twitter, and Instagram. They have been becoming extremely popular with almost all ages [5]. Accordingly, social networks [6] become an important and useful platform for advertising campaigns. However, disseminating information directly to all users on social networks is currently inefficient and costly. It is recommended to target a large number
of users to communicate each others, i.e., in order to find a certain group of people called KoLs on social networks to carry out campaigns to promote products in digital marketing to reach as many users as possible at the lowest cost. It is not only advertised with information on social networks, but also huge data in systems such as power grids [7, 8], computer systems [9], transportation systems [10]. The tracking COVID-19 persons [11] are also performed on networks using clustering approaches [12]. Therefore, considering as the rapid spread of information, which affects the scale of the network, is very necessary. For example, spreading fake news in the prevention and control of the Covid-19 epidemic in Vietnam from accounts in social media [13]. In the case of disease transmission, it is imperative to locate and immunize the most influential individuals who can prevent further spread of the virus because of these dangers usually begin with a small node, spread some nodes and coverage spread to the entire network [14, 15]. In a large-scale computer network, it is imperative to design a robust and secure architecture because the actual system is not interrupted suddenly, so creating redundant links with servers in the main system depending on their importance is a fairly effective solution [16]. To solve the problem of identifying influential nodes in social networks, scientists have investigated many algorithms with different approaches. One of the approaches used by many researchers is to determine the set of influential nodes in the network based on ranking the nodes in the network according to the score determined by the measure of the centrality of these nodes.

From the challenges in building the social network graph in particular and determining the influence nodes in the network in general, the paper has presented the process of identifying nodes and ranking the influence nodes in the social network. This paper has presented a novel algorithm for measuring users with these influences on a social network. The suggested algorithm combines Knowledge Graph and the learning techniques based on the vote rank mechanism to reflect user interaction activities on the social network. This proposed model has significant study contributions as follows: (1) construct a homogeneous graph from large data set collected by the method of building knowledge graph based on user interaction; (2) enhance voting rank among neighbors by dealing with voting process in real-time; (3) reduce the computation time of the proposed algorithm while updates some attributed of the nodes in each iteration instead of all the nodes. To validate the proposed method, the proposed method has been tested through homogeneous knowledge graph using open data sets and the case study of real-time user interactions together with influences for demonstrated method’s effectiveness.

The remainder of this paper is structured as follows: Literature review and related research is discussed in Section 2. Theoretical determination, preliminary, and research background is considered in Sections 3. The proposed model with suggested algorithms represents by steps in Section 4 with experimental results. The conclusion and observations provided in Section 5.

2 Literature Review

In related works [17], the investigation focuses on tracking influential nodes based on the decision-making preferences. The investigation has focused on identifying top-k influential nodes in social network [18]. Farzaneh et. al has investigated influence maximization based on community structure for improvement of time efficiency [19]. New techniques as calculating nodes’ centrality in graphs can be proposed relations under uncertainty to the edges on social networks [20]. As mentioned in the studies above, many centrality measures have been proposed. Measures in this approach are divided into 3 categories including: centrality measure based on local information, centrality measure based on semi-local information, and centrality measure based on global information. For example, the Degree Centrality (DC) [21] determines the number of neighbors of the node to evaluate the influence. The DC measure assumes that a node with many neighbors will have more influence. The PageRank (PC) [22] algorithm not only considers the number of neighbors of the node to evaluate the influence. The DC measure assumes that a node with many neighbors will have more influence.
networks. To solve the limitation of local information of the network, some other algorithms measure the influence of nodes based on the global information of the network are proposed such as Betweenness Centrality (BC) [23] and Closeness Centrality (CC) [21]. The BC determines the influence of a node by calculating the number of shortest paths through it. The CC centrality measure determines that the shorter the average distance between a node and other nodes in the network. These measures are improved an accuracy for small networks. Centrality measures based on local information and centrality measures based on global information have the same advantages and limitations as described above. Therefore, centrality measures based on semi-local information. To avoid an imbalance when focusing only on local or global information, it is necessary to take into account both these elements of the network. However, the conventional methods of determining the influence node in the past often have not taken into account the global and local information of the network simultaneously, leading to information loss and then the final result is often greatly affected. Recently, some investigations have proposed combined approaches for the measurements, such as the GSM model [24], gravity model [25], and node’s location and neighboring node information [26]. The gravity model is based on Newton’s gravity formula, taking into account the influence of the neighbors as well as the path information between the nodes. However, this calculation is difficult in the case of the network becomes more complex. To solve the difficult problem of big data and complex networks, another algorithm is proposed called GSM algorithm. It not only considers the influence of the node itself in the network but also focuses on the global influence of the nodes in order to calculate the influence score of the nodes in the network.

As different from the traditional approach that only determines the influence of the node by the centrality measure, another approach based on the voting mechanism is also being developed by many researchers. In related works of influential nodes [27], the VoteRank algorithm is based on the voting mechanism to identify influential nodes in the network. As doing the similar approach [28], the proposed EnRenew algorithm with the entropy information of the nodes to consider root nodes with its improvement of performance. In addition, the research proposed to improve the VoteRank algorithm called VoteRank++ [29]. Moreover, for social networks, the information on this platform is difficult to collect and represent because of its security characteristics [30, 31]. Therefore, we need to build a method to be able to collect and represent this data so that it is suitable for the algorithms to solve the problem. From the above studies, it can be seen that the centrality is an important measure to determine the influential nodes and the influence of the neighboring nodes to it are also the factors that make that node become popular more influence. In addition, the links between neighbors also have an impact on the propagation ability of a node, the more connections there are between neighboring nodes, the higher the influence of that node will be. Besides, combining different attributes and building weights for each attribute also makes determining the influence node set more accurate [32, 33]. Data on social networks is represented in a very complicated way, since it is difficult to apply algorithms by dealing with huge data [34]. In practice of the studies [35, 3], personal privacy, i.e., people hiding their information, makes it difficult to follow users on social networks and reduce the complexity of the graph. Duong et. al have investigated multiple Attributes by influence ranking of nodes [36] and VoteRank++ to find optimal influential nodes in social networks [37]. These studies have focused limited data sets with static environment of the social networks.

3 Preliminaries

3.1 Modeling social network data into a homogeneous graph

This investigation has proposed modeling social network data into a homogeneous graph by developing an interaction-based knowledge graph.

User’s relationship

Assume that the relationship between user $v_i$ and user $v_j$ if user $v_j$ has influenced with, commented on or reacted to any of user $v_i$’s comments/posts. $e_{ij}$ is the symbol for the connection between $v_i$ and $v_j$ as given by Eq.(1).

$$e_{ij} = \{r, c, s\}_{ij}, e_{ij} \in R^p$$

where $r, c, v$ are the number of user interactions such
as reactions, shares, and comments of user $v_j$ on posts of user $v_i$, respectively.

**Interaction-based knowledge graph** The interaction-based Knowledge Graph [38, 39, 40] is denoted as $G = (V, E)$ where $V = \{v_i\}, \{i = 1, \ldots, N_v\}$ is a set of users who are friends or followers and interact with each other. And $E = \{e_{i,j} \in R^p\}, \{i, j = 1, \ldots, N_E\}$ are the edges that indicate user interaction activities. The information gained from social networks is shown as interaction activity. In addition, the interaction-based knowledge graph enables us to understand behaviors and actions of specific users. Users with substantial interactions are intuitively influenced users. In actuality, even there are no substantial interactions, certain users are strongly impacted. Furthermore, edges only show the link between users without regard to the importance of the edge. A weighted function can be also mapped as defined by:

$$e_{i,j} = \phi(r, c, s)$$

where

$$\phi(r, c, s) = \alpha r + \beta c + \gamma s$$

with $\phi = \{\alpha, \beta, \gamma\}$ are hyper-parameters learned or trained by using Machine Learning tools. For example, these function are such as linear, or logistic regression, etc.

### 3.2 Typical centrality Measures

**Degree centrality**

DC [21] is a concept as definition for the number of edges, interacting with the number of edges node. $DC(i)$ of node $i$ is expressed by:

$$DC(i) = k(i) = \sum_j a_{i,j}$$

where $k(i)$ represents a degree of node $i$.

**Mixed core, degree and entropy (MCDE) algorithm**

The MCDE algorithm [2] considers a combination of indices of node position in the network, node’s order coefficient, and that node’s entropy. This algorithm is used to rank the nodes in the network. MCDE of node $v$ is calculated by:

$$MCDE(v) = \alpha KS(v) + \beta DC(v) + \gamma Entropy(v)$$

where $KS(v)$ is denoted as $G \{v_i\}$, $DC(v)$ is the degree centrality of the node $v$. $\gamma$ is the number of interactions of node $v$. The information entropy of any node $v$ can be calculated in

$$Entropy(v) = -\sum_{i=0}^{KS_{max}} p_i \log_2 p_i$$

with $p_i = \frac{\text{number of neighbors of node } v \text{ in the } i-\text{th } KS}{DC(v)}$.

To explain the MCDE algorithm, we have considered and calculated the MCDE measure for the nodes included in the graph network. As considering the example with node 1, we have $KS(1) = 3$, $DC = 7$, $p$. According to the formulas, we can apply the MCDE algorithm to the remaining nodes.

**EnRenew**

These two concepts are fed into the complex network in order to calculate node importance [28]. The information entropy of any node $v$ can be calculated in

$$E_v = \sum_{u \in \Gamma_v} H_{u,v} = \sum_{u \in \Gamma_v} -p_{u,v} \log p_{u,v}$$

with $p_{u,v} = \frac{d_{u,v}}{\sum_{d_{u,v}}}$ and $\Gamma_v$ is the set of neighbors of node $v$, $d_{u,v}$ is the degree centrality of the node $u$. $H_{u,v}$ is the ability to propagate information from node $u$ to node $v$. After each high impact node is selected, the algorithm improves the information entropy of all nodes in its local range according to the formula

$$H_{d^{-1}u} = \frac{1}{2^{1-k}} \frac{H_{d^{-1}u}}{E_k}$$

where $k$ is the average of the degree centrality of the entire network, $\frac{1}{2^{1-k}}$ is the coefficient decreases.

**VoteRank++**

With the VoteRank++ approach [29], nodes with different degree centrality will have influence scores voted on by different node. Like VoteRank algorithm, VoteRank++ is divided into 4 main stages

**Initialization**: The influence score $vs_v$ for node $v$ is value 0, initialized by default, and the score of voting of each node $va_v$ is calculated by the formula:

$$va_v = \log \frac{k_v}{k_{max}}$$

**Voting**: While voting is conducted during this phase. Each node $v$ receives a vote equal to the total of the voting ability scores of its neighbors. This
is considered as the score of influence of that node, as expressed by

\[ VP_{uv} = \frac{k_v}{\sum_{w \in \Gamma_v} k_w} \quad (11) \]
\[ vs_v = \sqrt{\| \Gamma_v \| \sum_{u \in \Gamma_v} VP_{uv} \cdot va_u} \quad (12) \]

The node with the highest influence score is considered as the node that propagates the influence. In addition, the selected node will not be allowed to join as subsequent voting rounds by setting that node’s voting ability score to 0.

**Update:** The VoteRank++ algorithm improves the reduction of the voting ability score to two-hop influence on its neighbors by the formula:

\[ va_v = \left\{ \begin{array}{l}
\lambda \cdot va_v, v \text{ is a first-order neighbor} \\
\sqrt{\lambda} \cdot va_v, v \text{ is a second-order neighbor}
\end{array} \right. \quad (13) \]

where parameter \( \lambda \in [0, 1] \)

**Iteration:** The voting and updating steps will be repeated until l influence nodes are selected, where l is a predefined constant.

**Information Entropy**

Information entropy [28] is a well-known notion in information theory. In general, the more unpredictable or random an occurrence is, the more data it contains. Information entropy is expressed by the following:

\[ H(X) = H(x_1, x_2, \ldots, x_n) = -\sum_{i=1}^{n} p(x_i) \cdot \log p(x_i) \quad (14) \]

where \( p(x_i) \) is the probability of event \( x_i \) and \( X = \{x_1, x_2, \ldots, x_n\} \) is set of possible events. One of the most important uses of information entropy in the field of social science is the entropy weighting technique. The entropy weighting approach is frequently applied to calculate weights of qualities in multi-attribute decision-making situations. It is also used to evaluate the associated nodes in social networks, due to its good performance. Assume there are \( n \) qualities to take into account. The weight of attribute \( i \) abbreviated \( w_i \), is calculated as follows:

\[ w_i = 1 - H_i \quad (15) \]

where \( H_i (i = 1, 2, \ldots, n) \) represent each attribute of the information entropy.

### 4 Proposed Model

The proposed model is able to design Voterank-based knowledge graph for improvement of multi-attributes influence nodes on social networks is divided in four steps as follows:

**Step 1:** Construct weights for attributes

**Step 1.1: Calculate attribute measure score**

To combine three attributes including \( I_{DC}(v) \) indicates the influence of the node’s degree and the degree of its neighbors \( v \), \( I_{KS,im}(v) \) respectively, we denote the influence of the node’s k-shell and the k-shell of its neighbors \( v \) and \( I_C(v) \) represent the influence of clustering coefficient in hierarchical nodes. Hence, \( v \) is calculated by Eq. (16), Eq. (17) and Eq. (18).

\[ I_{DC}(v) = DC(v) + \sum_{u \in \Gamma_v} DC(u) \quad (16) \]

\[ I_{KS,im}(v) = KS_{im}(v) + \sum_{u \in \Gamma_v} KS_{im}(u) \quad (17) \]

\[ I_C = e^{-C}, \sum_{u \in \Gamma_v^2} C_u \quad (18) \]

**Step 1.2: Build a weighting formula with Entropy Information**

Let \( w_1, w_2, w_3 \) be considered a weight corresponding to \( I_{DC}(v), I_{KS,im}(v) \) and \( I_C(v) \), respectively. They are calculated using entropy information [28] as follow:

Firstly, a decision matrix with its values \( I_{DC}(v), I_{KS,im}(v) \) and \( I_C(v) \) for all nodes presented in the social network.

\[ D = \begin{bmatrix}
I_{DC}(1) & \cdots & I_{DC}(n) \\
I_{KS,im}(1) & \cdots & I_{KS,im}(n) \\
I_C(1) & \cdots & I_C(n)
\end{bmatrix} \quad (19) \]

To normalize the multi-attribute decision matrix is the next step. Matrix \( D \) is normalized to matrix \( R \) since each index has a multiple dimension as follows.

\[ R = \begin{bmatrix}
r_{11} & \cdots & r_{1n} \\
r_{21} & \cdots & r_{2n} \\
r_{31} & \cdots & r_{3n}
\end{bmatrix}, \quad r_{ij} = d_{ij} / \sqrt{\sum_{j=1}^{n} (d_{ij})^2} \quad (20) \]
Secondly, calculating information entropy of each rating metric is given by Eq. (14), the information entropy of index \( j \) is expressed by:

\[
E_i = -\frac{1}{\ln n} \sum_{j=1}^{n} r_{ij} \ln r_{ij}, \quad i, j = 1, 2, 3
\]

Finally, to determine the weight of each metric, the weights of index \( j \) is calculated by:

\[
w_i = \frac{1 - E_i}{2 - \sum_{i=1}^{3} E_i}, \quad i = 1, 2, 3
\]

**Step 2: Calculate voting ability score** The voting ability score \((va_v)\) is obtained by considering the order coefficient, which is based on the k-shell decomposition as well as the clustering coefficient of the node along with its neighbors. The voting ability of node \( v \) is calculated mathematically as

\[
va_v = \log(1 + \frac{score_v}{score_{max}})
\]

Note that \( score_v \) of each node \( v \) is calculated by:

\[
\text{score}_v = w_1 I_{DC}(v) + w_2 I_{JS}(v) + w_3 I_C(v)
\]

where \( w_1, w_2, w_3 \) is a weight corresponding to the index as calculated by Eq. (22). Each node’s state is represented as a tuple \((vs_v, va_v)\), where \( vs_v \) is the voting score of node \( v \) as determined by its neighbors, and \( va_v \) is the voting score of node \( v \) as determined by its neighbors.

**Step 3: Calculate influence score by voting score**

A voting score called a voteRank is used to determine the of a node as an influence score, as defined by the following.

\[
vs_v = \sqrt{\sum_{u \in \Gamma_v} |va_u - \sum_{u \in \Gamma_v} w_{uv} va_u|
\]

where \( w_{uv} \) is a weight as calculated the distance of nodes between \( u \) and \( v \), \( w_{uv} = 1 \) in unweighted networks and \( \Gamma_v \) is the neighbor set of node \( v \).

**Step 4: Update the voting score**

The updated voting score of the neighbor nodes is expressed by the Eq. (13). The voting score between a node’s first-order and second-order neighbors is reduced if it is determined as influential with the shortest distances.

**Step 5: Repeat voting score and influence score**

Repeat steps 1, 2 and 3 until \( l \) influential nodes, where \( l \) is a constant.

### 4.1 Performance metrics

The susceptible infected recovery (SIR) [41, 42] model is a conventional infectious disease model as a descriptive information transfer. The SIR model consists of all nodes divided into three categories as follows: the susceptible, the infected, and the recovered nodes. Susceptible node \((S(t))\) signifies the number of nodes that are diseased-susceptible at time \( t \), Infected node \((I(t))\) is the number of those infected, and recovered node \((R(t))\) is the number of those recovered at this time. Every susceptible node has communicated by contracting all these nodes by infected at each time interval with probability \( \beta \). Additionally, every infected node recovers with the probability \( \mu \) at every time step to become a recovered node.

Figure 1 illustrates the parameters to adjust the SIR model. Specifically, to consider the influence of a node in the graph, the SIR model uses the input of three factors including: the node determines the influence, the probability of infection and recovery. Initially, it is an initialize the node to determine the influences in state I and the remaining nodes in state S. Nodes in state S belong to node \( \Gamma \)’s neighborhood possibly to get an information with infection probability \( \beta \). At the same time of propagation, nodes in state I switch to state R with a recovery probability \( \Gamma \) that the node has no collection of being propagated again. The propagation can be stoped when the graph reaches the “stable” state. Hence, there are no more nodes in the graph in state I. To limit the randomness of the model, the experiments of the model with the results are averaged over the total number of experiments. Note that the value of \( \beta \) plays a significant role in controlling the propagation speed.

The infected scale \( F(t) \) [43]: In the process of information diffusion according to the SIR model, the number of nodes that are recovered in changes over time throughout the network. At any time \( t \), the infected scale \( F(t) \) is the total number of nodes in the social network that have propagated the information and the number of nodes recovered up to
time \( t \) divided by the total number of nodes in the entire network. Propagation scale is the most realistic measure of the effectiveness of an influence algorithm in the network over time. The formula for determining the infected scale \( F(t) \) is given by:

\[
F(t) = \frac{n_i(t) + n_R(t)}{n}
\]

(26)

where \( n_i(t) \), \( n_R(t) \) and \( n \) are respectively the number of infected nodes at time \( t \), the number of recovered nodes up to time \( t \) and the total number of nodes in the network.

The final infected scale \( F(t_c) \) [44]: is an important metric that corresponds to the degree of influence that information eventually propagates in the network. It is the small number of nodes in the network, which corresponds to the number of nodes in the network that have propagated information then recovered the information diffusion simulation of the SIR model. Assume that the SIR simulation model terminates at time \( t_c \), then the measure \( F(t_c) \) lists all the nodes in the network that have propagated information then recovered in the network. The following formula is developed to determine the final infected scale \( F(t_c) \) as given by

\[
F(t_c) = \frac{n_R(t)}{n}
\]

(27)

where \( n_R(t) \) and \( n \) are the number of recovered nodes and the total number of nodes in the network, respectively.

5 Results and Discussions

5.1 Data sets

5.1.1 Modeling crawled data into a homogeneous graph

This investigation has selected the social networking platform Facebook to collect data and construct in graphs. This is a platform that is widely used and regularly updated with statuses and interactions. The proposed model has applied to the application of Scrapy tool to collect data sets using Python programming language to build graphs between users on social networks. Data collected from individuals includes [35]: user information, information about articles as well as interactions, comments, and shares of user’s posts. This data is graphically represented and depicts user activities with posts by other users. However, this data is not suitable for algorithms to determine the influence node because of heterogeneous graph. To transform into a homogeneous graph, the study has applied to a data modeling method based on user interaction, as described in the previous section.

5.1.2 Data sets description

The investigation has performed in experiments with the proposed algorithm on six available data sets to gauge its effectiveness, as follows:

- **Jazz**: The dataset represents the interactions in the network of Jazz musician. With the nodes in the graph representing Jazz musicians and the edges in the graph representing the relationship among musicians if they play together in a band [45].

- **Email**: A network of email exchange among students of the University of Rovira Virgili, Spain. With the nodes in the graph representing email addresses and the edges in the graph representing the relationship among these email addresses if there are exchangeable among them.[46].

- **Brightkite**: Users of a network on the Brightkite social network are based on these locations. Nodes in the graph represent accounts on the Brightkite social network and the edges in the graph representing the relationship among accounts if they check in the same location. [47].

- **Condmat**: Co-author network among researchers on the topic of Condensed Matter.
Figure 2. The infection scales $F(t)$ against time $t$ on the networks.
Nodes in the graph represent the researchers and the edges in the graph represent the relationship among researchers if they are the same author as their major [48].

- Ego-Facebook: Dataset is a set of users on a social network containing information about the user’s relationship on Facebook. Nodes in the graph represent accounts on the social network Facebook and the edges in the graph in the relationship among accounts if they are friends relationship to each other. [49].

- Kg-Facebook: Data set of users collected on the social network Facebook using knowledge graph method based on user interactions. Nodes in the graph represent accounts on the social network -Facebook and the edges in the graph represent the relationship among accounts, described by the method in Section 3.1

<table>
<thead>
<tr>
<th>Network</th>
<th>N</th>
<th>M</th>
<th>⟨k⟩</th>
<th>k_max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jazz</td>
<td>198</td>
<td>2,742</td>
<td>8.94</td>
<td>100</td>
</tr>
<tr>
<td>Email</td>
<td>1,133</td>
<td>4,451</td>
<td>9.62</td>
<td>71</td>
</tr>
<tr>
<td>Brightkite</td>
<td>58,228</td>
<td>214,078</td>
<td>7.35</td>
<td>1,134</td>
</tr>
<tr>
<td>Condmat</td>
<td>23,133</td>
<td>63,479</td>
<td>8.08</td>
<td>281</td>
</tr>
<tr>
<td>ego-Facebook</td>
<td>4,039</td>
<td>88,234</td>
<td>43.69</td>
<td>1,045</td>
</tr>
<tr>
<td>kg-Facebook</td>
<td>369,310</td>
<td>458,994</td>
<td>2.49</td>
<td>30,259</td>
</tr>
</tbody>
</table>

Table 1. The basic topological characteristics of the networks

The data is publicly uploaded at the author’s github link1. In Table 1, N and M are the number of nodes and connections, respectively and k_max and k denote the maximal and average degree of the network, respectively. The above networks belong to the public network dataset often used in the problem of determining the affected node, fully meeting the diverse requirements of different types of networks in reality. According to the above table, the data set meets a variety of network types in practice, with the kg-Facebook network having the largest number of nodes and relationships.

5.2 Experimental results

The ability of a set of significant determined nodes to distribute information was simulated in the research using the SIR propagation model. The index of the average shortest path length between spreaders are both used in the study as indicators of how decentralized the cluster of nodes is determined to be distributed. The study also selected 4 other baseline methods including DC [21], MCDE [2], EnRenew [28] and VoteRank++ [29]. These methods are widely used and highly effective in current studies.

- DC defined as the number of edges occurring on a node is known as the number of edges node.
- The MCDE algorithm considers a combination of indices of node position in the network, node’s order coefficient, and that node’s entropy.
- EnRenew algorithm aimed to identify a set of influential nodes via information entropy by calculated as initial spreading ability with information entropy, and then select the node with the largest information entropy and renovate its l-length reachable nodes’ spreading ability by an attenuation factor.
- VoteRank algorithm improves on two issues. (1) the voting power of a node is related to the initialization process; (2) each node can vote for its neighbors in various approaches during voting process.

As shown in the experimental results in Figure 2, Figure 3, Figure 4, Experimental results show that brown line represents the results of the EnRenew algorithm, the orange line represents the results of the DC algorithm, and the green line represents the results of the MCDE algorithm, the black line represents the result for the VoteRank++ algorithm, and the red line represents the result for the proposed algorithm EAVoteRank++. With the experimental results, the experiments has been determined 3% of the most influential nodes in the graph as the node corresponding to ρ = 0.03 for the amendment in the propagation that contains the final infected scale \( F(t_c) \) and the infected scale \( F(t) \).

In the experiments, Figure 2 shows the experimental results with the scale evaluation index \( F(t) \) for each time \( t \) regarding to the SIR propagation model. With the aid of this index, we have assessed the spread of impact for influence nodes produced by each algorithm. These results are averaged for the numbers of 1000 separate trials across

\[1https://gitlab.com/duongpv.hust/social-network-datasets.git]
Figure 3. Evaluation of $F(t_c)$ in the final infection scales with ratios of initially infected nodes $\rho$
Figure 3. Evaluation of $F(t_c)$ in the final infection scales with ratios of initially infected nodes $\rho$.

Figure 4. The ratios of an infect rate $\beta$ and the final ration in infection scale $F(t_c)$.
data sets with 100 times over two sizable data sets. With the selection of a variety of affected nodes for each algorithm, the number of affected nodes are also different. From the results in Figure 2, it can see that with the same number of initial seed nodes. The EAVoteRank++ algorithm as shown in red line achieves the highest propagation results tested all the experimental data. As for the results of the DC and EnRenew algorithms, these algorithms have the worst performance since the reason can be seen that these two algorithms only consider 1 aspect of the node’s influence. For weighted and unweighted datasets (kg-Facebook), the EAVoteRank++ recommendation algorithm still shows its superiority. At the first times $t = 0$, in most datasets, the difference between algorithms is not much because the selection of influence nodes is now of the same number. From this point forward, the number of nodes affected by the seed nodes selected by the EAVoteRank++ algorithm has been performed larger than that of other methods. By taking advantage of the semi-local measurements for the combination with the voting mechanism, the algorithm has been reduced by the computational cost, which is also the factor that makes the EAVoteRank++ algorithm highly efficient as well as the calculation speed.

For various ratios of infected nodes in the beginning, the final effect scales $F(t_c)$ are shown in Figure 3. The experimental results using averaged infection rate $\beta = 1.5$ and 1000 separate tests for setting up the environment. The purpose of this experiment is to examine the effects of different techniques and beginning spreader numbers on the ultimate ranges. Unquestionably, more initial spreaders cover a larger region. The fact that the proposed algorithm consistently ranks top and sees its ultimate influence expand under the same starting spreader ratio is evidence that this algorithm performs impressively on these networks. Furthermore, information can move quickly throughout the network with nodes based on the proposed algorithm. This result demonstrates more clearly the efficiency of the proposed algorithm compared with other baseline algorithms. The results of most of the above experiments on six data sets are better than those of other deterministic algorithms.

The proposed algorithm gives a list and ranks the influential nodes with high influence, proving the effectiveness of the algorithm on network graph data types. With the large data set of Kg-Facebook, the difference among influences of the seed nodes performed by the algorithms is relatively small since the nodes in this network often focus on a group of buttons. While the number of seed nodes is small, the results of all methods are relatively similar. The range of influence in the seed nodes proposed by EAVoteRank++ can expand and propagate in the whole network when $\rho$ is larger. It shows that the improvements of EAVoteRank++ effectively to diffuse information with the nodes as the initial number of seed nodes is larger. For data sets either Jazz or Hamster, the resulting difference is not much since the number of nodes in the relationship of the nodes is small, leading to the propagation of the method with its efficiency.

The spread process is significantly impacted by the infection rate in the SIR model. No matter whatever source spreaders are used, information cannot be disseminated successfully when is little. While is huge, the network can transmit information swiftly. In this experiments, the results are the average of 1000 independent runs with $\rho = 0.03$ except kg-Facebook. The results of kg-Facebook are the average of 100 independent runs due to the large number of nodes. The final effect scales $F(t_c)$ with various infection rates are shown in Figure 4 for various methodologies. Figure 4 clearly shows that the proposed algorithm is capable of achieving the largest spread scale, or one that is very near to it, under a variety of conditions, particularly on the networks of ego-Facebook, kg-Facebook, Email, Jazz, and Condmat. It is indicated that the proposed algorithm has a greater capacity for generalization than the baseline technique.

Experimental results of the proposed algorithm running with six data sets are better than those of other deterministic algorithms. The proposed algorithm gives a list and ranks the influential nodes with high influence, tested on many cases with different probabilities in the SIR model. This proves the efficiency of the algorithm on network graph data types.

**Conclusion**

In summary, experimental results have figured out the influence node, as presented in the construction of a homogeneous graph from social net-
work data using the method of building a knowledge graph based on interaction. This paper has considered a new algorithm in the direction of voting approach to identify important nodes in the social network while consolidating multiple attributes, taking into account the extent and location of the nodes in the network and their neighborhoods. The algorithm also proposed to weight each of the above attributes with the entropy theoretical model to determine the point of each node to achieve the most optimal efficiency. We have applied voting score by combining the node’s direct influence score with the node’s indirect influence score.

In order to develop high efficiency in the future, the algorithm performs appropriate and effective improvements. Either social network data or complex networks are also becoming more complex. Further investigation will improve the proposed algorithm on networks with a large number of nodes with these relationships performs on dynamic networks to match the actual data. To consider reducing the cost of calculating metrics and techniques for weighting with corresponding measures. Take advantage of the homogeneous graph is modeled by using network embedding technique to represent the node features for enhancement of the proposed algorithm together with a Deep Learning model.

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