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An Efficient Algorithm for Influence Blocking Maximization based on Community Detection

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***Abstract*—Popularity of online social network services makes it a suitable platform for rapid information diffusion ranging from positive to negatives information. Although the positive diffused information may welcomed by people, the negative information such as rumor, hate and misinformation content should be blocked. However, blocking inappropriate, unwanted and contamination diffusion are not trivial. In particular, in this paper, we study the notion of competing negative and positive campaigns in a social network by addressing the influence blocking maximization (IBM) problem to minimize the bad effect of misinformation. IBM problem can be defined as finding a subset of nodes to promote the positive influence under Multi-campaign Independent Cascade Model as diffusion model to minimize the number of nodes that adopt the negative influence at the end of both propagation processes. In this regard, we proposed a community based algorithm called FC_IBM algorithm using fuzzy clustering and centrality measures for finding a good candidate subset of nodes for diffusion of positive information in order to minimizing the IBM problem. The experimental results on well-known network datasets showed that the proposed algorithm not only outperforms the baseline algorithms with respect to efficiency but also with respect to the final number of positive nodes.**

Keywords— Social Network Analysis; Influence Blocking Maximization; Community Detection; Fuzzy Clustering; Centrality Measures.

I. Introduction

As online social networks (OSN) increasingly are growing each day, they are becoming one of the most important factors in everybody's life. Social networks make information diffusion faster and easier than other social media particularly for viral marketing and influence maximization. In recent years, many studies have been done on information diffusion problem motivated by influence maximization [1]–[8]. Influence maximization tries to find the most influential nodes in a social network to maximize diffusion of information; viral marketing is one of the main applications of influence maximization. In viral marketing producers try to introduce their products to a huge number of users through social networks by diffusion of information. Beside positive impacts, OSN have negative impacts, too. One of its bad impacts is diffusion of misinformation, rumors and other unfavorable information that can spread faster with more terrible effects by using OSN. Recent sstatistics [9] show that on some social networks, such as *Twitter* and *Facebook*, the fake news spread so fast that make users confused in detecting the correct ones. Bad effects of rumor spreading can be dangerous in some cases, for example in August, 2012, thousands of people in *Ghazni* left their houses in the middle of the night in horror after the rumor of an earthquake spreads [10]. Another example is the spread of misinformation about swine flu in *Twitter* [11] which caused a huge panic in the population. According to these examples although social networks are the main source of good activities and makes life easier for many people, they are not reliable for all time even sometimes dangerous due to such issues.

In order to make social network a reliable platform, we need some tools to limit the bad effects. Finding a set of strong connected nodes to the whole network and spreading the positive information thorough them can be a good approach. Finding a set of positive nodes for spreading positive influence against negative one is called influence blocking maximization (IBM). Research show that finding centrality measures is a good approach to find important nodes in a network [12]. In this paper, our contribution is to find a good candidate subset of positive nodes for spreading positive news in order to minimize the bad effects of negative news. In this case, we propose to use different aspects of central nodes in a network based on community detection to find a subset of positive initial spreaders. Due to common properties of many social networks having several communities of people with common interests and activities, the main idea of this study is to identifying community structures and then choosing positive spreaders. We experimentally show that centrality nodes in large communities can have a good effect on spreading positive information against negative one by showing number of negative nodes as results.

In information diffusion problem on social networks, different models have been introduced [13], [14]; among them two models namely independent cascading model (ICM) and linear threshold model (LTM) [15] are known as popular models. In this work, we assumed that both positive and negative propagations are using a recent version of ICM as Multi-campaign Independent Cascade Model (MCICM) [16].

Many of the community detection algorithms focus on disjoint communities; however, a node can belong to two or more communities. In this paper, the algorithm which used in this work for community detection is a kind of new fuzzy overlapping community [17]. Also, it is one of the most important kinds of overlapping community detection in which each node belongs to each cluster with different percentages. The fuzzy clustering algorithm that we used consists of three steps. First the similarity of each node with each other is compared using the new measurement method based on local random walk introduced. Second in order to keep the original node distance as much as possible, the network structure mapped into low-dimensional space by the multidimensional scaling (MDS). Third, clustering the nodes into community are done by using fuzzy c-means. This method presented in [17] and it had good results.

In this paper, we propose a community and centrality heuristic approach concept to tackle the issues of time consuming and realistic modeling of influence blocking maximization. According to this concept we proposed our algorithm called FC_IBM algorithm. Clusters of social networks show that similar nodes tend to cluster together [12]. FC_IBM algorithm detects the community in social network and then selects influential individuals based on high centrality. We compare these methods on some different well-known datasets. During the execution of the algorithm, a subset of positive influence spreaders is taken by FC_IBM algorithm and the positive diffusion starts to spread on MCICM diffusion model to block negative diffusion which is spreading in the network on the same diffusion model with high priority. Choosing a subset of nodes with these centrality measures among large communities have a good effect on blocking contamination by spreading positive information because of the strong connecting that a node with these features in a community can have.

The rest of this paper organized as follows: a brief review on the recent studies is provided in section II. The problem definition is described in section III. Description of the proposed algorithm using fuzzy clustering and centrality measures are given in section IV. Experimental results on some well-known datasets are reported in section V. Finally section VI concludes the paper.

II. RELATED WORK

Many studies have been conducted on influence maximization (IM) [4], [7], [18], however a limited number of studies have been done on influence blocking maximization. In this section, we will briefly introduce the prior works regarding rumor controlling in online social networks and some works based on communities in this field.

Sine, our work is based on influence blocking maximization. We investigated some limiting studies for rumor diffusion. In earlier works [19], the authors introduced blocking a certain number of links in a network to reduce the bad effects of rumor in a network. In [20], *Chen et al.* presented an efficient algorithm to maximize the positive influence when negative propagations appear. The works of [16], [21], [22] consider to block the influence of rumor by initiating a set of protective individuals.

The identification of influential users in a social network is a key problem that has received a huge attention in recent years. Early works relied on heuristics techniques to select the set of influential users. *C. Budak et al.* [16] are among the first groups who studied about misinformation contamination problem. In particular, they used multi-campaign independent cascade model and solved the problem of finding a subset of individuals to start propagating “good” campaign to minimize the rumor diffusion in the social network. Refs. [21] and [23] studied this problem under the competitive linear threshold model and the Opportunistic One-Activate-One (OPOAO) model, respectively [24].

Later works on this problem showed a *(1-1/e)*-approximation. The existing approaches in this field are time consuming so cannot control the large social networks. Due to this problem some works have been done by clustering for minimizing the size of the network [25]–[29]. Recent studies on this field focus on two different categories, unknown opponent strategies and comparative influence maximization.

In unknown opponent strategies, it is not practical to assume the opponents’ strategies are known, therefore in this category each player does not know about other players’ strategies. In [30], the authors models the competitive influence model problem as a multi-round multi-party game. *Li et al* consider another model of competitive influence model [31]. In this model the strategy space consists of all IM algorithms that can be adopted by players. The goal is to find a Nash equilibrium strategy for each player to maximize each player’s influence.

In comparative influence maximization the diffusion model for comparative influence maximization considers two different kinds of relationships between two diffusions N and P which are (1) competition and (2) complementary. In competition if a node adopts the influence of P, it has a lower probability to adopt N. [32] and in complementary if a node adopts the influence of P, it has a higher probability to adopt N. [33] and [34].

III. PROBLEM DEFFINITION

Influence blocking maximization problem is referred to finding a subset of positive nodes to block negative diffusion. The main target of this problem is to start a positive diffusion to spread positive information to the nodes of the networks which are not still polluted by negative diffusions. The main challenge is to find an optimal subset of nodes to start spreading positive information for blocking negative diffusion as much as possible. We proposed **FC_IBM** algorithm based on fuzzy clustering Fig. 1, for finding positive initial nodes.

In diffusion process of this work a node can have three different states such as *N-active*, *P-active* and *no-active*. Before start of diffusing, all of the nodes except negative and positive initial subsets of nodes are in *no-active* state. When positive diffusion reaches to a node its state changes to *P-active* and its state stays *P-active* till the end of diffusion process. When negative diffusion reaches a node its state change to *N-active* and it doesn't change till the end of the both diffusions. If neither positive diffusion nor negative diffusion reaches a node, its state stays no-active. If both diffusions reach a node, negative one has priority.

IV. Proposed Algorithm

In this work, we assumed that negative nodes have been already detected and both diffusions have the same diffusion models. Both diffusions start to spread together but negative diffusion has priority against positive one. For example if both negative and positive diffusions reach to a same node, negative diffusion has priority and its state change to *N-active*.

Figure 1 illustrates the pseudo-code of the **FC_IBM** algorithm. First we select the top-*k* biggest communities from discovered communities by FuzzyClustering, denoted as C_i, $0<i<k+1$which are sorted (lines 1-2, algorithm 1). Then we choose top k communities and add top m_k centrality nodes of each large k clusters relative to number of rumored nodes of each clusters and denote them as C^{mk}, where C_i^{mk} is the set of top-*mk* centrality nodes in the i-th large community C_i. Then the positive nodes are selected from the C^m set. Since FuzzyClustering cannot identify the important location of nodes in each C_i^m, centrality is considered as the only attribute that distinguishes good positive nodes. In this work we used three centralities, Degree, Betweenness and Closeness. We selected the highest centrality node in each C_i^m as the positive nodes $K = \{k_1, k_2, k_3, \dots, k_k\}$(lines 6-8 algorithm 1). For having a better result we heuristically substitute selected nodes (e-nodes) which start from second node of each C^{mk}_i with other nodes (b-node) which start from last node of K (k_k) down to k_i (lines 11-14 algorithm 1) to get better results and minimum the negative nodes (lines 15-27 algorithm1) by computing IBM. IBM is the number of negative nodes and the better result of IBM is the minimum one.

In following parts, we will provide preliminaries which are useful for the paper.

A. Graph model

A social network can be modeled as a directed graph $G = \langle N, E\rangle$ consists of N nodes and E edges. Node a is neighbor of node b if and only if there is an edge between them as $e_{ab}\in E$.

Algorithm 1. FC_IBM

Initialization

Centrality type {Degree, Closeness, Betweenness}

Input: Graph G(V, E); number of total seeds k; parameters p; N set of negative nodes;

Output: k seeds set

Begin Algorithm

01: **Call** FuzzyClustering(G)
02: K←ϕ;//seed set
03: Select top-k biggest communities from the communities in FuzzyClustering(G)
04: **For each** selected community C_i **do**
05: Add top-m_k Centrality nodes according to number of rumor nodes in each cluster and add them into set C_i^{mk};
06: **For each** C_i^{mk} **do**
07: K←K ∪ the most Centrality node in C_i^{mk};
08: $I_k(t)$ ← execute MCICM on G with S and N;
09: //$I_k(t)$ number of negative nodes
10: *IBM*← $|I_k(t)|$ //save the minimum number of negative nodes
11: **For each** community C_i **do**
12: **If** size(C_i) > avg($\sum^k_{i=1}$ size(C_i)) **then**
13: Add C_i in LC; //LC the set of large communities
14: Sort LC based on community size;
15: ei←0; //ei index of e_node
16: **for each** C_i in LC
17: bi←2; //bi: index of b_node
18: **while** true **do**
19: b_node← the bi-th large centrality node in C_i^{mk};
20: e_node← the seed candidates K_{k-ei} in K;
21: replace the e_node with b_node in K;
22: $I_k(t)$ ←execute MCICM on G with K;
23: **If** | $I_k(t)$ |> *IBM* **then**
24: Restore the replacement in line 20;
25: **Break;**
26: *IBM*←| $I_k(t)$ |;
27: bi←bi+1; ei←ei+1;
28: return K;

End Algorithm

Fig. 1. Pseudo-code for the proposed algorithm for finding a subset of positive initial nodes

B. Diffusion model

Independent cascade model is one of the most well-known diffusion models that have been used in different contexts. In the IC model, a process starts with an initial set of active nodes and unfolds in discrete steps. When a node v activates in step t, it has a single chance to activate each of its inactive neighbor w with probability P_{vw}. The process runs until no more activation is possible.

We used Multi-Campaign Independent Cascade Model (MCICM) which introduces process of two cascades simultaneously in a network [16]. We have two cascades P and N as positive and negative cascades and two initial sets P(k) and N(k). Each node can have three different states such as *P-activate*, *N-activate* or *no-active*. When v actives in step t, by cascade of P (or N), it has only a single chance to *P-activate* (or *N-activate*) its neighbor w. If *N-cascade* and *P-cascade* tries to activate a node at a same time, *N-cascade* has priority. Once a node changed its state to a *P-activate* (or *N-activate*) it will stay unchanged for the rest of the cascade. The process runs until no more activation is possible.

In following sections three used centrality measures in this paper are introduced [35].

C. Degree centrality

In a graph G = ⟨*N*, *E*⟩, degree of a node n is number of edges incident to the node. For a directed graph, there are two different kinds of degrees, out-degree and in-degree. Out-degree of a node is the number of edges from that node to the other nodes and in-degree of a node is the number of edges from other node to that node. For example in Fig. 2 out-degree of node 1 is 3 and in-degree of node 1 is 0.

In an undirected graph there is only one kind of degree, for example in Fig. 2 degree of the node 5 is 2. In this work, we have assumed that all of the networks are undirected graphs. In this work, maximum degree is one of the features that are used to find a subset of positive influence nodes.

D. Closeness centrality

Closeness is a measure of centrality in a network. It is calculated as reverse of sum of the length of the shortest paths between the node and all the other nodes in a graph. By this definition for the closeness we can figure it out that the more central a node is, the closer it is to all the other nodes. Closeness was defined by Bavelas (1950) [36] that is:

$$C(\nu)=1/\Sigma_{\gamma}\, d(\gamma,\nu) \tag{1}$$

Where $d(\gamma,\nu)$ is the shortest path between γ and ν .

E. Betweenness centrality

Betweenness centrality is a measure of centrality in a graph based on shortest paths. The betweenness centrality for each node is the number of these shortest paths that pass through the node. Freeman (1977) [37] first defined betweenness centrality as follow:

$$g(v)=\Sigma_{s\neq v\neq t}\, \sigma_{st}(v)/\, \sigma_{st} \tag{2}$$

Where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(v)$ is the number of those paths that pass through *v*.

F. fuzzy overlaping community detection

Fuzzy overlapping community is one of the most important kinds of overlapping community detection in which each node belongs to each cluster with different percentages. This algorithm consists of three steps. First the similarity of each node with each other is compared using the new measurement method based on local random walk introduced in the paper. Second in order to keeps the original node distance as much as possible the network structure mapped into low-dimensional space by the multidimensional scaling (MDS).Third, clustering the nodes into community by using fuzzy c-means.

Many of the community detection focus on disjoint communities, however, a node can belong to two or more communities. For example a student of Amirkabir University is connected to different social groups like university group, Iran group and family group. There are two types of overlapped communities: *crisp* and *fuzzy*. The crisp overlapping community means a node fully belong to its communities, for example in above example that student belongs to all those groups but in fuzzy overlapping community that student belongs to each group with different belonging coefficients.

V. Experiments

In this section, we evaluated the performance of proposed algorithm with respect to three different centrality measures on four different real datasets Dolphin [38], Jazz [39], Zachary [40], Football [41] and Facebook [41]. The descriptions of these networks are given in table 1. Following section presents experiment results for blocking maximization. All implementation were developed in MATLAB and all the experiments were launched on a system with hardware configuration of Intel® Core™ i7-4702MQ CPU @ 2.20GHz and 6 GB RAM. In the simulation MCICM model is used for the diffusion model and the simulation number of running methods on datasets is 10000 times, therefore the average number of negative nodes and their variances were taken as results.

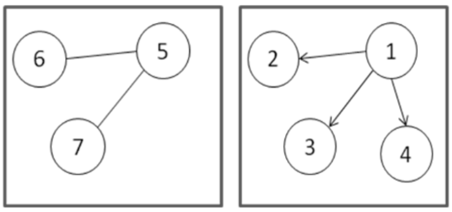

Fig. 2. An exmape for degree centrality

Table 1. Description of networks for simulation.

Network	Nodes	Edges	Description
Karate	34	78	Zachary's Karate Club Network
Dolphins	62	159	Networks of Dolphins
Football	115	613	Network of Amarican College Football Team
Jazz	195	5484	Network of Amarican musicians
Facebook	4039	88234	Social network

A. *Experimental results*

To verify validity of this algorithm, 5 percent of nodes in each dataset are selected randomly as negative initial nodes and 5 percent as positive nodes which these two sets don't cover each other. Also for the sake of comparison, we compare the proposed algorithm (using community structures and centrality measures as *FC_IBM_Degree*, *FC_IBM_Degree* and *FC_IBM_Degree*) with the algorithm without considering the community structures (as Degree, Betweenness and Closeness) [42].

The experiment result of blocking effect on Zachary dataset is shown in Fig. 3. As shown in Fig. 3, FC_IBM does significantly better in most cases and FC_IBM_Closeness has the best result while FC_IBM_Betweenness has the worst result. By running these algorithms on Jazz dataset, its average and variance in Fig.4 shows that FC_IBM has significantly better result. On Dolphin dataset, Fig. 5, FC_IBM does significantly better than other methods. On Football dataset, Fig. 6, FC_IBM does significantly better than other methods and also Fig. 7 shows that FC_IBM algorithm has significantly better result on a huge dataset like Facebook, too.

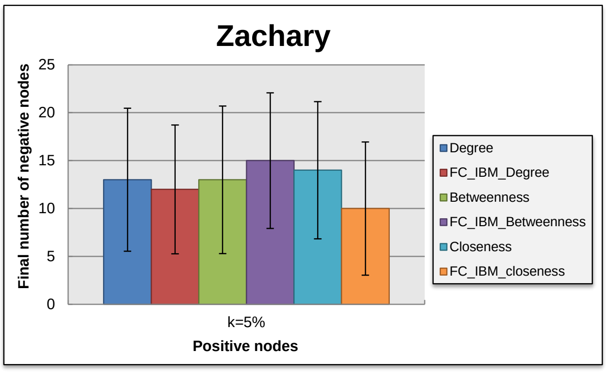

Fig. 3. Results on Zachary dataset

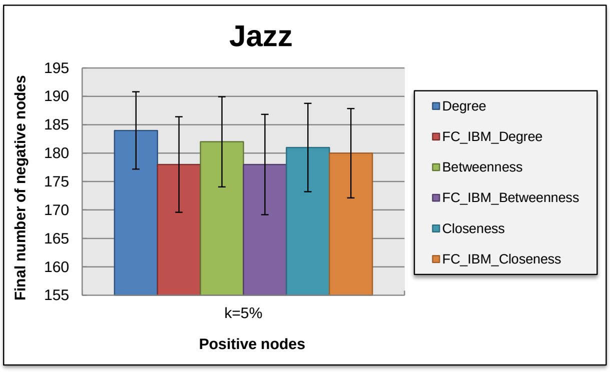

Fig. 4. Results on Jazz dataset

VI. CONCLUSION

In this paper, we proposed FC_IBM algorithm using community structures and centrality measures consists of *FC_IBM_Degree*, *FC_IBM_Degree* and *FC_IBM_Degree* for solving IBM problem by finding a subset of positive influence initial nodes with high centralities inside the communities of networks for starting a positive diffusion to block negative one. We used MCICM diffusion model for spreading both negative and positive diffusions. The experimental results on

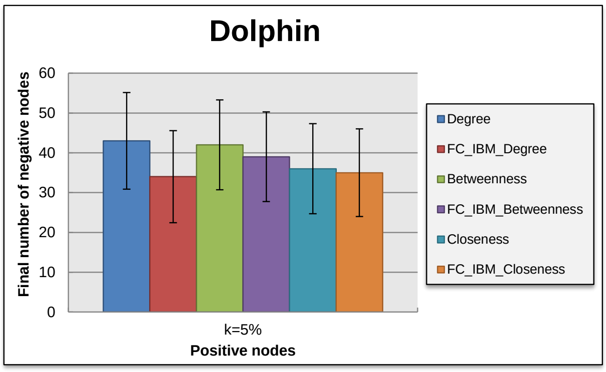

Fig. 5. Results on Dolphin dataset

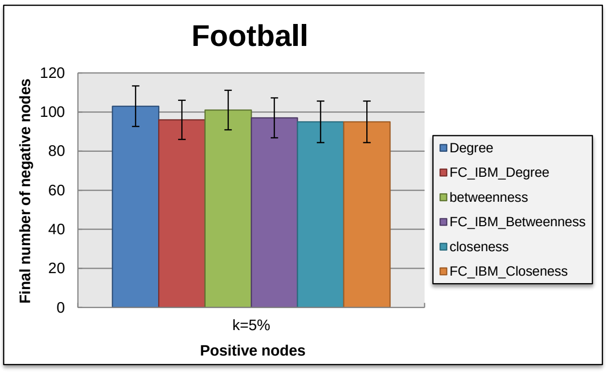

Fig. 6. Results on Football dataset

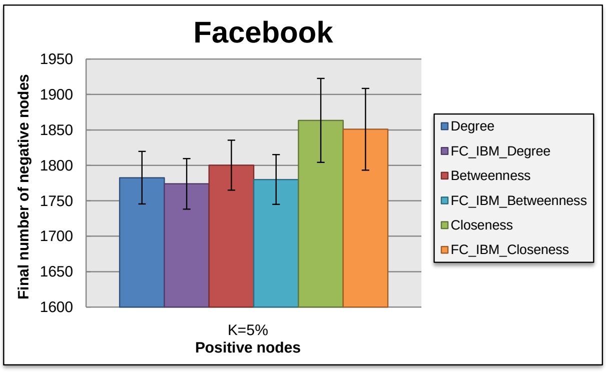

Fig. 7. Results on Facebook dataset

some different well-known datasets with different sizes released that the *IBM_FC* algorithms outperform the centrality based algorithms with respect to the final number of positive nodes.

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