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Design and Analysis of Perspectives in Social Theory for Directed Signed Social Networks

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Abstract: In today's era most people use social platforms or social media to share their views or ideas for their business purposes or to promote their product. Since past decade there is exponential growth in the of social networks. We have focused on the social balance and status theory in the signed social networks. In SSNs lot of researchers has explored or incorporated the concept of social balance theory to enhance the community detection problem. But social balance theory is more appropriate in UDSSNs not for DSSNs. To reduce or overcome this problem we have incorporated the concept of social status theory in which direction of ties are considered as not possible in undirected signed social networks. In SSNs we have used many metrics in terms of mathematical analytical tool to compute the values of each node or high degree of each node using real-world dataset. So, in SSNs the highest value or degree of each node in overlapping communities has the high social status as well as highly influencers node in the directed signed social networks. By using these metrices we can achieve the social status or highly influencers node which explore the behaviors of each node or people in the directed signed social networks.

Keywords: *signed social networks, in-degree, out-degree, directed graph, Overlapping Community, Directed signed social networks, Undirected signed social networks.*

1. Introduction

To analyse these online SSNs there are two different theories. They are: Structural Balance Theory and Social Status Theory Structural, Balance Theory is the fundamental theory formulated by Heider in 1946. Based on the concept of Friend-of-a-Friend (FOAF), this theory is a notion to understand the structure, cause of tensions and conflicts between the two sentiments (positive and negative) in a network of actors (users). Further, Cartwright and Harrary in 1956 modelled it in terms of signed graphs. This theory rests on the assumption that certain configurations of positive and negative edges are socially more probable than others. Ignoring the identities of the actors, four configurations are possible: "my friend's friend is my friend", "my friend's enemy is my enemy", "my enemy's friend is my enemy", "my enemy's enemy is my friend". According to the structural balance theory, a balanced triad is one with either one or three positive links (i.e., odd number of positive links) among three people. the first two triads are balanced as they have an odd number of positive links while the latter two are unbalanced as they have even number of positive links. This theory is pertinent on undirected networks only. Social Status Theory suggested by Guha et al., and further developed by Leskovec et al., proposes to use status of a person as the factor to decide whether a person will make a link (positive or negative) with another person in the network. Status can be in terms of social status. In directed signed social networks (popularity, fame) or it can be economical status (money, power). PageRank is one of the most popular ways to calculate status scores in social networks.

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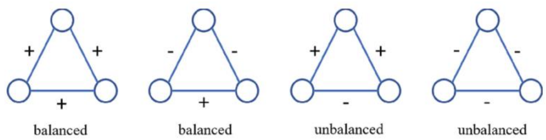

Fig 1 Depicts the balanced and unbalanced social theory with triads relationship.

According to this theory, if individual $\boldsymbol{A}$ (creator) makes a positive link to individual $\boldsymbol{B}$ (recipient), then $\boldsymbol{A}$ believes that $\boldsymbol{B}$ has higher status than him, whereas a negative link originated from individual $\boldsymbol{A}$ to $\boldsymbol{B}$ indicates that $\boldsymbol{A}$ considers status of $\boldsymbol{B}$ lower than him. It is evident that the status theory is more suitable for directed networks. To check whether triads of a network satisfy status theory, take each negative link in a triad, inverse its direction and the flip the sign of the link (positive sign) then the resultant triad should be acyclic in nature. Computation of Status of a node: The status of a node x in a directed network can be computed as follows:

$\xi(x)=d^{+}(x)+ d^{-}(x)- d^{+}(x)- d^{-}(x)$ (1)

where, $d^{+}(x)$ and $d^{-}(x)$ denotes the number of positive and negative links received by the node x from other nodes in the network respectively. Similarly, d^{+} (x) and d^{-} (x) is the number of positive and negative links generated by the node x in out. the network, respectively.

Social balance theory is a concept in social network analysis that explores the dynamics of relationships and attitudes within a social network based on the concept of balance. The theory posits that individuals in a network strive for balanced relationships, meaning that their social connections align with their attitudes and preferences. According to social balance theory, relationships can be categorized into three types: Positive relationships: These are relationships where two individuals share positive attitudes towards each other. For example, two friends who have a positive opinion of each other. Negative relationships: These are relationships where two individuals have negative attitudes towards each other. For example, two individuals who have a conflict or animosity towards each other. Balanced relationships: These are relationships where two individuals have opposite attitudes, such as one person liking the other while the other person dislikes them. This balanced relationship can help to alleviate tension and maintain stability in the network.

The theory suggests that individuals in a social network strive for balance by either forming new relationships to reduce imbalance or adjusting their attitudes towards existing relationships. For example, if two friends have a mutual friend, they both dislike, they may try to resolve the imbalance by either ending the friendship or adjusting their negative attitudes towards the mutual friend. Social balance theory has several implications in social network analysis. It helps explain the formation and dissolution of relationships within a network, as well as the emergence of social groups and subgroups. It also provides insights into how individuals navigate conflicts and strive for harmony in their social interactions. Researchers in social network analysis use social balance theory to understand and predict patterns of relationships and attitudes in various social contexts, such as friendship networks, online communities, and organizational networks. By studying the dynamics of balance and imbalance, researchers can gain insights into the underlying mechanisms that shape social networks and influence individual behavior within them.

This can result in the formation of hierarchical structures or the emergence of central nodes that have a significant impact on network dynamics. Moreover, social status can influence the diffusion of information and behaviors within a network. Individuals with higher social status often serve as opinion leaders or trendsetters, and their attitudes, preferences, and behaviors may be adopted by others in the network. This phenomenon is known as social influence, where individuals with higher status have a greater ability to shape the beliefs and behaviors of others. In social network analysis, researchers examine the role of social status through various measures and indicators. These include measures of centrality (e.g., degree centrality, betweenness centrality) to identify individuals with higher status and their influence within the network. Researchers also analyze the effects of social status on information flow, decision- making processes, and social dynamics within the network. Understanding the impact of social status in social network analysis can provide insights into social stratification, inequality, and the distribution of resources and opportunities within a network. It helps uncover the mechanisms through which social status influences network formation, behavior, and social outcomes.

Balance theory in social network analysis is a concept that examines the cognitive and affective balance or imbalance among relationships within a social network. It is based on the idea that individuals strive for cognitive consistency and prefer relationships that are balanced, meaning that they align with their own attitudes and beliefs. The theory was originally developed by Fritz Heider in the context of social psychology and later extended to social network analysis by Theodore Newcomb and Leon Festinger. Balance theory focuses on the cognitive evaluation of relationships in terms of positive and negative sentiments.

According to balance theory, balance is achieved when the patterns of positive and negative ties among individuals in a triad (a group of three individuals connected by relationships) conform to a particular structure. There are two types of balanced structures: Triadic Balance: A triad is considered balanced when all three relationships are either positive or mixed (consisting of two positive and one negative relationship). In a balanced triad, there is harmony and consistency in the network because the positive and negative sentiments align.

Structural Balance: Structural balance extends the concept of triadic balance to larger networks. It suggests that a network is balanced when the relationships between triads in the network follow certain patterns. In a balanced network, positive relationships tend to cluster together, and negative relationships tend to be either absent or connect separate clusters of positive relationships. The theory also proposes a principle known as the "friends of friends are friends" principle. According to this principle, if two individuals share a positive relationship, their mutual connections are more likely to develop a positive relationship as well. This principle contributes to the formation of balanced structures within a network. Balance theory has several implications in social network analysis. It helps explain the formation of alliances, conflicts, and the overall structure of social networks. It also sheds light on social influence dynamics, as individuals are more likely to align their attitudes with their friends and connections to achieve cognitive consistency. Researchers use balance theory to analyze the patterns of positive and negative relationships within a network and examine their implications for information diffusion, group dynamics, and social cohesion. By studying balance theory in social network analysis, researchers gain insights into the cognitive and affective processes that shape relationships and the overall structure of social networks.

Status theory in social network analysis focuses on the role of social status and hierarchical positions within a network. It examines how individuals' positions in terms of status influence.

their interactions, influence, and overall network dynamics. Status can be based on various factors, such as occupation, wealth, education, or reputation. Status theory examines how individuals' status positions affect their network connections, social influence, and access to resources within the network. Status theory suggests that individuals with higher social status tend to have more connections and influence within the network. They often occupy central positions and are more likely to be sought out for information, advice, or resources. This is known as the "status-based preferential attachment," meaning that individuals with high status attract more connections and have a greater influence on network dynamics.

Moreover, status theory explores the impact of status on social influence and decision-making processes within a network. Individuals with higher status often have more persuasive power and are more likely to shape the opinions and behaviors of others. Their decisions and preferences carry more weight and can lead to the adoption of certain beliefs or behaviors within the network. Status theory also examines how status hierarchies can lead to the formation of cliques, subgroups, or power imbalances within a network. Individuals may be more likely to form connections with others who have similar or complementary status positions, resulting in the reinforcement of existing status differentials and social stratification. Researchers in social network analysis study status theory by analyzing measures of status, such as prestige or centrality indicators. They examine how status positions influence network structure, the flow of information, social influence, and overall network dynamics. Additionally, researchers may explore the relationship between status and other factors, such as homophily, social capital, or tie strength, to gain a deeper understanding of the mechanisms underlying status effects in social networks. Understanding the role of status in social network analysis helps uncover the dynamics of power, influence, and social stratification within networks. By studying status theory, researchers gain insights into how social status shapes network connections, social influence, and access to resources, contributing to a more comprehensive understanding of social dynamics within networks.

2. Background and survey literature

In directed signed social networks, groups of individuals who establish connections and interactions with one another based on shared characteristics or interests can be referred to as communities. These communities can be formed around various subjects such as political ideologies, hobbies, or professional fields. The connections between people within a community are typically represented by directed and signed edges, where directed edges indicate the direction of the relationship, and signed edges indicate the nature of the relationship (positive or negative). By studying these communities, one can understand the spread of information, influence, and opinion dynamics within the networks. In directed signed social networks, communities can also be determined using multiple techniques like modularity maximization, spectral clustering, and label propagation [1-3]. These techniques assist in uncovering the fundamental structure and organization of the networks and can reveal the impact and influence of various individuals or groups within the community. Additionally, gaining knowledge about the dynamics of these communities can offer insights into the processes of forming opinions, the spread of false information, and the emergence of leaders and influencers within the network. Furthermore, examining communities in directed signed social networks can aid in understanding the development and changes of social groups, and how they are affected by external factors such as political or economic events. In directed signed social networks, communities can also have a vital role in the formation of social capital and trust. Positive relationships within a community can indicate a high level of trust and cooperation, while negative relationships can indicate distrust or competition [4,5]. These dynamics can have a substantial impact on the functioning of the community and its ability to accomplish common goals. In studying communities in directed signed social networks can reveal crucial information about the social dynamics of society and aid in understanding how individuals and groups interact with each other. Researchers had explored lot of work in unsigned and signed social networks [7,8]. They had used only positive relationships till now but in signed social networks we have focused on positive as well as negative edges of directed signed social networks. In directed signed social networks, individuals or entities that are a part of multiple communities simultaneously are referred to as nodes of overlapping communities [10,11].

3. Proposed algorithm for overlapping communities in DSSNs.

The proposed work presents the details of the algorithm for the proposed metric like degree of the node and highly influencer node which computes social status for each node of overlapping communities in a directed signed social network.

Algorithm: To compute the status, degree, and value of each influencer node for overlapping communities in a DSSN.

Input: Adjacency matrix *A* of size *n* * *n*, where *n* is the number of nodes.

$$A(i,j) = \begin{cases} +1, \text{if node } i \text{ makes positive link with node } j \\ -1, \text{if node } i \text{ makes negative link with node } j \end{cases} \quad (1)$$

and *M* is a matrix of size *m* * *n* which represents community structure, where *m* is the number of communities and *n* is the number of nodes.

$$M(i, j) = \begin{cases} 1, \text{if node } j \text{ is in community } i \\ 0, \text{otherwise} \end{cases} \quad (2)$$

Output: result matrix of size *m* * *n* consisting of the degree, high influencer, and social status value of each node in each community.

The following steps are followed to compute social status for each node of overlapping communities in a DSSN:

Step 1: Calculate for each node positive incoming degree (*p_in*), positive outgoing degree (*p_out*), negative incoming degree (*n_in*), and negative outgoing degree (*n_out*). For each node v_k, calculate $p\_out_{(k)}$, $p\_in_{(k)}$, $n\_out_{(k)}$ and $n\_in_{(k)}$ from signed adjacency matrix *A*

if $A_{(k,t)} = 1$

$p\_out_{(k)} = p\_out_{(k)} + 1$; $p\_in_{(t)} = p\_in_{(t)} + 1$;

elseif $A_{(k,t)} = -1$

$n\_out_{(k)} = n\_out_{(k)} + 1$; $n\_in_{(t)} = n\_in_{(t)} + 1$;

End

End

Then, calculate p^{total}, which represents the factor which contributes to the high status of the node and n^{total} which representing the factor contributing to the low status of the node, where.

$$p^{total}_{(k)} = p\_in_{(k)} + n\_out_{(k)} \quad (3)$$

$$n^{total}_{(k)} = p\_out_{(k)} + n\_in_{(k)} \quad (4)$$

Step 2: Now, to calculate the weights for the positive and negative contributions of nodes, take two parameters, let's say ρ and σ, respectively.

$$w\_p_{(k)} = \text{p} * p^{total}_{(k)} \quad (5)$$

$$\widehat{w\_n_{(k)}} = \sigma * n^{total}_{(k)} \quad (6)$$

Step 3: Now, for each community i in the set of overlapping communities C, let's say that p deg are the links which contribute to the high status of the node in that community, and n deg are the links which contribute to the low status of the node in that community.

For each node v_k that belongs to community i, compute p_deg(i, k), which con- tributes to the high-status value of a node, is the sum of the number of incoming positive links to node k and the number of outgoing negative links from node k from the i-th community. Similarly, n_deg(i, k), which contributes to the low status of node k, is the sum of the number of positive outgoing links from node k and the number of negative incoming links to the node k in the i-th community.

p_in(i, k);

p_out(i, k);

n_in(i, k);

n_out(i, k);

$$p\_deg_{(i,k)} = p\_in_{(i,k)} + n\_out_{(i,k)} \quad (7)$$

$$n\_deg_{(i,k)} = p\_out_{(i,k)} + n\_in_{(i,k)} \quad (8)$$

Step 4: Now, we compute positive contribution, which aids the high status H(i, k) of node k and negative contribution L(i, k), which aids the low status of node k. For each node vk to all communities

$$H_{(i,k)} = \frac{p\_deg_{(i,k)}}{\sum \forall i p\_deg_{(i,k)}} \quad (9)$$

If p deg(i, k) > 0, then calculate intermediate negative contribution as:

$$\widehat{L_{(i,k)}} = n^{total}_{(i,k)} - n\_deg_{(i,k)} \quad (10)$$

The final negative contribution is given as:

$$L_{(i,k)} = \frac{\widehat{L_{(i,k)}}}{\sum \forall i \hat{L}_{(i,k)}} \quad (11)$$

Step 5: The final weight for the negative contribution will be calculated as:

$$w\_n_{(k)} = \widehat{w\_n_{(k)}} * \sum_{\forall i} L_{(i,k)} \qquad (12)$$

Step 6: The social status value of each node k in community i will be computed as:

$$SF_{(i,k)} = \frac{w\_p_{(k)} * H_{(i,k)} - w\_n_{(k)} * L_{(i,k)}}{|w\_p_{(k)} - w\_n_{(k)}|} \qquad (13)$$

4. Implementation and computation of parameters in overlapping communities in DSSNs.

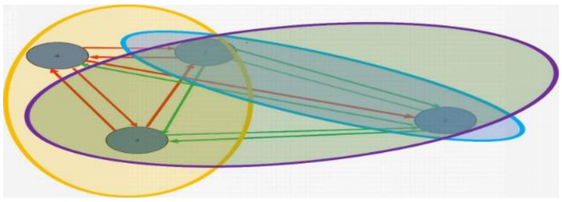

Fig 2 Overlapping community in directed signed social networks [DSSNs].

$$A = \begin{bmatrix} 0 & 1 & 1 & -1 \\ 1 & 0 & 1 & 1 \\ -1 & 1 & 0 & -1 \\ -1 & -1 & -1 & 0 \end{bmatrix}$$

Adjacency matrix

$$M = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \end{bmatrix}$$

community structure

To compute the degree of each node in overlapping communities

In community 1 node 2, calculate $p\_in_{(2)} = 2$, $p\_out_{(2)} = 3$, $n\_in_{(2)} = 1$, and $n\_out_{(2)} = 0$ from adjacency matrix A. Similarly we can compute for node 1 also as $p\_in_{(1)}= 1$, $P\_out_{(1)}= 2$ and $n\_in_{(1)}= 2$, $n\_out_{(1)}= 1$

In community 2 node 1 and 2 having same values as they are lies in the community 1 and community 2,

So,in community 2 now values of node 3 as follows:

$p\_in_{(3)} = 2$, $p\_out_{(3)} = 1$, $n\_in_{(3)} = 1$, and $n\_out_{(3)} = 2$

Now in community 3 nodes 1, 3 and 4 are lies in the same community and we have to compute the values

for node 4 as follows:

$p\_in_{(4)} = 1$, $p\_out_{(4)} = 0$, $n\_in_{(4)} = 2$, and $n\_out_{(4)} = 2$

Then, using Equations (3) and (4) the values of node 2 for community 1 and similarly cab ne computed for all nodes in each overlapping communities like 1 2, and 3 respectively.

$p_{(1)}^{total}$ = 2 and $n_{(1)}^{total}$ = 3 and $p_{(2)}^{total}$ = 2 and $n_{(2)}^{total}$ = 4

and for community 2 as follows: $p_{(3)}^{total}$ = 4 and $n_{(3)}^{total}$ = 2

Overlapping community 3 for node 4 as follows:

$p_{(4)}^{total}$ = 3 and $n_{(4)}^{total}$ = 2

Now to compute the weights for the positive and intermediate negative contribution of nodes, let us take the

parameter values of ρ = 0.8 and σ = 0.2. Now, using Equations (5) and (6)

Computation for node 1 and node 2 in overlapping community 1

$w\_p(1) = 0.8 * 2 = 1.6$ and $w\_n_{(1)} = 0.2 * 3 = 0.6$

$w\_p(2) = 0.8 * 2 = 1.6$ and $w\_n_{(2)} = 0.2 * 4 = 0.8$

For overlapping community 2 with node 3 as follows:

$w\_p(3) = 0.8 * 4 = 3.2$ and $w\_n_{(3)} = 0.2 * 2 = 0.4$

For overlapping community 3 with node 4 as follows:

$w\_p(4) = 0.8 * 3 = 2.4$ and $w\_n_{(4)} = 0.2 * 4 = 0.8$

Now, calculate the links in overlapping community which contribute to increasing and decreasing the social status of node 2, respectively, in community 1. In all communities, we have to compute p_deg(1, 2) and n_deg(1, 2) using Equations (7) and (8).

p_deg(1, 2) =2

n_deg(1, 2) =2

p_deg(2,1) =1

n_deg(2,1) =1 and respectively we can compute the values for each nodes in overlapping communities in DSSNs.

The positive contribution of links which shows the high social status of node 2 in community 1 calculated as from Equation (9).

$H_{(1, 2)} = 2/3 = 0.6667$

By using Equations. (10) and (11) we have to calculate intermediate and final negative contribution, respectively, which aids the low social status of node 2 in community 1 as condition p deg(1, 2) > 0 is satisfied

$L^b(1, 2) = 4 - 2 = 2$

$L_{(1, 2)} = 5 = 0.4$

The final weight for negative contribution will be calculated from Eq. (12)

w $n_{(2)}$ = 0.8 * 1 = 0.8

Finally, the social status value for node 2 in community 1 will be calculated from Eq. (13) as:

SF(1, 2) =1.6 * 0.6667 − 0.8 * 0.4

Similarly, social status values, degree of each node and highly influencer node for node 2 in community 2 is 0.0667. Using overlapping communities, we can compute social status for each node of overlapping communities in DSSNs that may be used to solve or reduce the different problems like sparsity, missing links, new formation of nodes for future reference and node density analysis as well as node behavior in DSSNs.

5. Exploring of datasets in Directed Signed Social Networks [DSSNs]

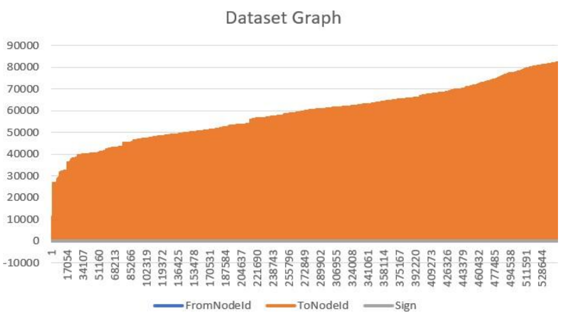

Fig 3 analysis of dataset and relationship with positive as well as negative sign for directed signed social networks.

Snap dataset Epinions with signed social networks which depicts the number of edges and number of nodes and their relationships among the nodes as positive and negative sign in the directed signed social networks [DSSNs]. On the basis of social networks metrics, we have computed the degree of nodes, closeness and betweenness of the nodes using proposed algorithm in directed signed social networks for [DSSNs].

6. Implementation and Result analysis in Directed Signed Social Networks

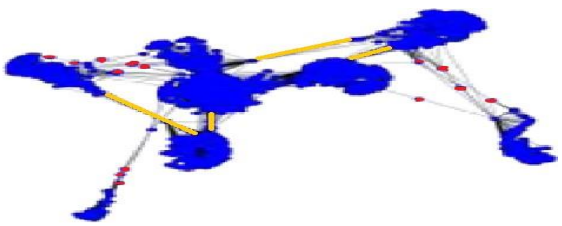

Fig 4 Depicts the analysis of closeness and betweenness of the node in DSSNs.

Figure 4 depicts the closeness and betweenness of each node based on real-world dataset in the signed social networks. In the networks red ball represents the betweenness and closeness of each node based on the distance from each other and if a node has high betweenness and closeness that node identify for the highly influencers node which have the highest degree of the node in the signed social networks.

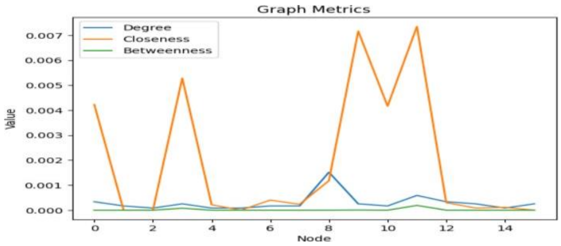

Fig 5 depicts the position of the node with different attributes in signed social networks.

Figure 5 the graph generated by using our proposed approach describes three different network metrics: degree, closeness, and betweenness of each node in DSSNs. The x-axis of the graph represents each node in the network, and the y-axis represents the value of each metric. Each line in the graph represents a different metric, with the blue line representing degree, the orange line representing closeness, and the green line representing betweenness of each node in the signed social networks.

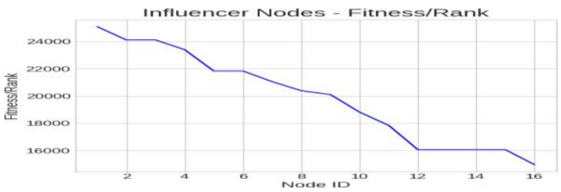

Fig 6 Graph depicts the fitness/Rank of the node in the signed social networks.

Figure 6 depicts the fitness/rank of the influencer nodes based on the node location. The x-axis represents the node ID, and the y-axis represents the fitness/rank of the influencer nodes. The blue line represents the fitness/rank of the influencer nodes, with each point on the line representing a specific node. The graph shows that there are more values in each column, but this is just a few data that have been inserted into it. This information can be useful in various fields, such as marketing and social media analysis, where identifying influential individuals is essential for targeted marketing and outreach efforts using signed social networks.

7. Conclusion and Future scope

In signed social networks using overlapping communities suffering from balance structure due to positive and negative signs of the actors or ties. We have proposed new methodology to compute the social status of a node or high degree of each node in overlapping communities using directed signed social networks with inclusion of real-world dataset. So, we have computed the new metrices using overlapping communities in DSSNs. In DSSNs proposed attributes have focused on the tie's direction with sign representation. In DSSNs link prediction and highly influencer's node has incorporated using overlapping communities. The highly influencer which depicts the high degree of the node or high-status values in the overlapping communities signed social networks. Our findings enhance the perspective to explore the social circles of the node in the overlapping communities in DSSNs. In overlapping communities, we have discovered the behaviors of the node or people by using social status as well as highly influencing node or people. In future we may proceed to find the missing links or new formation of links among the nodes in the signed social networks. In signed social networks, we may reduce or overcome the sparsity problem using machine learning or nature inspired algorithm or model based on real-world dataset.

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