Influence Node Analysis using Monte Carlo and Clonal Selection Algorithm for Influence Maximization

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***Abstract*—In viral marketing, Influence maximization (IM) is the most prominent and significant process of determining the subsets of nodes in social network that enhance the spread of information. Many of the approaches proposed for the influence maximization incur low efficiency due to massive data and are found to be inadequate to cover large amount of prevailing data. In this research, Influence Maximization based on Clonal Selection Algorithm (IM-CSA) is proposed to increase the performance of the Influence maximization process. The proposed method involves in detecting the community based on Louvain method and Monte Carlo simulation technique is applied for Independent Cascade. In this proposed approach, to determine the probability of influence value of nodes, Monte Carlo method is applied to perform the sensitive analysis on the input parameters. The Clonal Selection Algorithm (CSA) has the adaptive unit with competitive process of selection that improves the adaptive fit in the information. In this CSA method, the nodes in the network are sorted based on their influence values and in turn the nodes with less influence are removed which helps to significantly reduce the computational time and memory usage of the proposed method. The most influence nodes in the network are determined by the mutation in the CSA method. The proposed method is evaluated using real world dynamic network datasets and it is empirically found that the proposed IM-CSA method shows higher performance than the existing methods in terms of time and influence spread.**

Keywords—Clonal Selection Algorithm, Independent Cascade, Influence Maximization, Influence node analysis, Louvain method and Monte Carlo simulation

I. INTRODUCTION

In recent years, the tremendous developments in the online social networks such as Twitter, Instagram and Facebook have remarkably made them to become thriving places for viral marketing [1]. In social networks, Influence Maximization (IM) method finds a seed set of k users so that the aggregate influence of seed users is maximized. IM techniques are required in various applications such as rumor control, revenue maximization, social recommendation, network monitoring, viral marketing, etc. [2]. Social network data have been used in sentiment analysis, opinion mining, stock market prediction and marketing. In these areas, researchers have been attracted by the processes and dynamics through which information and behaviors spread through social networks. Understanding the information spread in human social structure has high impact on the product promotion and behavior trends [3]. It is common and realistic to organize influential events to determine a set of persons interested in the themes of an event by providing better social interactions to attract a higher number of persons to participate in the event thereby resulting in lower communication cost [4]. The interpersonal influence is found to be the most important factor in the success of viral marketing, which has been empirically studied in various contexts [5].

Social networks are considered as graphs of relationships natural to organized societies. Advertising, trends, news, ideas, or information of event will use these relationships to spread to the users starting from an initial set of information providers [6]. For Influence maximization, most researchers use solutions based on the centralized influence diffusion models such as Linear Threshold (LT) model and the classic Independent Cascade (IC) model [7]. The scale of information spread is measured from the origin of the information or source node in the graph. The starting node should be carefully selected to spread the influence in the graph [8]. The problem of learning graphical models with latent variables has been analyzed to be less efficient [9]. Many research has been conducted for influence maximization in social media, but achieving efficiency is a major requirement [10].

Our proposed IM-CSA approach uses Monte Carlo and Clonal Selection Methods to carry out node influence analysis. The first phase of our approach is to use Monte Carlo (MC) method to determine the probability of influence nodes based on sensitivity measure on input parameters. The MC approach employs the correlation on the network input data to determine the sensitivity of parameters. The second phase of our approach uses Clonal Selection Algorithm (CSA) to sort the nodes based on influence values and to remove the nodes with less influence values. The mutation based on Least Square Error (LSE) is carried out to determine the most influential nodes. The step in the CSA method of removing the nodes with less influence values helps to significantly reduce the time and amount of memory required by the method. In our study, two social network datasets are used to evaluate the performance of the proposed IM-CSA method and compared with the existing methods. Here the input data is used to construct the network and community in the network is detected based on the Louvain method. The Monte Carlo simulation is used for the independent cascade that measures the influence spread value. The CSA method is used to find the best affinity value nodes in the network. The experimental analysis shows that the proposed CSA method has higher performance in the influence maximization when compared with the existing methods in terms of time and influence spread.

The rest of the paper is organized as follows. In section 2, we present some of the previous work related to Influence Maximization. Section 3 provides detailed discussion on our proposed approach IM-CSA – Influence Maximization using Monte Carlo and Clonal Selection Algorithm. The experimental setup and performance evaluation of our proposed approach are presented in Section 4, followed by Concluding Remarks in section 5.

II. RELATED WORK

Maximization of influence propagation in social media has garnered more interest among researchers for viral marketing quite recently. This section provides a brief survey on the related work in the literature which propose methods that involve in the maximization of influence propagation.

Song, *et al*. [11] established Influential Node Tracking (INT) problem with the conventional Maximization problem (IM) to track the influential node in dynamic settings. Upper Bound Interchange Greedy (UBI) algorithm is proposed to track the influential node in the growing network. Influential seed is used for construction instead of start from ground and implementing the node replacement to increase the influence coverage. The UBI method is tested on three real large-scale dataset and this shows that the method has the higher performance in terms of running time and influence coverage. The diffusion technique can be used to increase the performance of the UBI method.

Tang, *et al*. [12] proposed influence maximization method based on martingales named as IMM, which is a statistical tool. The developed method is evaluated on the large social media dataset, which is up to 1.4 billion edges. The experimental analysis shows that the IMM method has the higher performance with minimum computation overhead than existing methods. The method supports large number of social media data and improves the performance effectively, but the computation time is required to be reduced.

Jung, *et al*. [13] combines the method of Influence Ranking (IR) and Influence Estimation (IE) for influence maximization in the Independent Cascade (IC) and its extension (IC-N), which has negative Opinion. The developed method is named as IRIE and shows that IRIE method has better scalability than other existing methods in influence maximization. The experimental analysis shows that the IRIE method is more robust, having less memory usage and faster than existing methods. The IRIE method can support the large-scale social media dataset with less computation time, but the efficiency of the method is required to be increased and the method needs to be tested on dynamic network.

Sankar, *et al*. [14] developed the bio-inspired algorithm inspired by waggle dance to select the initial set of nodes, which is significant in rapid convergence towards a sub-optimal solution in minimum runtime. The waggle dance technique is the communication process of bees and utilize the global-local search of artificial bee colony in the influence maximization problem. The performance is evaluated in the twitter hashtag related with the non-violent protest in the moral policing spread to many parts of India. The performance of the developed method is high compared to the existing methods. The efficiency and scalability of the method are required to be improved for stable influence maximization.

Heidari, *et al*. [15] proposed State Machine Greedy for the fast greedy algorithm that improves the existing method from the reducing of two parts: counting the traversing nodes and Monte-Carlo graph construction for the diffusion simulation. The experimental analysis shows that the speed of the method is increased compared to the existing method. But the coverage of the method is found to be low and initialization technique is required to be used to increase the performance.

In [16] He, *et al* presented a two-stage iterative framework for the analysis of influence maximization in social networks. In this approach benefit of each node is computed based on the First-Last Allocation Strategy (FLAS). In order to reduce the computational complexity, the candidate nodes are selected based on the descending order to remove the less influence nodes. The performance of the proposed two-stage iterative framework is evaluated using eight network data and the experimental studies show that the proposed approach has higher performance, but the efficiency of the approach is affected by the low convergence performance of the developed model based on PageRank.

A swarm intelligence-based approach with reshaping of social network data to identify the influential nodes has been proposed by Şimşek and Kara in [17]. In this work, graphs are used to represent the social network data and nodes are used to represent individuals. Here the nodes are sorted in descending order based on the influence of the nodes and nodes are renumbered accordingly. This approach uses two swarm intelligence methods - Grey Wolf Optimization (GWO) and Whale Optimization Algorithm (WOA) for the influence analysis. The performance of the developed method is evaluated using real social network data and the results show that the developed method has higher efficiency in the influence analysis, but the GWO and WOA methods trap in the local optima which affects the efficiency of the proposed model.

MinCDegKatz and MaxCDegKatz d-hops based on combination of centrality measure to analyze the node influence has been proposed by Alshahrani, *et al* [18] where the degree centrality is considered as local measure and the

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Kartz centrality is treated as global centrality metric on the graph. The performance of the method is evaluated using the two proposed algorithms with Independent Cascade (IC) and Linear Threshold (LT). The experimental study uses the network data to evaluate the performance of the proposed method in influence node analysis and the result shows that the developed models have higher efficiency in node influence analysis, but the proposed two algorithms have lower efficiency in measuring the influence spread in the analysis.

III. PROPOSED METHOD - IM-CSA

Influence Maximization method analyzes the spreading of information in the social network and finds the accurate influence which helps in vital marketing. To determine the influence nodes, the existing methods process all the nodes in the network which requires more time and higher memory. In this research, Influence Maximization based on Clonal Selection Algorithm (IM-CSA) is proposed to determine the influence nodes in the social network. In the CSA method, the nodes are sorted based on influence values and then the nodes with less influence are pruned. Figure 1 provides the block diagram of the proposed IM-CSA method which clearly illustrates the phases in the process of the proposed method. The input data has been read and network graph is constructed based on the given data. Communities in the social network are detected using the Louvain method and the information transfer is analyzed.

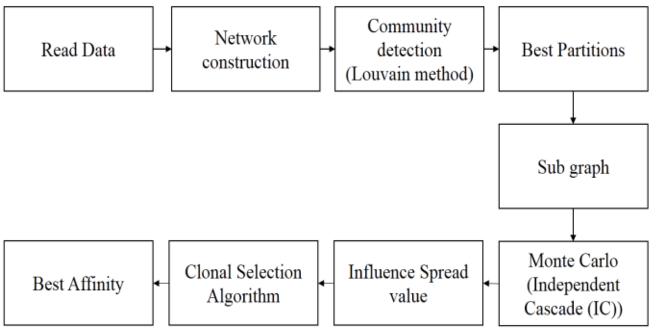

Figure 1. The block diagram of IM-CSA method

A. Community Detection based on Louvain method

Louvain method (LM) [19] is applied for the community detection which uses local information and is most suitable for the analysis of large-weighted network. This method involves two steps. The first step involves maximizing the network modularity Q by assigning each node to a chosen community. The gain is calculated based on moving a node i into a community C is given in Eq. (1).

$$\Delta Q = \frac{\sum c + k_i^c}{2m} - \left(\frac{\sum c + k_i}{2m}\right)^2 - \left[\frac{\sum c}{2m} - \left(\frac{\sum c}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)\right]$$
(1)

where the sum of the weights of the edges incident to nodes in C is denoted as $\sum C$, the sum of the weights of the edges incident to node i is denoted as k_i, the sum of the weights of the edges from i to nodes in C is denoted as $\sum C + k_i$, the sum of the weights of all the edges in the network is denoted as m.

The second step involves constructing new network based on nodes of communities previously found. Then these two steps in the process are iterated continuously until a significant improvement of the network modularity is obtained.

The best partitions are selected from the network based on the communities found in the network. Independent cascade is measured based on the Monte Carlo technique and subgraphs are plotted for the partitions.

B. Monte Carlo Technique

To find the influence maximization in Independent cascade, Monte Carlo method is applied. Monte Carlo is applied in various fields such as finance, quantum mechanics, and radiation transport physics etc., to analyze the multidimensional integral that is measured as expectation A of a random variable W, as in Eq. (2).

$$\mathcal{A} = E[w] \int_{D_X} dx\, p_X(\Delta Q) \int_{D_{Y(X)}} dy\, p_Y(y; x) \widehat{w}(x, y) \quad (2)$$

where for the random variables or vector X and Y, the associated probability densities are denoted as p_X and $p_Y(y;\ x)$ & the domains as D_X and $D_{Y(x)}$. The function $\widehat{w}$ is used to define the random variable W that associates X and Y to W as $W = w(X, Y)$. Monte Carlo integration analyzes the unbiased estimator of A based on sampling n Independent and Identically Distributed (IID) random variables X_i and Y_i. In this scenario all the X_i are IID as X, and all the $Y_{i(x)}$ are IID as $Y(x)$). The Monte Carlo estimator A_n is given in Eq. (3).

$$\mathcal{A} = E[A_n] with A_n = \frac{1}{n} \sum_{i=1}^{n} \widehat{w}(X_i, Y_i) \quad (3)$$

In practical application, Monte Carlo has the limitation of achieving required precision estimate with high computational cost. The Monte Carlo-estimate standard deviation $\sigma^2_{A_n}$ is inverse proportional to $\sqrt{n}$. A quality measure is applied in Monte Carlo estimator considering computational cost and precision into account [20 - 23], as in Eq. (4).

$$\epsilon_{A_n} = \frac{1}{\sigma^2_{A_n} C_{A_n}} \quad (4)$$

where the computational cost is denoted as C_{A_n} and $\sigma^2_{A_n}$ is the variance of A_n. Several variance reduction methods are applied in Monte Carlo such as antithetic sampling, control variates, stratified sampling, and importance sampling to increase the efficiency [17] depending on specific problem.

Here the Monte Carlo technique is used to measure the influence spread and the Clonal search algorithm is used for the influence maximization.

C. Clonal Selection Algorithm

CSA is inspired from the biological immunity system selection process to find optimal solution. To identify higher influence nodes, CSA method is provided with nodes with the probability of influence as inputs. Recently, CSA

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method is successfully applied in fields of optimization, wind power forecasting, power systems commitment unit and pattern recognition. The CSA process steps are given briefly below [24 - 26]:

Step 1: CSA randomly generates the initial antibodies (population) in the allotted range. Neural Network NP-free parameters antibody is applied. Let N denote the amount of the population, then antibody i in generation g is given as in Eq. (5).

$$Z_i^g = [Z_{i,1}^g, Z_{i,2}^g, \dots, Z_{i,NP}^g], \quad \forall i = 1,2,\dots,N \tag{5}$$

Step 2: Objective function is calculated to determine the affinity antibodies with related antigen. Error value is used to sort the antibodies and the antibody with lowest Least Square Error (LSE) is presented first.

Step 3: Antibodies in classified population are copied based on their position. The number of copies from antibody i, is shown in Eq. (6).

$$nc_i = Round\left(\frac{\mathcal{A}}{i}\right), \quad \forall i = 1,2,\dots,N \tag{6}$$

Thus, an antibody with a lower LSE is copied more than an antibody with higher LSE. The number of all copied antibodies is given as in Eq. (7).

$$NC = \sum_{i=1}^{N} Round\left(\frac{\mathcal{A}}{i}\right) \tag{7}$$

Step 4: Hyper Mutation operators are applied to mutate NC antibodies.

Step 5: Computation of the LSEs of mutated antibodies. Among N Main antibodies and NC mutated antibodies, antibodies NS $(NS < N)$ with lowest LSE are chosen. These NS antibodies enter to the next generation.

Step 6: $N - NS$ antibodies are created for the next generation randomly, to increase CSA search diversity. Thus, the algorithm gives an opportunity to escape from local optimums.

Step 7: Generation number is increased from g to $g + 1$. Latest generation best antibody is selected based on LSE minimization as ultimate solution to the CSA or generation count is satisfied. Otherwise, go to the step 2, and continue until termination. The antibodies NS gives nodes with higher influence values which is the ultimate solution.

Clonal selection algorithm analyzes the influence maximization in the community and exhibits higher performance. The experimental results of the proposed IM-CSA method are discussed in the next section.

IV. EXPERIMENTAL RESULTS & DISCUSSION

Influence maximization techniques in social media analyze the spread of information in the social network. These techniques help in the viral marketing for promoting the product that has been launched. Existing methods in Influence Maximization have low performance due to the largescale data and low coverage of the method. In order to solve these problems, IM-CSA method is proposed in the Influence Maximization. The proposed IM-CSA method is evaluated on the two real world dynamic dataset such as HepPh and HepTh. The experiment analysis is carried out to compare the IM-CSA method with the three existing methods - UBI [11], IMM [12] and IRIE [13]. The IM-CSA method is analyzed in terms of the memory usage, execution time and average influence spread. Uniform Activation (UA) is the commonly used propagation model that is applied on each edge.

Dataset: HepPh and HepTh are two real network datasets used in this method for the evaluation purpose. Both network datasets collected with window size set as 3 years with one-month difference in time. The statistics of the network datasets are shown in the Table 1.

Table 1. Statistics of the network dataset

Dataset	Nodes	Edges	Date
HepPh	34.5K	421.5K	1992 - 2002
HepTh	27.7K	352.8K	1992 - 2002

Experiment setup: The simulation is performed in the python 3.6 with networkx and community. The system consists of intel i7 process with 8 GB of RAM and 500 GB hard disk.

Parameter settings: The seed size k is set as 30 and propagation probability is assigned as 0.05. Initial population is 100, clone rate is set as 0.2, and selection size is 10.

Methods/Datasets	HepPh (ms)	HepTh (ms)
UBI [11]	22	17
IMM [12]	38	32
IRIE [13]	50	37
IM-CSA	5	13

Table 2. Execution time

Due to the large amount of data present in the social network, the execution time of the proposed approach is an important factor to be considered for evaluation. The faster Influence Maximization algorithm is required to process the massive data. Table 2 shows the execution time of the proposed IM-CSA and the time taken by the existing methods - UBI, IMM & IRIE to process the two dataset such as HepPh and HepTh which are used to measure the performance of the IM-CSA method. It is evident from the Table 2 that the proposed IM-CSA method has higher performance compared to other existing methods in the Influence Maximization. The execution time of the IM-CSA method for the HepPh dataset is 5 ms and for the dataset HepTh is 13 ms. The clonal selection algorithm has adaptive information units and competitive process for selection that helps to analyze the node effectively with less execution time.

Figure 2 shows a bar graph depicting the execution time of the Influence Maximization techniques used in the proposed and existing methods. It is clearly seen that the

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proposed IM-CSA method has lower execution time compared to the other three existing methods. As discussed earlier, the Monte Carlo method determines the probability of influence nodes based on the sensitive analysis on parameters. Further, the CSA method sorts the nodes in the network based on Monte Carlo influences value and mutation is performed to determine the nodes with higher influence value. In other words, the Monte Carlo performs sensitive analysis to select the nodes with high influence values and CSA method sorts them based on influence values to determine only significant nodes that help to reduce the computation time. Further, it is seen that the proposed IM-CSA method has lower execution time for both the datasets. The proposed method has lower execution time for HepPh dataset than for HepTh dataset. The UBI method has the second lowest execution time in both datasets and is in the range of 17 to 22 ms.

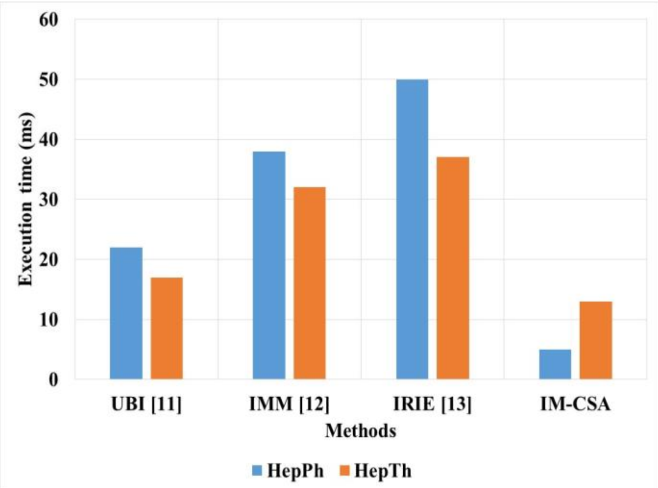

Figure 2. Execution time in influence maximization

Table 3. Average Influence spread

Methods	HepPh	HepTh
UBI [11]	71.02	64.36
IMM [12]	71.24	65.43
IRIE [13]	70.64	64.88
IM-CSA	129.26	117.21

The measured average influence spreads of the various methods have been tabulated in Table 3 and compared with other existing methods to determine the method providing highest influence spread. It is observed that the proposed IM-CSA method has highest influence spread when compared to the other three existing methods which clearly shows the effectiveness of the proposed IM-CSA method. As highlighted earlier, the proposed IM-CSA method employing Monte Carlo effectively analyzes the correlation between sensitivity of the parameters in the network and the influence of nodes to determine the probability of influence nodes and further the CSA approach uses mutation to provide most influence nodes. This shows that the proposed IM-CSA method is capable of spreading information with higher influence. As shown in the Table, the average influence spread of the IM-CSA method in HepPh dataset is 129.26 and in the HepTh dataset is 117.21.

The average influence spread of various methods is measured and compared with the existing methods, as shown in the Fig 3. As evident from the figure, the proposed IM-CSA has higher influence compared to the other existing methods. This is due to the prime fact that the Monte Carlo method identifies potential influence nodes based on effective analysis of probability of node influences based on sensitivity measure of input parameters. Further, the CSA method after sorting the nodes based on their influence values, performs mutation to determine the best influence nodes. Hence the proposed method provides higher influence spread due to the benefits of adaptive information unit and competitive process that enhances the performance of the proposed IM-CSA method.

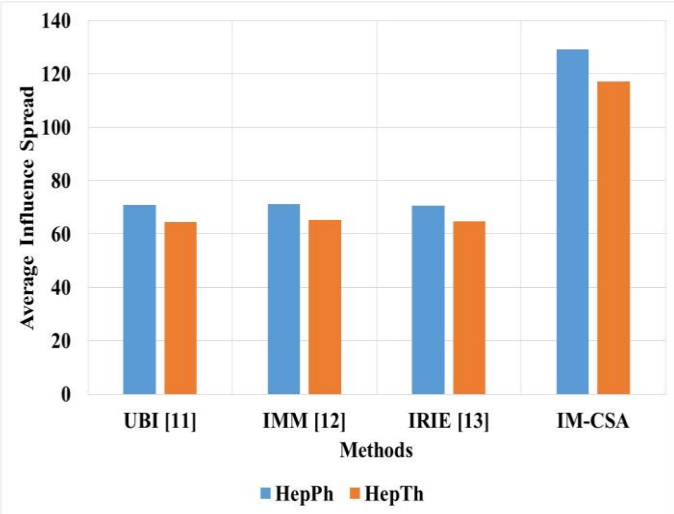

Figure 3. Average Influence spread of various methods

The memory usage of the proposed IM-CSA method is measured for two datasets and compared with each other as shown in the Table 4. It is observed that the memory usage of the proposed method is lower than UBI approach for the HepPh dataset. The proposed IM-CSA method has memory usage of 29.3 MB when compared to the existing method UBI which uses 29.5 MB of memory. It is also noticed that the IM-CSA method has slightly higher memory usage than the other existing methods for HepTh Dataset. Whereas the IRIE and IMM method have lower memory usage, but the performance of these two methods is lower than the proposed IM-CSA.

Figure 4 shows the Bar Chart depicting the memory usage of various methods in the Influence Maximization process. As discussed, the proposed IM-CSA method has lower memory usage than UBI method for the HepPh dataset. It is to be noted that based on the sensitive analysis the Monte Carlo method determines the potential influence nodes and the mutation performed on the influence nodes by the CSA method selects the nodes with higher influence value. The CSA method sorting process removes the nodes with less influence values that significantly reduces the memory usage.

Table 4. Memory usage

Methods	HepPh (MB)	HepTh (MB)
UBI [11]	29.5	26.3
IMM [12]	27.8	24.5
IRIE [13]	28.9	26
IM-CSA	29.3	26.7

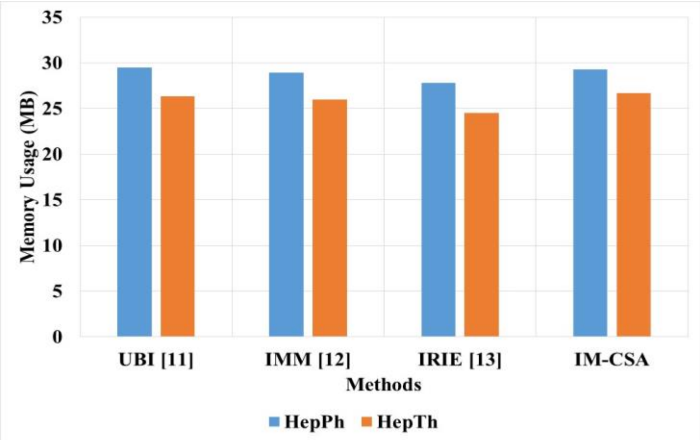

Figure 4. Memory usage of different methods

The results show that the CSA removes the nodes with less influence value thereby significantly reducing the computation time and memory usage of the method. The Monte Carlo method sensitive analysis helps to improve the CSA method to determine the best influence nodes resulting in higher influence spread. Hence, the proposed IM-CSA method has higher performance compared to other existing methods in the Influence Maximization process. Further, the execution time of the proposed IM-CSA method is lower compared to other existing methods. Therefore, the proposed IM-CSA method is found to be more efficient compared to other existing methods.

V. CONCLUSION

Influence Maximization based on social network is the viral marketing technique that increases the spreading of information. Many methods have been proposed in the Influence Maximization to increase the information spreading. Existing methods have the drawback of the low data coverage and less efficiency in the spreading. In this research, CSA is proposed in the Influence Maximization process to increase the efficiency. The proposed method has the benefits of the adaptive information unit and competitive process in the selection that enhances the performance of the information spreading. The community in the social network is detected based on the Louvain method and Monte Carlo simulation is used for independent cascade. The Monte Carlo method is applied to determine the probability of influence of nodes and CSA method sorts the nodes based on their influences. The CSA method finds the best affinity value in the social network using mutation and that helps to increase the information spread. The proposed method is evaluated using real world dynamic network datasets and it is experimentally found that the proposed IM-CSA method shows higher performance than the existing methods in terms of time and influence spread. The future work of the method involves in selecting the initial nodes to increase the performance. Further, more real world dynamic social network datasets will be used to show the effectiveness of the proposed method.

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