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A Systematic Review of Social Network in the Influence Maximization; Louvain Method, Monte Carlo Method and Linear Threshold

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Abstract
Influence maximization is the method of identifying the nodes of the small subsets in the social network which might enhance the spread of data. Most of the methods that have been developed for influence maximization present low efficiency due to the huge information and insufficient to cover more information. In this study, the Meta heuristic method based on Multi-Criteria Decision Making (MCDM) method is discussed and tackles the influence maximization issues in social networks. The influence maximization model applied for the community method classified the diffusion influence modeling into community detection and independently performing the community detection and the model-assisted by the greedy method tackles the influence maximization method. The Community based Context-aware Influence Maximization (C2IM) method utilizes a community-based method to enhance the efficiency of time that significantly decreases the space of search. The community-based Louvain method has solved the influence maximization issues and efficiently identifies the seed nodes. The greedy method has the challenges of large-scale information issues, complexity time, quality problems, and limited seed quality.

Keywords: *Influence maximization, linear threshold, Louvain method, Monte Carlo, Particle Swarm optimization algorithm.*

Introduction

Considering the important challenges in social network influence maximization, several researchers focused on domains such as computer science, social science, politics, economics, and biology [1]. The Data mining technique is widely used for optimizing decision marketing and viral marketing, representing the social network in the nodes as a customer, and Markov random field method is utilized for estimating the customer's influence. [2].

Influence maximization has crucial applications such as advertising targets, viral marketing, formation of opinions, maximization revenue, recommendation personal recommendation, and control of the rumor. [3]. Influence Maximization is a discrete optimization problem, and the greedy hill-climbing algorithm has better accuracy and low-efficiency problems [4]. The challenges of influence maximization have different variants like the location of information, context awareness Influence Maximization, the interest of the user, and developing the topic effectiveness. Compared with the traditional methods which are heuristic-based and greedy, community-based methods have decreased the computational time and enhanced the performance [5].

Viral marketing has played important role in successful marketing and advertising their products and the idea of viral marketing is utilized by some e-commerce industries. The exclusive ratio with degree-modified centrality methods referred to as the semi-local method is proposed to detect the influential nodes from the network in the diverse location [6]. A new method comprising a two-stage iterative framework for the influence maximization of Social networks is proposed in [8]. The Traditional methods include different data models such as the Context-aware Linear Threshold model (CLT), Community Detection Algorithm (CDA), Non-Desirable Nodes Finder (NDF), and Seed Selection Algorithm (SSA). The model assisted by the greedy method has the challenges of unsuitable large-scale information issues, complexity time, quality problems, and limited seed quality [9]. The influence maximization applied the community method that classified the diffusion influence modeling into community detection and independently performed the community detection [10]. The proposed hybrid model of linear threshold and independent cascade methods based on two topic-aware social influence propagation of the model suffered from the problem of efficiency due to generalization lacking.

2. Related Work

FENG CAI et al. [11] have introduced a method called the reverse reachable index method based on a random walk (RSRW) to select potential high-impact nodes from those communities. In this work, the community structure has been used to achieve influence maximization more quickly. To achieve the goal of different weights for different users and the diversification of effect likelihood, the conventional independent cascade model has been enhanced simultaneously. The experimental findings on four datasets demonstrate that CBIM-RSRW can increase the effect of the chosen node while also reducing the time required to discover the highly influential seed node. The nodes with greater influence, nevertheless, took longer to acquire.

Jianxin Li et al. [12] have introduced a metric to measure the community-diversified influence and address a series of computational challenges. A novel CPSP-Tree index and two algorithms have been created. This study also investigates the case where the group definition is ambiguous. Five real-world social network datasets were used in rigorous experimental experiments to confirm the quality and efficiency of the suggested solutions. However, it makes sense in many applications in marketing campaigns that the activated nodes might be studied in the future to disseminate further data.

Shashank Sheshar Singh et al. [13] presented a discrete particle swarm optimization strategy to maximize influence in social networks based on learning automata. The update rule of velocity and position vectors for each action of learning automata was redefined using LAPSO-IM, which was then demonstrated to optimize the local influence evaluation function. The experimental findings on six actual networks demonstrate that the suggested algorithm outperforms DPSO in terms of influence spread while using almost the same amount of computational time. However, the LAPSO-IM generates a very approximate fitness value with a $pop > 150$ for six real-world social networks.

Sahar Kianiana and Mehran Rostamnia [14] developed an effective path-based approach to solve this issue from two complementing angles while modifying the suggested algorithm in large-scale networks. The suggested algorithm's performance in seven real-world networks was assessed through extensive practical trials, and the findings were contrasted with several other cutting-edge methods. The outcomes showed that the suggested algorithm outperformed its competitors by providing an exceptional balance between quality and efficiency. The present techniques' fundamental flaw, however, is that they depend on community structure as well as community detection algorithms.

3 Taxonomy

This Research analyzes different influence maximization methods in the existing models with limitations and advantages. Propagation-based linear threshold models, simulation-based Monte Carlo models, and community detection-based Louvain methods are commonly applied for influence maximization. An overview of the influence maximization models block diagram is shown in Figure 1.

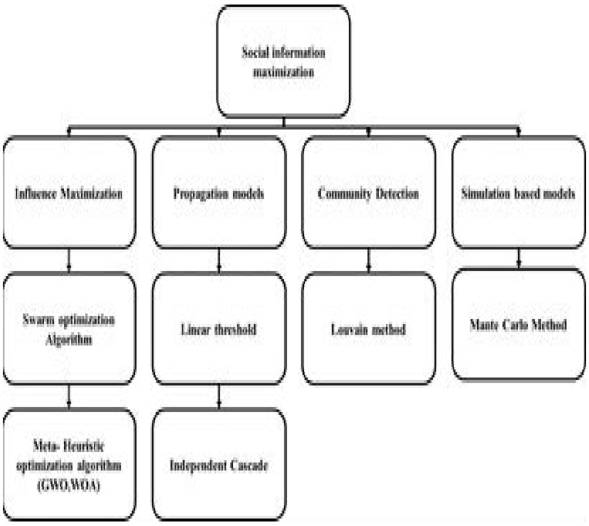

Fig. 1. The Block Diagram of the Influence Maximization Method

3.1 Influence Maximization- Particle Swarm Optimization Algorithm

Eberhard et al. proposed a Particle swarm optimization algorithm (PSO)[15] that is fast and robust in tackling non-differentiable and non-linear issues. The PSO method sustains a large group of particles (swarm), where the model represents each particle as the solution of the candidate in a search for multi-dimensional space. The particle begins at initial random positions and investigates via the variable velocity with search space to identify the minimum or maximum of a set of the objective function. All the best positions discovered between all the particles are called the global best in the whole swarm distribution. The following steps of the PSO algorithm are given below:

Initialization: Create N particles of the population with search space into the velocity and random positions.

Evaluation and update best positions: All the particles of the fitness value in the population are computed by applying the given objective function. It then computes the best position of personal particles by examining their recent fitness values which are better than the Last fitness value. The best position of the population is determined if the fitness of the current value identifies any particle better than the last particle.

Position updates and velocity: In every iteration, each position and velocity of particles are computed according to the following formula,

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 (P_i(t) - X_i(t)) + c_2 r_2 (P_g(t) - X_i(t)) \quad (1)$$

$$X_i(t+1) = X_i(t) + V_i(T+1) \quad (2)$$

Where, $V_i(t)$= position change rate, $X_i(t)$, I = particle position, T= iteration

ω = Initial weight, c_1 = Cognitive

c_2 = Social coefficients and r_1, r_2 = Uniform random no in the range

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$P_i(t)$ = Best value with position and P_g = position of global best particle

Termination: Stop

3.2 Meta Heuristic Model –Whale Optimization Algorithm

The whale optimization algorithm (WOA) [16] is the stochastic optimization algorithm that is used for the search agent's population to identify the optimization issues of the global optimum method

The population-based method uses the search process that begins with generating a new set of solutions randomly for specified issues. The WOA algorithm performs optimization at each step to enhance the candidate solutions. The bubble net feeding behavior is a behavior followed by humpback whales for hunting behavior for detecting and attacking prey.

The humpback whale's behavior is simulated in the encircling mechanism of the WOA method. This is illustrated in fig 2 and. fig 3. The bubble net hunting model uses the equation given in (3).

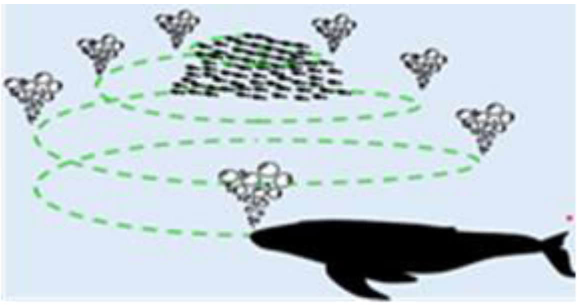

Fig. 2. Hunting behavior of Bubble-net [16]

$$X(t+1) = \begin{cases} X^*(t) - AD\rho < 0.5 \\ D'e^{bl}\cos(2\pi t) + X^*(t)\rho \geq 0.5 \end{cases} \quad (3)$$

ρ = Random number in the range [0, 1].

$D' = |X^*(t) - X(t)|$= Distance of the I the pray whale

b = Constant, l = Random number in range [-1,1]

t = Current Iteration

$D = |CX^*(t) - X(t)|, \quad A = 2ar - a, C = 2r$

r = Random vector in the range [0,1].

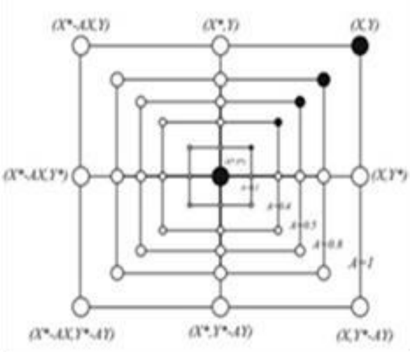

Fig. 3. Encircling Prey and Bubble Net Hunting of Mathematical Models [16]

3.3 Linear Threshold Model

The main advantage of the algorithm is that it decreases the number of investigated nodes without loss of quality to reduce its execution time. Experimental results based on two well-known datasets show that the introduced algorithm is much faster and at the same time more efficient than the state-of-the-art algorithms. The linear threshold [17] processes those Boolean variables of n-tuples that maps to a Boolean single variable. The function is defined by each variable choosing a weight w_i and weight of target w. Consider $G = (V, E, b)$ that$(u, v) \epsilon E$, the live edge method equal to the linear threshold model. Each node $v \epsilon V$ suitable at probability with one edge that equals the edge of the weight X= accessible space and $\delta_X(S)$= Total no of nodes accessible S.

If an edge is selected, it is life else it is dead. Then a diffusion process is carried out on the live edges. The influence of a node is equal to the number of nodes that are accessible from the node. Let X be the accessible space and let $\delta_X(S)$be the total number of nodes that are accessible from members of S;

The calculated influence followed as,

$$\delta(S) = \sum_X \Pr[X] \,.\, \delta_X(S) \qquad (4)$$

$$\delta_X(S) = \sum_{v \epsilon V} I(S, v, X) \qquad (5)$$

$I(S, v, X)$= Index function equal to 1

$$\delta(S) = \sum_{v \epsilon V} \sum_X Pr|X|.I(S, v, X) = \sum_{v \epsilon V} \gamma_{S,v} \qquad (6)$$

$\gamma_{S,v}$=Probability of activation node

In the method, directed paths only considered, Let $P = (v_1, v_{2,} \dots, v_m)$, and $(v_{1,} v_j) \epsilon P$ the edge of the path. The probability of activation path P is:

$$P[p] = \prod_{(v_1, v_1) \epsilon P} b_{v_i, v_j}$$

Therefore:

$$\gamma_{u,v} = \sum \prod_{P \epsilon P(u,v)} \Pr[P] \qquad (7)$$

Ex, The influence of node z and node x is$\gamma_{u,v} = 0.3 * 0.2 + 0.4 = 0.46$, so let $\gamma_{u,v}^{V-S}$ the total influence of node v on node u in the subgraph $V - S$, So $((V/S) \cup \{u\})$ means$V - S + u$. The linear threshold model is used to map a Boolean variable of n-tuples and The Louvain method is used for influence maximization. Finding an optimized path with k members is an NP-Complete problem. Hence a method needs to be investigated that provides a good estimation of the solution within an acceptable period.

3.4 Community Detection Based Louvain Method

The state-art-of-the-art method is called as Louvain method [18]. The local data based on the model is well-matched for analyzing the weighted large networks. It is applied in two steps: Step 1 - The community is assigned to each node selected to enhance the modularity network Q; The gain described from the transformation of a community C into a node i can be evaluated as in Eq.(8)

$$\Delta Q = \frac{\sum C + k_i^C}{2m} - \left(\frac{\sum C + k_i}{2m}\right)^2 - \left[\frac{\sum C}{2m} - \left(\frac{\sum C}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)\right] \quad (8)$$

Where, $\sum C$ = Sum of the weights, C= inside edges, and $\sum C$

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weights of the sum of the incident edges to nodes in k_i, C,$\sum C + K$ is an edge from i, C, m overall networks into the edges; Step 2 – This step makes an original network containing nodes found in the previous community. This process is iterated until an important development of the modularity network is acquired.

Once the networks in the community were detected, the network selected in the best partitions of the subgraph was plotted and the Monte Carlo method based on the cascade independence is calculated.

3.5 Simulation-based Monte Carlo method

The Monte Carlo method [19] is utilized to processing of the independent cascade into the maximizing influence method. Most of the research utilized the integration of the Monte Carlo method (computing financial, physics, and transport radiation) to estimate the integrals of multidimensional that can be Random variables W of an expectation A as in Eq (9).

$$\mathcal{A} = E[w] \int_{D_X} dx\, p_x(\Delta Q) \int_{D_{Y(X)}} dy\, p_Y(y;x) \widehat{w}(x,y) \quad (9)$$

Where random variables of vectors are X and Y,(domains are defined there$D_{Y_{(x)}}$and D_X as associated densities of probability $p_Y(y;x)$ and p_X, and random variable W, the function $\widehat{w}$ defined that Y and X associates $W = w(X,Y)$. The Monte Carlo integration method allows estimating an unbiased estimator sampling A by independent n and distributed identically random variables X_i Y_i. The following equation(10) is defined by the estimator of Monte CarloA_n.

$$\mathcal{A} = E[A_n] with A_n = \frac{1}{n}\sum_{i=1}^{n} \widehat{w}(X_i, Y_i) \quad (10)$$

The practically utilized by the integration of Monte Carlo is the limitation of the computational prohibitive cost needed to acquire an evaluation with the needed precision (The derivation $\sigma_{A_n}^2$ of the inversely proportional to $\sqrt{n}$). This research has motivated to increase the efficiency which is a measure of the quality of the Monte Carlo estimator taking into account both its computational cost and precision [20 - 23], as in Eq. (11).

$$\epsilon_{A_n} = \frac{1}{\sigma_{A_n}^2 C_{A_n}} \quad (11)$$

Where the variance is A_n and C_{A_n}as a computational cost needed to estimate an A_n. The focus on the main problem, different variance-decreasing methods may

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allow for maximizing the efficiency (e.g. stratified sampling, importance sampling, antithetic sampling). The short note presents a method that improves the Monte Carlo efficiency for issues where the unconditional sampling of the random variable X is computationally expensive. Whereas the only contribution X is the variability of the conditional random variable$Y$. The principle to review the Monte Carlo estimator in that sampled Y is often more than$X$. The analysis of the present short notes allows the specific to present an easy way to implement a system to manually compute the samples of an optimal number Y per sample X. The spread influence values are considered by the Monte Carlo Method.

4. Comparative Analysis

The Influence maximization method including analysis in the social network is a crucial marketing method that enhances the spreading of data. The influence of social media is a part of marketing that describes the ability of individuals to affect other persons thinking in an online social community. The comparative analysis of the influence maximization is presented in Table 1

Authors	Methodology	Advantages	Limitations
Baghbani et al. (2021) [1]	• The linear threshold method in the influence maximization issues solved by utilizing the method of linear programming with multiplication, linear programming and rounding randomized (MLPR)method	• The MLPR techniques utilizing Linear programming (LP) method tackles the problem of influence maximization in the Linear threshold issues. • The model assisted by the Linear programing (LP) method addresses the problems such as CBC, CPLEX and GLPK.	• The MLPR method has the limitations like non-incremental and seed size runtime does not increase. • The model assisted by the LP has the limitations of objective function which is not easy to specifically be defined. • The model assisted by the Monte Carlo (MC) method has the limitations such as inefficient computational and parameter poor.
Samir et al. (2021)[2]	• The Louvain K-Shell-Generalize (LKG) method, a hybrid scalable method to identify the influential top user's in networks	• The model assisted by the Gray wolf optimization algorithm tackles the IM problem forming as an optimization issues with function	• The model assisted the community detection method has the limitations such as effectiveness of cost and maximization of spread size influence and interconnectivity communities of clear rules

	of social, acceptable for both undirected and directed networks.	of cost. • The model addresses the problem of effective cost solution for the influence maximization issue. • The model assisted by the community detection method decrease the complexity and solves the research issues.	lacking. • The model assisted by the Grey wolf optimization method has the limitations such as low accuracy, bad ability of local searching and convergence slow.
Biswas et al. (2021) [3]	• The meta heuristic method based on Multi Criteria Decision Making (MCDM) method tackles the social networks in influence maximization issues.	• The model assisted by the greedy algorithm (GA) address the approximation solution of good quality with IM issues. • The model supported by the Simulated annealing (SA) tackles the optimization problem and signed networks in the influence maximization issues.	• The model assisted by the Ant colony algorithm (ACO) has the limitations such as Phase stagnation, convergence slow, exploitation and exploration rate. • The model assisted by the genetic algorithm and evolutionary algorithm has the limitations such as expensive computational, complexity with non-scale well, clear phenotype genotype distinction is lacking.
Qiu et al. (2021) [4]	• The new model of the Local-Influence-Descending Differential Evolution (LIDDE) method tackles the influence maximization (IM) issues.	• The model assisted by the swarm intelligence method tackles the issues such as LAPSO-IM, DPSO, ELDPSO, DDSE and influence optimization problems. • The model assisted by the differential original evaluation method tackles the optimization of continuous problems	• The model supported by the swarm optimization algorithm has a limitation such as local optimum falling easily, dimensional space is high, convergence low rate.
Wang et al.(2021)[5]	• The new method of the community overlapping structure based on influence maximization	• The model assisted by the greedy algorithm tackles the influence maximization of the hard NP problem,	• The model assisted by the greedy algorithm has the limitations of does not identify the globally optimum solution due to not considering for all

	method and coverage gain of node.	decrease the computational and performance increased	the information.
Kumar et al. (2021) [6]	• The exclusive ratio with degree modified centrality methods referred to as semi local method to detect the nodes influential from the network in the diverse location.	• The model assisted by the discrete optimization and greedy techniques tackles the influence maximization issues.	• The model assisted by the node centrality has the limitation of local node data only captured. • The model assisted by the pretty good privacy method has the limitation of complicated administration ,compatibility problems and more complexity.
Tian et al.(2020) [7]	• The hybrid models of linear threshold and independent cascaded methods based on two topic-aware social influence propagation of models.	• The model assisted by the heuristic system tackles the problems of meta learning in the topic-aware influence maximization (TIM) issues. • The model assisted by the embedding node tackles the influence maximization generic issues.	• The model suffering from the problem of efficiency due to generalization lacking.
He et al. (2019) [8]	• The new method of the Social networks in the two stage iterative framework for the influence maximization. • The Results applied the two hop measure and last iteration, the First-Last Allocating Strategy (FLAS) method computed the benefit for the spreading each node. • The Removal of the Apical Dominance (RAD) method to decide the nodes of seed from nodes of	• The model assisted by the hybrid methods of iterative ranking with influence estimation methods solves the influence maximization problem. • The model assisted by The large scale network based on the community based method for influence maximization (CoFIM) solves the IM issues.	• The model has the limitations such as accuracy unstable and efficiency unguaranteed. Low efficiency and large scale networks not acceptable. • The model assisted by the iterative method has the limitations such as needed extra resources and attentions management, smaller projects not suitable.

	candidate.		
Singh et al.(2019) [9]	• The Community based Context-aware Influence Maximization (C2IM) method utilize a community based method to enhance the efficiency of time that significantly decrease the space of search. • The Traditional of different data models such as Context-aware Linear Threshold model (CLT), Community Detection Algorithm (CDA), Non-Desirable nodes Finder (NDF) and Seed Selection Algorithm (SSA).	• The model solves the problems like influence maximization, efficiency of time, accuracy and seed effectiveness. • The model assisted by the community based methods solves the influence maximization issues and efficiently identify the seed nodes. • The model assisted by the Non-Desirable Nodes Finder (NDF) method address the nodes are undesirable.	• The model assisted by the greedy method has the challenges of large scale information not suitable, same complexity time, quality problem and seeds quality limited.
Huang et al.(2019) [10]	• The influence maximization applied the community method that classified the diffusion influence modeling into community detection and independently performing the community detection.	• The models tackle the problem of choosing set size of seed nodes and maximize spread influence in the social network.	• The model assisted by the latent dirichelet conditions (LDC) has the limitations such as topic modeling is not suitable for dataset and length documents more short. • The model assisted by the seed selection and community detection has the limitations such as complexity of nontrivial, scalability and efficiency also limited.

Conclusion:
Influence maximization applied in the social network is the crucial marketing that enhances the spreading of data. Most of the models have been developed in the influence maximization that enhances the data spreading. The State of the method has the limitations such as low information coverage and spreading in low efficiency. In this study, the Meta heuristic method based on Multi-Criteria Decision Making (MCDM) method is discussed and tackles the social networks in influence

maximization issues. The influence maximization model applied for the community method classified the diffusion influence modeling into community detection and independently performed the community detection and the greedy method tackling influence maximization issues. The community-based Louvain methods solve the influence maximization issues and efficiently identify the seed nodes. The hybrid model of seed selection and community detection has the limitations such as the complexity of nontrivial, scalability, and limited efficiency also. Future work is required to develop a method to determine the original value to enhance the performance.

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