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Influence Maximization in Social Networks : A Literature Review

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ABSTRACT

The main aim of Influence Maximization (IM) in a given social network aims is to find set of seeds of group of users or individuals who are responsible for maximum information diffusion or dissemination of information, opinion or ideas. Since decades, Influence Maximization remained an active area of research specifically in analysing Social Networks. Due to the practical and potential importance of this problem, it has been studied in different variations and above if various states of art algorithms and methodologies have been proposed. This paper introduces literature review of various existing and ongoing works in and around IM problem in Large Scale Social Networks (LSSN) focusing on location property. This will help the researchers to understand the existing work on design, methods and algorithms adopted so far.

Keywords : Location Based Social Networks, Influence Maximization, Big Data Analysis, Diffusion Models

I. INTRODUCTION

Abrupt evolution of large scale social networks(LSSN) such as Twitter, Facebook, QQ, QZone, Skype, Tumblr, Viber, Instagram, WeChat, WhatsApp and advances in localisation technologies and techniques have essentially enhanced social networking services which allows a number of users to easily share their geo- spatial location and location related content in the physical world; whereas other users are now able to enlarge their social networks using various features provided by these services like friend suggestions by Facebook using location history gathered. This Location data has the capability to bridge the gap between providing deeper understanding about users, user preferences and behaviour. Much information about location can be extracted from a tweet; moreover links, nodes, hash-tags, topic-of-message like features was found contributing to diffusion.

IM is the domain in Social-Network Analysis that has gained much attention in few decades. In this problem a node set is selected so that influence spread can be maximized in social network. Identification and seed selection in social network is widely applicable in the areas of Sociology, Biology, Economy and Marketing. The common objective in the study of such networks is to find minimum seed set that has the capability to influence large population. In term of Spatial, the problem is called as Socio Spatial Influence Maximization and when this problem is studied using parameter location then this problem is termed as Location Aware Influence Maximization (LAIM).

Zhou[22] found IM came from viral marketing for product promotion which took advantage of word-of-mouth effect. The authors found that research was carried out only on online phase whereas business model connects both online and offline aspects, location property played a prevalent role here. The authors worked on the idea to bring online customers to offline shops. To explore the offline user's location preferences behaviour, location property and historical location information are required. The location information can be easily captured from user behaviour, check-in records and mobility information of user. There could be various factors that could determine user mobility to a location like the user distance to a particular location, friends suggestions, user interest, social relationship influence [22,25,27] whereas Hossinpour et.al.[34] supported that most influential nodes had spatially distributed neighbours and suggested that the determinism of influential users should be such that highest number of followers are inside and around Query Point or Query Region. Identification of influential nodes should be dynamic and immediate. The neighbour nodes were analysed using the concept of line graph. There are four phases or states namely: online-active state, in-active state, offline-active state and closed state. Running time and influence spread will increase with the increase in number of product locations [22,25] and spatial distribution increase with increase in number of nodes[34]. Zhang [25] laid emphasis on multifactor propagation and worked in two phases for the situation when there is a multiple product location: offline and online.

II. RELATED WORK

Social-Networks can be tabulated in the form of relational databases and can be defined as social entity sets such as organisations, people and crafts having interactions or relationships among them. What is dynamic in nature and consists of complex connections, social network is either directed or undirected. Now-a-days people have started to integrate the most popular social-networks and these social- networks have the ability to contribute in changing community behaviour, communication and information nature. Social-Network can be measured alike graphs which can capture information of people in nodes and the connections between them are represented with edges. In a social network there are basically two types of nodes: active and inactive. Nodes receive information from their neighbours and change the state to active and this process continues.

The main exchange of information took place along weak ties loose acquaintance style connections whereas strong ties were responsible for knowledge generation, preservation and decision making[28] Information is social network disseminates through walls posts, in the form of messages and one-bit pokes form. The communication between the members of social network with their neighbours whether online or offline was discontinuous. Information spreading takes place because of discrete communication steps and frequency of occurrence of these events have a strong impact on the communication pathways; hence forms dynamic communication backbone [6].

Hossenpour et.al.[34] found that people trusted their relatives most and what the most valuable nodes for direct recommendation. The line graph has the tendency to preserve all the information of a network; relationship between the nodes; indirect neighbours are also considered with direct neighbours. The author's primary focus was on reduction of computational load. Overlapped vertices could also be considered due to line graph.

III. SOLUTION METHODOLOGIES

IM problems are non-deterministic NP hard problems, so there doesn't exists any optimal solution to the problem. Taking this hardness issue under consideration, over the years many researchers have developed various solutions to the problem, which were grouped and diagrammatically represented in figure1. This paper covered the important taxonomies and has grouped them based on their working principle and described them below:

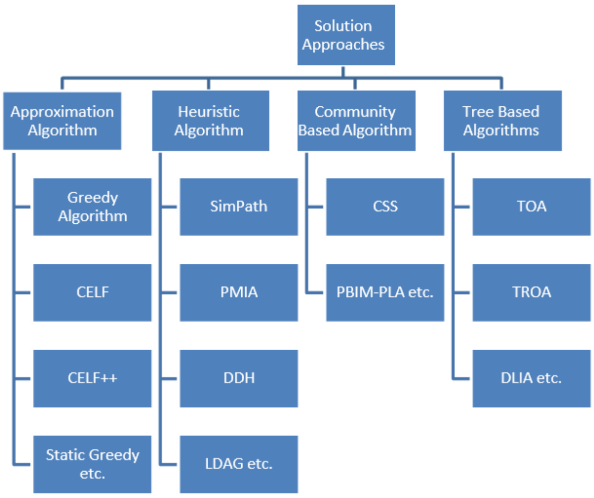

Figure 1 : Solution approaches to Influence Maximization problem

Approximation Solutions

The approximation algorithms focused on accuracy and efficiency meanwhile scalability and effectiveness were neglected. The algorithms give solution close to optimal solution but don't work well with large scale social networks because as the size of network grows, the running time of algorithms grows heavily.

Heuristic Solutions

The heuristic algorithms were designed to overcome the issues of approximation algorithms and to work reliably with large scale social networks. It improves the running time of algorithms and reduced the high computational cost and complexity, although accuracy was inadequate.

Community Based Solutions

In these solutions, the social networks were divided into communities due to various favourable properties of communities. This is an intermediate step in which communities were detected in underlying social network and bought down to community level, with this scalability is highly improved. These solutions don't give any worst case time bound.

Tree Based Solutions

In these solutions, the user information, check-in data, mobility data, spatial, topic and geographical information of users are stored in the nodes of tree. This is an intermediate step and extracted information could be utilized to select most influencing users and compute their topic preferences. The trees were traversed in depth first order and several algorithms were proposed based on this method. In LBSNs the paramount property i.e. location bridges between real world and online social networks. Some of the popular websites that store location data are: FourSquare, Gowalla, Brightkite, Twitter, Facebook.

Information diffusion

In Computation of influence spread, Diffusion Models plays the prominent role in IM problem. Societal influence is a result of information diffusion and various diffusion models are adopted for the study of diffusion process and capture the collective behaviour of agents.

Diffusion was firstly studied in 1897 by Sociologist Gabriel Tarde as a descriptive concept when process of emulating beliefs, users motives transmission was thrice as diffusion in social network. Diffusion has been applied to many fields such as dissemination of knowledge about news among users, medical drugs among doctors diffusion of Smart Card Technology diffusion of news policy and Technology adoption of hashtags diffusion of microfinance diffusion patterns of scientific articles and many more.

Diffusion models

Hu et.al.[20] Worked on IM in social networks and defined influence with diffusion models , which explicitly represented process of step-by-step information diffusion dynamically. According to the authors online social- networks were a large platform of information dissemination and the data-warehouse has a number of potential applications. The authors found that using a new product or innovation: cascade effect should be put forward to a large population. However, it was a challenge to select influential users set with less cardinality than given number due to budget issue. Diffusion function is non negative, monotone and submodular [7].

Independent Cascade Model(IC): a stochastic information diffusion model in which information flow in network dynamically through cascade. Information in the IC model disseminates in discrete steps is sender centric. In this model nodes work in two states namely active state and inactive state.[2,4-7,23,26,27]

Linear threshold model(LT) is a probabilistic model which was used by Kempe et. al.[4] for the first time in their seminal work. In this model, all the activated neighbour nodes will try to activate that particular node and the activation process success will depend on the summation of incoming active neighbours, where the activation probability of activated neighbours should be greater-than or equal-to the Node
Threshold.[4,6,10,14] In this model negative influence is possible which was used by Zhu et.al.[28].

Mixed Diffusion Model considers status of the targeted nodes. This model initiated with the primary set of seed nodes. Now this primary set had a single chance to activate their neighbours similar to ICM. Alternate to an arbitrary propagation probability for influencing their neighbours and according to LTM, it considered only a part of active neighbours of targeted node. When the aggregate weight of these nodes and their neighbour nodes exceed the threshold, the targeted nodes change their state from inactive to active.

Multi Factor Propagation (MFP) worked in the situations when there are multiple product locations including online and offline phase. In offline phase several factors were considered: the distance, user interest and friends evaluation to determine whether user visits product location. [25]

In Weighted Cascade Model (WC) the edge weight in graph is reciprocal to node degree. This model was also used by kempe et al.[4]. Polarity Independent Cascade Model is extended by introducing quality factor q in signed social network to incorporate negative influence. In Maximum Influence Arborescence (MIA) model influence based similarities are calculated between users based on spectral clustering. LAIM is NP-hard under MIA model and its influence spread was found sub-modular and monotone.[28] Under the MIA model, there is no ambiguity and nodes are activated only through maximum influence path having maximum activation probability. Moreover, MIA prunes insignificant path through threshold.

Two Phase model consists of transition between the offline behaviour and the online behaviour. The users will experience offline if these are influenced online by other users before determining the acceptance of the product. There are two diffusion phases: online and offline; and four states of a user: in-active, online- active, offline-active and closed. [17,18]

Path based Influence Maximization (PB-IM): It considered high interactive connectivity community property to tackle micro level issues. Weights were added to paths from a node to other reachable node tom estimate the influence spread of a node in the community. It performs simple traversal of paths, which increase the speed of diffusion. It accompanied of Two Steps: Unit Community Detection and Community Merging. [29]

Community based Influence Maximization (CB-IM): The Influence spread in community was re-evaluated for only those nodes wherefrom seed has been selected. It reduced re-evaluation number by addressing the Macro level issues.[29]

Hybrid Influence Maximization: To solve the orthogonal issues at macro and micro level Ko,Cho,Kin[26] introduced hybrid influence maximization diffusion model. It contains two stages: community detection and seed selection.

Gong Diffusion Model: To imprecise the influence inside the two-hop area of a node set, a Local Influence Estimation function is employed. This function is used to compute the one-hop and two-hop influence spread both in IC models and WC models.[23]

Absolute Influence Model: To avoid insignificant influence among locations, the number of bridging visitors should be greater than pre-determined threshold.

Relative Influence Model: When there is a huge difference between the numbers

Approximation algorithm

Almost all the Optimization problems in the world are NP hard and no deterministic algorithm could exist to solve this problem in polynomial time. Therefore, it is fitter to turn to an approximate solution to the problem within nominal time. It will guarantee worst case solution quality but is time consuming. kempe et. al. [4] were first to propound IM problem. The authors manifest it NP-hard and formulated a simple greedy algorithm that picks the most influential nodes in every step and repeat this step n times to comprise the seed set with n nodes. However the greedy algorithm executes Monte Carlo Simulations that is time consuming process and less efficient; moreover the number of times influence function σ(A) calculated was quite high. The authors proved that influence spread with simple greedy algorithm is 63% of the optimum seed set. It provides influence spread within (1-1/e) guaranteed. Despite this it suffers from scalability issues. The authors had propagated influence in network using Stochastic Cascade and named it as IC, WC and LT Model.

Researchers ameliorate this algorithm in two ways one by reducing the number of σ(A) calls and another by efficient calculation of σ(A) calls. For boosting of scalability problem Leskovec et. al. [6] formulated an improvement approach CELF. CELF utilised the Sub- modular property of IM significantly reducing the evaluations on influence spread of vertices. It accelerates running time up to 700 times speed up. Goyal et. al. propounded and extension of CELF and named it is CELF++ by further reducing the number of σ(A) calls. CELF++ was proved to be 35- 55% faster than CELF. However, these algorithms of bridging visitor, different threshold should be taken for different locations. couldn't be applied to large scale social networks.

Chen et.al.[5] housed Centrality based methods to find influential nodes of high Centrality value. Properties like Betweeness and Eigen vector Centrality were used to select early adopters whereas Degree centrality was used to select opinion leaders.

Cheng et. al.[17] worked on the dilemma between accuracy and scalability and demonstrated static greedy algorithm which worked in in 2 steps. Firstly it ran P number of Monte Carlo simulation where edges were refined based on analogous diffusion probability. In phase II it took an Empty set and then seed nodes were selected having maximum average marginal gain selected from sample snapshot. This step is repeated until k nodes were selected. The computational time was reduced by two orders of magnitude. It outperforms Maximum Degree

Heuristic, Degree Discount Heuristic, PMIA, MIA algorithms in influence spread.

It was further improved by Chen et.al[7] by reducing its running time. They formulated two algorithms new greedy and mixed greedy. In new greedy algorithm the edges which were not useful in influence propagation were eliminated. To propound Mixed Greedy algorithm, the Greedy algorithm was combined with CELF. The running time of CELF was reduced effectively about 15% to 34%, keeping influence spread equivalent to original algorithm.

The greedy algorithm was further laboured to retrieve top-k initial seed nodes and named as Extended Greedy Algorithm. This algorithm used the monotonic and sub-modular property of independent cascade model. Idea behind this was the selection of a vertex into seed set with influence spread maximum at present stage. To estimate the lower bound of influence spread 1-hop or 2-hop friends relationship was used. The enhanced greedy algorithm maintained the approximation ratio of simple greedy algorithm and MFP model to make influence spread and proved them better than IPH and RIS-DA algorithms in varying number of product locations[25]. In order to reduce the computational time and proved its superiority over Degree Discount Heuristics, Maximum Degree Heuristics and PMIA algorithms in term of Accuracy and Scalability Cheng et. al[17] proposed Static Greedy Algorithm. R number of Monte Carlo simulations was run and edges were selected based on associated diffusion probability. Initially an empty set was taken and process was repeated until k nodes were selected having maximum average marginal spread in all sampled snapshots.

Table 1 : Approximation Algorithms for Influence Maximization Problem

Name of Algorithm	Authors and References	Asymptotic Time Complexity	Model Used	Benchmarks
Simple Greedy	Kempe et. al.[4]	O(KmnR)	IC & LT	Accuracy
New Greedy	Chen et.al. [7]	O(KRm)	IC	Efficiency
New Greedy	Chen et.al. [7]	O(KRTm)	WC	Efficiency
Mixed Greedy	Chen et.al. [7]	O(kRm)	IC	Efficiency
Mixed Greedy	Chen et.al. [7]	O(KRTm)	WC	Efficiency
CELF	Leskovec [6]	O(KmnR)	IC&LT	Efficiency
CELF++	Goyal et.al.[14]	O(KmnR)	IC&LT	Efficiency
Static Greedy	Cheng et. al.[17]	O(nlogn + m)	TP	Accuracy & Stability
Extended Greedy	Zhang et.al.[25]	$O(\|V\|\log\|M\|^{\|N\|}+2\|V\|+k\log\|V\|)$	IC	Efficiency & Effectiveness

Table 2 : Heuristic Algorithms for Influence Maximization Problem

Name of Algorithm	Authors and Reference	Asymptotic Time Complexity	Adopted Model	Benchmarks
DDH	Chen et. al.[2]	O(klogn+m)	IC & WC	Efficiency, Scalability
LDAG	Chen et.al.[10]	$O(n^2+kn^2logn)$	LT	Scalability, Efficiency
SP1M	Kimura and Saito[5]		IC	Scalability, Efficiency
PMIA	Chen et.al.[27]	$O(nt_{i\theta}+ kn_{o\theta}n_{i\theta}(n_{i\theta}+logn))$	IC	Efficiency, Effectiveness
SimPath	Goyal et.al.[14]	O(KmnR)	LT	Efficiency, Effectiveness
DPSO	Gong.et.al.[23]	$O(k^2logk.n.n.\overline{D}^2.g_{max})$	IC&WC	Efficiency, Effectiveness
TPH	Zhou et.al.[18]	O(klogn + m)	TP	Efficiency, Effectiveness
MR	Zhou et.al.[18]	O(nlogn + m)	TP	Efficiency, Effectiveness

Community based solutions Community is a subset of seeds connected compactly amongst and sparsely connected with others. Most of real world social networks comprise a community like structure in it. In Network Analysis, Community Detection is very important problem and fascinated efforts from various disciplines. Li et. al.[29] defined community to be a group of users with similar patterns who contact frequently and are probably to influence each other inside the group. To solve the Macro level issues Ko, Cho & Kim [26] used the property of community structure: influence spread in a single community is similar to whole social network, neighbour communities have higher influence spread that influences the farther community nodes, nodes inside a community are connected tightly.

IM-PLA algorithm finds the influential nodes within a community that relied on label propagation. However, the algorithm has smaller influence spread then Greedy algorithm and it only considered the degree of each node. Whereas, Wang et. al.[35] simplified the original graph simply by where edge weight is larger than predefined threshold. It accurately estimated the influence spread in terms of running time only. The influence spread between communities was based on live edges. They found influential nodes seed set in mobile social networks; however this algorithm was found less efficient than Community Based Seed Selection Algorithm [30].

If influence was very close to whole network then the community structure is of very high quality [26]. Path based community detection outperforms [35] in terms of accuracy and performance. It relied much more on edges rather than live edges and found communities which were more desirable for seed selection. The influence spread of a node is computed by adding the weights of all paths in a single traversal of path.

Li et. al. [29] computed the influence by implemented MIA diffusion between uses and propounded an effective CSS algorithm. The algorithm effectively found seed based on offline PR-tree based indexes which precomputed user's community based inferences and the marginal influence of those who would be selected as seeds with high probability online preferentially. They adopt the Spectral Clustering Algorithm for Directed Weighted Graph algorithms and defined the social influence based similarity metric under this category which hence brings down the problem at community level with the use of community detection strategy on the underlying social networks at intermediate level. These algorithms don't give any worst case bound on influence spread. The adopted methodology was found much efficient than other methods with same influence spread. Communities were also detected between nodes on underlying social network. Most of the algorithms were topological structures oriented and attempted to find non overlapping communities (Modularity Maximization, Random Walk based method, Spectral Clustering). However some work also focused on overlapped communities (Bai algorithm, Ma et. al. algorithm).

Tree based algorithms

The beneath principle behind tree based algorithms is storage of user information inside the nodes. A binary tree was decomposed from series parallel graph where each node represented as series- parallel graph and leaf node represented the edges of subgraph. Influence spread was computed in this special case of directed graph.

In PR-tree index structure [29], location information and information about the geographical preferences of users was not possible to store. Depth First Order tree traversal leads in efficient identification of the targeted users. Best on this PR-tree, CSS algorithm was devised which frequently selected the users with most unpropitious influence using offline indexing in their communities. Henceforth, to find the targeted users and derive their preferences efficiently Su et. al.

[27] devised a TR-tree based index structure; the tree was then traversed in depth-first-order to verify in records of users as the nodes of the tree contained topic preferences. However it was a challenge to obtain preferences of targeted nodes for the given query. Thereafter the authors demonstrated three algorithms : TOA, TROA and DLIA. Although TOA method was used for seed selection, approximated initial influence might not be accurate. Moreover maximal geographical preferences were obtained and all candidate seeds were inserted into Priority Queue whereas TROA inserted candidate seeds with large influence in Priority Queue one at a time. TOA and TROA still took large time in computation of marginal influences exactly for some candidate nodes, in order to further improve DLIA algorithm was propounded.

Zhang et. al [25] proposed hybrid inverted R tree(HIR) based on R tree and inverted tree for solving multi location influence maximization problem and for improvement in search efficiency of offline phase. The index structure of HIR- tree was disk resistant and page size was of 8kb. HIR-tree simultaneously computed three factors of offline phase such as speed up of the query of each user potential consuming location, pruning of search space, and give its time complexity as O(|V| log|M||N|) and space complexity as O|N|. HIR-tree is spatially partitioned and utilised in extended greedy algorithm [8].

IV. DISCUSSIONS AND CONCLUSION

In this paper, we briefly discuss the work done in the area of Influence Maximization and give contribution to the theoretical aspects of existing models, methods, algorithms and state-of-art-methodologies. Influence Maximization is studied taking location as an important parameter and finds that there are still lots of room for improvements and further research. We found that in the early stage accuracy and efficiency were considered important parameters for algorithms development but as the network grows; thirst for efficiency and effectiveness lie at the heart. Moreover, because of rapid evolution and dynamic nature of social networks and enhancement of technology, new algorithms need to be designed for application specific usability, scalability and effective memory efficient computations. It could be further researched from different perspectives due to its wide applicability in the areas of Computational Science, Recommendation systems, Social Science, Medical Science, Natural Science,

Mathematics, Epidemiology, Marketing, Cognitive Science, Bio-informatics and Physics.

Based on the underlying phenomena in selection of seed node, we have divided the proposed solutions into four types: Approximation solution, Heuristic solutions, Community based solutions and Tree based methods. Along with it we have also analysed the benchmarks on which the research was carried out; and discussed the solidity and shortcomings of these approaches.

In Future research could be carried out by incorporating different models and methods. We strongly recommend the incorporation of community-based methods with tree-based methods. Community Detection and Community Clustering fields are actively studied but there is need for improvements in efficiency.

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