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Agent Based Smart Influence Maintenance in Social Networks

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ABSTRACT:

In different domains, like marketing, e-business, and social computing, Most existing studies focus on how to maximize positive social impact to promote product adoptions based on static network snapshots. Such approaches can only increase influence in a social network in short-term, but cannot generate sustainable or long-term effects. In this system, we will maintain long-term influence in a social network and propose an agent-based influence maintenance model, which can select influential nodes based on the current status in dynamic social networks in multiple times. Within the context of our Analysis, the experimental results shows that multiple-time seed selection is capable of achieving more constant impact than that of one-shot selection.

Keywords: – Influence maintenance, influence diffusion, long-lasting influence, agent-based modeling.

I. INTRODUCTION

In various domains, such as e-business, marketing, and social computing. Most studies cases focus on how to increase positive social impact to stimulate product adoptions based on static network snapshots. Such approaches can only increase influence in a social network in short-term, but cannot generate sustainable or long-term effects. In this system, we will maintain long-term influence in a social network and propose an agent-based influence maintenance model, which can select influential nodes based on the current status in dynamic social networks in multiple times. Within the context of our investigation, the experimental results indicate that multiple-time seed selection is more capable of achieving more constant impact than that of one-shot selection. This System claim that influence maintenance is crucial for supporting, enhancing and assisting long-term goals in business development. The proposed approach can automatically maintain long-lasting impact and achieve influence maintenance [1].

With the prevalence and advancement of the Internet, on-line social networks have become an important and efficient channel for information propagation. The propagation relies on one of the social phenomena, i.e., social influence, indicating that one's opinions or behaviors are affected by his or her contactable neighbours in the social network [2]. Influence message is a Prevalent and tactile portray of social influence, which 'travels' mostly through the network topologies via users' sharing and posting behaviors. By leveraging the power of social influence, a great many business owners attempt to expand the market and increase the brand awareness through the 'word-of-mouth' effect. In recent years, influence maximization draws tremendous attention to both researchers and domain experts. Influence maximization attempts to identify a set of influential users committed to spreading a piece of influence message to their neighbours, such as adopting a product, expecting that they can propagate influence and maximize the positive impact across the entire network [3]. The selected group of influencers is called seed set, and the seeding process is named as seed selection. From a business perspective, influence maximization corresponds to short-term marketing effects, which tend to cause sudden profit spikes that rarely last [4]. Whereas, long-term marketing is typically more beneficial since it emphasizes on long-term and sustainable business goals. Specifically, long-term influence can establish brand awareness and continually produce results even years down the road; thus, without having long-term marketing strategies, shortterm success may be short-lived [5]. Motivated by this background, in this research, we aim to achieve constant impact for longterm marketing by investigating the preservation of a particular type of influential situation or status, called influence maintenance. There are many limitations for short-term (or even oneshot) influence maximization when being utilized in real business cases. First, it focuses on how to maximize the influence of one-shot investment. Based on the risk management theory and best practice [6], with the same budget, the multiple-time investment could enable a better business strategy. For example, in a stock market, very few investors purchase stocks with all the money at only one time. Second, a great many business owners intend to expand the lifespan of influence, so that the brand awareness can be enhanced and increased in the long run [7]. Influence maintenance not only cares about the quantity of users being affected but also considers constant influence impact. Influence maintenance needs to be supported by a formal influence diffusion model which possesses two attributes:

(1) The model is capable of capturing the temporal feature of a social network;

(2) The model can monitor the status of a particular influence.

II. LITERATURE SURVEY

1. Pattern-Based Mining of Opinions in Q&A Websites:

This study gives Informal testimony contained in resources such as Q&A websites (e.g., Stack Overflow) is a precious resource for developers, who can find there examples on how to use certain APIs, as well as opinions about pros and cons of such APIs. Automatically identifying and classifying such opinions can alleviate developers' burden in performing manual searches, and can be used to recommend APIs that are good from some points of view (e.g., performance), or highlight those less ideal from other perspectives (e.g., compatibility). They propose POME (Pattern-based Opinion MinEr), an approach that leverages natural language parsing and pattern-matching to classify Stack Overflow sentences referring to APIs according to seven aspects (e.g., performance, usability), and to determine their polarity (positive vs negative)[15].

2. Complementary Aspect-based Opinion Mining:

This Research work provides Aspect based Opinion Mining concept, Aspect-based opinion mining is finding elaborate opinions towards a subject such as a product or an event. With explosive growth of unequal texts on the Web, mining aspect-level opinions has become a promising means for online public opinion analysis. In particular, the explosion of various types of online media provides diverse yet complementary information, bringing unprecedented opportunities for cross media aspect-opinion mining. Along this line, we propose CAMEL, a novel topic model for complementary aspect-based opinion mining across asymmetric collections. CAMEL gains information correlative by modelling both common and specific aspects across collections, while keeping all the corresponding opinions for contrastive study.

3. Agent-based Influence Maintenance in Social Networks:

In this research, Author addressed the influence maintenance problem. An agent-based influence model was proposed, which can be applied to investigate the strategies for long-term marketing. Experiments were conducted to evaluate the proposed model. The experimental results revealed that given the same budget and limited time frame, multiple-time investment is superior than oneshot investment in terms of influence maintenance. We believe that our findings can shed light on the understanding on influence maintenance for long-term marketing.

4. Stigmergy-Based Influence Maximization in Social Networks:

In this research, we studied a novel approach i.e., stigmergy - based algorithm, to begin the influence maximization problem in a separated environment. In the meanwhile, SIM model has been proposed and systematically elaborated. Experiments have been conducted to evaluate the performance of SIM. Experimental results reveal that SIM outperforms the traditional seed selection approaches, including greedy selection, degree-based selection and random selection, by considering both electiveness and efficiency. Moreover, SIM is applicable for large-scale networks and even functions without a global view.

5. Diffusion in Social Networks:

A Multiagent Perspective: In this research, authors make a systematic review of the essential elements and models of diffusion in SNs from a novel perspective, a multiagent perspective. From this perspective, It summarize the essential elements in diffusion to diffusion actors, diffusion media, and diffusion contents. Those three types of elements can, respectively, be modeled as interacting agents, interaction environments, and interaction objects in MASs. Then, the diffusion models in existing studies can be understood as the agents' decision-making models and protocols in interaction, which are reviewed from the viewpoint of corresponding multiagent interaction models. Through the review and analysis of existing studies, we find that diffusion in SNs can be understood well via the interaction in MASs and that there is a close corresponding relation between them. Therefore, the author think that the related study results on multiagent interactions can be applied to advance the study of diffusion in SNs.

6. The Agent-based Timeliness Influence Diffusion (ATID) Model

The ATID model is a decentralized influence diffusion model which utilizes the advantages offered by ABM. The influence propagation in social networks demonstrates a networked evolutionary pattern driven by individuals' actions. In this model, each agent maintains its ego-network and makes decisions of performing social activities based on both timeliness degree of the influence message and its preference. There are multiple reasons to make a user to pull out a social behaviour, such as influence from neighbours in the same social networks, affected by any external events, or the user actively posts some messages without getting influenced by anybody. In users deliberately post messages after influenced by the neighbours, and each individual's repository and historical records contain enough evidence for statistical analysis.

III. PROPOSED SYSTEM

In this proposed system we are going to detect Influence. Here we are going to use different seed selection technique for detecting Influence. Figure 1 shows the proposed System work in detail

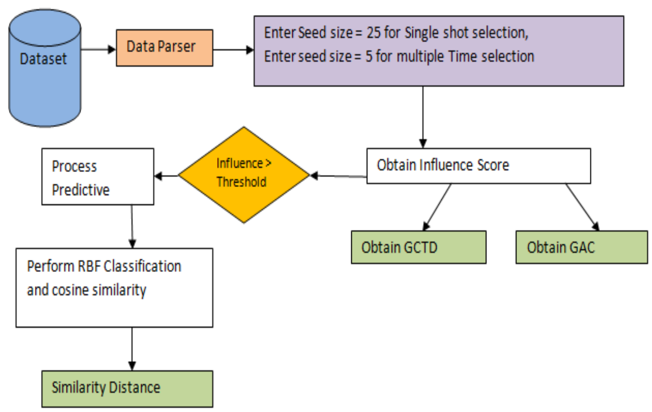


Figure 1: Proposed System Overview

As Shown in Figure System start execution with Input as data Set i.e. Wikivotes, Ego Facebook , Email Enron data. Once system receives input. it performs functions as mentioned below.

1. Parser Loads To Node and From Node
2. User need to provide seed size
   Enter Seed size = 25 for Single shot selection, Enter seed size = 5 for multiple Time selection
3. Calculate Influence score.
4. Obtains GCTD (Global Cumulative Timeliness Degree)
5. Obtains GAC (Global Activation Coverage)
6. Obtain Threshold value and perform prediction.
7. Performs RFB Classification and Cosine similarity
8. To Evaluates calculate seed selection time and similarity distance

Algorithm

Improvised Algorithm using LinkHashMap

Input: Dataset with two attribute

Output: Key /Value Mapping

Step 1: Get Set Of Entry Objects

Step 2: Convert it Into Stream

Step 3: sort it by passing Entry Comparing By Value

Step4: Collect result into new Linked HashMap

as it maintains insertion order

IV. EXPERIMENTAL RESULT

4.1 Dataset Details:

Datasets. In the experiments, the following three datasets are used.

• Ego-Facebook dataset:
collected by McAuley et al. using a Facebook application, which is archived in Stanford Large Network Dataset Collection. It contains profile and network data from 10 egonetworks, consisting of 193 circles, 4,039 users and 88,234 edges.
Dataset Link: http://snap.stanford.edu/data/egonets-Facebook.html

• Email-Enron
which covers all the email communication. It has been posted to the web by the Federal Energy Regulatory Commission .The Enron email network has 36,692 nodes and 367,662 Edges. To diminish the computing time, we capture a sub-graph with 10k nodes for the experiment.
Dataset Link : https://snap.stanford.edu/data/email-Enron.html

• Wiki-Vote
Dataset, which incorporates administrator elections and votes history data from 3 January 2008. There are 2,794 elections with 103,663 total votes and 7,066 users participating in the elections. Nodes refer to Wikipedia users and edges represent votes from one user to another .
Dataset Link : https://snap.stanford.edu/data/wiki-Vote.html

Performance Metrics:
The relationship between the input and output variables of a system understand by employing the suitable performance metrics like sensitivity and specificity. The general formula for calculating the sensitivity and specificity of Influence detection rate is given in the equation.

$$\text{Sensitivity} = \frac{\text{Number of TP}}{\text{Number of TP} + \text{Number of FN}} \times 100$$

$$\text{Specificity} = \frac{\text{Number of TN}}{\text{Number of TN} + \text{Number of FP}} \times 100$$

Where, TP is represented as true positive, FP is denoted as false negative, TN is represented as true negative and FN is stated as false negative. In addition, the accuracy, precision and recall are the suitable evaluation metrics for finding the effectiveness of Influence detection rate. Precision and recall are the measure of statistical variability and a description of random errors.

The general formula of accuracy, precision and recall for determining Influence detection rate is given in the equation

Accuracy = TP+TN/TP+FP+FN+TN

Precision = TP/TP+FP

Recall = TP/TP+FN

F-score is the measure of accuracy test and it considers the both precision P and recall R of the test in order to calculate the score. The general formula for F-score measure is given in the equation.

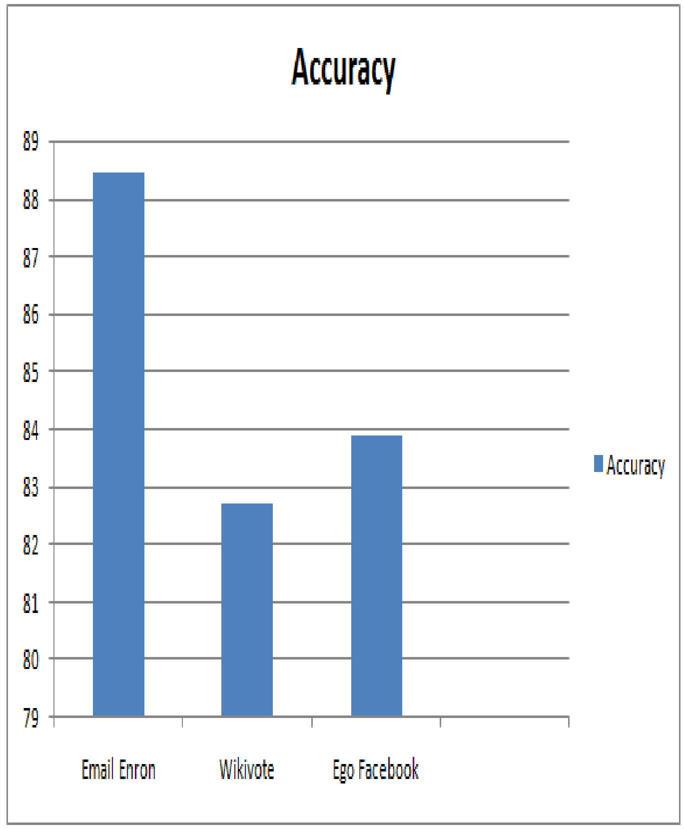
F1 Score = 2*(Recall * Precision) / (Recall + Precision)

Cosine Similarity

$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

4.2 Performance Analysis of Proposed work

Precision and accuracy are terms used to explain structures and strategies that degree, estimate, or expect. In these types of instances, there is a few parameters you desire to recognize the value of. This is called the true value, or genuinely, fact. The method provides a measured value, that you want to be as close to the true value as possible. Accuracy with Email Enron Dataset is 88.5% for wikivote it is 82.88% and for Ego facebook it is 83.9 %.



Graph for Different data set accuracy using proposed Algorithm

Figure 2. Performance Analysis of Existing System

From that, Avarage accuracy is 87 %

The experimental results shows an encouraging Influence Detection rate of more than 85% indicating that our method significantly outperforms previous Base Paper work.

Following Below Details shows the comparison of base system similarity score with proposed system.

Similarity score defines the similarity between obtain Seeds and excluded seeds, hence less is the similarity more is the accuracy.

Table 1 Similarity score comparison of base paper and proposed system

Dataset	one-shot selection vs. multiple-time selection 5×5				One-shot selection vs. Multiple-time selection 25×1				Multiple time selction 5×5 vs. Multiple-time selection 25×1			
	Base Paper Values			Proposed System Values	Base Paper Values			Proposed System Values	Base Paper Values			Proposed System Values
	Jaccard	Dice	Sequence	Cosine Similarity	Jaccard	Dice	Sequence	Cosine Similarity	Jaccard	Dice	Sequence	Cosine Similarity
Email Enron	0.442	0.284	0.365	0.165	0.498	0.3332	0.424	0.165	0.094	0.051	0.113	0.165
Wiki Vote	0.622	0.452	0.54	0.36	0.73	0.576	0.65	0.36	0.424	0.27	0.394	0.36
Ego Facebook	0.768	0.624	0.631	0.187	0.792	0.656	0.668	0.187	0.477	0.315	0.383	0.187

Table 2 Time and thread comparison of existing and proposed system.

Metrics	Existing System	Proposed system
Time required for seed selection	200 Milliseconds	85 Milliseconds
Threads	Multi threads	Single thread

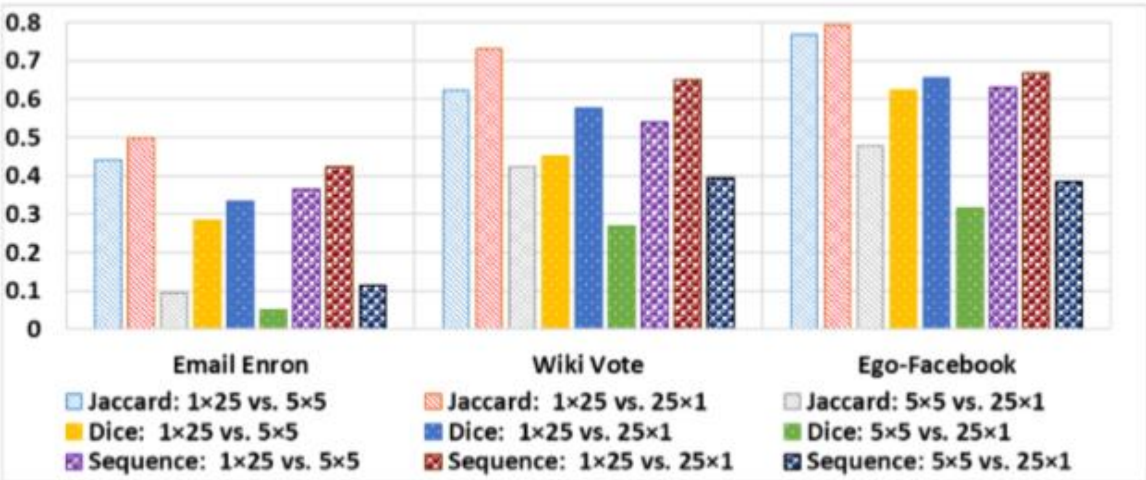


Figure 3. Existig System Seed Set Variation Comparison under Different Strategies

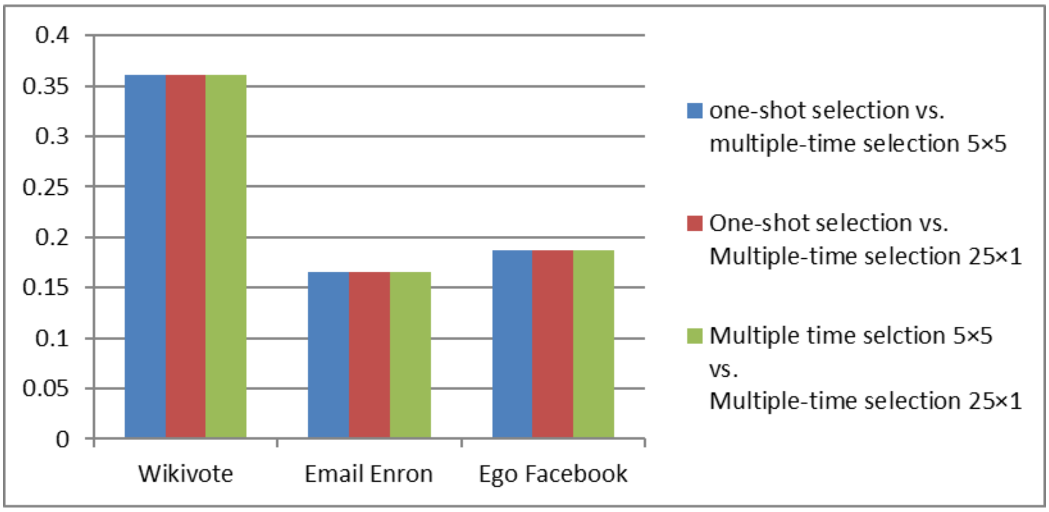


Figure 4. Proposed System Seed Set Variation Comparison under Different Strategies

V. CONCLUSION

In this System, we systematically implemented the influence maintenance problem, which targets the long-term and sustainable business goals. The implemented system has taken the following points in consideration and enhanced existing system.

1. The time step is not fixed ;
2. For each investment, the seed set size is not fixed;
3. The seed selection point can be a variant;

Many features of both individuals and influences can be enabled in the when analyzing the social influence diffusion phenomenon. We have also proposed a novel seed selection algorithm i.e. Improvised Algorithm using LinkHashMap which is capable of maintaining long-term influence effectively. Extensive testing is conducted, and the empirical results show that the proposed model is capable of enhancing long-term influence in less time than existing system.

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