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

***IndexTerms* – 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, short-term success may be short-lived [5]. Motivated by this background, in this research, we aim to achieve constant impact for long-term 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.
On the other side, in most existing on-line social media applications, information cannot be delivered to the users directly, but cached in individual's message repository, pending for users to access. The timeliness of a particular influence message becomes an important factor to be considered. More specifically, an individual reading list in on-line social networks, such as Weibo1 , is typically presented as a stack, which turns out to be last-post-first-read. Thus, the accessing priority of a particular message keeps decreasing over time, and posting or sharing behaviours are not supposed to be triggered without reading it.

In [8], Author conducted very preliminary research work on modelling maintaining influence under a particular social context. In this paper, we systematically elaborate and formulate the influence maintenance problem, which tends to maximize the constant impact of a particular influence by considering time-series. Also, we proposed a decentralized influence propagation model, i.e., the Agent-based Timeliness Influence Diffusion (ATID) model. In the ATID, the diffusion process is considered as a networked evolutionary phenomenon, users are modelled as autonomous agents, and each maintains its local information incorporating friendship affiliation list, message repository and posting histories.

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].

They evaluated POME by

(i) comparing the pattern-matching approach with machine learners leveraging the patterns themselves as well as n-grams extracted from Stack Overflow posts;

(ii) assessing the ability of POME to detect the polarity of sentences, as compared to sentiment-analysis tools;

(iii) comparing POME with the state-of-the-art Stack Overflow opinion mining approach, Opiner, through a study involving 24 human evaluators. Our study shows that POME exhibits a higher precision than a state-of-the-art technique , in terms of both opinion aspect identification and polarity assessment.

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. An auto-labelling scheme called AME is also proposed to help discriminate between aspect and opinion words without elaborative human labeling, which are further enhanced by adding word embedding-based similarity as a new feature. Moreover, CAMEL-DP, a nonparametric alternative to CAMEL is also proposed based on coupled Dirichlet Processes. Extensive experiments on real-world multi-collection reviews data demonstrate the superiority of our methods to competitive baselines[10].

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 one-shot investment in terms of influence maintenance. We believe that our findings can shed light on the understanding on influence maintenance for long-term marketing.

Author studied on how to maintain long-term influence in a social network by proposing an agent-based influence maintenance model. Within the context of our investigation, the experimental results reveal that multiple-time seed selection is capable of achieving more constant impact than one-shot selection[11].

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.

In this work, a stigmergy based approach has been proposed to tackle the influence maximization problem. They described the influence propagation process as ant's crawling behaviors, and their communications depend on a kind of biological chemicals, odor The amount of the spice allocation is concerning the factors of influence propagation in the social network. The model is able to analyze influential relationships in a social network in separated manners and identifying the influential users more efficiently than traditional algorithm[14].

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.

However, although this survey shows that a multiagent perspective can be envisioned to be a powerful paradigm for modeling and investigating diffusion in SNs, there are still many issues that must be addressed if we want to apply multiagent technologies truly and effectively. Especially, the complexity of diffusion is considerably larger than the complexity of multiagent interactions; diffusion processes are natural phenomena that can be difficult to predict, but MASs are artificial and can be predesigned. Therefore, we the proposed model, we assume should improve the suitability and practical feasibility of multiagent methods to study diffusion in SNs[12].

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 behavior, 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. Furthermore, each user agent (e.g., vi) has a different frequency of accessing its repository, i.e., freq(vi). It can be seen that freq(vi) is equivalent to the probability of vi accessing a particular message msgp in its repository at time tm, i.e., Pf (vi , msgp, tm)[1].

III. PROPOSED SYSTEM

(i) System Architecture

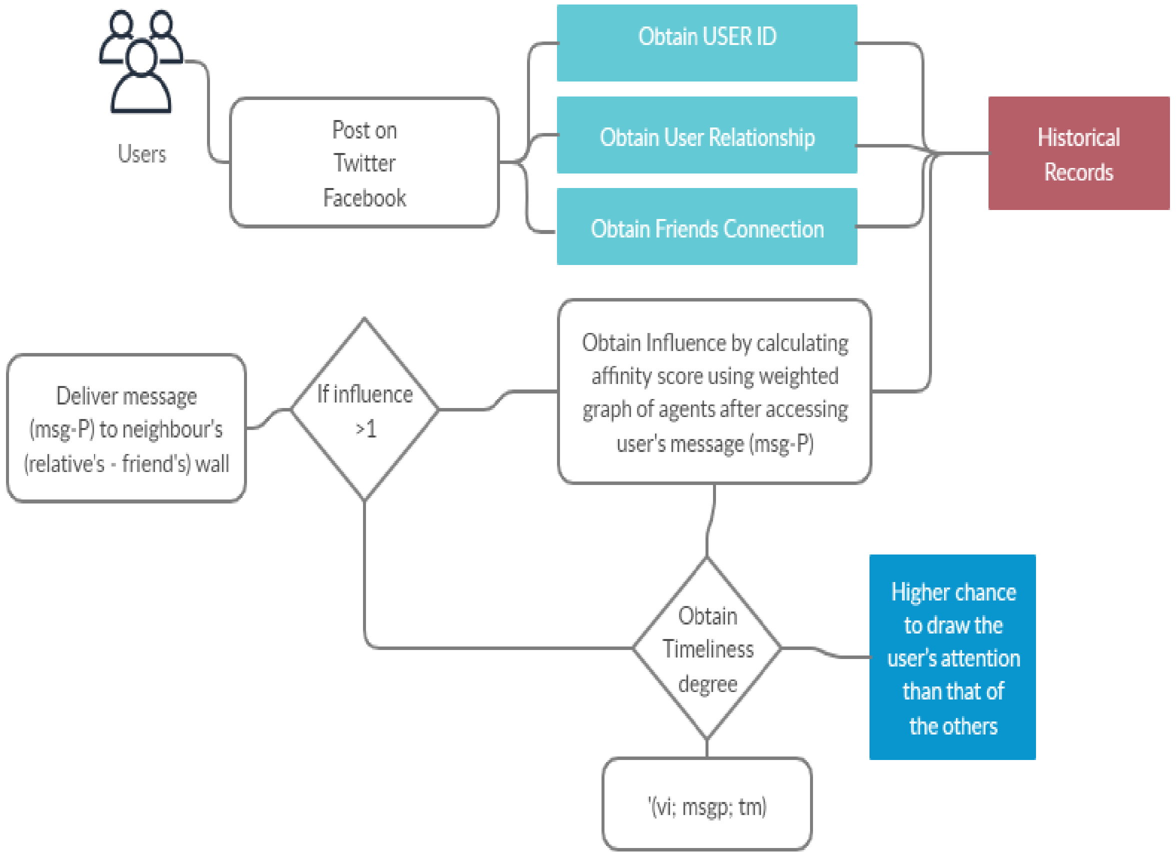

Figure 1. System design

As Shown in Figure 1. System start execution with Input as Users Post on Social Media i.e. Facebook, twitter.

Once system receives input using Historical Data it performs 3 functions as mentioned below.

Obtain User ID

Obtain User Relationship

Obtain Friends connection

Using result of these 3 functions we obtain influence by calculating affinity score using weighted graph o0f above functions. If influence of user Message is greater than 1 then deliver message to neighbour's (friend's wall)

Using affinity score we Obtain Timeliness degree f message if timeness degree is high then there is higher chance to draw the user's attention than that of the others

ii)System Flow:

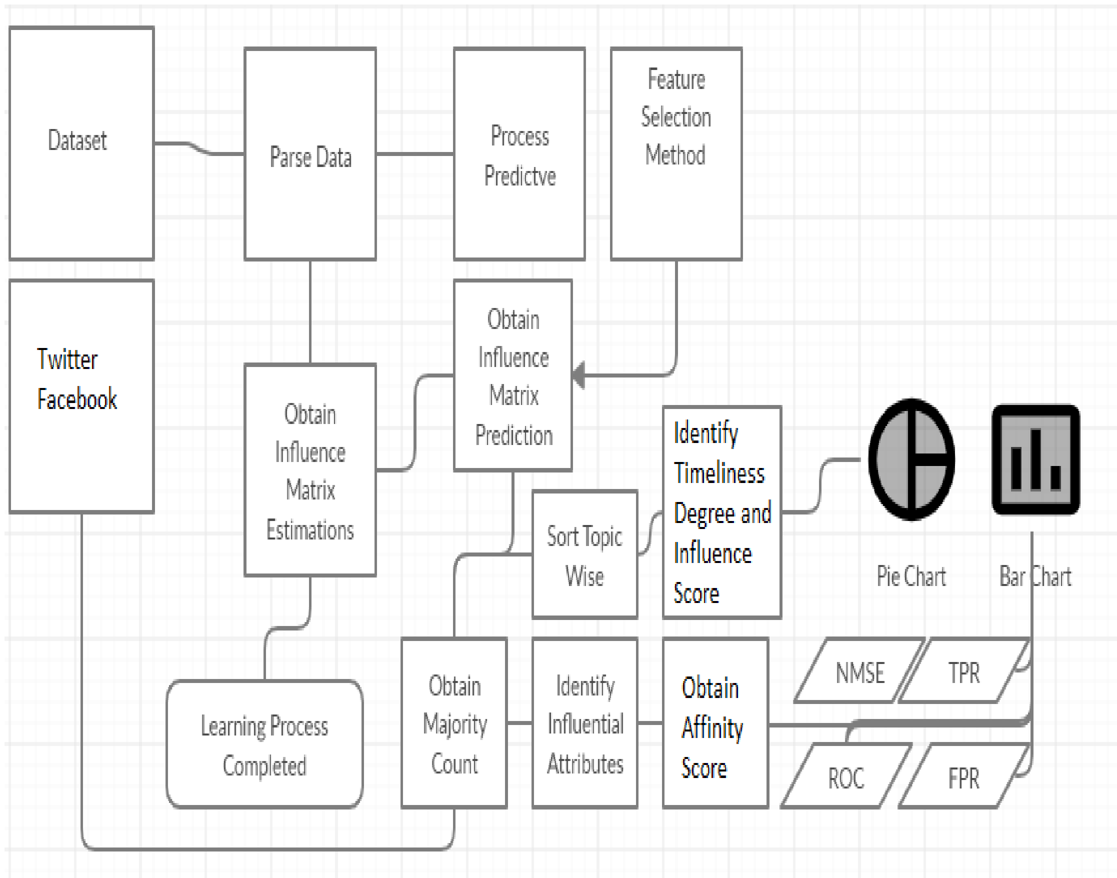

Figure 2. Flow Diagram

Problem Formulation : The influence maintenance is defined as the process of preserving a particular type of influential situation or the state of influence being preserved, which derives from the influence maximization problem. Specifically, given a finite budget k (seed set size) and a limited timespan [t0, tm], an investment (seed selection) occurs once every n time steps, thus, the investment time steps I = {tN×n|N∈ NΛN ×n < m}, where tN×n represents a particular seed selection point. There are |I| times of investment considered for maintaining the influence. Influence maintenance aims to find a solution of identifying the seed set AtN×n for each time step tN×n to maximize the influence lifespan of msgp. Thus, the selected seed sets A is a collection of seeds identified from each investment time step, i.e., A = {At|t∈ I} and P t∈tN×n |At| = k. We assume that the same amounts of seeds are supposed to be selected for each selection point, and any seeds cannot be selected more than once. In other words, given {Ai, Aj} ⊆ A, then |Ai| = |Aj |, Ai ∩ Aj = ∅. The overall effective influence lifespan of msgp in the entire social network is evaluated by using Global Cumulative Timeliness Degree (GCTD) of a specific timespan [t0, tm], i.e., ξmsgp . The Global Timeliness Degree (GTD) of msgp at a particular time step tn can be calculated by using Equation following equation:

$$\varepsilon_{msg}^{tn} = \sum (vi, msgp, tn)$$

EdgeRank is the Facebook algorithm that decides which stories appear in each user's newsfeed. The algorithm hides boring stories, so if your story doesn't score well, no one will see it.The first thing someone sees when they log into Facebook is the newsfeed. This is a summary of what's been happening recently among their friends on Facebook. Every action their friends take is a potential newsfeed story. Facebook calls these actions "Edges." That means whenever a friend posts a status update, comments on another status update, tags a photo, joins a fan page, or RSVP's to an event it generates an "Edge," and a story about that Edge might show up in the user's personal newsfeed.

Affinity Score

Affinity Score means how "connected" a particular user is to the Edge. For example, I'm friends with my brother on Facebook. In addition, I write frequently on his wall, and we have fifty mutual friends. I have a very high affinity score with my brother, so

Facebook knows I'll probably want to see his status updates. Facebook calculates affinity score by looking at explicit actions that users take, and factoring in 1) the strength of the action, 2) how close the person who took the action was to you, and 3) how long ago they took the action.

Explicit actions include clicking, liking, commenting, tagging, sharing, and friending. Each of these interactions has a different weight that reflects the effort required for the action more effort from the user demonstrates more interest in the content. Commenting on something is worth more than merely liking it, which is worth more than merely clicking on it. Passively viewing a status update in your newsfeed does not count toward affinity score unless you interact with it. Affinity score measures not only my actions, but also my friends' actions, and their friends' actions. For example, if I commented on a fan page, it's worth more than if my friend commented, which is worth more than if a friend of a friend commented. Not all friends' actions are treated equally. If I click on someone's status updates and write on their wall regularly, that person's actions influence my affinity score significantly more than another friend who I tend to ignore. Lastly, if I used to interact with someone a lot, but less so now, then their influence will start to wane. Technically, Facebook is just multiplying each action by 1/x, where x is the time since the action happened.

Edge Weight

Each category of edges has a different default weight. In plain English, this means that comments are worth more than likes. Every action that a user takes creates an edge, and each of those edges, except for clicks, creates a potential story. By default, you are more likely to see a story in your newsfeed about me commenting on a fan page than a story about me liking a fan page. Facebook changes the edge weights to reflect which type of stories they think user will find most engaging. For example, photos and videos have a higher weight than links. Conceivably, this could be adjusted on a per-user level--if Sam tends to comment on photos, and Michelle comments on links, then Sam will have a higher Edge weight for photos and Michelle will have a higher Edge weight for links. It's not clear if Facebook does this or not.

Time Decay

As a story gets older, it loses points because it's "old news." EdgeRank is a running score--not a one-time score. When a user logs into Facebook, their newsfeed is populated with edges that have the highest score at that very moment in time. Your status update will only hit the newsfeed if it has a higher score--at that moment in time--than the other possible newsfeed stories. Facebook is just multiplying the story by 1/x, where x is the time since the action happened. This may be a linear decay function, or it may be exponential it's not clear.Additionally, Facebook seems to be adjusting this time-decay factor based on 1) how long since the user last logged into Facebook, and 2) how frequently the user logs into Facebook. It's not clear how exactly this works, but my experiments have shown time-decay changes if I log into Facebook more.

CONCLUSION

In this article, we systematically studied the influence maintenance problem, which targets the long-term and sustainable business goals. To the best of our knowledge, this paper is the first full research work that characterizes the influence maintenance in social networks. The distributed influence diffusion model, i.e., the ATID, presented in this article can also pave the way in exploring influence propagation social pheromone, since it concentrates on modelling the agent's personalized traits and behaviours, tracking the temporal feature of a social network, as well as the status of influence messages. Many features of both individuals and influences can be enabled in the ATID when analyzing the social influence diffusion phenomenon. We have also proposed a novel seed selection algorithm, i.e., the TIH, which is capable of maintaining long-term influence effectively.

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