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ADAPTIVE DIFFUSION OF SENSITIVE INFORMATION IN ONLINE SOCIAL NETWORKS

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Abstract —In this paper, We introduce the time factor into the user payoff, enabling the GT model to not only predict the behavior of a user but also to predict when he will perform the behavior. Both the global influence and social influence are explored in the time dependent payoff calculation, where a new social influence representation method is designed to fully capture the temporal dynamic properties of social influence between users. Experimental results on Sina Weibo and Flickr validate the effectiveness of our methods.

INTRODUCTION

The current studies on information diffusion modeling can be divided into two categories:theory-centric models and data-centric models. Theory-centric models mainly come from epidemiology, sociology and economics. The most widely-studied diffusion models of this category are the epidemic model,the independent cascade model and the linear threshold model. Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission These models are helpful for studying the information diffusion problems such as influence maximization problem [6, 4, 5]. However, they assume that the users in the network are passively influenced to spread information. Due to the lack of support from actual diffusion data, these models do not have the ability of diffusion prediction. Data-centric models are usually learned from actual information diffusion data, and can be divided into macromodels and micro-models. Macro-models [9, 11] can generate diffusion cascades whose macro properties are similar to that of actual diffusion cascades. But they still can not predict the information diffusion process. This limitation is addressed by micro-models, which can predict whether a user in a social network will be activated by a piece of information.

Since the information diffusion process is caused by user behavior, information diffusion prediction is actually user behavior prediction. Most micro-models [7, 10] can predict the behavior of a user, but they can not predict when the user will perform the behavior. In this paper, we propose a novel information diffusion model (GT model) for temporal dynamic prediction. In contrast to traditional theory-centric models, the GT model regards the users in the network as intelligent agents. It can capture both the behavior of individual agent and the strategic interactions among these agents. By introducing the time-dependent payoffs, the GT model is able to predict the temporal dynamics of the information diffusion process. Different from most data-centric models, the GT model can not only predict whether a user will perform a behavior but also can predict when he will perform it. We make the following contributions in this work:

LITERATURE SURVEY

AUTHORS: Dong Li; Shengping Zhang; Xin Sun; Huiyu Zhou; Sheng Li;

Modeling the process of information diffusion is a challenging problem. Although numerous attempts have been made in order to solve this problem, very few studies are actually able to simulate and predict temporal dynamics of the diffusion process. In this paper, we propose a novel information diffusion model, namely GT model, which treats the nodes of a network as intelligent and rational agents and then calculates their corresponding payoffs, given different choices to make strategic decisions. By introducing time-related payoffs based on the diffusion data, the proposed GT model can be used to predict whether or not the user's behaviors will occur in a specific time interval.

AUTHORS: Li, D., Zhang, S., Sun, X., Zhou, H., Li, S., & Li, X. (2017).

In recent years, with the rapid development and demanding requirements of online social networks [1], [2] (e.g., Twitter, Facebook, Flickr), tremendous interests have arisen from the study of information diffusion. An example of information diffusion is: When someone adopts a piece of information, his or her neighbors may be influenced and then consider adopting the same information. Usually, information diffusion is caused by user actions, for example, users perform re-tweeting actions to diffuse tweets on Twitter. Therefore, information diffusion also can be regarded as user action diffusion.

PROPOSED SYSTEM

- In the existing system, the system addresses the issue of predicting the temporal dynamics of the information diffusion process. We develop a graph-based approach built on the assumption that the macroscopic dynamics of the spreading process are explained by the topology of the network and the interactions that occur through it, between pairs of users, on the basis of properties at the microscopic level.

- We introduce a generic model, called TBaSIC, and describe how to estimate its parameters from users behaviours using machine learning techniques. Contrary to classical approaches where the parameters are fixed in advance, T-BaSIC 's parameters are functions depending of time, which permit to better approximate and adapt to the diffusion phenomenon observed in online social networks. Our proposal has been validated on real Twitter datasets.

- Experiments show that our approach is able to capture the particular patterns of diffusion depending of the studied sub networks of users and topics. The results corroborate the "two-step" theory (1955) that states that information flows from media to a few "opinion leaders" who then transfer it to the mass population via social networks and show that it applies in the online context. This work also highlights interesting recommendations for future investigations.

DISADVANTAGES OF EXISTING SYSTEM:

- There is no Information diffusion prediction
- Very less security due to lack of Information Prediction

PROPOSED SYSTEM:

- The system proposes a novel information diffusion model (GT model),where, between different choices (behaviors), the user jointly considers all his interacting neighbors' choices to make strategic decisions that maximizes his payoff.
- The system proposes a time-dependent user payoff calculation method in the GT model by exploring both the global influence and social influence.
- The system proposes a new social influence representation method, which can accurately capture the temporal dynamic properties of social influence between users.
- The system conducts experiments on Sina Weibo and Flickr datasets. The comparison

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results with closely related work indicate the superiority of the proposed GT model.

Advantages

- ➢ Information diffusion prediction is efficient and fast.
- ➢ The system gives more security on Information Prediction.

IMPLEMENTATION

MODULES DESCRIPTION:

- **Admin(Web Server)**

In this module, the Admin has to login by using valid user name and password. After login successful he can do some operations such as View all image Posts ,View all Video Posts ,List All similar interests Posts based on Community ,List Users Based on Community and authorize the same user ,List All Search History ,View all image and video posts by rank wise, View all diffusion sets(both image and video posts) ,View all friends links.

Upload Videos

In this module, the admin can upload n number of videos. Admin want to upload new image then he has enter some fields like image name, image color, image description, image type, image usage, browse the image file and upload. After uploading successfully he will get a response from the server. Initially new uploaded image rank is zero. After viewing that image rank will re-rank.

Search History

This is controlled by admin; the admin can view the search history details. If he clicks on search history button, it will show the list of searched user details with their tags such as user name, user searched for Video name, time and date.

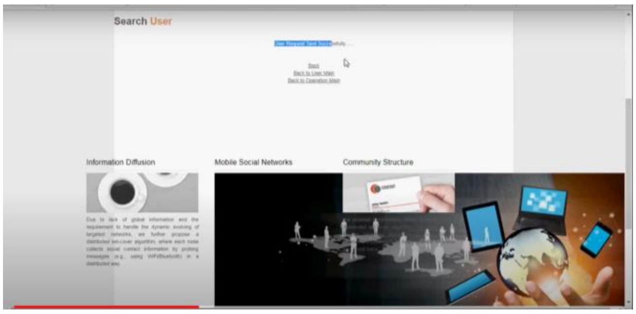
Rank of videos

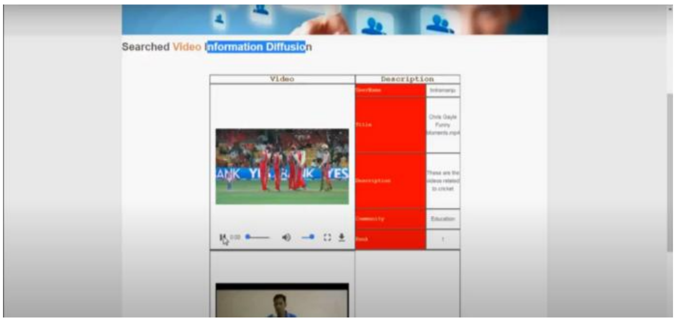
In user's module, the admin can view the list of ranking videos. If admin click on list of ranking videos, then the server will give response with their tags videos and interests or reviews and rank of videos.

- **User**

In this module, there are n numbers of users are present. User should register before doing some operations. And register user details are stored in user module. After registration successful he has to login by using authorized user name and password. Login successful he will do some operations like Request friend to other user, View your Detail, View all image posts based on your community ,View all video posts based on your community, View all posts based on other user interests, View posts based on user interests, View all image and video posts based on ranks, Search posts based on contents

SAMPLE OUTPUT SCREENSHOTS





CONCLUSION

In this paper, A novel information diffusion model in this paper. It regards the users in a social network as intelligent agents, and jointly considers all the interacting users to make strategic prediction. By introducing the time dependent payoffs, the model has the capability to predict the temporal dynamics of information diffusion process. Both the global influence and social influence are explored for user payoff calculation, where the social influence representation method is newly designed for fully capturing its temporal dynamics. Experimental results have confirmed the rationality and effectiveness of the proposed model.

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