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Comparison on Attention Automaton Sensing Collective user Interests in Social Network Communities

S. Poornima, R. Rangaraj
PG & Research, Department of Computer Science, Hindusthan College of Arts and Science, Coimbatore, India

ABSTRACT

Social activity at present requires substantial fraction of time on the web for information dissemination. Content sharing results in a complex interplay between individual and attention received from others. The wide-spread adoption of various technologies leads to new approaches that differ from traditional approaches for information sharing among the communities. The attention of communities will be based on the unique features. The previous research works still does not help us to quantify the collective attention affinity that exists in user group and dynamics of attention between collective users is different from individual user. The paper deals with a study that addresses the above limitations.

Keywords: *Attention, automaton, community attention, Individual attention*

I. INTRODUCTION

Social network emerges as a platform for connecting people to share information. Online social networks are an opportunity to study the propagation of ideas, the formation of social bonds and viral marketing, and others. Social networks pay the way for the big data that involves in self-tracking of any kind of information by the individual or in groups. Group users or collective users who are bound together as followers of an account or placed within close geographic proximity plays an innovative role in what becomes popular and receiver's attention. The attention is the deciding factor in information spread. The information or specific category potentially receives more attention. The collective intelligence is the main trait in human interactions with which we can attempt to predict the future collective is the one of the limitation addressed. The group user in Twitter RT a particular tweet then it is a collective attention [1]. Fig 1 shows base social network structure.

Figure 1: Social Network

The categories that remain relatively consistent for a long time period aims to understand the individual user attention which may probably miss the large community. The individual attention contrast people who focus a large fraction of interaction with their small set of friends who disperse the attention widely. Face book is an example for the individual attention. The balance of attention is relatively stable over time by the individual. In individual attention the activities based on information share or communication will be involved with higher focus than observation. The paper analyses the limitation of dynamics of collective attention and individual attention.

II. METHODS AND MATERIAL

A. Related Work

Attention is the primary part in social network [10]. Attention in the social network is captured by the behavior of social network nodes in face of competing choices of interaction [9]. The collective attention dynamics is substantially different from individual attention [12]

B. Individual Attention

Kossinets et al [2]. Studies study how link activity can lead to different pathways for information flow over multi-step referred as temporal dynamics of communication in online data that provide structural insights and are not apparent from analyses of the pure social network topology. Wilson et al. [3] mainly focus on aggregate measures on activity distribution, the network structures results from threshold links by the activity level. And also addresses the distribution of attention levels as an attribute operating at the individual level by understanding how the attribute varies across people and groups, and how it relates to other individual attributes.

Bimal Viswanath et al [4] studies about the evolution of activity between users in the Face book social network to capture this notion and found that links in the activity network tend to come and go rapidly over time, and the strength of ties exhibits a general decreasing trend of activity as the social network link ages. The next measure is related to other quantitative trade-offs between focus and dispersion in an individual's network, such as the geographic spread of one's friends and the search ability of social networks [5].

C. Collective Attention

The adoption of social media made competition among ideas for finite attention. Many researches show that a combination of social network structure and finite attention is a sufficient condition for emergence of dynamics of social networks [6]. Measurements of novelty factor indicate the novelty within group's decays with a stretched-exponential law, suggesting the existence of a natural time scale over which attention fades [7].

Social network links in the online social network are not equal; its strength varies based on the frequency of interaction among the linked users. The paper [8] analyzes the interaction dynamics in a large online social network and insights from the analysis to derive a generative model of social interactions that can capture fundamental processes underling user interactions.

Lerman et al [13, 14, and 15] propose a stochastic model to describe the social dynamics of web users, based on Digg's case study. The stochastic model focuses on describing the aggregated behavior of the system, including average rate at which users contribute new stories and vote on existing stories. Recent studies of collective attention on social media sites such as Twitter, Digg and YouTube [16, 17, 18] have clarified the interplay between popularity and novelty of user generated content. Probabilistic based automaton [11] is proposed for quantifying the attention of the social network communities for the collective users with two key concepts by attention shift tendency and categorical affinity.

D. Problem Definition

Understanding the dynamics of collective attention is very useful, helping content producers and intermediaries better manage information flows under the constraint of human attention. It also brings clarity in judgment of what, when and why some trend becomes popular, which has great relevance to monetization of online content.

Although social data mining reveals popularity and novelty of trends as a good indicator of attention patterns of users, it still does not help us quantify the collective attention shifts in communities or the categorical attention affinity that exists in users groups. Most importantly, it gives us few indications as to whether collective attention is at all computable (in terms of a model of computation) and whether we can predict the likelihood of a future trend to receive sustained attention and dynamics of collective attention is substantially different from individual attention is the limitation which is to be addressed.

E. Attention Automaton

Attention precedes online activity which is a model attention of user communities to comprehend the base difference between user groups. The collective users or group of users who are close in the geographic area can play an important role in what becomes popular and receives attention. Many researches deal with the individual attention and miss the insight of collective attention by the large community.

Attention automaton works based on assumption that user group's attention will be based on their characterization by the trends of the group as they are derivative of cumulative topics publish by the group. Based on the trends the attention of user group is Y is judged by the trends appearing in TTL (Time to Live).

The attention changes from one to another Let Distr (X) denote the set of all possible probability distribution over X and A be the attention automaton consisting of four components

1. A set SA of states.
2. A non-empty set S^0A of start states.
3. An action signature $sig_A= (E_A, I_A)$ consisting of external and internal actions respectively. We assume that E_A and I_A be mutually disjoint and the complete set of possible actions is $Act_A = E_A\ U^I{}_A$.
4. A transition relation $\Delta A \subseteq S_A \times Act_A \times$ Distr (X).

The final component of the automaton is the probability of the transition between the two states.

III. RESULTS AND DISCUSSION

Performance of Attention Automaton

The performance of the automaton is to predict most probable future states. Random, ARIMA (Auto Regressive Integrated Moving Average) and automaton is compared with the metrics precision, recall and F-score (harmonic mean of precision and recall) in the user groups of various geographical locations.

Random predicts future trends based on the forthcoming TTL. ARIMA predicts the future in series. Automaton predicts q trends that will cause the automaton to jump from state to state which produce better performance in F-score when compared to random and ARIMA schemes by selecting 10 various locations worldwide to test the performance of automaton.

The average F-score shows that attention automaton performs better than ARIMA and Random selection scheme. Table 1: shows 10 locations and their F-score obtained in the test on user groups in the world.

Table: 1 10 locations and their F-score obtained in the test on user groups in the world.

User Group	Random	ARIMA	Automaton
New York	0.18	0.29	0.42
Los Angels	0.17	0.30	0.46
Baton Rauge	0.14	0.38	0.53
Boston	0.19	0.34	0.44
London	0.15	0.36	0.40
Paris	0.14	0.27	0.43
Dublin	0.16	0.37	0.56
Atlanta	0.18	0.35	0.55
San Francisco	0.13	0.33	0.40
Glasgow	0.19	0.35	0.48

These locations were tested for 3 months to predict the trend by the three schemes in which Automaton can predict more accurately than Random and AIRIMA schemes are analyzed. So attention automaton can predict the collective attention and based on the balance of attention which also predicts the individual attention in long run.

IV. CONCLUSION

In this paper, we presented a study about the collective attention and individual attention in the social network. The task of understanding user attention in responds to social activity is very much important for several web applications. In individual attention the measure has important practical implications: by proposing the modelling method an individual's balance of social attention can properly tailor that individual's experience to match the preferences for keeping in touch mostly with top contacts, or with a more diverse set of people.

In collective attention a probabilistic approach of automaton can be proposed for the quantifying the social network communities. Thus attention automaton has significant potential in boosting marketing and advertising applications.

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