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Long-term memory of rating behaviors for the online trust formation

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HIGHLIGHTS

- There is long-term memory in collective rating behaviors before and after the trust formation.
- The Hurst exponent of trustors decreases 9.76% before and increases 10.02% after trust formation.
- There is a significant correlation between user degree and collective rating behavior patterns.

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ABSTRACT

Investigating the dynamics of long-term memory in online rating behaviors is significant for understanding the evolution mechanism of collective behaviors and trust formation for online social networks. Since users are allowed to deliver ratings in many online systems, ratings can well reflect the user's opinions. In this paper, we empirically investigate the long-term memory, measured by the Detrended Fluctuation Analysis, in collective rating behaviors before and after the trust formation. The results for the Epinions data set show that, comparing with the null model generated by the reshuffle process, the Hurst exponent of trustors (trustees) decreases 7.12% (9.05%) before and increases 7.36% (9.20%) after trust formation, which stably remains close to 0.5 in null model I and 0.6 in null model II, suggesting that the collective rating behavior plays an important role for the trust formation. Furthermore, we divide users into 8 groups according to the user degree and find that the correlation of the user degree and the variation of Hurst exponent, measured by the Pearson Correlation Coefficient, is 0.8629 and 0.8620 before and after trust formation respectively, reflecting a significant correlation between user degrees and collective rating behavior patterns. Finally, we select the users without creating other trust relations around the trust formation time and the result suggests that the collective rating behaviors indeed change for the trust formation. This work helps deeply understand the intrinsic feedback effects between collective behaviors and trust relationship.

1. Introduction

A fundamental property of social networks is that people tend to have attributes similar to those of their friends. There are two conventional reasons for this. Firstly, people tend to form relationships with others who are already similar to them. This phenomenon, which is often termed social homophily, has a long history of study in sociology [1]. Secondly, the contrary

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reason is that the process of social influence [2] leads people to adopt behaviors and opinions exhibited by those they have social relations with; this effect is at work in many situations where new ideas diffuse by word-of-mouth or imitation through various social networks [3]. The two forces of social relations and similarity are both seen in a wide range of social settings: people turn to adopt opinions based on the relations they make with others currently; and people simultaneously form new relationships as a result of their existing activities [4]. The studies on these forces and their interplay have been quite difficult by now since collecting data about an individual's social networks and activities over time is both expensive and error-prone. For instance, the results of some survey-based network studies can be influenced by common external factors such as interviewer effects, recall limitation and other influences [5].

Online systems, however, provide a precious opportunity to study large-scale behavior patterns [6–8]. Though online users' real identities are usually protected from public viewing, there is information of online behaviors such as the rating behavior that represents people's preference [9,10], which is helpful to improve the advertising strategy and online service. Initially, through the dynamic information of people's online behaviors, such as selecting or rating items, many remarkable patterns have been uncovered in the evolvement of online users' preference [11–13]. Especially, the interevent time of rating behaviors displays the bursty nature characterized by short timeframes of intense activity followed by long times of no or reduced activity [14–16]. Furthermore, the task-based queuing model [17,18] and the interest-driven model [19–22] have been proposed to describe the origin of the bursty nature. In contrast to the bursty nature of the interevent time, the memory effect of the online user behavior itself has been explored [23,24], such as anchoring bias [25], and the Markovian model is widely used to describe the short memory effect [23,26]. In addition, the long-term dynamical patterns of online user behaviors, which can hardly be characterized by the Markovian model [27], have been found that there is a long-term memory effect of users' collective behaviors [28,29].

However, the remarkable results from the macroscopic view might only help understand the evolvement of collective behaviors without the social influence. Thanks to the online systems like Epinions where people are able to not only express their preference by posting ratings but also express their trust by forming trust relations, researchers can acquire the rating records and trust relations to investigate the correlation between the formation of social ties and the changes of user behaviors [30]. In this paper, we analyze the changes of long-term memory in online rating behaviors before and after the trust formation in the Epinions. Firstly, we estimate the Hurst exponent of online rating behaviors in 7 weeks before and 7 weeks after the trust formation time via Detrended Fluctuation Analysis (DFA) [31]; and the global empirical result demonstrates that there is a significant decline before the trust formation and a gradual increase afterwards in the long-term memory of both trustors' and trustees' rating behaviors. Secondly, we introduce two null models where rating records are shuffled into random order for removing the temporal patterns; and the result of the null models that both trustors' and trustees' Hurst exponent values are stable at around 0.5 and 0.6 can be suggested that the empirical results of the real data are indeed generated by the real rating behaviors and not disturbed by the length of rating records in each time interval. Moreover, considering the heterogeneity in rating behaviors of different users, we divide all trust pairs into 8 groups by user degrees and investigate the correlation between the variation of long-term memory of rating behaviors and the user degree by the Pearson Correlation Coefficient (PCC) [32]; and the result indicates that the more experienced a user is the more significant the variation of rating behaviors around the trust formation is. Furthermore, we select the users who only create 1 trust relation at the trust formation time without creating any other trust relations in the 3 days before and 3 days after that; and the result indicates that the rating behaviors of trust pairs indeed change for the trust formation. In conclusion, according to the empirical analysis of the rating behavior dynamically changing before and after the trust formation, we might suggest the correlation between the trust formation and the variation of online users preference and the correlation is increasingly significant with the user degree increasing.

2. Long-term memory

Long-term memory, also called long-range dependence or persistence, basically refers to the level of statistical dependence between two points in the time series [33]. The long-term memory of rating behaviors representing the predictability of users' online preference is significant to develop the recommendation systems and provide the better online services [34–36]. In order to analyze the dependence, we use exponential decay as the threshold. The behavior is considered to have long-term memory if the statistical dependence decays more slowly than an exponential decay and as a power-like decline with the increasing time intervals. Generally, Hurst exponent (H) is referred as the index of dependence that is widely used to measure the long-term memory of a given time series variable [37,38]. The value of the Hurst exponent can be between 0 and 1. If the value is 0.5, then it indicates that there is no correlation between the values in the data. If the value is between 0.5 and 1, it indicates that the time series data is persistent. It means that if the values are increasing right now, then it is more likely that it will be followed by another increase in the short term. Similarly, if the values are decreasing right now, then it is more likely that it will be followed by another decrease in the short term. If the value is between 0 and 0.5, it indicates that the time series data is anti-persistent. It means that if the values are increasing right now, then it is more likely that it will be followed by a decrease in the short term. Similarly, if the values are decreasing right now, then it is more likely that it will be followed by an increase in the short term. Initially, Hurst estimated the Hurst exponent by the Rescaled Range (R/S) Analysis to determine the optimum dam sizing for the Nile river's volatile rain and drought conditions [39]. However, the R/S analysis cannot be applied in the non-stationary time series due to its inaccuracy. For the non-stationary time series, it is essential to remove the trend in the time series, which is known as "detrending" [40]; and therefore, Peng