Chaos, Solitons and Fractals 109 (2018) 26–30

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Frontiers

The dynamics of online ratings with heterogeneous preferences in online review platform

Yuhan Zhang [a], Xin Feng [b], Ye Wu [c,*], Jinghua Xiao [d]

[a] School of Science, Beijing University of Posts and Telecommunications, Beijing 100876, China
[b] School of Management Science and Engineering, Hebei GEO University, Shijiazhuang 050031, China
[c] School of Journalism and Communication, Beijing Normal University, Beijing 100876, China
[d] School of Science, Beijing University of Posts and Telecommunications, Beijing 100876, China

ARTICLE INFO

Article history:
Received 16 November 2017
Revised 25 January 2018
Accepted 4 February 2018

Keywords:
Word-of-mouth evolution
Complex system
Heterogeneous preferences
Self-selection bias

ABSTRACT

Nowadays online consumer reviews (OCR) has increasingly received scholars' attention as an important form of word-of-mouth. Recent study shows that online reviews of a product, such as a book or a restaurant, have effect on long-term consuming behavior and the future rating of the product, it mainly reflects that the early high rating of a product will lead the decrease trend of rating over time. To confirm the existence of the effect and explore how it works, over 180,000 reviews on Dianping.com were collected to investigate the behavior patterns and intrinsic dynamics. In this paper, four temporal evolution patterns were observed via evaluating the cumulative average rating series for each restaurant. Moreover, a conceptual model considering the influence of heterogeneous preferences and the self-selection mechanism was introduced, and the numerical results coincided with the empirical analysis well enough to support the hypotheses. We find special preferences result in tendentious consumption and unrepresentative reviews, these reviews lead the potential consumers to over- or under-estimate the products and directly affect the subsequent ratings. The conclusions of this paper can contribute to the specific policies to adjust the initial rating effect for the specific marketing strategies.

1. Introduction

People have tendency to share their consumption experiences and information with others, and word-of-mouth has increasingly important impact on consuming behavior [1]. With the development of the Internet, word-of-mouth has gradually evolved into the large scale of the online complex network, so it could be easily replicated and saved to support the scholars' research in the online consumer reviews (OCR) field, especially referring to consumers' positive and negative evaluations based on their consumption of related products [2]. Primary factors about the reasons of posting OCR are concluded: desire for social interaction, care for subsequent potential consumers, and to build up and enhance their self-worth and reputation [3]. Nowadays, OCR not only play a decisive role on consumers' consuming decision, but also provide a good way for merchants to increase sales [4], that's why research on online reviews and ratings has gradually become a hot topic.

Some studies have already shown that previous OCR can affect subsequent individual's commenting behavior such as the posting incidence (i.e. whether to post a new comment) and the ratings (i.e. what to post). Some research suggests that positive ratings environments increase following posting incidence, as well as negative ratings environments discourage posting behavior [5]. Ratings of OCR are influenced by both consumption experiences and previous reviews, thus show some dynamic character [5,6]. As individuals display conform or deviate under the effect of information in society [7], controversy exists in the influence mechanism of OCR. Lee found higher existing movie ratings increase the probability of following people to publish higher ratings, which also means herding [8]. However, Wu found people tend to express opposite opinions from the observed online reviews, which caused the depolarization of the rating, so that most of books' rating series in Amazon are in decline [9]. It's worth mentioning that Godes also found the decrease trend but their explanations are slightly different—— follow-up consumers would be more likely to be misled by the previous reviews and then the probability of dissatisfaction increases [10], moreover, some research found discrete published OCR means more decision-making risk for follow-up potential consumers [11]. The significance of OCR is whether it can objectively reflect the quality of products as well as help subsequent consumers in establishing suitable psychological expectations to make more sensible consuming decision, however,

* Corresponding author.
E-mail address: wuye@bupt.edu.cn (Y. Wu).

https://doi.org/10.1016/j.chaos.2018.02.003
0960-0779/© 2018 Published by Elsevier Ltd.

only randomly selected data can lead to unbiased analysis based on statistics. Li first raise the self-selection bias in OCR [12]. Self-selection bias generally falls into two categories: acquisition bias and under-reporting bias. Acquisition bias means only those with high purchase propensity and high preferences would make consuming decision, and under-reporting bias means not all buyers will comment (i.e. silent consumers exist). Taken together, self-selection bias in OCR leads to the biased estimation of product quality [13]. Ma found more frequent and more words of reviews can reduce the biases [14]. Besides, some of the online review sites encourage relationships between users like allowing one to become a fan or a friend of another which can create some different on commenting behavior too. Rating similarity is found higher after the formation of the friends relationships [15] as well as Goes found that popular users tend to produce more reviews and their reviews are more negative and more varied than normal [16].

Products can be divided into two types, the experience and the search [17,18]. For the search goods like electronic products, consumers can cognize products through the collection of information before consumption, review of these products are relatively objective. In the contrast, reviews of experience goods such as movies and restaurants are deeply influenced by individual preferences and thus to be subjective [19,20], that means even though consumers can also view a large amount of information from other people before they consume, the information is relatively subjective.

The above research focused on the review sites in English. In order to explore the dynamics of OCR in Chinese sites, we analyzed the online reviews of 1894 restaurants from Dianping.com, and summarized as four temporal evolution patterns: (1) declining monotonically and then being stable, (2) declining with undershooting characteristic and then being stable, (3) first rising and then being stable, (4) being constant over time. Next, we introduce a conceptual model with heterogeneous preferences and self-selection mechanisms, the model results coincide with the four temporal evolution patterns found in the empirical data well to support the hypotheses. The numerical results of the model show that once a product enters the OCR platform, consumers with specific preferences tend to consume early, and their reviews tend to deviate from the general opinion of the public, and therefore fail to be representative. Because the existing OCR help to build the psychological expectations of potential consumers, and have impact on consumption decision, which in turn affects the number of follow-up consumers and the rating of the product in the future. Taking into account the impact of these factors can help potential consumers make wiser decisions.

2. Empirical analysis

A sample of OCR data is collected from Dianping.com. As one of the most popular online word-of-mouth websites in China, Dianping.com provides consumer reviews for local restaurants and other service industry, and mainly focus on restaurant reviews. Therefore, the reviews data of Dianping.com can help to study the reviews from Chinese users. Our study focused on the OCR of restaurants in Beijing, each review contains some important characteristic, including rating, published time, restaurant ID, user ID, and text content (Table 1). Firstly, we excluded those restaurants with less than 100 reviews, and then 1894 effective restaurants and 189,400 effective reviews are collected. Secondly, we sort all the reviews of each restaurant by timestamp. The ratings are varying from 1 to 5 points, representing the satisfaction: poor, general, good, very good and excellent. According to the statistical analysis, the average score of 1894 restaurants is 3.7.

Four temporal evolution patterns are summarized by analyzing the reviews series, as shown in Fig. 1. In pattern a, the cumulative average rating of the restaurants first monotonically declines then gradually becomes relatively stable; In pattern b, it first declines with obvious undershooting characteristic and then becomes relatively stable; In pattern c, it first rises and then becomes relatively stable; In pattern d, it remains constant over time.

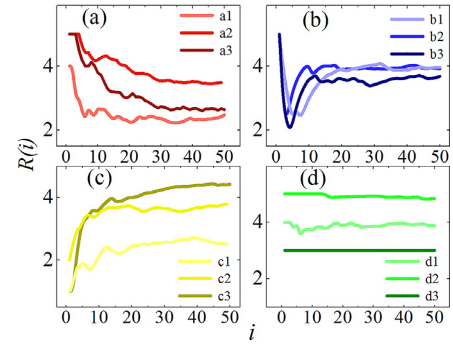

Fig. 1. Four temporal evolution patterns of comments. The four graphs show the time series of cumulative average ratings of 12 sample restaurants and 3 curves in each graph corresponding to the three different restaurants in our data set. The horizontal coordinate represents the number of reviews a restaurant accumulate, and the vertical coordinate represents the cumulative average rating. In each graph, reviews are clearly not random but show visually discernable patterns over time. Restaurants a1, a2, a3 meet pattern a, first monotonically decline then become relatively stable. Restaurants b1, b2, b3 meet pattern b, first decline with obvious undershooting characteristic then become relatively stable. Restaurants c1, c2, c3 meet pattern c, first rise and then become relatively stable and restaurants d1, d2, d3 meet pattern d, the curves remain constant and have little change over time.

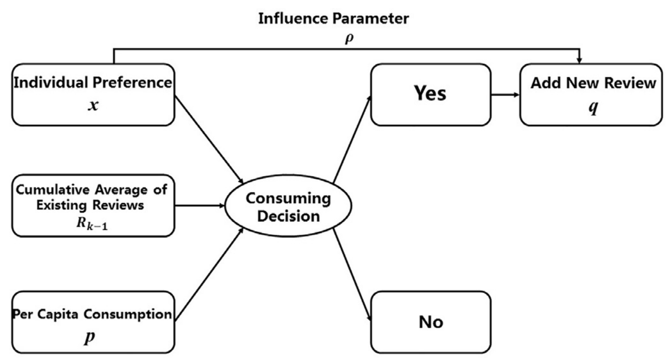

Fig. 2. Schematic of the model. The flow chart of the model. A potential customer with individual preference x for a experience product like a restaurant, trying to make a consuming decision by viewing the cumulative average of existing reviews R_{k-1} and the information of expense amount per person p. If he decides to go dining, then he would publish a new review and grade this restaurant based on his dining satisfaction, the parameter ρ describes the effect of individual preference on the rating of the new review.

3. Model and simulation

To examine the evolution patterns we found in the data set, a model is introduced to fit the trend over time. Because reviews of experience goods such as movies and restaurants are deeply influenced by individual preferences, two main hypothesis of the model are proposed: (1) The former reviews would affect the subsequent potential consumers' consuming decision. (2) The ratings are influenced by individual preferences. This model simulates the process of consuming and commenting, and our study focuses on the following two stages, which are the stage of consuming decision and commenting after consumption, as shown in Fig. 2:

The basic idea of this model is to consider the effect of individual preference on consuming decision and commenting behavior for experience products. Our model is applied to the catering, which is the typical experience product. There are three factors af-