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TOWARDS EXPLORING WHEN AND WHAT PEOPLE REVIEWED FOR THEIR ONLINE SHOPPING EXPERIENCES

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Abstract

Web 2.0 technologies have attracted an increasing number of people with various backgrounds to become active online writers and viewers. As a result, exploring reviewers' opinions from a huge number of online reviews has become more important and simultaneously more difficult than ever before. In this paper, we first present a methodological framework to study the "purchasing-reviewing" behavior dynamics of online customers. Then, we propose a review-to-aspect mapping method to explore reviewers' opinions from the massive and sparse online reviews. The analytical and experimental results with real data demonstrate that online customers can be sectioned into groups in accordance with their reviewing behaviors and that people within the same group may have similar reviewing motivations and concerns for an online shopping experience.

Keywords: E-commerce, online review, review dynamics, opinion mining

1. Introduction

Online review, a form of customers' feedback on E-commerce, has become an important channel for both consumers and producers to provide product information from a customer's perspective (Park and Lee 2009, Zhu and Zhang 2010). It has been witnessed that Web 2.0 technologies have attracted an increasing number of people with various backgrounds to become active online writers and viewers (Cheng et al. 2012). As a result, a great number of reviews have been generated with different motivations (Kraut and Resnick 2012), in which the reviewing behaviors are more diverse and the language words used in reviewed contents are sparser than those generated by people who have similar backgrounds and a pure motivation for sharing information of product quality. Therefore, to understand information more precisely from massive and various online reviews, a feasible way is not only to explore what users said, but also why they said.

However, in real applications, reviewers will not explain why they post reviews online, especially for those extrinsic reasons - such as status, financial reward, or social influence. Fortunately, part of a reviewer's motivations can be observed by her/his reviewing behaviors, such as reviewing quality (posting a long or short review), promptness (posting a quick or lazy review), and attitude (posting review actively or passively) (Liu et al. 2008). By observing actual reviewing behaviors, we can infer immediate reasons why they review, even if they only write occasional reviews (Brown 2012). For example, if one were offended, or staffs were rude in online shopping process, people might take a quick reaction to express a grievance or warn others. Thus, the task of exploring reviewers' behaviors (how they said) and further understanding reviewers' exact opinions from massive and sparse online reviews becomes more important, especially, when these reviews are associated with some specific reviewing behaviors.

In literature, most research has focused on mining the contents of reviews, for opinion (feature) extraction (Dave et al. 2003, Hu and Liu 2004, Pang and Lee 2008, Zhang et al. 2010), sentiment analysis (Cui 2006, Pang and Lee 2008), collaborative filtering (Zhang et al. 2014, Almahairi et al. 2015), and sales forecasting (Chintagunta et al. 2010, Yu et al. 2012). Whereas, customers' reviewing behaviors have been overlooked. In this work, we employ the reviewing behavior dynamics method and the review-feature-based opinion mining method to explore the relationship between people's reviewing manners (i.e., timely) and their reviewing opinions (what they talk about). The main contributions of this paper lie in two aspects. First, we present an analytical framework to explore the customers' reviewing behavior dynamics. Second, we present a review-to-feature mapping method to solve the opinion mining problem for exploring the aspects from a novel perspective of customer purchasing-reviewing behavior similarity.

The rest of this paper is organized as follows. Section 2 presents related work. Section 3 sketches out the methodology in detail. Section 4 shows and discusses the experimental results. Section 5 summarizes some managerial insights and Section 6 concludes the paper.

2. Related Work

2.1 Online Behavior Dynamics and Customers' Reviewing Motivations

Human behavior dynamics deals with the effects of multiple causal forces in human behaviors, including network interactions, groups, social movements, and historical transitions, among many other concerns (White 2009). Empirical studies on web browsing (Goncalves and Ramasco 2008), online reviewing communities (Wang 2010, Gilbert and Karahalios 2010), online music listening (Hu et al. 2008), online instant messaging (e.g., QQ) (Chen et al. 2010), and online microblog replying (e.g., Twitter) (Sousa et al. 2010) found that the time interval between two consecutive reviews on the same topic, known as the inter-event time, followed a power-law distribution.

Although online reviewing has become notably popular in B2C systems, few efforts have been undertaken to examine the dynamic aspects of online opinion formation. It is valuable to mention that Wu and Huberman (2010) studied the dynamics of online opinion formation by analyzing the temporal evolution of very large sets of users' views. Their work is different from our study in that the former focused on the dynamic aspects of online opinion formation: i.e., how opinions about books, movies, or societal views fluctuated over a long time before reaching a final consensus, or how they underwent systematic changes over time. However, our work seeks to understand the dynamics of customers' reviewing events for an online product and the associated review contents and review motivation identification problem.

Some previous research also studied the motivations for posting reviews online (Wang and Fesenmaier 2003). The classic characterization of motivation as broadly extrinsic or intrinsic was used to discuss motivations for contributing to online communities (Kraut and Resnick 2012). Since online communities bring together individuals with shared interests in joint action or sustained interaction, a very recent work presented by Johnson et al. (2014) studied the formation of the power-law distribution via the mechanisms of preferential attachment, least efforts, and direct (or indirect) reciprocity.

2.2 Opinion Mining and Feature Extraction

Opinion mining, also known as sentiment analysis (Pang and Lee 2008), opinion summarization (Zhuang et al. 2006), or subjectivity analysis (Liu 2010, Ghose and Ipeirotis 2011), plays an important role in online business. The basic technology used in opinion mining is text-mining (Ghose and Ipeirotis 2011), which is used to derive insights from user-generated contents and is primarily originated in the computer science literature (Hu and Liu 2004, Pang and Lee 2008). Thus, previous text-mining approaches focused on automatically extracting the opinions of reviews (Dave et al. 2003). The task of sentiment analysis is to judge whether a review expresses a positive, neutral, or negative opinion (Liu 2010). The typical work uses the method presented by Pang and Lee (2008) on sentiment classification at the document level. Opinion summarization is the task of producing a sentiment summary (Hu and Liu 2004). This method differs from traditional text summarization by reducing a larger corpus of multiple documents into a short paragraph conveying the meaning of the text. It is interested in features or objects on which customers have opinions. In some real applications, readers are often interested not only in the general sentiment towards an online item but also in a detailed opinion or analysis of each aspect of the item. These considerations underline the need to detect interesting aspects in an online review data set by extracting the reviewed features (Titov and McDonald 2008).

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately with a method of early expert annotation (Pang and Lee 2008) and recent new technologies from machine learning. For example, in Ghose and Ipeirotis (2011), the authors presented a method to look into the text to extract features impossible to be observed by a simple numeric rating. Zhang et al. (2010) presented a feature-based ranking technique to mine customer reviews. In the past several years, several probabilistic graphical models have been proposed to address the aspect-based opinion mining problem (Jo and Oh 2011), which aims to extract aspects and their corresponding ratings from customer reviews. The object feature, opinion extraction, and opinion polarity detection were formulated as a joint structure tagging problem to summarize feature-based reviews (Li et al. 2010).

Although the online review (text) mining related research has accumulated fruitful results, it does not examine the total underlying information, for example, the dynamic aspects of online opinion formation (Wu and Huberman 2010). In this study, we attempt to explore the hidden aspects from massive data in combination with the observations of customers' two important behaviors of purchasing and reviewing online.

3. Methodology

In this study, we present a methodology framework for analyzing online reviews. This framework primarily consists of three parts: the review extraction subsystem (RES), the reviewing dynamics study subsystem (RDSS), and the review opinion mining subsystem (ROMS).

The RES is used to extract reviews from B2C websites and to separate the behavioral information and the review contents (text) from the initial data set (subsection 3.1). Sequentially, the behavioral data would be input into the RDSS to study the dynamics of customers' "purchasing-reviewing" behaviors (subsection 3.2.2), and these behaviors would be segmented into different groups according to their characteristics (subsection 3.2.3). Next, the reviewed contents would be grouped according to the segmentations of their "purchasing-reviewing" behaviors. Finally, the contents in each group are processed into a set of word vectors to mine group-based opinions in the ROMS (subsection 3.3). Figure 1 shows the main procedure.

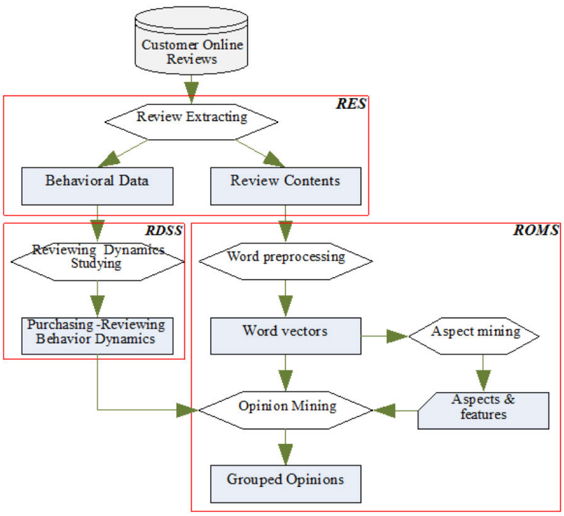

Figure 1 The main procedure

3.1 Review Extraction

The main task of the RES is to extract large scale and high-quality users' reviews from a B2C website. All the review data extracted by the RES for an online product is denoted by C. For the i^{th} review $c_i \in C$, $(i = 1, \cdots, |C|)$, the important reviewing information can be summarized in Table 1.

The contents in $c_i(PT)$ and $c_i(RT)$ are reviewing-behavior-related information whereas the content in $c_i(RE)$ is the textual review.

Table 1 Important information extracted from an online review c_i

Notation	Description
$c_i(PT)$	Time point of customer shopping online
$c_i(RE)$	Customer's reviewed contents (text)
$c_i(RT)$	Time point of customer reviewing online

3.2 Reviewing Behavior Dynamics

The specific "dynamics" studied in this work deals with the effects of multiple causal forces in customers' reviewing behaviors. To that end, in the RDSS, the data series of "purchasing-reviewing" behaviors is generated firstly, and then these data would be divided into appropriate segments (groups) such that the customers' "purchasing-reviewing" behavior dynamics (distribution trend) in each group is similar to each other.

3.2.1 "Purchasing-Reviewing" Data Series

For each review $c_i \in C$, we calculate the "purchasing-reviewing" time interval x_i (in day time) and its frequency as

$$\begin{cases} x_i = c_i(RT) - c_i(PT), \\ y_i = frequency(x_i). \end{cases} \tag{1}$$

Here, function *frequency* is used to measure the total number of x_i in C. For instance, $frequency(2) = 5$ means that there are 5 users who hold the same "purchasing-reviewing" time interval of 2 days.

For all the reviews in C, a data series can be generated as

$$T = \{(x_i, y_i)\}_{i=1,\cdots,|C|}. \tag{2}$$

Data series T can be used to analyze the customers' reviewing dynamics.

3.2.2 Power-Law Distribution Fitting

Evidence in literature has shown that the distribution of T can be used to check the similarity of users' behavior dynamics (Chen et al. 2010, Sousa et al. 2010). Moreover, if T follows a typical non-Poisson process and is characterized by a power-law distribution, it means that the reviewing behaviors on a B2C website have been affected by extrinsic motivations, intrinsic ones, or both (Yan et al. 2012). To verify the assumption about the distribution of the time interval between two consecutive customers' behaviors, a linear regression based on the least-squares method is used to fit the power-law function curve.

Let x denote the time interval of the two behaviors of "purchasing-reviewing" and y denote the probability of each time interval, and then (x_i, y_i) is the i^{th} observation of variable pair (x, y). The function of the power-law distribution curve is $y = ax^{-b}$, where $a > 0$. Accordingly, the method can be specified as follows (Newman 2003):

- Take the logarithm on both sides of $y = ax^{-b}$ and then substitute u for $\ln x$ and v for $\ln y$, the power-law distribution function is transformed into a linear equation: $v = \ln a + (-b)u$;
- Use the value of (x_i, y_i) to calculate (u_i, v_i);
- Calculate the estimated value of a and b as $\hat{b} = -\dfrac{\sum u_i v_i - \sum u_i \sum v_i}{n\sum u_i^2 - (\sum u_i)^2}$ and $\hat{a} = \exp\{average(v) + \hat{b} \bullet average(u)\}$ via a least-squares regression method.

3.2.3 Data Series Sectioning

In this study, a data series sectioning method based on the Mann–Kendall trend test (Mann 1945), one of the widely used non-parametric tests to detect significant trends in time series, is proposed to divide the "purchasing-reviewing" data series, i.e., T, into appropriate number of segments, so that the "purchasing-reviewing" behaviors in the same segment are similar to each other.

Taking the change of $\{y_i\}_{i=1,\cdots,|C|}$ with respect to $\{x_i\}$ as the potential trend, the sectioning procedures for data series $T = \{(x_i, y_i)\}$ can be specified as follows:

- Set $p_1 = (x_1, y_1)$ and $p_{|C|} = (x_{|C|}, y_{|C|})$ as two starting points. For any point $p_i = (x_i, y_i)_{i=2,\cdots,|C|-1}$, it needs to calculate the distance between p_i and line $\overline{p_1 p_{|C|}}$, i.e., $d_i = \dfrac{|(p_{|C|} - p_1)| \times |(p_1 - p_i)|}{|(p_{|C|} - p_1)|}$, to identify $p_{i^*} = (x_{i^*}, y_{i^*})$ as the third starting point (it segments T into two parts of $\{p_1, \cdots, p_{i^*}\}$ and $\{p_{i^*}, \cdots, p_{|C|}\}$) such that $i^* = \arg_{\{d_i \geq d_0\}} \max\{d_i\}$, where d_0 is a predefined threshold that can be set generally as the average value of d_i;
- Calculate two distances, i.e., d_j between point $p_j = (x_j, y_j)_{j=2,\cdots,i^*-1}$ and line $\overline{p_1 p_{i^*}}$ and d_k between point $p_k = (x_k, y_k)_{k=i^*+1,\cdots,|C|-1}$ and line $\overline{p_{i^*} p_{|C|}}$, to identify $p_{i^{**}} = (x_{i^{**}}, y_{i^{**}})$ as the fourth starting point, where $i^{**} = \arg_{\{d_j \geq d_0, d_k \geq d_0\}} \max\{d_j, d_k\}$;
- Repeat the above processes until all the distances in the same iteration are less than the threshold d_0. Then the data series sectioning is completed.

Figure 2 illustrates an example for sectioning a data series into five sections (the dashed line).

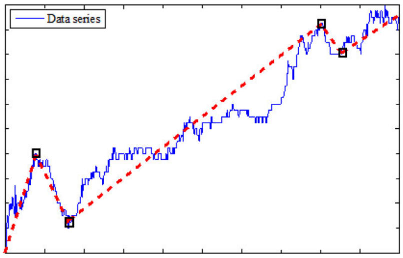

Figure 2 Partitioning sample data series into five sections

3.3 Review Aspects Based Opinion Mining

The ROMS is responsible for identifying the potential opinions from massive reviews. In the following, we first introduce the concept of review feature space, then propose a review-to-aspect mapping method to map a reviewed word onto one feature of a given aspect, and finally, implement data mining method on these aspects.

3.3.1 Reviewing Space, Aspects and Feature Words

In this work, we introduce a taxonomy of "space-aspect-word" to illustrate the three semantic levels in a set of online reviews. Given an online good in a B2C website, assume that there exists a review space, Ω, in which, any element is an aspect of online shopping experience and each aspect can be represented by various character words with close semantic similarity.

Now, the problem is how to determine the elements of Ω, i.e., the aspects and the associated features (character words). As a semi-supervised process, the aspect mining process can be conducted with a three-step annotation method (Uren et al. 2006).

At the first step, we determine the types of topics in Ω by assuming that there is a set of predefined subspaces Ω^i and Ω which may be a representation of one topic. Thus, $\Omega = \bigcup \Omega^i$. Previous studies on feature selection in the text domain have been a great help in providing guidance and motivations for this study (Jurca et al. 2010, Wan et al. 2011). For the typical online reviews in a Chinese B2C website, we can summarize six types of feature spaces in Table 2.

Table 2 Review spaces for the online reviews in a Chinese B2C website

Subspace type	Note
Ω^f	Function related aspects
Ω^a	Appearance related aspects
Ω^v	Value related aspects
Ω^s	Service related aspects
Ω^{sp}	Positive-sentiment related aspects
Ω^{sn}	Negative-sentiment related aspects

At the second step, we determine the character words for Ω via a general Natural Language Processing method. Firstly, $c_i(RE)$ will be split into words. Then, the noise and meaningless words will be cleaned and only a set of valuable semantic words, S_i, are left:

$$S_i = \{s_k\}, \quad (3)$$

where $i = 1, \cdots, |C|$ and $k = 1, \cdots, |S_i|$.

At the third step, a set of aspects are generated for reviews C as follows:

- Select a set of typical reviews C' from C as a training data set. Conduct the LDA-based method (Jo and Oh 2011) on the training data to get a set of aspects and their associated features (Table 3). The label of w_i is added manually.
- Associate each aspect, w_i, with an appropriate subspace Ω^j where $j = \{f, a, v, s, sp, sn\}$.

Table 3 Associate a set of words with one aspect

Aspect	Character Words
w_1	$s_{11}, s_{12}, \cdots, s_{1j}, \cdots, s_{1n_1}$
$\vdots$	$\vdots$
w_i	$s_{i1}, s_{i2}, \cdots, s_{ij}, \cdots, s_{in_i}$
$\vdots$	$\vdots$

At last, an example for the obtained "space-aspect-word" taxonomy is shown in Table 4. The contents of "character words" show the terms used originally by reviewers, while those of "aspect" filter out the latent similar semantics from various expressions. Obviously, Ω^i summarizes the abstract managerial insights.

Table 4 An example for reviewing space, aspects, and feature words

Ω^i	Sample aspects	Sample character words
Ω^f	operation	camera, shoot, run, speed, etc
	performance	auto, mode, speed, etc.
Ω^a	color	red, blue, etc.
	design	appearance, package, paint, etc.
Ω^v	price	charge, fee, cost, expense, etc.
	promotion	discount, gift, etc.
	brand	Nikon, Nike, reputation, etc.
Ω^s	logistic	shipment, delivery, transport, etc.
	call center	problem, manner, solution, return, etc.
Ω^{sp}	positive, etc.	good, fast, nice, amazing, fun, great, etc.
Ω^{sn}	negative, etc.	bad, low, not worth, poor, terrible, etc.

3.3.2 Review-to-Aspect Mapping Process

In the data mining process, if we conduct a mining algorithm, such as term- frequency and clustering, on $\bigcup\{S_i\}$ directly, we will encounter the problem of data sparsity for the following reasons: first, the words used in these reviews are very sparse because of the different backgrounds (e.g., personal education and reviewing motivations) of various reviewers (Cheng et al. 2012); second, a large number of synonyms are used to express the same view for the online shopping experience (Liu 2012). This will make the mining process very inefficient. To address the problem, we could map each element in S_i to a high level semantic representation, i.e., aspect or subspace, with a limited loss of information.

Known from Table 3, aspect w_i is an appropriate semantic representation for a set of words, i.e., $\bigcup\left\{s_{ij}\right\}$. Therefore, if there exists a mapping method ϕ such that $\phi(s_k) = w_j \in \Omega$ where $s_k (k = 1, \cdots, |S_i|)$ is the $k-th$ semantic word of S_i, then we can transform S_i into an aspect vector $av_{c_i(RE)}$.

For example, $c(RE) =$ "The price is relatively high, but I like its painting". The semantic word vector $S =$ {price, painting} where $s_2 =$ "painting" is not a standard feature in Ω. If there exists a method of ϕ such that $\phi(s_2) =$ "color" ("color" is an aspect in w_i), then we can transform S into $av_{c(RE)} =$ {price, color}. Here, the key function of ϕ establishes a linkage between various semantic words and an aspect in Ω. In this work, we use a review-to-aspect mapping method to solve the problem as:

- For each word $s_k \in S_i$,

$$\phi(s_k) = \begin{cases} w_i, dist(s_{ij}, s_k)_{j=1,\cdots,n_i} \le dist_0; \\ Null, \text{ otherwise}, \end{cases} \tag{4}$$

where $dist(\bullet)$ may be any method that can measure the similarity of w_i (or the initial semantic word s_{ij} of w_i) and s_k, for example, the string-based, corpus-based (Gomaa and Fahmy 2013), or cluster-based (Aggarwal and Zhai 2012) similarity method. $dist_0$ is a predefined threshold.

- Obtain an aspect vector $av_{c_i(RE)}$ for $c_i(RE)$;
- Repeat the above steps until all the reviews are processed.

Finally, all the reviews in C can be transformed into a transactional dataset V as follows:

$$V = \begin{pmatrix} \Omega & w_1 & \dots & w_j & \dots \\ & & \vdots & & \\ av_{c_i(RE)} & v_{i1} & \dots & v_{ij} & \dots \\ & & \vdots & & \end{pmatrix}, \tag{5}$$

where:

$$v_{ij} = \begin{cases} w_j, \text{ if the } j^{th} \textit{ aspect} \text{ in } \Omega \text{ is reviewed in } c_i(RE), \\ Null, \text{otherwise.} \end{cases}$$

3.3.3 Aspect Based Frequent Pattern Mining

With the review-to-aspect mapping process, we can transform the customers' reviews $c_i(RE)$ (in form of natural language sentences) into a vector of review aspects, $av_{c_i(RE)}$. As aforementioned, the customers' "purchasing -reviewing" behaviors can be segmented into groups. Accordingly, $av_{ci(RE)}$ and $av_{c_j(RE)}$ could be partitioned into the same group of V_k if (x_i, y_i) and (x_j, y_j) are in the same segment k.

Another interesting work in this study is to identify the customers' opinions in different groups. Data set $V_k = \bigcup\left\{av_{c_i(RE)}\right\}$ is a transactional database, in which the meaningful sparse terms in the original corpus are represented by their corresponding aspects. Thus, two tasks are involved in mining the customers' reviewed opinions (at a high level of managerial insights):

- Frequent pattern mining is conducted on V_k to explore the hot and common concerns (opinions) in grouped people. Since the sparsity of V_k is typically much smaller than that of the initial corpus, we introduce the cosine measurement to evaluate the interestingness of the mined patterns (Wu et al. 2012): For a $I = \{i_1, i_2, \cdots, i_K\}$, $K \geq 2 \in Z_+$, the cosine value of I is defined as :

$$\cos(I) = \frac{\sup p(I)}{\sqrt[k]{\prod_{k=1}^{K} \sup p(\{i_k\})}}. \quad (6)$$

- Correlations between aspects $w \in \left(\bigcup \Omega^i\right)_{i=\{f,a,v,s\}}$ and sentiment words $w_s \in \left(\Omega^{sp} \bigcup \Omega^{sn}\right)$ are analyzed to identify the sentiments distributed in different groups of customers.

4. Experiment Results

In this section, we present a case study to demonstrate the proposed method.

4.1. The Data

In the experiment, reviews for four online goods were selected from the website of www.jd.com, one of the most well-known B2C online shopping malls in China. The first good is the "*Nikon D90*" digital camera[1] (hereafter referred to as "*D90*") because it has many features and characteristics needed to be evaluated before purchase. The second is the "*Badminton racket*"[2] (hereafter referred to as "*Racket*") because it has only a few features needed to be evaluated before purchase. Additionally, *One Hundred Years of Solitude* (Chinese version)[3], one of the Garcia Marquez's famous book, was collected because it needed a relatively long time to experience. Furthermore, the "*Arabella*" wine[4] was collected because it needed a relatively short time to experience. Table 5 summarizes the characteristics of the experiment data set.

Note that as the reviews were mostly submitted by the users in China, they were written in Chinese. In the following, we perform experiments with data in Chinese and report the results in English (sometimes in both).

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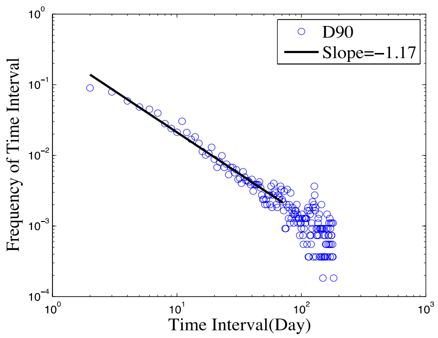
1 http://club.jd.com/review/134178-1-0.html
2 http://club.jd.com/review/219337-0-1-0.html
3 http://club.jd.com/review/10658646-0-1-0.html
4 http://club.jd.com/review/338415-1-1-0.html

Table 5 Data set used in experiment

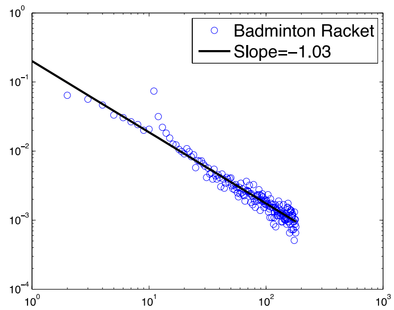
Goods	Reviewing Time	$\lvert C\rvert$	$\min(x_i)$	$\max(x_i)$	$\min(c(RE))$	$\max(c(RE))$
D90	2008-11-06, 2011-12-31	5460	0	182	13	442
Racket	2010-05-22, 2013-12-08	13733	0	180	2	566
Book	2011-06-01, 2013-12-08	49422	0	181	2	4000
Wine	2011-02-14, 2012-07-25	4246	0	181	12	192

4.2 When Do Customer Review?

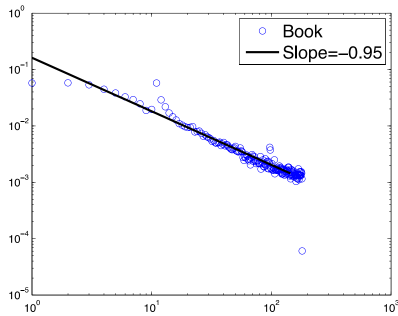
To study when customers review in www.jd.com, we first calculate the "purchasing-reviewing" data series T_{D90}, T_{Racket}, T_{Book}, T_{Wine} (in days) with relation (1) for "D90", "Badminton racket", "Garcia Marquez's book", and "Arabella" wine respectively. Then fit and test the characteristics of these reviewing data series with the power-law distribution. Second, we draw the frequency distribution diagram of the time interval and divide the reviewing into three groups of instant, medium-term, and long-term behaviors. Finally, we explore the customers' reviewing motivations.



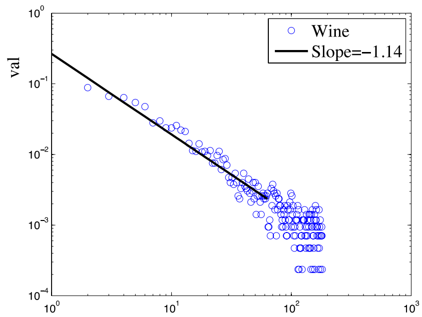
(a) "D90" digital camera



(b) Badminton racket



(c) Garcia Marquez's book



(d) "Arrabella" wine

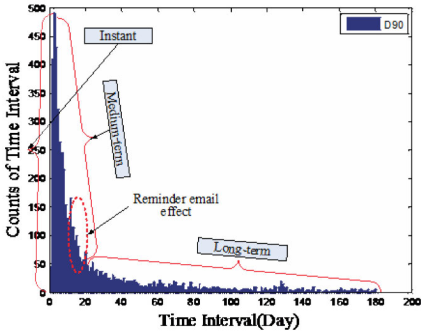
Figure 3 Double-logarithmic plots for the four online products

4.2.1 Distribution of "Purchasing-Reviewing" Data Series

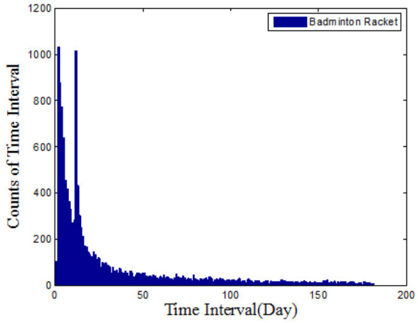
For T_{D90}, the fitted power-law distribution function is $y = 0.3131x^{-1.17}$. The goodness of fit is $R^2 = 0.9551$ and the statistical K-S test is satisfied, meaning that the frequency (proportion) of the "purchasing-reviewing" time intervals follows the power-law distribution with the exponent of −1.17. Similarly, T_{Racket}, T_{Book} and T_{Wine} follow the power-law distribution, with exponents of −1.03 ($R^2 = 0.941$), -0.95 ($R^2 = 0.949$), and −1.14 ($R^2 = 0.921$), respectively (See Figure 3).

Power-law distribution characterizes an important number of human endeavor behaviors. It means that a high-frequency population is followed by a low-frequency population which gradually "tails off" asymptotically. The distributions of the frequency of "purchasing-reviewing" time intervals for the four selected items are shown in Figure 4.

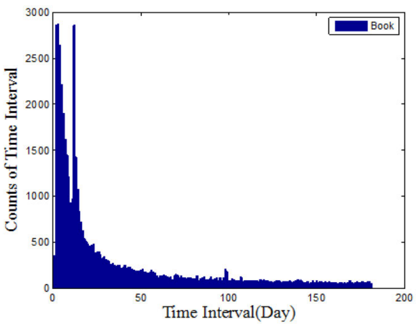
These experimental results show that reviewing behaviors on www.jd.com may have similar dynamics. Moreover, the power-law distribution of the "purchasing-reviewing" time intervals suggests the reasons why online community development should move to a highly socialized and multi-theoretic explanations (Johnson et al. 2014). This work integrates customer behaviors and reviewing motivations to explain the formation of such a distribution.



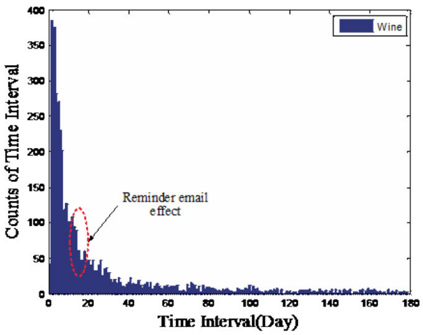
(a) "D90" digital camera



(b) Badminton racket



(c) Garcia Marquez's book



(d) "Arrabella" wine

Figure 4 Frequency distributions of the "purchasing-reviewing" time intervals

4.2.2 Instant, Medium-Term, and Long-Term-Reviewing Behaviors

In this study, the people with similar "purchasing-reviewing" intervals are grouped together while time is the most relevant property with human behavior dynamics of online reviewing.

Setting the threshold of d_0 as the average time interval of all the "purchasing-reviewing" data, we can divide the reviewing behaviors into three groups of instant, medium-term, and long-term reviewing behaviors with the "purchasing-reviewing" data series sectioning method. Obviously, the reviewing behaviors in the same group are expected to have similar dynamics:

- *instant reviewing:* the customers review the experience of online shopping in a short timeslot after purchasing;
- *medium-term reviewing:* the customers will review their online shopping experiences in a medium length of time after purchasing;
- *Long-term reviewing:* the customers would review their online shopping experiences in a relatively long timeslot.

Table 6 Time series sectioning for T_{D90}, T_{Racket}, T_{Book}, T_{Wine}

Reviewing type	Timeslot (days)	# Of Reviews (%)	Avg. frequency
Instant	0-2	9852 (13.52)	821.0 (high)
Medium-term	3-20	33799 (46.39)	469.4 (Medium)
Long-term	21-180	29210 (40.09)	45.5 (low)

As can be observed in Table 6, approximately 13.52% of the customers finished the reviewing within 0-2 days (instant reviewing). This distribution indicates that a lot of consumers would like to publish their reviews for the product soon after their purchasing actions. 46.39% of the people's time intervals are within 3-20 days (medium-term reviewing). Additionally, 40.09% customers would review their online shopping experience more than 20 days later (long-term reviewing).

Moreover, in Table 6, we can see clearly that a high-frequency population (the instant reviewing group) is followed by a low-frequency population (the long-term reviewing group) which gradually "tails off". In the following, we try to explore who are in these groups and why they make a reviewing.

4.3 What Do People Review?

Because the power-law distribution has a strong characteristic of heterogeneity (Gheorghiu and Coppens 2004), we should make it clear what valuable information is contained in these reviews. Especially, we are interested in the opinions distributed in the three different groups.

We can see that the reviewing dynamics are similar for the four datasets (See Figure 4) but different in parameters. Without losing generality, the following text mining experiments are conducted on the reviewing data for "D90" because it is a complicated and expensive machine for ordinary users so that it gained more aspects reviewed online than the other products. Also, similar mining tasks can be easily implemented to the reviewing data for any other products.

4.3.1 Data Preprocessing

First, a word segmentation method is adopted to tokenize the reviewing text into words. Then, the following types of words are removed: stop words, meaning less words, and words with very a low frequency.

Second, a minimum set of 15 review aspects is established in accordance with the principle of maximum coverage (Hiroya and Manabu 2009), which can cover most of the aspects reviewed in www.jd.com for “D90”. The subspace is as follows:

$$\Omega^{f}_{D90} = \{Camera, Video, Operation, Quality, General\ fuction\}$$
$$\Omega^{a}_{D90} = \{General\ feeling, General\ appearance\}$$
$$\Omega^{v}_{D90} = \{Brand, price, Gifts\}$$
$$\Omega^{s}_{D90} = \{Platform, process, Delivery, Packaging, Service\ attitude\}$$
$$\Omega^{sp}_{D90} = \{Good, Fast, Like\}$$
$$\Omega^{sn}_{D90} = \{Bad, Low, Dislike\}$$

Notes: A platform denotes the software system of online business, such as a website.

Finally, by using a LDA-based method, a word-aspect mapping table like Table 3 is generated (see appendix A), which can be used to map the reviewing words into aspects efficiently.

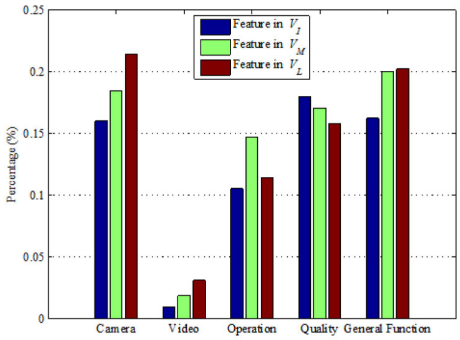
In the following, data set V would be partitioned into three subsets of V_I (for the instant-reviewing behavior), V_M (for the medium-term-reviewing behavior), and V_L (for the long-term-reviewing behavior) respectively.

4.3.2 Hot Aspects in Different Groups

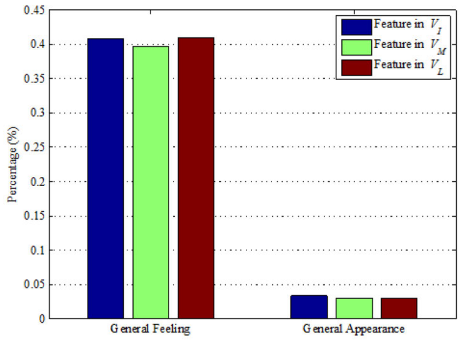
Hot aspects in online reviews reflect the common concerns regarding a product. The frequencies (proportions) of reviewed aspects in V_I, V_M, and V_L are presented in Figure 5 in accordance with their subspaces.

Some interesting information can be drawn from the figures:

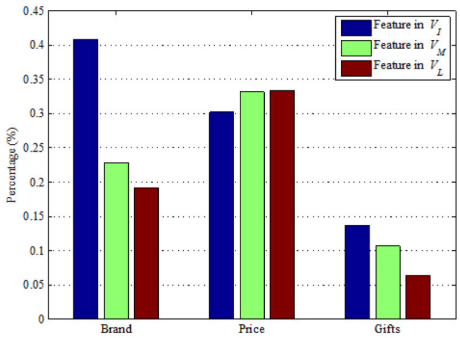
- The longer the “purchasing-reviewing” interval, the more function related aspects were reviewed (See “Camera”, “Video” and “General function” in Figure 5(a)), but the less aspect of quality was reviewed (See “Quality” in Figure 5(a)). In addition, the customers who had medium-term reviewing behaviors focused more on the function of operation than the others.
- There is no significant difference among the three groups in reviewing appearance related aspects (Figure 5(b)).
- With the increase of “purchasing-reviewing” interval, reviewers paid more attention to the “Price” aspect. On the contrary, the reviews for both topics of “Brand” and “Gifts” are decreasing (Figure 5(c)).
- The shorter “purchasing-reviewing” behaviors (instant and medium term) are more likely to comment on service aspects (Figure 5(d)).



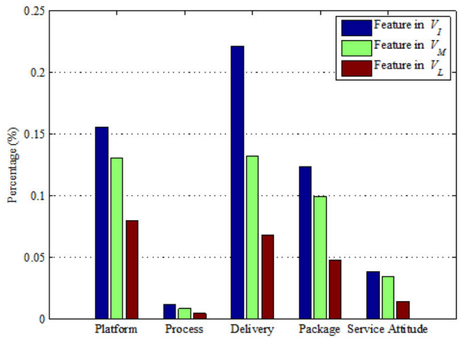
(a) Function-related aspects



(b) Appearance-related aspects



(c) Value-related aspects.



(d) Service-related aspects.

Figure 5 Reviewed aspects for "D90"

Table 7 Top-five concerns regarding "D90"

Reviewing type	Top-5 concerns
Instant	General feeling; Brand; Price; Delivery; Platform
Medium-term	General feeling; Price; Brand; General function; Camera
Long-term	General feeling; Price; Camera; General function; Brand

The top-five hot words in different groups of reviewing behaviors are summarized in Table 7, from which we can see that:

- All three groups are commonly concerned with "General feeling," "Price", and "Brand". Especially, the instant group users paid more attentions to the aspect of "Brand" than the other group users.
- The top concerns in the medium-term and long-term-reviewing groups are almost the same, but the long-term group paid more attention to the aspect of "Camera", one

key function of "D90". One possible explanation is that the medium-term and long-term reviewing people took more time to experience the function-related features of "D90".

- A special concern in the instant-reviewing group is "Delivery".

These results hold the following implications. From a customer's perspective, the instant-reviewing people mostly concern themselves with the product value (i.e., "Brand" and 'Price") and the delivery service, but they have less idea about the key functions of the "D90" (i.e., "Camera" function) because they review so quickly that they might not spend sufficient time experiencing the new product before reviewing it. In contrast, the medium-term and long-term-reviewing customers are more concerned with the function of the product.

From a producer's perspective, with respect to a precious commodity like camera "D90", "Brand" is an important aspect for online shopping customers, especially for those quick response people. Since the long-term-reviewing customers would pay much attention to the product aspect of "Price" and consequently a producer should hold a reasonable strategy to retain the product value.

From an E-commerce broker's perspective, the concern for service will gain more quick response from the customer's side. In addition, so many reviews focused on the aspect of "General feeling", meaning that some people publish their comments casually and have no willingness to share exact opinions with others.

4.3.3 Aspects Correlations

In this section, we conducted frequent pattern mining experiments with parameters minimum $\text{supp} = 55(0.1\%)$ and minimum *cosine*=0.3. Some interesting patterns are shown in Table 8.

Table 8 Interesting FPs mined from Ω_{D90}

Reviewing Type	Interesting FPs	(supp, cos)
Instant	{General function, Price}	(102.0, 0.495)
	{Brand, Price}	(78.0, 0.303)
	{Platform, Delivery}	(64.0, 0.370)
Medium-term	{General function, Price}	(346.0, 0.504)
Long-term	{General function, Price}	(224.0, 0.495)
	{Operation, Camera}	(87.0, 0.321)

Presenting the top correlations in Figure 6, the {"General function", "Price"} (supp = 672.0, cos = 0.5) connection is extremely significant with a high weight, followed by the {"Price", "Brand"} (supp = 383.0, cos = 0.267) connection. These two correlations indicate that, for the experiences of shopping "D90" online, the "General function" (usage), "Price" (cost-effective), and "Brand" (long-term credibility) are the most noted. They may be common values of all users who buy the product and thus have been paid sustained attention to.

The customers in the instant-reviewing group pay special attention to the {"Brand", "Price"} correlation, indicating that these were the factors that initially affect customers' purchasing decisions. The {"Platform", "Delivery"} correlation indicates the important role of the delivery in the online shopping experience and it is reviewed frequently by instant-reviewing customers.

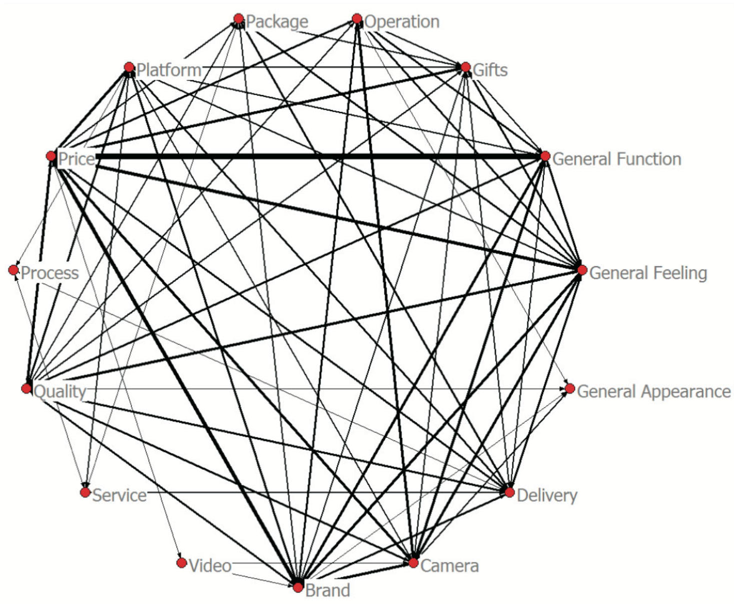


Figure 6 Paired feature relations in Ω_{D90}

4.3.4 Sentiment Analysis

In this work, two experiments were conducted to find the common sentiments of the reviewers and the correlations between these sentiments. To that end, two descriptions of "+" and "−" are introduced to denote the positive and negative sentiments respectively.

Given two aspects $w \in \left(\bigcup \Omega^{i}_{D90}\right)_{i=\{f,a,v,s\}}$ and $w_s \in \left(\Omega^{sp}_{D90} \cup \Omega^{sn}_{D90}\right)$, such that $\{w, w_s\} \subset av_{c_i(RE)}$, where $av_{c_i(RE)}$ is a record in relation (5), the sentiment of w is marked as follows:

$$\begin{cases} w+, \text{ if } w_s \in \Omega^{sp}_{D90}, \\ w-, \ if\ w_s \in \Omega^{sn}_{D90}. \end{cases} \tag{7}$$

For each aspect V_I, V_M, and V_L, the general method for sentiment analyzing is frequent pattern mining, which is based on the results of review-to-aspect mapping and sentiment representation with relation (7). The results are reported in Figure 7.

For the function aspects, it is plausible for "Camera", "Video", and "General function" to gain more positive reviews (Figure 7(a)) and for "Operation" to gain less negative reviews (Figure 7(b)) in the long-term reviewing group because these reviewers had a relative long time to experience the functions and accumulated more skills to operate the machine.

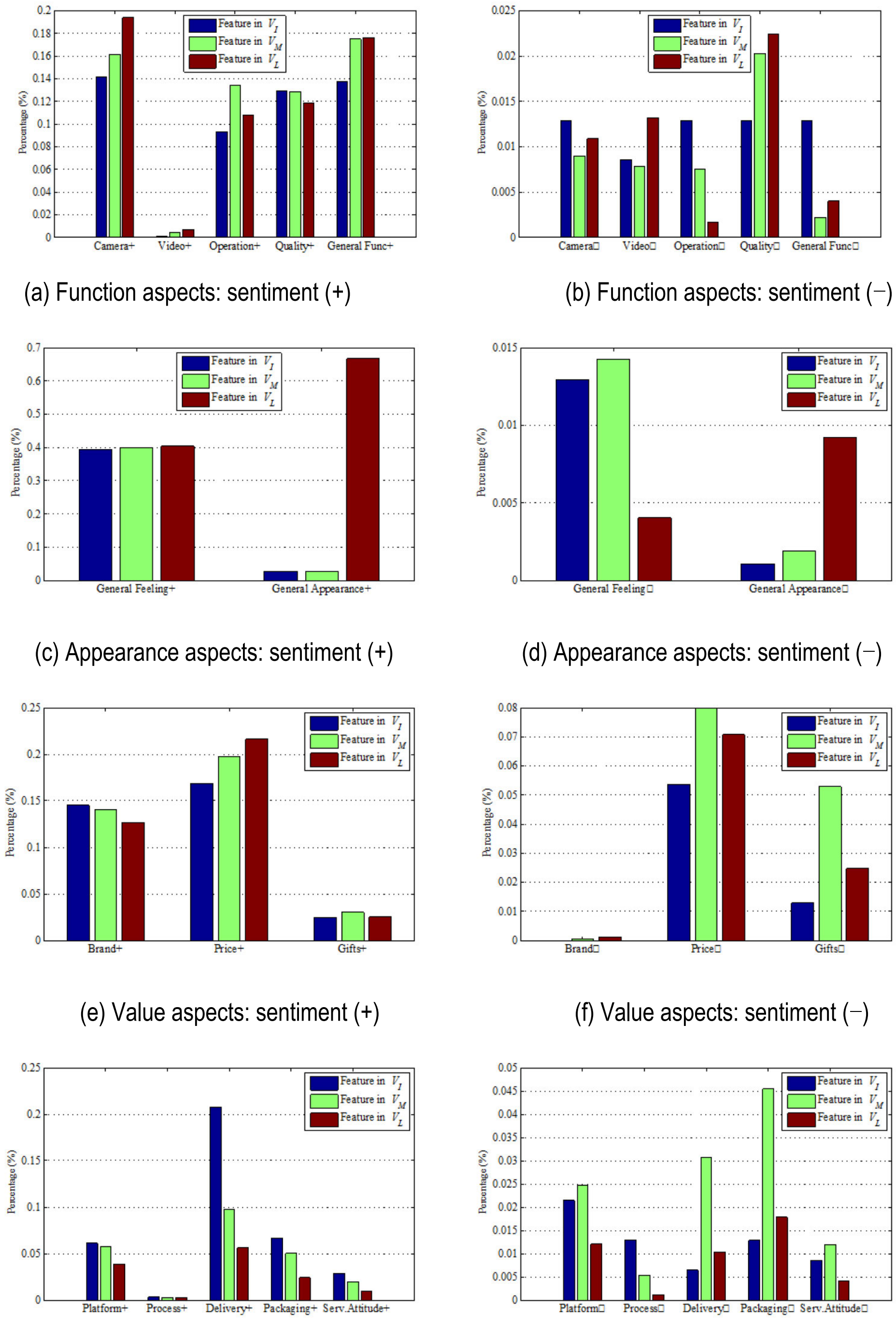
People who demonstrate long "purchasing-reviewing" behaviors (more experiencing time) are more likely to approve the design of product appearance. So "General appearance" gains much more positive reviews (Figure 7(c)) while "General feeling" gains less negative reviews from the long-term reviewing people (Figure 7(d)).

Since "D90" is a valuable product, we can see that the "Brand" aspect has more positive reviews from the quick response people than from the others. Simultaneously, "Price" gains more and more positive reviews along with the "purchasing-reviewing" interval becomes longer (Figure 7(e)), implying that "D90" has a good property in retaining its value. Interestingly, "Price" also gains many negative comments from the medium- and long-term "purchasing-reviewing" groups. By checking the original text, it shows that most of these people complained about their missing "Gift" from the seller rather than the price per se (Figure 7(f)).

Taking the online shopping as a whole process, individuals may have two different experiences of a product (provided by a good producer) and a service (provided by an E-commerce seller), in which, the latter is a momentariness experiment. Figure 7(g) shows that the shorter the "purchasing-reviewing" behavior, the more positive comments on the service aspect are made.

The top aspects with positive and negative sentiments are collected as shown in Table 9. The fact of "Price" appears frequently in both negative and positive sentiments suggests that "Price" is an important aspect in E-commerce although people may have conflicting viewpoints about it. Moreover, the "Delivery" aspect in the instant-reviewing group, the "General function" aspect in the medium-term-reviewing group, and the "Camera" aspect in the long-term-reviewing group were all positive. These results may give readers a deep impression on both delivery service and key functions of the product.

Additionally, the mined frequent patterns for aspect correlations show that "D90" is satisfactory to customers with a high cost-effectiveness (Table 10).



(a) Function aspects: sentiment (+)

(b) Function aspects: sentiment (−)

(c) Appearance aspects: sentiment (+)

(d) Appearance aspects: sentiment (−)

(e) Value aspects: sentiment (+)

(f) Value aspects: sentiment (−)

(g) Service aspects: sentiment (+)

(h) Service aspects: sentiment (−)

Figure 7 Sentiments of reviewed aspects (features) for “D90”

Table 9 Top positive and negative sentiment aspects for “D90”

Reviewing type	sentiment(+)	sentiment(−)
Instant	General feeling; Delivery; *Price*	Price; Platform; General feeling
Medium-term	*General feeling*; *Price*; General function	Price; Gift; Packaging
Long-term	*General appearance*; *Price*; Camera	Price; Quality; Gift

Table 10 Interesting FPs of sentiment features in Ω_{D90}

Reviewing type	Interesting FPs	(*supp, cos*)
Instant	***{General function(+), Price(+)}***	(83.0, 0.585)
Medium-term	***{General function(+), Price(+)}***	(286.0, 0.577)
Long-term	***{General function(+), Price(+)}***	(186.0, 0.547)
	{Operation(+), Camera(+)}	(78.0, 0.310)

5. Managerial Implications

Reviews for online shopping experiences have been exerting an increasingly powerful influence on follow-up consumers’ choices and previous customers’ relationships. A deeper understanding of when customers will review and what motivates them to write is therefore of both theoretical and practical significance.

In fact, if a consumer’s “purchasing-reviewing” time interval is relatively short, the customer’s evaluation contents are 1) service-related and 2) what is the customer personally interested in. For the latter, a bias opinion may be reviewed online. On the contrary, a relatively long time interval means that the experience with a product/service is more complete and profound; thus, a customer may provide more reviews about the function of the product. Because the E-commerce system relies much on unpaid volunteers to write reviews, it can provide some incentives at appropriate time to encourage users to publish reviews online. These implications can help B2C sellers to manage consumers’ relationships and adjust online marketing strategies accordingly.

Especially, our experimental results hold managerial insights for Chinese B2C online markets:

1) The most common concerns in all groups were the “General feeling” and “Price” (Table 7). This result indicates that the cost is a main factor that affects people in conducting online purchase. Thus, a price related marketing strategy for a B2C website should be designed carefully. There should be a balance between attracting new customers and keeping good relationships with old ones.

2) A special top concern of the instant-reviewing group and the medium-term-reviewing group is “Brand” (Table 7). In the online B2C market, Chinese users are highly

concerned with the brand of the product, and the famous-brand product will obtain more positive reviews (Figs. 7(e) and 7(f)).

6. Conclusions

In this paper, we present a methodology framework to study massive customers' online "purchasing-reviewing" behaviors. Also, we present a review-to-aspect mapping method to explore the reviewers' opinions for an online shopping experience in massive and sparse reviews. The analytical and experimental results with real data from a Chinese B2C website of www.jd.com demonstrate that the reviewers grouped by the similar reviewing behavior dynamics can reveal certain information about reviewers' motivations and concerns for an online shopping experience. This study obtains two major findings:

1) The frequency of time intervals between consumers' purchasing a good online and their publishing reviews follows a power-law distribution, providing new evidence for the study of human behaviors online. Moreover, similar reviewing behavior dynamics exist for different online shopping experiences in the same B2C website.

2) Different people may use various words to express the same view for an online shopping experience, leading to the sparse distribution of words and increasing difficulty in analyzing customers' opinions. Review-to-aspect mapping is a feasible method to address this problem. By this method, people can obtain opinions from a group of consumers and then summarize management oriented patterns from these online review data.

In conclusion, sorting out information from massive review data is of significance for the online E-commerce system. This task is not just to identify what users said, but more importantly to discover how (when) the users said.

The latter results may help people to study customers' reviewing motivations and further to use customer-generated reviews effectively. This work has two limitations. First, this study does not conduct a comparative analysis with an international B2C website, such as Amazon.com. Wang (2010) found that the behavior dynamics of Yelp reviewers followed a power-law distribution and Gilbert and Karahalios (2010) determined that the power-law curve governed Amazon's reviewing community. Thus, it will be interesting and useful to do a comparative analysis of the reviewed contents and credibility. Second, the proposed method would be better if an efficient algorithm could be designed to generate the aspect space Ω automatically.

Acknowledgments

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Appendix A: The Word Aspect Mapping Table

Table 1 Function-related aspects: Ω^f

Aspect	Reviewing words (in Chinese)
Camera	白平衡(White Balance), 饱满(Full), 逼真(Naturalness), 长焦(Telephoto), 成像(Imaging), 发灰(Turn grey), 分辨率(Resolution), 成像(Imaging), 光照(Lighting), 糊片(Blurriness), 画面纯净(Purity), 近焦(Near Focus), 滤镜(Filter Lens), 跑焦(Out of Focus), 偏冷(Cooler), 偏色(Color Cast), 漂移(Shift), 曝光(Exposure), 清晰(Clearness), 人像(Portrait), 闪光灯(Flash), 微距(Micro), 虚化(Blur), 遮光(Shade), 摄影(Photography), 感光(Sensitive), 暗角(Vignetting), ISO, 像素(Pixel)
Video	播放(Play), 捕捉(Capture), 动感(Motion), 短片(Short Film), 放映(Play), 高清(High Definition), 横纹(Striation), 摄像(Recording), 视频(Video), 条纹(Stripe)
Operation	安装(Install), 按钮(Button), 编辑(Edit), 变焦(Zoom), 擦拭(Wipe), 菜单(Menu), 操控(Operation), 操作系统(OS), 测光(Photometry), 称手(Fitness), 充电(Charging), 单点对焦(Focusing), 格式化(Formatting), 功能键(Function Button), 开机(Power On), 快捷键(Shortcut), 连拍(Burst), 拨轮(Thumb wheel), 拧紧(Tighten), 手动(Manual), 试拍(Test), 重启(Reboot), 自动(Automatic), 组装(Assembling)
Quality	变形(Deformation), 标杆(Benchmark), 标头(Normal Lens), 超声波马达(USM), 对焦速度(Focus Speed), 防伪(Anti- Counterfeiting), 工程塑料(Plastics), 工艺(Technology), 够实(Solid), 合格证(Qualification), 合金(Alloy), 开关灵敏(Sensitive Switches), 零快门(Zero Shutter), 毛糙(Crude), 镁铝(Magnesium and Aluminum), 磨砂面(Frosting Surface), 松动(Loosen), 涂层褪色(Coating Fade), 脱胶(Degumming), 异响(Noise), 噪点(Noise), 自动对焦失灵(Focus Failure)
General function	电池续航(Battery), 防尘(Dustproof), 防抖(Anti-shake), 防水(Waterproof), 防雨(Rainproof), 防震(Shockproof), 丰富(Rich), 附加功能(Additional Function), 场景划分够用(Good Enough), 兼容(Compatible), 抗冻(Frost-resisting)

Table 2 Appearance-related aspects: Ω^a

Aspect	Reviewing words (in Chinese)
General feeling	新手入门(Beginner), 中端机(Mid-Class), 街机(Arcade Camera), 结实(Solid), 紧俏品(Hottest Products), 经典单反(Classic), 抢手货(Popular), 入门单反(For Beginner), 稍微重(Heavy), 神机 (MagicCamera), 神品 (Masterpiece), 实用 (Practical), 实在 (Reality), 中规中矩(Well-Behaved), 沉稳(Steady), 大方(Generosity), 大气(Ambition)
General appearance	超薄(Ultrathin), 大个(Big), 大块头(Chunk), 简洁(Concise),小巧(Exquisite), 弧形(Arc), 简单(Simplicity), 厚实(Solid), 硬朗(Hale and Hearty), 扯眼球(Attractive), 不花哨(No Fancy), 成色(Fineness), 新(Brand New), 夺目(Marvelous), 高雅(Elegant), 豪华(Luxury), 好看(Good-Looking), 款式(Model), 拉风(Showy), 美观(Attractive), 曲线(Curve), 时髦(Fashion), 外观(Appearance), 颜色(Color)

Table 3 Sentiment-related aspects: Ω^{sp} and Ω^{sn}

Aspect	Reviewing words (in Chinese)
Positive	棒极了(Awesome), 漂亮(Beautiful), 安静(Quiet), 便捷(Convenient), 货真价实(Genuine Goods at a Fair Price), 耐用(Durable), 稳定(Stable), 物有所值(Value for Money), 行货(Licensed Good), 整洁(Neat), 正品行货(Genuine Product), 超棒(Super good), 齐全(Complete), 强悍(Tough), 非常棒(VeryGood), 高级货(Premium Product), 贵重(Valuable), 帅气(Cool), 威猛(Powerful), 夺目(Marvelous), 高雅(Elegant), 豪华(Luxury), 好看(Good-Looking), 负责(Responsible), OK, 耐心(Patience), 热心(Enthusiastic)
Negative	陈旧(Obsolete), 凑合(Passable), 离谱(Extravagant), 猛涨(Skyrocket), 便宜(Cheap), 迟迟(Tardy), 等待(Waiting), 忍无可忍(Beyond Endurance), 差劲(Lousy), 扯皮(Wrangle), 恶心(Sick), 气愤(Anger)

Table 4 Value-related aspects: Ω^{v}

Aspect	Reviewing words (in Chinese)
Brand	不丢面子(Save Face), 不丢身价(Social Status), 大品牌(BigBrand), 放心机(Rest Assured Camera), 机皇(Camera King), 尼康(Nikon), 尼克尔镜头(Nikkor Lens), 声誉(Reputation), 王牌(Trump Card), 王者(King), 众口皆碑(All Pillar), 众所周知(Everyone Knows)
Price	昂贵(Expensive), 变动(Change), 便宜(Cheap), 补差(Price Difference), 价格不菲(Cost a Fortune), 底价(Floor Price), 划算(Good Deal), 活动价(Promotion Rate), 价钱(Price), 降价(Cut Price), 较低(Lower Price), 较高(Higher Price), 京东价(JD.com Price), 经济(Economics), 离谱(Extravagant), 猛涨(Skyrocket), 平民化的价格(Ordinary Price), 烧钱的(BurnMoney), 稍贵(Expensive), 省钱(Save Money), 市场价(MarketPrice), 调价(Adjustment), 涨价(Inflation), 打折(Discount), 价廉物美(Cheap)
Gifts	赠送(Gift), 京东券(Jingdong Coupon), 保护薄膜(ProtectiveFilm), 电池(Battery), 背包(Knapsack), 背带(Back strap), 存储卡(Memory Card), 读卡器(Card Reader), 返券(Coupons), 附属软件(Software), 挂绳(Lanyard), 保护罩(Cover), 积分(Credit), 肩带(Shoulder Harness), 金士顿(Kongston), 内胆包(InsideBag), 品胜电池(Pisen Battery), 清洁套装(Cleaning Kit), 液晶屏保护贴(LCD Protector), 原装包(Original package)

Table 5 Service-related aspects: Ω^{s}

Aspect	Reviewing words (in Chinese)
Platform	代理商(Agent), 网站(Website), 供不应求(Out of Stock), 供货(Supply), 货源充足(Sufficient Supply), 京东商城(JD.com), 库存(Inventory), 零售商(Seller), 门店(Store), 缺货(Stockout), 信得过(Trustworthy)

Process	保价(Keep Price), 报修(Reparation), 采购(Procure), 撤单(Withdraws), 发货(Shipment), 发票(Invoice), 返修(Repair), 分期付款(Installment), 盖章(Seal), 换货(Replacement), 银行(Bank), 拒收(Reject), 开票(Invoicing), 看货(Inspection), 赔偿(Compensation), 签收(Sign for), 收货(Receiving), 售后服务(After SalesService), 调包(Switching), 退货(Return), 退钱(Refund), 维修(Maintenance), 下订单(Place an Order), 选购(Choosing), 验货(Examining), 预订(Reservation)
Delivery	按时(On Schedule), 包送(Free Shipping), 保存(Preserve), 超快(Ultra-fast), 迟迟(Tardy), 等待(Waiting), 第三方物流(Third Party Logistics), 飞快(Very Fast), 隔天(EveryOther Day), 加急(Urgent), 京东配送(Jingdong Distribution), 快递员(Courier), 神速(Marvelously Quick), 顺丰物流(ShunFeng Express), 特快(Express), 物流速度(Speed), 忍无可忍(Beyond Endurance), 遗失货品(Lost Item), 邮政(PostService), 圆通快递(YuanTong Express), 长途运输(Long Distance), 自提(Self Delivery)
Packaging	包裹(Package), 包装箱(Packing Box), 标贴(Label), 已拆动(Unpacked), 表面(Surface), 查封(Seal Up), 拆箱(Unpacked), 打包(Packing), 封条(Seal Tape), 盒脏(DirtyBox), 划痕(Scratch), 挤压(Squeeze), 气垫(Air Cushion), 气泡(Air Bubble), 损害(Damage), 损坏(Spoil), 外包(OuterPacking), 完好(Intact), 印痕(Imprint), 有防拆(Tamper), 原封(Seal Unbroken), 纸箱(Paper Box), 周转箱(Turnover Box)
Service attitude	鄙视(Look Down), 扯皮(Wrangle), 答复(Formal Reply), 怠慢(Snub), 到位(in Place), 恶心(Sick), 负责(Responsible),感谢(Thank), 工作人员(Staff), 借口(Excuse), OK, 客服(Customer Service), 开箱检查(Inspect), 抗议(Protest), 蛮横(Peremptory), 耐心(Patience), 气愤(Anger), 热线电话(Hotline), 热心(Enthusiastic), 投诉(Complain), 营业员(Assistant), 优质服务(Good Service), 咨询(Consult)

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