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Research on E-commerce Service Improvement Based on Text Mining of Negative Review Information

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Abstract. The rise of e-commerce platforms has enabled more consumers to choose to shop online, resulting in a sharp increase in online review data. The large amount of review data hides consumer satisfaction factors for goods or services. These textual data objectively reflect consumer satisfaction. Among them, consumers' negative reviews are more worthy of attention. This article takes 50,000 pieces of data of five representative products on JD.com as the research object. Through word frequency statistics, keyword extraction and cluster analysis of text data, it is concluded that the main factors for consumers' negative reviews are: customer service Attitude, logistics speed, damaged packaging and price fluctuations.

Keywords: text mining; K-meams algorithm; online comments; keyword extraction

1. Introduction

According to the statistics of the 45th "Statistical Report on Internet Development in China", as of March 2020, the number of Internet users in my country has reached 904 million, and the Internet penetration rate has reached 64.5%. Among them, the number of online shopping users in my country has reached 710 million, accounting for 78.6% of the number of Internet users, and the growth rate is relatively fast.

The popularity of the Internet has promoted the development of e-commerce. E-commerce sites such as JD.com and Taobao have changed the way people consume. Taking the "Double Eleven" in 2019 as an example, the cumulative transaction volume of Tmall and JD.com totaled 472.8 billion yuan, which to a certain extent reflects the importance of online shopping in the lives of netizens.

With the gradual improvement of e-commerce platforms, after consumers purchase a certain product or service, their evaluation can influence the purchasing behavior of other consumers. A large number of consumer reviews have a huge impact on businesses. The evaluation of products or services can be divided into positive reviews, neutral reviews, and negative reviews. A good evaluation includes a satisfied shopping experience and affirmation of a product or service. A negative evaluation is an evaluation given by consumers after an unpleasant experience of purchasing a product. Studies have shown that negative reviews have stronger influence, more characteristics and explanatory properties. For potential consumers, they will collect existing negative reviews of consumers who have purchased and make purchasing decisions. Therefore, how to reduce or even eliminate the impact of negative reviews on potential consumers is of great significance to e-commerce platforms and businesses.

2. Literature review

2.1. Defining the concept of negative reviews

Scholars have different opinions on the definition of online negative reviews. Richins (1983) believes that online negative reviews are behaviors that consumers slander a company or a certain product. Luo (2009) believes that the purpose of online negative reviews is to dissuade others from unpleasant experiences and recommendations of certain products. Lee & Song (2010) pointed out that online negative reviews are formed during and after consumption, and are the expression of consumers' negative experience of products or services. In summary, although scholars have their own opinions on the concept of negative reviews, there is overall consistency, which is mainly manifested in the unpleasant experience and dissatisfaction of consumers after purchasing the product.

2.2. Research status of online reviews

There are many perspectives on the research of online reviews. Baek and Ahn (2012) conduct sentiment analysis on collected online review texts. Pu (2019) et al. used SVM to encode the overall opinion sentence for document sentiment classification, and proved its effectiveness with product reviews and movie reviews. Some scholars have studied the impact of the number of reviews (Basuroy, et al., 2003; Liu, 2006) and other related variables (Khare, et al., 2011; Lee, et al., 2008) on consumers, There are also studies on positive reviews (Chevalier, et al., 2006) or the number of negative reviews (Lee, et al., 2008). For example, when studying the impact of negative online reviews on consumer product attitudes, Lee et al. tested the proportion of reviews and believed that as the proportion of negative online reviews increased, consumers' attitudes toward products became worse. Cao Q (2011) et al. examined various functions of online comments (basic style and semantic features), and used text mining technology to extract semantic features from comment texts, and concluded that semantic features have more influence on voting comments than other features. Reyes (2012) provides relevant suggestions for facing language such as sentiment analysis, opinion mining, and decision-making through the analysis of online comments. Chen (2013) believes that the shorter the time interval from purchase to review, the more readers think the review text is useful. Korfiatis (2012) believes that the lower the complexity of the sentence, the more effective readers will think of the review text.

3. Data acquisition of negative reviews

3.1. Data selection

There are many e-commerce platforms, such as JD, Tmall and Pinduoduo. Since the quantity and quality of online reviews on these platforms vary, the most suitable platform must be selected from among many e-commerce platforms. In this article, JD.com was selected as the data sample source platform for the following reasons:

1. According to website visits and website popularity, a comprehensive ranking of JD.com, Tmall and Pinduoduo (updated on August 30, 2020) through Alexa website ranking is shown in Table 1 below. From the table below, we can see that the Alexa global ranking, Chinese website ranking and industry ranking of JD.com are all above the other two websites.

Table 1: Summary table of ranking of various e-commerce platforms

Platform name	Alexa global ranking	Chinese website ranking	industry ranking
Jingdong	11	22	1
Tmall	30	274	6
Pinduoduo	2319	2973	102

2. This article is based on negative reviews as a sample of research data. By observing the negative reviews of major e-commerce platforms, the review system varies. Because the JD website has a negative review column, and the data crawling is relatively convenient, this also makes the data selected in this article more targeted.

According to the above analysis, the negative reviews on JD.com have a good representativeness, and useful information for businesses can be mined from the content of the text reviews. Therefore, this article selects negative comments on JD.com as the research object.

3.2. Data crawling

The data selected in this article are the negative reviews of five types of products, including fresh food, computers, mobile phones, books, and furniture, which are representative products on the JD website. Since the Python language has many advantages over other programming languages in terms of data crawling, the Python language can use numerous extension libraries to achieve data acquisition. The rules for crawling the review data of returning customers in Python language are shown in Figure 1, and the process of crawling data in Python language is shown in Figure 2.

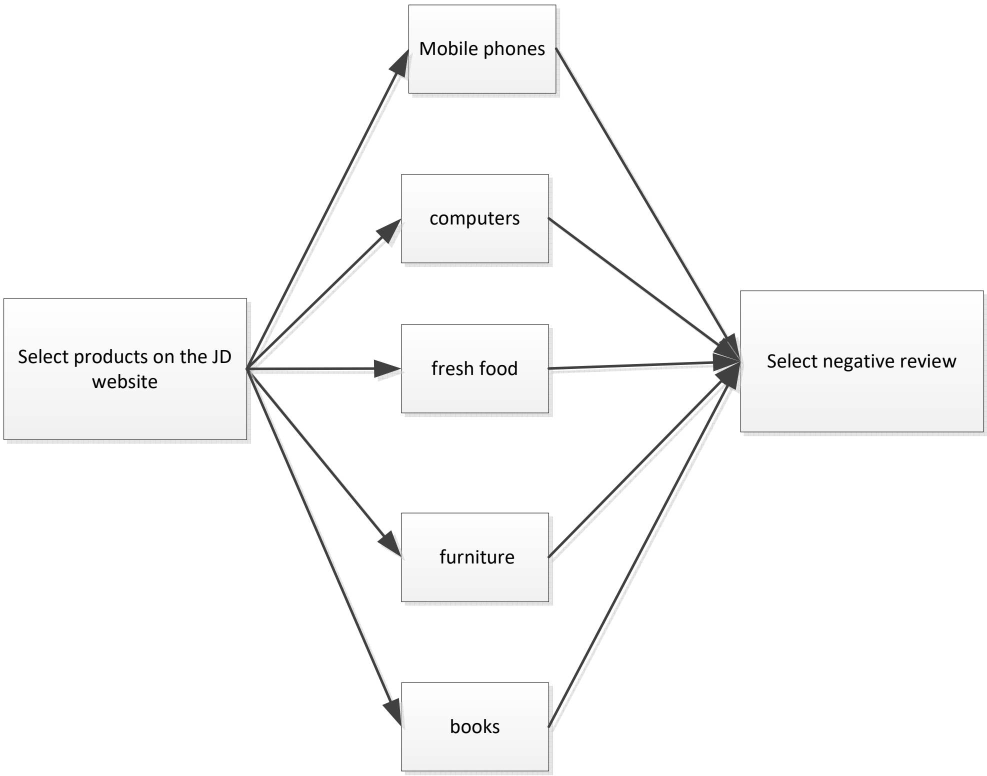

Figure 1: Diagram of data crawling rules

Figure 2: Flow chart of data crawling

4. Feature analysis based on text mining

4.1. Word frequency statistics

It is of great significance to count the frequency of words appearing in the entire text. The dissatisfaction factors of consumers can be roughly predicted from the word frequency statistics. The frequency statistics of negative reviews of five types of commodities are shown in Table 2 to Table 6.

Table 2: Frequency statistics of negative reviews on mobile phones

Standby time	866	Exterior	359
Take pictures	782	Sound effect	335
Screen	746	battery	329
Effect	621	Recharge	288
Speed	601	Huawei	275
Headset	571	shape	252
Features	541	express delivery	226
Run	531	Few days	201

Table 3: Frequency Statistics of Computer Negative Comments

Customer service	1201	Return	386
Price cut	612	A month	368
Boot up	594	Blue screen	341
Screen	524	Few days	314
Game	481	system	308
After-sales	461	effect	308
Run	418	price	305
Less than	410	sound	299

Table 4: Frequency Statistics of Negative Furniture Reviews

installation	936	Return	274
Customer service	792	taste	250
Logistics	535	master	239
Merchant	424	work	228
Ship	362	shopping	224
Screw	325	Poor	214
Product	297	After-sales	203
Image	284	Delivery	198

Table 5: Frequency statistics of negative comments on fresh food

Fresh	1164	thaw	296
Taste	803	fruit	281
package	700	Head	270
Customer service	603	Find	262
express delivery	558	Cheap	256
good to eat	548	image	256

Taste	520	Logistics	255
Merchant	397	time	252

Table 6: Frequency statistics of negative reviews of books

Content	943	damaged	215
package	621	Genuine	212
Customer service	433	Logistics	210
express delivery	427	recommend	194
Piracy	409	story	194
One	375	Ship	183
Paper	367	Cover	182
Print	350	translation	176

4.2. Keyword extraction

Keywords refer to words that can reflect the main content of a text to a certain extent. Keyword extraction is an important content in text analysis. Keyword extraction methods mainly include: TF-IDF, TextRank, Rake, Topic-Model, etc. This article is based on the jieba library of Python language for keyword extraction, and its implementation is based on the principle of TF-IDF.

Term Frequency-Inverse Document Frequency (TF-IDF), TF stands for term frequency, calculated as the frequency of the word w_i in the document d_j divided by the sum of the frequency of all words in the document d_j, as shown below:

$$TF_{w_i,d_j} = \frac{I(w_i,d_j)}{\sum_i I(w_i,d_j)}$$

Here I represents the frequency count. IDF represents the frequency of reverse documents, calculated as the total number of documents $|D|$ divided by the number of documents containing the word w_i plus the logarithm of 1, as shown below:

$$IDF_{w_i} = \log(\frac{|D|}{1+|\{j : w_i \in d_j\}|})$$

The idea of TFIDF is that if a word appears more frequently in a document but less frequently in other documents, then this word is a feature word, so for the word w_i in the document d_j, its TFIDF value is defined as follows:

$$TFIDF_{w_i,d_j} = TF_{w_i,d_j} * IDF_{w_i}$$

This article uses Python's jieba library to extract keywords for five types of commodities. The extraction results are as follows:

Table 7: Keyword extraction table

Product category	Key words									
Furniture	Customer service	Install	Logistics	Ship	Merchant	Screw	Return	Poor	Material	After sale
Mobile phones	Standby	Take pictures	Screen	Headset	Sound effect	Customer service	Effect	Features	Speed	run
Computers	Customer service	Boot up	Price cut	Screen	After-sales	Blue screen	Mouse	Return	Black screen	game
Books	Content	Packing	Express delivery	Piracy	Customer service	Paper	One	Printing	Paper	Genuine
Fresh food	Fresh	Taste	Express delivery	Packing	Customer service	Taste	good to eat	Merchant	Fleshy	thaw

Based on the results of the extracted keywords and the statistical results of the word frequency, these five products all mention the keywords of customer service, express delivery, and logistics.

5. Factor analysis of negative reviews

5.1. Clustering algorithm

Cluster analysis is a process of dividing information into clusters based on the similarity and difference of information. The similarity of objects in the same cluster is higher, and the similarity between different clusters is lower. The degree of similarity between data objects is affected by its value range. In the process of cluster analysis, different clustering methods are used to cluster, and the results obtained are also different.

Common clusters include K-means, MeanShift, DBSCAN, GMMs, AHC, etc. This article uses the most widely used K-means algorithm. K-means algorithm is a simple iterative clustering algorithm that uses distance as a similarity measure. The given data set is divided into k categories, the center of each category is obtained from the average of all points in the category, and each category is represented by the cluster center.

In the process of clustering, the use of uncorrelated variables will increase the noise in the clustering process and affect the actual clustering results. Therefore, in order to improve the clustering effect, dimensionality reduction (Dawei, et al., 2018) is needed to improve the accuracy of clustering.

5.2. Clustering results

This article takes the negative reviews of mobile phones as an example for cluster analysis, and constantly adjusts the K value. Among them, the four clusters have the best results. Each cluster in the classification is clearly distinguished. The tags and comments corresponding to each category are shown in Table 8.

Table 8: Mobile phone clustering results table

Category label (topic)	High-frequency words (partial)	Number of comments	Sort by topic
Customer service	Customer service, attitude, service, after-sales, reply	4422	1
package	Packaging, broken, bad	3281	2
Logistics	Express delivery, delivery, service, arrival, time	1857	3
Price	Reduced price, just bought, less than, place an order	1639	4

6. Conclusions and suggestions

6.1. Conclusion

In response to consumers' negative reviews of products on e-commerce platforms, combined with the previous negative review text analysis, it is found that the current e-commerce services have the following problems:

(1) The customer service responds slowly or does not respond, and the customer service attitude is poor. The communication between the customer and the customer service can understand the service and attitude of the business, so that the business can establish a good service image in the mind of the customer.

(2) The logistics speed is slow, and a small number of express delivery services are poor. The logistics speed will be affected by various reasons. Some businesses choose small logistics companies to reduce logistics costs. The imperfect facilities and management of these logistics companies greatly reduce the timeliness of logistics.

(3) The packaging is crude and damaged when delivered. Some logistics companies do not have good packaging services. If the packages are handled or squeezed during logistics transportation, they are prone to damage or leakage.

(4) The price fluctuates greatly, and the price drops shortly after purchasing the goods. Consumers have given feedback on the fluctuations in the sales price of online shopping products, and even the prices of some products are very different immediately after purchase.

6.2. Suggestions

(1) Optimize the customer service system. First, improve customer satisfaction through training on customer service skills and service awareness. Secondly, the communication between customers and customer service is supervised, which can more effectively improve customer satisfaction.

(2) Improve the logistics service infrastructure. Improving logistics infrastructure is the basic prerequisite for improving logistics services. The logistics service infrastructure should be able to be improved from these aspects: firstly, optimize the logistics and transportation equipment, select the corresponding transportation equipment according to the actual delivery goods, to prevent problems such as damage to the goods; secondly, optimize the logistics transportation network and improve the timeliness of logistics Sex. Finally, improve the quality of logistics service practitioners.

(3) Merchants should avoid fluctuations in commodity prices within a short period of time and formulate corresponding price protection measures, so as to more fully protect the interests of consumers. For example, within a certain period of time when consumers purchase goods, if the price of the goods decreases beyond a certain range, consumers can apply for price protection. After the application is successful, consumers should be compensated accordingly.

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