Research on Online Comment Reply Topics Based on LDA

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Abstracts: Online shopping has become a mainstream consumption mode. As an important tool to evaluate online shopping experience, online comments have been studied repeatedly on their usefulness and comment topics. However, few scholars have explored which aspects managers mainly respond to. In this paper, the mobile phone industry is taken as a template and the LDA model based on TF-IDF is used to calculate the number and semantic intensity of evaluation and reply topics. Through this model, the author summarizes the topics most often used by managers when responding to consumer comments. The results showed that managers were more likely to rate the phone's hardware and promotions when evaluating the response reviews.

Keywords: LDA Reply to topic Comment Reply

1 INTRODUCTION

As of December 2021, the scale of China's online shopping users has reached 842 million, and online shopping has become the most popular shopping method nowadays. Given the virtualization and non-contact characteristics of online shopping, consumers can only form "indirect interactions" with products by visualizing the experience cues of others (Baoku Li and Tingting Guo, 2019) As a result, online reviews become the most important factor in consumers' decision to purchase a product or choose a service (Wang, Xuhui et al. (Wang, Xuhui et al., 2017). On the one hand, through online reviews, customers can make their own decisions. On the one hand, through online reviews, customers can quickly screen the quality of goods, the strength of the actual function, the merchant's service attitude, the speed of third-party logistics, etc., as a way to make shopping decisions; on the other hand, information technology has given rise to a large number of online reviews, taking a Netflix cake from Three Squirrels as an example, its Tmall user online reviews have reached 14,087, and in front of the massive amount of review information, it is difficult for consumers to In the face of the huge amount of review information, it is difficult for consumers to judge the information for objective and effective usefulness evaluation, and they are caught in the "choice dilemma" of usefulness, and the "sufficiency paradox" arises between customer demand and usefulness supply of online reviews. Therefore, it is particularly important to judge the usefulness of online reviews.

However, most of the existing studies focus on the content factors of online reviews or the additional attribute factors of reviews, the former including the sentiment orientation of reviews, the length of reviews, whether reviews with pictures, etc., and the latter mainly including the

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reviewer's rating, the time of reviews, the reviewer's purchase history, etc., but often ignore the role of online review responses by managers in consumers' online shopping, so that the "sufficiency paradox" caused by the huge number of online reviews is not helped. The "sufficiency paradox" caused by the large number of online reviews can not be helped. In fact, when potential consumers make shopping choices, they will not only care about the purchaser's real purchase feelings, but also shift their attention to the more information-centric manager's responses. Moreover, according to the theory of cognitive equilibrium reduction, when buyers get a bad consumption experience, they will seek the manager's reply in order to seek the reason for this bad experience; potential consumers will also correct their perceptions of the product from the manager's reply after paying attention to the negative reviews, which shows that the manager's reply is significant for buyers.

With this in mind, this article focuses on the merchant responses to online reviews and summarizes the most involved words in the cell phone industry.

2 THEORETICAL BASIS

Service Remediation Theory (SRT) believes that service remediation is an activity carried out by companies to resolve customer complaints about perceived service failures. Companies use service remediation activities to make up for mistakes in the service process, and timely remedial measures can not only win back customers, but also increase customer loyalty and satisfaction. Therefore, potential consumers get more information through product or service reviews on the Internet. Cognitive balance theory is also called "cognitive consistency theory". The basic idea is that people always try to maintain the balance and harmony of their internal cognitive system, which includes cognitive factors such as beliefs, thoughts, feelings, attitudes, and actions. An unbalanced cognitive state is motivational in nature and motivates a person to change some elements of his or her cognitive system in order to restore the balance of the cognitive system. The theory has a phenomenological character and has influenced the fields of study of interpersonal perception, behavioral attribution, attitude and attitude change, and interpersonal relationships in social psychology, and constitutes a major orientation in contemporary social psychology.

According to service remedy theory, if consumers feel uncomfortable consumption experience, if there is a suitable compensation measure, it will reverse the customer's consumption feeling and increase loyalty. However, most of the previous studies on managerial responses are based on quantitative influences (Chen, Yuangao et al. (Chen, Yuangao et al., 2021, Xie et al., 2014, Lee and Song, 2010, 2017) , such as the text length of manager responses (Liu, Ying and Li, Baokou, 2021) However, according to cognitive equilibrium theory, consumers break the balance in their mind when they encounter a consumer experience that exceeds their expectation and need to build a new balance in their mind so they leave a bad review, and potential consumers need to read the merchant's response in order to balance their impending purchase risk (Ying Mengxi, 2019) Therefore, the content of the merchant's response affects the potential consumer's prediction of this purchase risk, and the response time affects the effect of the former. Therefore, in this paper, from the perspectives of manager response richness and response time, we obtain 18,664 reviews of 5 products of the same type in Jingdong through python crawler code to study the moderating mechanism of manager responses on the usefulness of reviews from an empirical case.

3 STUDY DESIGN

3.1 Sample and data collection

The crawler program based on python programming language is used to collect online reviews of cell phone products on the Jingdong platform. Since Jingdong is a sales platform with a relatively large sales volume and sales of electronic products in China (briefly, the status of Jingdong, such as the percentage of sales of electronic products, etc.), the Jingdong platform is chosen as the collection object. The content of the collection includes the text content of user comments, the star rating given by the user, the number of likes on the comments, the user response time, the manager response time, the manager response text, whether it is a member, gender, etc.

This study takes the commodity reviews of four equally priced commodities, Huawei mate40pro, Huawei mate30 5G version, Huawei p30, and One Plus 8plus, as actual cases, with the review interception dates from April 12, 2019 to September 25, 2021, and crawls the four commodity reviews from Huawei Jingdong self-owned store and One Plus Jingdong self-owned store on the Jingdong platform, which is more adept at selling electronic commodities After reading the deactivated word text downloaded from the Internet, since the target customers and users of this price range are mostly young or middle-aged business people, the comment statements used are almost free of novel online face characters, etc. Then we use the Jieba library in python, which has become more mature now, to split the words, and finally use the pd package of the pandas library in python to pre-process the text, in order to remove the spaces, stray punctuation marks, tone words and other meaningless words and phrases that may be contained in each comment, so that the single comment becomes a word text without punctuation marks and stop words. and stop words.

3.2 Semantic strength measurement

This paper uses the TF-IDF-based LDA topic probability model to calculate the response semantic strength.LDA topic model is an unsupervised learning algorithm, i.e., it does not require manual classification annotation when importing data.Its main function is to confirm the number of topics in a text and get the ratio of important words under each topic number, and get the topic words through semantic refinement.TF-IDF is a word frequency-based weighting technique, often used in information retrieval and data mining, when a word appears more frequently in that text (i.e., when TF is higher) and less frequently in the text base or text dictionary (i.e., when IDF is higher), then the word has a higher representative meaning for the text. Since this technique is unsupervised learning and does not require manual classification annotation, the only thing that needs to be manually confirmed is the topic count. The methods for topic count confirmation generally have confusion degree (Wang, Tao et al., 2015) , log-likelihood function (Ma et al., 2018) , topic similarity function (Walters et al. et al., 2007) The log-likelihood function cannot portray the generalization ability, so it will affect the prediction effect; the topic similarity calculation method is relatively simple and more suitable as a constraint; the perplexity is suitable for unsupervised learning and most widely used. Therefore, in this paper, we use the method of perplexity to confirm the number of topics, and after confirming the number of topics, we can get the words and proportion under each topic, and then count them into each comment, so that the probability of each comment is the manager response intensity.

The specific method is based on the response data of managers obtained by python crawler as mentioned above, using Jieba thesaurus to pre-process the words and load the deactivated words to get clean words; then using Dictionary function in gensim.corpora library to count the pre-processed data and realize the word frequency vectorization; finally using gensim.model LdaModel in gensim.model to calculate the perplexity and complete the topic-document frequency matrix.

4 EMPIRICAL ANALYSIS

(1) Number of topics selected

In this paper, the number of topics of the LDA model is confirmed by calculating the confusion degree. From Fig. 1, it can be seen that the rate of decline is the fastest when the number of topics transitions from 4 to 5, and the perplexity is at a relatively low value among all the topics, considering that too many topics will lose the meaning of clustering, the number of topics is determined to be 5 in combination with the actual.

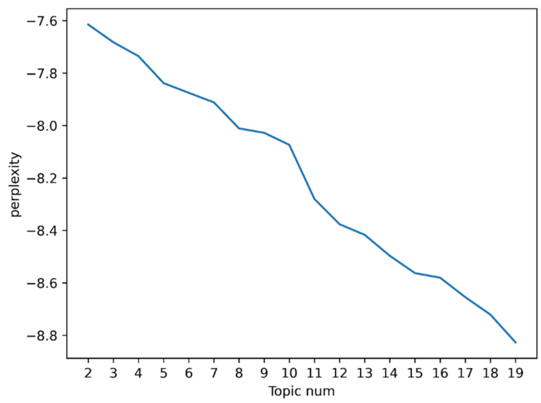

Figure 1 Confusion level under different themes

(2) Theme-document distribution visualization

By studying the results of topic word distribution, we are able to obtain the topic words corresponding to each topic and the proportion in that topic. In this paper, according to the proportion of topic words, we select the 18 topic words with the highest proportion in each topic to produce Table 1, which provides the basis for the topic description in the later paper.

From Table 1, we can see that the subject words of the same topic have common point in content, and the meanings of the subject words of different topics differ greatly from each other, indicating that the LDA model can better classify the documents, and each topic can be classified by extracting the lexical meaning of the subject words to summarize their types.

Table 1 Results of topic word distribution of LDA model based on TF-IDF

	Topic I		Theme 2		Theme Three		Theme Four		Topic V	
0	Power consumption	0.0058	Fingerprint	0.0076	Go for it!	0.0158	Events	0.0101	Cell phone	0.0077
1	Cell phone	0.0054	Price	0.0066	Dear	0.0112	Price	0.0092	Applications	0.0057
2	Power saving	0.0052	Unlock	0.0065	Customer Service Hotline	0.0105	Shopping Mall	0.0073	Charging	0.0050
3	Amount of electricity	0.0051	Events	0.0062	Sincerely	0.0104	million	0.0062	Network	0.0044
4	Photo shoot	0.0045	Reduction	0.0052	Thank you	0.0102	Mood	0.0061	Caton	0.0042
5	Use	0.0045	Cell phone	0.0048	Call	0.0100	Promotion	0.0059	Use	0.0042
6	Screen	0.0044	will	0.0048	Observation	0.0100	Time	0.0058	Time	0.0040
7	Products	0.0040	Film	0.0047	At your service	0.0096	Determine	0.0057	Run	0.0039
8	Shooting	0.0040	Please	0.0042	Support	0.0092	Offers	0.0056	Stable	0.0035
9	Battery	0.0038	Different	0.0041	Feedback	0.0090	the general public	0.0054	Fever	0.0035
10	Settings	0.0037	Impact	0.0040	Details	0.0086	Giving back	0.0053	We recommend that you	0.0034
11	Resolution	0.0036	Mood	0.0040	Use	0.0086	Hope	0.0053	Li	0.0034
12	Question	0.0036	Use	0.0040	Versions	0.0085	Beautiful	0.0053	Huawei	0.0033
13	Bring	0.0036	Shopping Mall	0.0037	Pleasant	0.0084	Timing	0.0052	Clearance	0.0033
14	Services	0.0035	Don't	0.0037	Latest	0.0083	Launch	0.0052	Result	0.0033
15	Replacement	0.0035	Possible	0.0034	carry out	0.0082	Don't	0.0052	Try	0.0032
16	In time	0.0035	Jingdong	0.0033	System	0.0081	Different	0.0052	feel	0.0032
17	Mode	0.0034	Protection	0.0032	Official	0.0077	Understanding	0.0051	All	0.0032
18	We recommend that you	0.0034	Dodo	0.0031	Life	0.0075	Dodo	0.0051	Daily	0.0031

(3) Description of each topic

As shown in Table 1, by extracting the meanings of the words extracted from the 5 themes (i.e. summarizing the meanings of the words to get the focus of each theme), theme 1 contains "battery", "screen", "resolution Theme 1 contains "battery," "screen," "resolution," etc., which are closer to hardware facilities; Theme 2 contains "price," "activity," "film," etc., which are more oriented to promotional activities; Theme 3 contains Theme three contains words such as "cheer", "dedicated", "thank you", etc., which are more inclined to official terms, and theme four is mostly "price" The words "mall" and "event" can also be classified as promotions, and theme five contains "application" and "network". "jam" can be categorized as software functions. In this paper, the correlation analysis is further tested, and the results show that theme two and theme four are weakly correlated, while the other themes have different focuses, indicating that the theme similarity is low. (Shi Da et al., 2020) In order to avoid complete multicollinearity, Theme 4 was excluded from the subsequent regression analysis, following Starr's (Starr et al., 2020) method. Thus, a total of five themes were obtained for hardware facilities, promotional activities,, and,.

5. CONCLUSION AND DISCUSSION

This paper uses a TF-IDF-based LDA model to explore the themes of managerial responses on cell phone products based on previous scholars' research, and it can be seen through the model; merchant responses contain four main themes, namely hardware facilities, software facilities, polite words and sales activities.

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