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Original Research

A Novel Data-Driven Weighted Sentiment Analysis with an Application for Online Medical Review

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Abstract

Online reviews provide a lot of information for analyzing consumers' satisfaction with products. However, traditional methods analyze overall online reviews, which not only wastes human and material resources, but also produces data analysis deviation. Meanwhile, traditional methods cannot accurately mine the novel features of products after software update. Therefore, a new data-driven method is proposed to overcome the shortcomings of the traditional method. We screen helpful reviews through information entropy to get the product features that customers really care about. We also utilize the uncertainty of information entropy to find the product features that customers follow with interest. Then we obtain the ranking of customer satisfaction with products by weighted sentiment analysis of product features. A case of medical APP is used to verify the availability and effectiveness of the proposed method. The results show that using 56.72% of the original data, 92% of the consistent results can be achieved, and 8% of the novel features can be discovered. Our research method can also be applied to environmental science and other fields. Finally, some interesting conclusions and future research directions are given.

Keywords: helpfulness, online reviews, Data-driven, sentiment analysis

Introduction

As a major form of online communication, online reviews have been widely concerned by businesses and consumers [1-7], because online reviews provide a platform for consumers to share experience and exchange feelings. The generation of online reviews is the generation of big data. Accordingly, it is extremely significant for businesses and consumers to analyze online review data.

People's life is inseparable from the support of decision-making [8-10], and customer satisfaction is affected by the utility of decision-making. Customer satisfaction with products is driven by big data decision-making, including applications such as perceived satisfaction [11-12] and sentiment analysis [13-17]. However, for the big data of online reviews, will thousands of reviews cause data analysis results to be biased? Traditional online review methods analyze all comments, in which useless reviews and false reviews will lead to deviation of customer satisfaction, and can't effectively mine the novel product features after software upgrade. On the other hand, previous literature on the review helpfulness only predicted

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the helpfulness from the perspective of review valence [18], review volume [19], emoji meaning multiplicity [20] or review length [21-23]. However, there were few papers that analyze product satisfaction by helpful reviews.

In online medical reviews [24-25], customer satisfaction with medical products is influenced and dominated by helpful reviews. Specifically, in the face of the vast number of online comments and the complexity of reviews, customers can't read total medical product online reviews. Consequently, there exists uncertainty in customer product satisfaction. If businesses want to improve product satisfaction, they must make efforts on helpful reviews [26-27]. The uncertainty of customers' product satisfaction is most directly reflected in the low product satisfaction, which is mainly due to the following reasons: (a) information asymmetry [28-29]. It is difficult for customers to know the parameters of the products launched by the merchants, so they should refer to the online reviews. (b) Market competition is uncertain [30]. In the fierce market competition, it is not easy for businesses to predict the sales volume of products. (c) Information helpfulness [31-35]. Invalid comments and false comments will lead to lower product satisfaction for customers. The above issues are what customers must face when choosing products. Hence, when customers' product satisfaction is low, customers should refer to helpful reviews extracted by businesses. Accordingly, there is a hot issue in online reviews: in face of abundant online reviews, how can businesses provide customers with truly helpful online reviews to improve product satisfaction?

In the field of environmental science, online reviews have also been studied by some scholars. For example, Koch et al. [36] pointed out that online retailers should provide environmentally friendly packaging by analyzing the data of consumers in online retailing. Qiu et al. [37] investigated the impact of air pollution on consumers' online purchase behavior. Malekpour et al. [38] analyzed the online review data of thermostats, they pointed out that users usually do not discuss the energy consumption and cost saving of equipment. Liu et al. [39] analyzed the posts related to environmental pollution, they found the influencing factors of netizens' reviews on environmental pollution events. The above scholars have analyzed the online review data in the field of environmental science. However, the helpfulness of the review has not been considered by them. Therefore, it is inevitable to bring data analysis deviation, which is not conducive to the environmental management departments to make effective decisions.

In order to solve the problems faced by the businesses and environmental management departments, we use the concept of information entropy proposed by Shannon [40]. At the same time, a novel data-driven method is proposed to overcome the shortcomings of traditional methods [41]. Later, information entropy model is utilized to predict helpful online reviews, which made the information entropy method to be a main research direction in the field of online reviews. In addition, information entropy has been applied in other fields [42-43].

As an effective tool for predicting helpful reviews, information entropy is widely utilized in the field of online reviews. For example, Fresneda and Gefen [44] insisted that focusing on entropy can increase the evaluation of the helpfulness of reviews. Luo et al. mentioned that the sense of belonging of consumers and experts is a crucial antecedent affecting the helpfulness of comments [45]. Pighizzini et al. [46] introduced the helpfulness of information and examined the influence of supplementary information on the complexity of problem solving. Nevertheless, there are few papers related to screening out helpful reviews for research, mainly focusing on predictive helpfulness. Han [47] indicated that text length and multidimensional scoring lead to the reduction of review helpfulness. However. These are different from our work as follows: (a) they argue from the perspective of searching the influence of helpfulness, while we develop from the perspective of utilizing helpfulness; (b) They focus on mechanisms, while we focus on decision-making; (c) They study the optimization mechanism of review helpfulness on enterprise management, rather than consumer decision-making.

This work extracts helpful reviews through information entropy, and analyzes them to obtain customers' product satisfaction. The main contributions of this study are summarized as follows: (1) Different from many studies on the helpfulness of online reviews, our work focuses on the insight of utilizing helpfulness rather than predicting helpfulness; (2) Based on the traditional information entropy model, a method to solve the practical issue of review helpfulness is proposed; (3) This study acquires the factors affecting product satisfaction of five online medical software in China through text mining and weighted sentiment analysis; (4) Our research has expanded the application field of online reviews. For example, the proposed method is also applicable to environmental science. We can analyze review data of users and find the features that users really care about, so as to provide reference for environmental decision-making departments to formulate environmental protection measures.

The rest of this paper is arranged as follows: Section 2 proposes material and methods; Section 3 are results and discussion of case study; Section 4 concludes and proposes future research directions.

Material and Methods

Material

The material used in this paper is our research framework. The framework of this paper consists of five steps is shown in Fig. 1. First, the OCRs data of

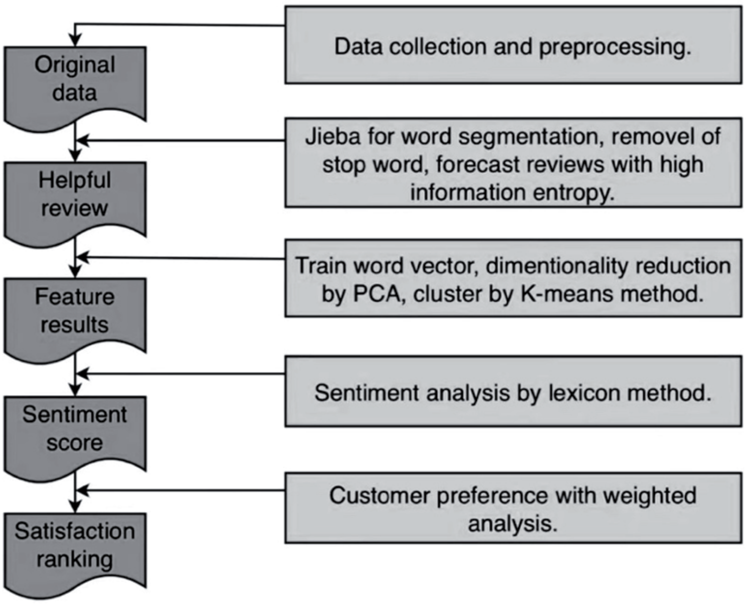

Fig. 1. The framework of the proposed method.

five medical APPs in the case study are obtained and preprocessed including word segmentation, tagging the part of speech, removal of stop words and helpless words by Python3.8 programming. The second step is to screen out helpful review text through information entropy. The third step is to reduce the dimension and cluster of the word vector to extract the product features. Use the sentiment lexicon for sentiment analysis in the fourth step. Finally, the TF-IDF weighting algorithm is used to obtain the weighted ranking of product satisfaction. Specific steps will be shown in detail in the following sections.

The innovation of our method is as follows: (a) The proposed method utilizes the technology of text mining and sentiment analysis to extract helpful reviews through information entropy model, and then obtains product satisfaction by analyzing helpful reviews. This is the difference between traditional methods and the proposed one. It can overcome the data deviation in the traditional methods and mine the novel product features after the software upgrade; (b) After obtaining the product features, we will give weight to the product features to better reflect the preferences of customers and obtain a more accurate product ranking. Previous articles rarely calculate the weight of product satisfaction. Our method can accurately grasp customers' preferences and help businesses improve revenue.

Method

Crawling and Preprocessing Data

Python is widely used in the mining and analysis of OCRs. In our study, python3.8 is used to program crawler software to crawl OCRs of five medical APPs: Ping An Health Cloud, DXY, WeDoctor, Chunyu Doctor and Zhiyun Health. After removing repeated and helpless OCRs through the preprocessing of first step, 34750 raw OCRs data are obtained. Different from English text analysis, English words are independent. While Chinese characters have no space between them, word segmentation is required. We select the widely used Chinese character segmentation software (Jieba word segmentation software). The Jieba word segmentation software can quickly scan all the single words that can form words in the reviews and also segment longer words again. It supports custom lexicon. Then, mark the part of speech. The second step of the preprocessing uses the stop word table of Harbin Institute of Technology to screen the words after word segmentation and eliminate helpless words and symbols, such as emoticons, qualifiers, prepositions, and URL, etc.

Method of Filtering the Helpful Reviews by Information Entropy

The less predictable information based on previous information, the higher the entropy and the more helpfulness of the information. Let the set H = $\{h_1, h_2, ..., h_n\}$ as each Chinese character in the reviews and $\Pr(h_i)$ as the probability of the occurrence times of each Chinese character in the reviews, and Eq. (1) represents the information entropy of OCRs.

$$E(H) = -\sum_{i=1}^{n} \Pr(h_i) \log \Pr(h_i) \tag{1}$$

We calculate the information entropy of the OCRs text combined with Eq. (1) by the programming of python3.8.

Product Feature Extraction, Dimensionality Reduction and Clustering

Our method firstly screens out helpful OCRs by using the principle of information entropy, and then to extract product features from these helpful CORs by the word vector method. β words with high TF-IDF values are selected as alternative feature words. In this paper, we set β = 200. Then, Word2vec is used for the conversion of word vector. The word vector has higher dimension after the conversion. Therefore, the principal component analysis (PCA) method is used for dimensionality reduction, which is to extract the most helpful information based on variance [48]. Generally, the contribution ratio of cumulative variance reaching 85% indicates that the effect of dimension reduction is great.

The effect of PCA dimension reduction is measured by the contribution ratio of cumulative variance. The definition of the first k principal components' contribution ratio of cumulative variance is shown in Eq. (2).

$$\frac{\sigma_1 + \sigma_2 \cdots \sigma_k}{\sigma_1 + \sigma_2 \cdots \sigma_n} \tag{2}$$

The variance of the kth principal component is σ_k, and the contribution ratio of cumulative variance means that the original n variables can be replaced by the first k principal components. If the contribution ratio of cumulative variance reaches 85%, the information loss is small and the goal of dimension reduction is achieved.

The K-means method is used to cluster the word vectors after dimensionality reduction. The Euclidean distance represents the similarity between the word vectors, as shown in Eq (3). The number of clustering centers can be set as required. We set K = 5.

$$d = \sqrt{\sum_{i=1}^{n} \left(X_i - Y_i \right)^2} \tag{3}$$

where d is the natural length of the word vector in n-dimensional space, that is, the distance from this point to the origin. x_i is the x-coordinate and y_i is the y-coordinate. After dimensionality reduction and clustering of the word vectors, the product features will be extracted.

Lexicon-Based Sentiment Analysis

Since the data of case study in this paper is from medical APPs reviews, which is composed of sentences, it is suitable for the lexicon-based sentiment analysis method [49]. The sentiment analysis process of this paper is as follows. First, construct a group of related sentiment words of medical APPs as seed words. Then, statistical methods are used to find the words representing opinions in the helpful reviews to compare with the seed words. According to the different parts of speech, sentiment polarity of words and sentiment intensity, the sentiment word score of the whole review is obtained. Finally, the overall sentiment tendency of the review is obtained based on the sentiment score.

The training process of the lexicon is shown in Fig. 2. The Word2vec is firstly used to construct word vectors, and then APP feature words are manually marked. The K-means method is then used to cluster feature words. After obtaining the APP feature words, divide the category and dimension of them.

The lexicon-based sentiment scores have different dimensions and orders of magnitude. If it is used directly, it will amplify the effect of the features with higher numerical value. Thus, we normalize the sentiment score by Eq. (4). Convert the sentiment score into a value between 0 and 1 through the min-max standardization method to facilitate the next data comparison and weighting for the data.

$$\frac{x_i - \min\left(x_i\right)}{\max\left(x_i\right) - \min\left(x_i\right)} \tag{4}$$

where x_i represents the sentiment score of the feature.

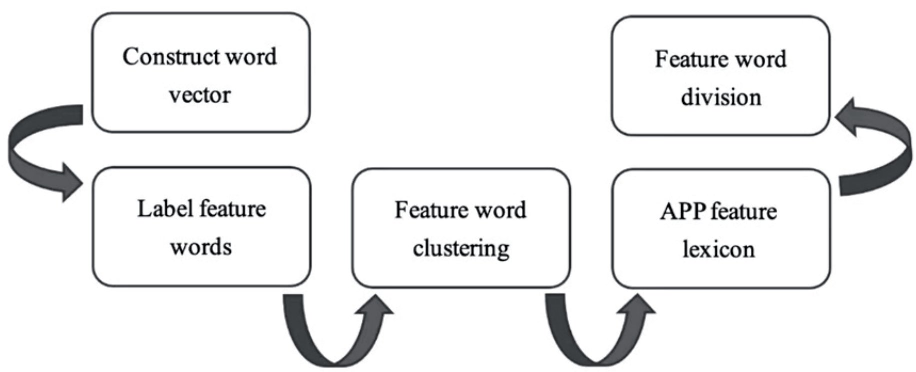

Fig. 2. The process of training Lexicon.

Weighted Analysis of Product Satisfaction

After obtaining the sentiment score, we conduct weighted analysis. Since the customers pay different attention to different features of the product, the weighted analysis of sentiment scores can obtain accurate ranking of customers satisfaction with the product and more accurate customers preferences for product. In this paper, TF-IDF method is used to calculate the weight of product features [50]. The formula for TF-IDF is as follows:

$$TF(t_i) = \frac{f_i}{F} \tag{5}$$

where t_i is the feature words, f_i is the number of occurrences of feature words, and F is the total number of such feature words.

$$IDF(t_i) = \log\left(\frac{N}{n_i} + 0.01\right) \tag{6}$$

where N represents the total number of reviews, and n_i is the number of reviews of feature words. Since the weight value calculated is relative, the base number can be any real number. We choose 2 as the base number.

$$\omega = TF(t_i) \times IDF(t_i) \tag{7}$$

The weight value is obtained by multiplying of TF and IDF is shown in Eq. (7). Due to the inconsistent length of various text reviews, the number of words and number of occurrences of feature words in the reviews vary greatly. The word frequency is greatly affected so that the normalization is required is shown in Eq. (8). K represents the number of features words. The weight of the primary features can be obtained by summing the weight of all the second-level feature features in the primary features.

$$\omega_i = \frac{TF(t_i) \times IDF(t_i)}{\sum_{i=1}^{n} \left\{TF(t_i) \times IDF(t_i)\right\}} \tag{8}$$

Results and Discussion

Analysis Results of Medical Reviews

The Crawling and Preprocessing of the Online Review Data

Five of the most commonly used medical APPs in China (Ping An Good Doctor, DXY, WeDoctor, Chunyu Doctor and Zhiyun Health) are selected for our case study. In order to ensure the completeness of data, we collected reviews from users of both Apple and Android platforms. The Python3.8 is used to program the software to crawl the raw reviews data and remove the repeated and helpless reviews. A total of 34750 raw reviews are obtained.

Filtering the Helpful Reviews

The Python3.8 programming and information entropy formula are used to calculate the information entropy of each review of the five APPs. According to the information entropy principle, the higher the information entropy is, the more helpful the information is. Therefore, we select the reviews whose information entropy score is greater than or equal to the mean as the helpful reviews. The 19711 helpful reviews are obtained through programming and Eq. (1) and the helpful reviews accounted for 56.72% of the raw reviews.

The Extraction of Product Feature, Dimensionality Reduction and Clustering

After the helpful reviews are screened by programming, the first 200 words are selected as alternative words according to the TF-IDF algorithm. The word vector return by the Word2vec conversion has higher dimension and PCA method is used to reduce dimension analysis. When the dimension is reduced to 53, the contribution ratio of cumulative variance reaches 85.403651%, which indicates a good effect of dimension reduction.

According to expert's opinions, we set K = 5 for the K-means clustering. Fig. 3 and Fig. 4 show the two-dimensional clustering effect of five APPs product features obtained by our method and traditional methods.

As the value of K is set as 5 by experts, the five primary features of APPs are as follows: offline activities (Feature 1), medical service (Feature 2), interaction of software (Feature 3), online diagnosis (Feature 4) and health science popularizing (Feature 5)

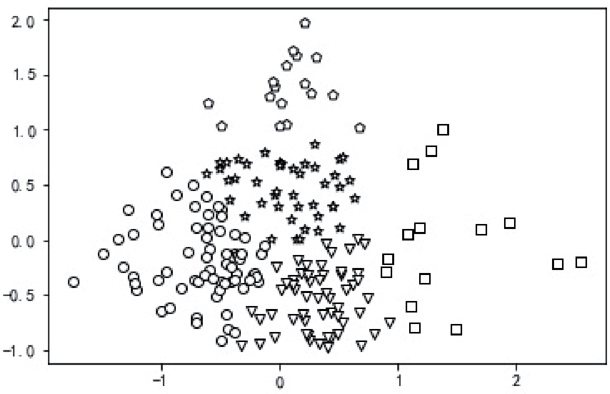

Fig. 3. The 2-D clustering of APP products features obtained by our method.

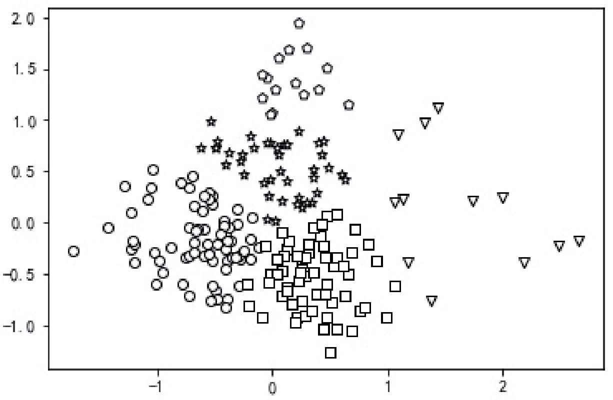

Fig. 4. The 2-D clustering of APP products features obtained by the traditional method.

are shown in Table 1 and Table 2. The 25 feature words are obtained as second-level features by our method and the traditional method, the same feature words are equal to 23. Because high information entropy represents high helpfulness of information, we only use 56.72% data to obtain consistency results of 92% feature extraction with the traditional method to effectively solve the issue of information overload. In addition, 8% of feature extraction results are inconsistent with those of traditional methods, which reflects the uncertainty of information entropy. The uncertainty means that the less information inferred from the previous text, the greater entropy is and more helpful information is. Applying the uncertainty of information entropy to reviews means that new words and new features appear in reviews because the software often needs to be updated. Therefore, in this paper, 8% difference in the results obtained by our method is due to the mining of new reviews and new product features after software upgrade . These helpful reviews may not be mined accurately due to frequency and quantity in traditional methods.

As shown in Table 1 and Table 2, due to the uncertainty of information entropy, there is no “crashing” and “reminder” in our method. It may be because the system is more stable after software upgrade and it changes from message reminder to call reminder after the software is updated. Hence, “crashing” and “reminder” are no longer the product features that customers currently care about. Similarly, due to the uncertainty of information entropy, compared with traditional method our method has two features such as “children” and “telephone”, indicating that users pay more attention to “children” and “telephone” currently. The customers currently hope to effectively solve their children’s diseases through online medical platforms. On the other hand, the elderly usually consults and sees a doctor online by mobile phone. Through the screening of feature words by information entropy, we find that what customers really care about recently is the service level of online medical APPs for the elderly and children. In traditional method, the helpless information

Table 1. The extraction of the features by our method.

Category	Offline activities	Medical service	Interaction of Software	Online diagnosis	Health science popularizing
	Marketing	Hospital	Experience	Diagnosis	Health
	Medical exams	Register	Version	Reply	Medical
		See a doctor	Interface	Patient	knowledge
		Queue	Confidence degree	Patient’s condition	Information
		Online		Speed	Suggestion
		Convenience		Doctor	
				Child	
				Telephone	

Table 2. The extraction of the features by the traditional method.

Category	Offline activities	Medical service	Interaction of Software	Online diagnosis	Health science popularizing
	Marketing	Hospital	Experience	Diagnosis	Health
	Medical exams	Register	Version	Reply	Medical
		See a doctor	Interface	Patient	knowledge
		Queue	Confidence degree	Patient’s condition	Information
		Online	Crashing	Speed	Suggestion
		Convenience	Reminder	Doctor	

and helpful information are analyzed simultaneously so that the new features after software updated cannot be extracted. However, these are the information that customers really care about at present. Briefly, our method can really mine the product features that affect customer decisions.

Discussion of Data Results

Analysis of the Product Sentiment Score

Our method firstly screens out the helpful reviews and then calculate an average sentiment score for product features. For example, taking DXY as the target product, the comparison between our method and the traditional method of the feature sentiment scores is shown in Table 3.

As shown in Table 3, the results of DXY feature sentiment scores obtained by the traditional method and our method have changed. As far as the DXY is concerned, there are some changes in the sentiment score data of each feature. The reason for the changes is the same as the reason mentioned above, that is, the uncertainty of information entropy has corrected deviation of the results. Nevertheless, the variation range is not very large, which is determined by the helpfulness of information of information entropy. In the next section, through analyzing the results of the ranking of weighted product satisfaction indicates that a single product feature satisfaction changed little. However, compare the analysis results of other similar products show that the product features satisfaction rankings can produce larger change. The reason is the uncertainty of the information entropy can rectify

Table 3. The comparison of DXY features sentiment score by the traditional method and our method.

	The traditional method	Average sentiment score	Our method	Average sentiment score
Offline activities	Marketing	0.4938	Marketing	0.4801
	Medical exams	0.4598	Medical exams	0.4598
Medical service	Hospital	0.4627	Hospital	0.4615
	Register	0.4554	Register	0.4510
	See a doctor	0.4576	See a doctor	0.4561
	Queue	0.4692	Queue	0.4709
	Online	0.4562	Online	0.4556
	Convenience	0.4990	Convenience	0.5075
Interaction of Software	Experience	0.4992	Experience	0.5031
	Version	0.4694	Version	0.4683
	Interface	0.4487	Interface	0.4450
	Confidence degree	0.4786	Confidence degree	0.4724
	Crashing	0.4491		
	Reminder	0.4823		
Online diagnosis	Diagnosis	0.4801	Diagnosis	0.4791
	Reply	0.4683	Reply	0.4643
	Patient	0.4842	Patient	0.4850
	Patient's condition	0.4434	Patient's condition	0.4423
	Speed	0.4635	Efficiency	0.4890
	Doctor	0.4766	Doctor	0.4760
			Child	0.4741
			Telephone	0.5113
Health science popularizing	Health	0.5120	Health	0.5262
	Medical	0.4988	Medical	0.5053
	knowledge	0.4956	knowledge	0.5051
	Information	0.4905	Information	0.4922
	Suggestion	0.4926	Suggestion	0.4942

Table 4. The comparison of word frequency and number of reviews to calculate weight.

The traditional method	Word frequency	Number of reviews	Our method	Word frequency	Number of reviews
Marketing	304	250	Marketing	261	209
Medical exams	483	348	Medical exams	467	334
Hospital	3778	3090	Hospital	3411	2762
Register	2929	2510	Register	2457	2078
See a doctor	1525	1396	See a doctor	1336	1216
Queue	795	762	Queue	680	651
Online	606	561	Online	560	520
Convenience	263	255	Convenience	238	230
Experience	408	377	Experience	369	339
Version	394	351	Version	329	287
Interface	465	450	Interface	417	402
Confidence degree	420	397	Confidence degree	353	334
Crashing	591	491	Diagnosis	1158	1039
Reminder	238	216	Reply	1190	1082
Diagnosis	1332	1202	Patient	462	375
Reply	1529	1416	Patient's condition	328	315
Patient	513	420	Efficiency	367	357
Patient's condition	349	335	Doctor	12033	7825
Efficiency	431	420	Child	188	174
Doctor	13743	9261	Telephone	244	200
Health	2730	6603	Health	2361	5920
Medical	612	571	Medical	554	514
Knowledge	694	646	Knowledge	559	514
Information	523	477	Information	420	381
Suggestion	690	651	Suggestion	623	589

the above data from each medical APP. The specific content will be discussed in detail in the weighted ranking analysis to further demonstrate the importance of our method in correcting the results of product satisfaction analysis.

The Calculation of Product Feature Weight

As the same as the deviation correction principle of the sentiment score in our method, the source data of product weight calculation also change is shown in Table 4. According to the changes of these data, the weights obtained by the traditional method are corrected so that our method can obtain more accurate customer preferences.

According to the data of Table 4 and Eq. (5), Eq. (6), Eq. (7) and Eq. (8), the calculated result is shown in Table 5. Table 5 shows the comparison of the second-level feature weight obtained by the traditional method and our method. Table 6 shows the comparison of the primary feature weight obtained by the traditional method and our method.

Compared with the traditional method, the change of weight obtained by using the uncertainty of information entropy shows that our method can accurately capture the dynamic preference change of customers after software features updated. As shown in Table 6, the weights of primary features obtained by our method are online diagnosis (0.375), medical service (0.325), health science popularizing (0.163), interaction of software (0.090) and offline activities (0.047). The online diagnosis has the highest weight, which is related to the fact that the main function of the five APPs is online diagnosis service. Moreover, because another important role of medical APP is to book doctor registration and queue in hospitals online. The medical service is

Table 5. The comparison of second-level feature weight between our method and the traditional method.

The primary feature	The traditional method		Our method	
	Second-level feature	Second-level feature weight	Second-level feature	Second-level feature weight
Offline activities	Marketing	0.016347187	Marketing	0.018016468
	Medical exams	0.024231980	Medical exams	0.028912948
Medical service	Hospital	0.099669109	Hospital	0.101843918
	Register	0.083901408	Register	0.083961326
	See a doctor	0.053428017	See a doctor	0.056513915
	Queue	0.033096064	Queue	0.035212075
	Online	0.027249819	Online	0.030907848
	Convenience	0.014085717	Convenience	0.016082888
Interaction of Software	Experience	0.020113407	Experience	0.022762333
	Version	0.019730023	Version	0.021126483
	Interface	0.022026553	Interface	0.024644367
	Confidence degree	0.020468419	Confidence degree	0.021854969
	Crashing	0.027433538		
	Reminder	0.013177237		
Online diagnosis	Diagnosis	0.048837339	Diagnosis	0.051748406
	Reply	0.053331234	Reply	0.052446157
	Patient	0.024685909	Patient	0.027791401
	Patient’s condition	0.017654017	Patient’s condition	0.020598774
	Efficiency	0.020740013	Efficiency	0.022350748
	Doctor	0.198439991	Doctor	0.169499272
			Children	0.013500450
			Telephone	0.017006022
Health science popularizing	Health	0.049460741	Health	0.043223297
	Medical	0.027401805	Medical	0.030674280
	Knowledge	0.030140126	Knowledge	0.030951124
	Information	0.024441902	Information	0.025163713
	Suggestion	0.029908444	Suggestion	0.033206813

Table 6. The comparison of primary feature weight between our method and the traditional method.

The Primary feature	Traditional method	Our method
Offline activities	(0.040579167)	(0.046929416)
Medical service	(0.311430135)	(0.324521972)
Interaction of Software	(0.122949177)	(0.090388153)
Online diagnosis	(0.363688503)	(0.374941231)
Health science popularizing	(0.161353018)	(0.163219228)

Table 7. The comparison of weighted sentiment score between our method and the traditional method.

The Primary feature	The traditional method	Weighted sentiment score	Our method	Weighted sentiment score
Offline activities	Marketing	2 (0.008072)	Marketing	4 (0.008650)
	Medical exams	4 (0.011142)	Medical exams	4 (0.013294)
Medical service	Hospital	4 (0.046117)	Hospital	4 (0.047001)
	Register	5 (0.038209)	Register	5 (0.037867)
	See a doctor	5 (0.024449)	See a doctor	4 (0.025776)
	Queue	5 (0.015529)	Queue	4 (0.016581)
	Online	5 (0.012431)	Online	5 (0.014082)
	Convenience	2 (0.007029)	Convenience	1 (0.008162)
Interaction of Software	Experience	3 (0.010041)	Experience	3 (0.011452)
	Version	5 (0.009261)	Version	4 (0.009894)
	Interface	4 (0.009883)	Interface	4 (0.010967)
	Confidence degree	5 (0.009796)	Confidence degree	5 (0.010324)
	Crashing	5 (0.012320)		
	Reminder	3 (0.006355)		
Online Diagnosis	Diagnosis	4 (0.023447)	Diagnosis	4 (0.024793)
	Reply	5 (0.024975)	Reply	5 (0.024351)
	Patient	4 (0.011953)	Patient	4 (0.013479)
	Patient's condition	5 (0.007828)	Patient's condition	5 (0.009111)
	Speed	5 (0.009613)	Efficiency	3 (0.010930)
	Doctor	3 (0.094576)	Doctor	4 (0.080682)
			Child	3 (0.006401)
			Telephone	3 (0.008695)
Health science popularizing	Health	2 (0.025324)	Health	1 (0.022744)
	Medical	4 (0.013668)	Medical	4 (0.015500)
	Knowledge	5 (0.014937)	Knowledge	5 (0.015633)
	Information	3 (0.011989)	Information	3 (0.012386)
	Suggestion	3 (0.014733)	Suggestion	3 (0.016411)

also a primary feature that users pay special attention to. Furthermore, from Table 5, due to the uncertainty principle of information entropy, the change of overall user preference caused by the change of importance of some second-level features after software updated can be effectively mined. Therefore, our method can also accurately mine the dynamic change of customer preference.

The Weighted Ranking of Customer Satisfaction for Product

The result of sentiment weighted analysis of product satisfaction can more accurately obtain the customer preference and satisfaction. We take DXY as target product to analyze and obtain the weighted ranking of each feature of the target product in the five APPs is shown in Table 7. Table 7 shows the comparative changes of the weighted sentiment score ranking of the features obtained by the traditional method and our method.

As shown in Table 7, the comparison between the ranking results of DXY weighted sentiment score obtained by the traditional method and our method shows that the ranking of several features has changed obviously. Hence, taking the product feature satisfaction into the ranking of similar products to compare can better satisfy the needs of competitive market analysis. Compared with the traditional method, the "marketing" of DXY has changed from the second to the fourth among the five APPs, and the "health" has changed from the second to the first. This may be because

Table 8. The number of positive reviews and negative reviews of Ping An Health Cloud features by our method and the traditional method.

The traditional method	Number of positive reviews	Number of negative reviews	Our method	Number of positive reviews	Number of negative reviews
Marketing	70	103	Marketing	53	63
Medical exams	32	44	Medical exams	31	18
Hospital	307	620	Hospital	291	463
Register	348	442	Register	284	296
See a doctor	224	444	See a doctor	175	251
Queue	84	130	Queue	77	87
Online	73	106	Online	69	72
Convenience	687	538	Convenience	20	40
Experience	100	50	Experience	88	29
Version	61	66	Version	50	22
Interface	134	81	Interface	91	41
Confidence degree	77	70	Confidence degree	64	29
Crashing	163	200	Diagnosis	152	105
Reminder	112	54	Reply	122	84
Diagnosis	190	168	Patient	55	28
Reply	143	135	Patient's condition	33	43
Patient	59	34	Efficiency	139	26
Patient's condition	39	52	Doctor	1542	1002
Efficiency	160	44	Child	43	20
Doctor	2107	1815	Telephone	230	97
Health	492	194	Health	344	91
Medical	142	76	Medical	119	54
Knowledge	116	31	Knowledge	92	14
Information	68	19	Information	27	26
Suggestion	135	84	Suggestion	91	54

the satisfaction of medical popularization knowledge in health science popularizing has changed in the five APPs after the software updated of DXY. It will lead to the marketing activity ranking of the DXY in five APPs has changed. Because after the software upgrade, due to the satisfaction of health knowledge popularization function is improved, the software has been recognized by users to increase customer satisfaction and the customers' loyalty. Thus, the strength of promotions on sales activity is relatively smaller than the other four APPs to cause the ranking drop. In addition, it is also possible that a new round of promotion after the update of other APPs to cause the change in the "marketing" ranking of DXY. Compared with the traditional method, "seeing a doctor" and "queue" have risen by one rank, which corresponds to the rise of "convenience" by one rank indicating that our method finds that after the update of DXY, it is more convenient to see a doctor and more efficient to register and queue online. Therefore, the "convenience" of the product has also risen by the same rank. In addition, because we use the uncertainty of the information entropy to capture the customer focusing on "children" and "telephone". The two features of DXY rank third, so the corresponding "version" ranking is also improved. It shows that due to the updated version, compared to the features that customers no longer care about by the traditional method, such as "reminder", the customers currently pay more attention to the reminding mode in the way of "telephone". Since the changes of the satisfaction ranking of the DXY mentioned above can be accurately analyzed by our method, the version ranking also changes with the improvement of satisfaction. To sum up, we not only solve the problem of information overload, but also analyze the change of product satisfaction ranking after the update of target product in real time. It can make us know ourselves and our competitors in the competition and more accurately grasp the customer-oriented market competition.

Tendency Analysis of the Customer Satisfaction for Product

To comprehensively analyze the product satisfaction, besides analyzing the ranking of weighted product satisfaction, we also analyze the product satisfaction tendency. It can analyze the polarity and intensity of the product satisfaction to more accurately grasp customers preferences and satisfaction for product, which is particularly important in the customer-oriented market competition. The comparison between the number of positive and negative reviews on the features of Ping An Health Cloud obtained by our method after screening helpful information and the data obtained by traditional method is shown in Table 8.

For the other four APPs, our method and the traditional method are also used to compare to obtain the figure of the ranking of the sentiment tendency of the five APPs. Fig. 5 is the ranking of the sentiment tendency obtained by the traditional method. Fig. 6 is the ranking of the sentiment tendency computed by our method.

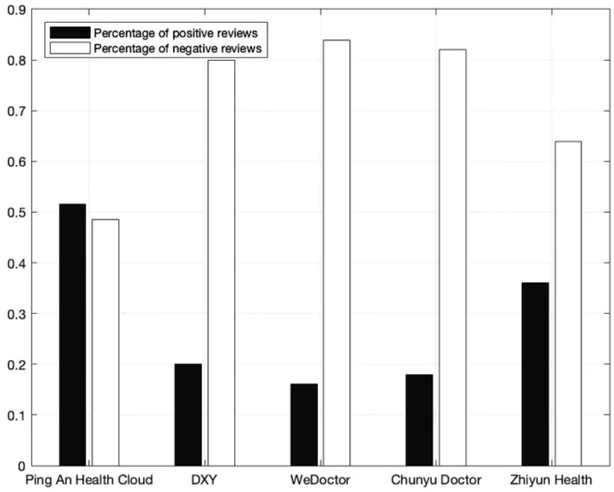

Fig. 5. The ranking of sentiment tendency obtained by the traditional method.

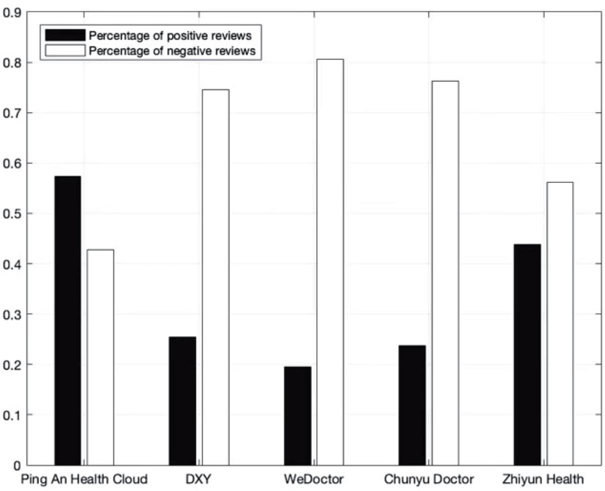

Fig. 6. The ranking of sentiment tendency obtained by our method.

From Fig. 6, it is concluded that the overall sentiment attitude of DXY, WeDoctor, Chunyu Doctor and the Zhiyu Healthy is that negative emotion is large. Among them, DXY, WeDoctor and Chunyu Doctor have more than 70% negative sentiment proportion. It shows that the overall satisfaction of customers of the three APPs is low. Negative reviews ratio of Zhiyun Health is greater than the positive, but they are relatively close. The positive sentiment tendency of Ping An Health Cloud is greater than the negative one, which is more than 10%. The customers for Ping An Health Cloud have the highest overall satisfaction. This is consistent with our ranking results of weighted sentiment scores. Compared to the traditional method and our method, as shown in Fig. 5 and Fig. 6, the results of the analysis of five APP positive ratio have increased in our method, that is satisfaction ratio has increased, because according to the principle of the uncertainty of information entropy, the increase of the features satisfaction after the software updated has been captured. Similarly, since the satisfaction ratio obtained by our method has increased, the dissatisfaction ratio has decreased compared with the traditional method. Therefore, our method can better obtain the dynamic change of product satisfaction tendency.

Further Discussion of the Ranking of the Product Satisfaction

Weighted ranking results of product features of five APPs can also determine the overall strength of competitors' products. We add and average the weighted sentiment scores of five categories of five medical APPs after the correction of information entropy, and obtain the weighted sentiment scores coordinates of five categories of five products is shown in Fig. 7. The performance of each product can be identified in the Fig. 7. The market can be more accurately grasped by the ranking analysis of product satisfaction.

As shown in Fig. 7, the weighted sentiment ranking result of the five APPs obtained by our method is basically consistent with the sentiment tendency ranking result obtained by our method. The main competitors of DXY are WeDoctor and Chunyu Doctor, and the stronger competitors are Ping An Health Cloud and Zhiyun Health. The target product should continue to maintain the advantage of the software in health science popularizing, and greatly improve

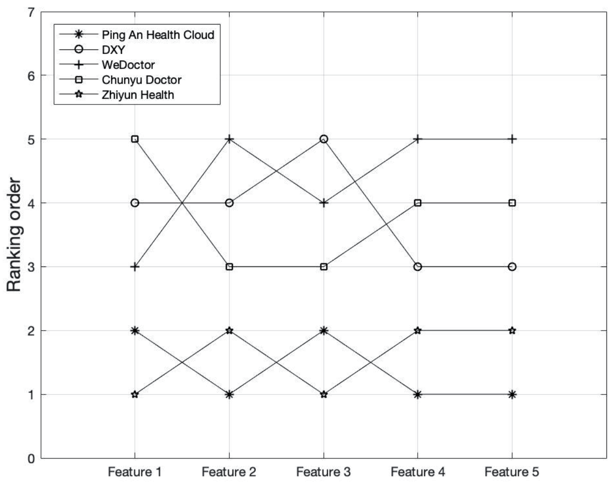

Fig. 7. The ranking of five kinds of feature satisfaction of 5 Apps obtained by our method.

customer satisfaction in interaction of software at the same time. Appropriately increasing satisfaction of offline promotional activities, online diagnosis and medical service can make DXY become a leader in the industry.

Conclusions

This paper selects helpful reviews with high information entropy through information entropy model, and then obtains product features by feature extraction and dimension reduction clustering. Simultaneously, lexicon method is utilized to analyze the sentiment of feature words. Finally, some interesting conclusions can be drawn through case study:

(1) The greater the information entropy of a review, the higher the helpfulness of the review. This tendency appears in total reviews, especially customers' specific preferences for product features. For customers with different preferences, considering different product characteristics, they can obtain the optimal purchase strategy.

(2) The proposed method can help businesses find the product features that customers follow with interest, and perfect their products according to consumers' preferences under the influence of market uncertainty, so as to improve revenue.

(3) The sentiment score and product feature weight change with the analysis of helpful reviews. It can be seen from the tables (obviously Table 3 and Table 5) that only by paying attention to helpful reviews can we know the sentiment score and weight of the product features that customers really care about. This shows that the proposed method is worth attaching great importance by online commodity managers.

(4) Paying attention to sentiment tendency ranking can determine the competitiveness of target products in a multi-product competitive environment. As shown in Fig. 6, helpful reviews can better reflect the dynamic changes of product satisfaction. Therefore, the analysis of customers' sentiment tendency can guide businesses to know themselves and their opponents, develop their strengths and avoid their weaknesses, maintain their own advantages and realize long-term profits in the fierce market competition.

In addition, it can be seen from Fig. 7 that each product has specific advantages under different product features. If we focus on improving the specific strengths of products, it is a good way to improve customer satisfaction. The comprehensive ranking of products is the reflection of customers' comprehensive preference. In the human-centered market economy environment, businesses should seriously serve every customer.

To sum up, after considering the helpfulness of reviews, this paper presents a solution for businesses to obtain better benefits from the perspective of decision-making. Environmental regulators can also use our methods to better formulate environmental protection measures. However, this paper also has some limitations. For example, the calculation methods of sentiment analysis and product feature weight through lexicon method and TF-IDF are still limited. It is a practice to discover an appropriate method to calculate weight and machine learning method for sentiment analysis.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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