Journal of Industrial Engineering and Applied Science
ISSN 3005-6071 (Print) | ISSN 3005-608X (Online) | Vol. 1, No. 2, 2023

Prediction of Sunshine Company's Product Participation in the Online Market based on Consumers' star Ratings and Reviews for Given Products

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Abstract: When shopping on line, reviewing product reviews often plays a very important role in making decisions for consumers. We will build models, study the relationship between user reviews and other metrics, and propose appropriate sales strategies for the company.

First of all, we need existing data for processing. We analyzed the star rating, the voting status of reviews, and the sales volume, and divided the reviews into three levels according to the length of the content of the paper. Finally, we reached the following conclusions:

1) The pacifier has the highest average star rating among the three types of products, and the highest sales volume;

2) Three categories of products have the largest percentage of Five Star reviews, and Microwave for two products, one star rating accounted for a relatively large proportion.

Secondly, the TF-IDF algorithm is used to extract keywords from user reviews, and combined with sentiment analysis, an emotional score is assigned to each review. Then, we establish a fuzzy evaluation model and use the reviews that have been scored to analyze the satisfaction of the product. In the end, we got a comprehensive evaluation of the three products, which were all expressed as satisfactory, and the satisfaction degree of the hair dryer was higher than that of the microwave oven and the pacifier.

Using the established model and the obtained data, we can find out the trend of star ratings over time, and filter out the most successful products and the most failed products. In particular, for the most failed products, we can describe keywords based on specific quality descriptions in user reviews, and find the shortcomings of the products to improve them. In addition, we built a model and found that after deleting a specific star rating, other users will be affected when they comment. Finally, we screened out specific keywords of five stars and one star respectively. With reference to their emotional scores, we can find that there is a high positive correlation between specific keywords and star ratings.

Keywords: Online Shopping, Product Review, Marketing Strategy, TF-IDF Algorithm, Fuzzy Evaluation

DOI: https://doi.org/10.5281/zenodo.10083502

1 Introduction

1.1 Background

With the rapid development of information technology in recent years,the integration of Internet technology and the socio-economic field has promoted the rapid development of the online market, and online shopping has penetrated into all aspects of people's lives. Among them, in the online marketplace created by Amazon, after consumers successfully purchase items, they can score and evaluate the purchased products on their platform. User satisfaction with the product can be reflected in the star rating of the product, and the buyer can also submit a text-based message to express opinions and evaluations on related products. Other users can make decisions about whether to buy the product by providing ratings based on star ratings and reviews that they find useful or useless. The company processes, analyzes, and investigates the product's market participation, time of participation, and the possibility of successful product design function selection.

1.2 The Discription of the Problem

Sunshine Company launches and sells three new products on the online market: microwave ovens, baby pacifiers, and hair dryers. This article will address the following two questions by identifying key patterns, relationships, metrics, and parameters of past customer ratings and reviews related to other competing products: First, derive online sales strategies; The second is to identify potentially important design features to enhance the attractiveness of the product.

2 Framework

1. Analysis of star rating, voting situation and sales volume. Analyze which of these three products has the highest star rating, and which category of each product has the highest star rating, and the impact of star ratings given by previous users on sales. In addition, which of the top five product_parents are sold, and in which year is the largest sales volume.

2. Emotional word processing and relevance analysis of reviews. In order to explore the impact of these reviews on sales volume and the specific impact of reviews, we need to conduct a comment correlation analysis. There are various forms of user reviews, in addition to giving star ratings, there is also a review of the previous user’s review, as well as their own text review. The text review cannot be used directly by us, so we need to extract the emotional words in the review and analyze it.

3. Product satisfaction analysis. The satisfaction that affects a commodity is manifold. User reviews, product factors, and user evaluations are three important manifestations of product satisfaction evaluation. Therefore, we analyze the satisfaction of the goods from these three aspects.

3 General Assumptions

Assumption 1: All users who purchased the product have left a review for the item, meaning that the number of reviews equals sales volume.

Assumption 2: The comments left by users are authentic and valid.

Assumption 3: The comments left by different users do not interact with each other.

Assumption 4: The comments left by users are not subjective.

4 Analysis and Solving of Question One

4.1 Preparation before data processing

The requirement of this question is to use the data provided to describe and analyze the purchase of three different types of products. It can be known from the data given that the analysis of the product can be carried out in terms of product sales, customer ratings, the number of useful reviews and total reviews, and the content of the reviews. Secondly, it is also important to analyze the products with better and worse sales among the three types of products. However, because reviews are in the form of text and have different lengths, they cannot be directly used for product evaluation. Therefore, you need to extract keywords from the content of each text review first, and then convert the keywords into mathematical symbol representations so that analysis.

4.2 Analysis of stars, votes and sales

First, import these data into excel. It is not difficult to find the average star rating, star standard deviation, median star rating, help rate, and 5-point review help rate for each type of product. Table 4-1 is as follows:

Table 4-1 Product Information Sheet

	Average star	Star standard deviation	Median Star Rating	Help rate	5 point review help rate
hair_dryer	4.116	1.300	5	0.850	0.912
microwave	3.445	1.645	4	0.843	0.902
pacifier	4.300	1.190	5	0.731	0.798

It can be seen from the table5.2-1 that the average star rating of hair_dryer is 4.116 stars, and the median star rating is 5 stars, indicating that users are still very satisfied with this product of hair_dryer. In addition, buyer comments helped 85% of product sales.

Microwave's average star rating is 3.445 stars, with a median star rating of 4 stars, which indicates that users are still quite satisfied with the hair_dryer product. In addition, buyer comments helped 84.3% of product sales.

The average star rating of Pacifier is 4.300 stars, and the median star rating is 5 stars, indicating that users are still very satisfied with the hair_dryer product. In addition, buyer comments helped 73.1% of product sales.

Comparing the star standard deviation of the three products, it can be known that the standard deviation of the pacifier is the smallest, that is, the pacifier is the smallest of the three products given by the buyer.

In addition, the 5-point review help rate is much higher than the overall help rate, which indicates that high-score reviews still have a relatively large impact on users' purchase of goods.

Secondly, the analysis focuses on a certain type of product, and analyzes the distribution of star ratings of this type of product, as shown in Figure 4-1:

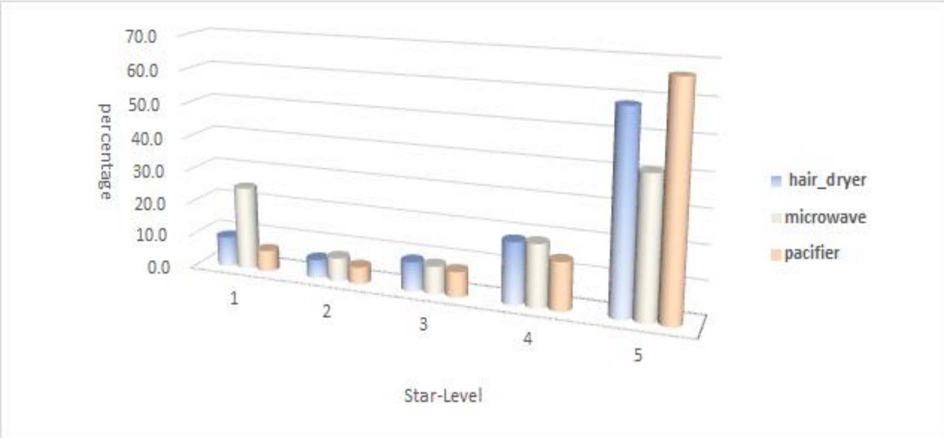

Figure 4-1 Proportion of three product stars

From these three pie charts, it can be seen that the proportion of five stars of each product is the largest, indicating that these three products are generally satisfactory. In the P chart and the H chart, the proportion of one star and two stars is only 11.3% and 14.6%, which indicates that most people do not have a disgusting attitude towards the product. In the M chart, the ratio of one star alone accounts for about 1/4, indicating that a relatively large number of people do not like this type of product.

After obtaining the star-rating ratio of various products, further analyze the sales situation of each type of product. Based on the number of times each product has been evaluated, we have calculated the top five products with the best sales among the three categories, as shown in Table 4-2 below:

Table 4-2 Top 5 Product List

	product_parent	star_1	star_2	star_3	star_4	star_5	sales	Average star	Total average star rating
h	732252283	36	29	57	110	355	587	4.225	**4.032**
	47684938	41	39	52	92	331	555	4.141	
	758099411	17	32	49	114	323	535	4.297	
	694290590	32	28	37	98	229	424	4.094	
	235105995	32	19	40	80	236	407	4.152	
m	423421857	50	18	41	111	174	394	3.865	**3.214**
	544821753	57	7	4	3	9	80	1.750	
	109226352	11	7	2	16	43	79	3.924	
	771401205	8	3	4	13	50	78	4.205	
	827502283	7	6	4	13	46	76	4.118	
p	246038397	30	29	46	101	627	833	4.520	**4.153**
	392768822	13	17	22	57	412	521	4.608	
	572944212	19	16	30	55	372	492	4.514	
	450475749	14	13	23	42	383	475	4.615	
	812583172	7	7	11	21	213	259	4.645	

It can be seen from the table that the average star rating of hair_dryer. Is 4.032 stars, the average star rating of microwave is 3.214 stars, and the average star rating of pacifier is 4.153 stars. It can be seen that among hair_dryer, microwave, and pacifier, the pacifier product is the best average star rating, followed by hair_dryer. In addition, it can be seen that among the P products, the product with the number 246038397 not only has the highest sales, 833, but also has an average star rating of 4.52, which is a relatively high score, so this product has been sold more successfully; instead, the number is 544821753 Not only does the product have a poor sales volume, the average star rating is also as low as 1.75, indicating that most users are dissatisfied after using the product.

The top five products in the hair_dryer, microwave, and pacifier have been identified in the table above. We then filter and refine the years in their review_date, and then count the annual sales of each product. (The total sales volume of each product below will be represented by the total sales volume of the five categories of products in the top five sales volume.) By solving with MATLAB software, the following trend graph can be obtained:

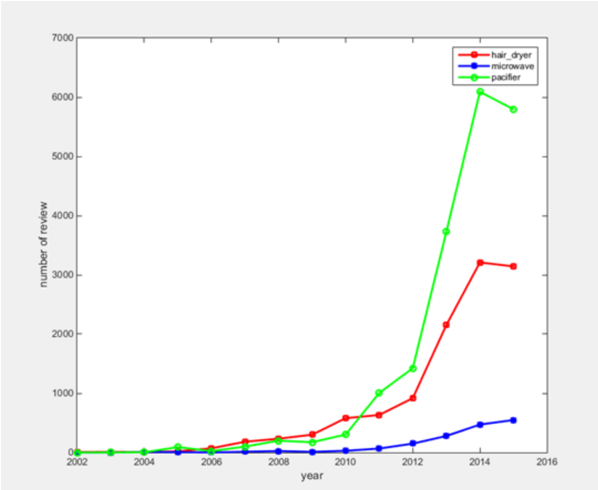

Figure4-2 Product trends over time

As can be seen from the above figure: the sales volume of hair_dryer, microwave and pacifier products are basically on the rise, but the sales volume of microwave products has reached an inflection point in 2014 and a downward trend in 2015. That is, in the 14 years from 2002 to 2015, hair_dryer and pacifier both had the largest sales volume in 2015, and microwave had the largest sales volume in 2014.

4.3 Comment Analysis

4.3.1 Rating of reviews

Because reviews are in the form of text and cannot be directly used for evaluation and analysis, we divide the content of all reviews of the three types of products into three levels according to the word count of the reviews, that is, not serious, more serious, and very serious. As shown in the following table:

Table 4-3 Distribution of seriousness of reviews

	Not serious	More serious	very serious
H	25.7%	70.5%	3.8%
W	20.2%	69.3%	10.5%
P	29.3%	67.8%	2.9%

As can be seen from the table above, the seriousness of the content of all reviews of the three types of products is roughly similar, and the ratio is more serious> not serious> very serious, and the number of serious people (including more serious and very serious) accounts for the majority Most users don't choose random reviews.

4.3.2 Relevance analysis of reviews

A serious and meaningful evaluation will often be used and referenced by other users who have not yet purchased the product, and will help when they purchase it. Therefore, we consider that there may be some relationship between a user's rating and the average star rating, useful votes, and total votes. We count the relevant indicators for each type of product separately, as shown in the following three tables:

Table 4-4 H-related indicators

Seriousness	Average star	Valid vote	Average effective vote	Total vote	Help rate
1	4.41	607	0.21	1077	0.56
2	4.02	17685	2.19	20983	0.84
3	3.94	6702	15.51	7386	0.91

Table 4-5 W-related indicators

Seriousness	Average star	Valid vote	Average effective vote	Total vote	Help rate
1	4.23	168	0.51	418	0.40
2	3.31	4704	4.2	5791	0.81
3	2.81	4207	24.89	4562	0.92

Table 4-6 P-related indicators

Seriousness	Average star	Valid vote	Average effective vote	Total vote	Help rate
1	4.52	943	0.17	1657	0.57
2	4.22	10957	0.85	15272	0.72
3	4.04	3761	6.79	4489	0.84

Here:

"1" means not serious;

"2" means more serious;

"3" means very serious.

The data were imported into SPSS software, and correlation analysis was used here. The calculation formula for the correlation coefficient is:

$$\rho_{x,y} = \frac{\frac{1}{n}\sum_{j=1}^{n}(x_j - \mu_x)(x_j - \mu_y)}{\delta_x \cdot \delta_y}$$

The correlation coefficient is between -1 and +1, which is$-1 \leq \rho_{x,y} \leq 1$.When the absolute value of the correlation coefficient is less than 0.3, it is low correlation; when the absolute value is between 0.3 and 0.7, it is moderate correlation; when it is 0.7 to 0.8, it is highly correlated; when it is above 0.8, it is very highly correlated.

The correlation coefficients between the indicators can be obtained through the software. Only the correlation coefficients related to the degree of seriousness are intercepted here, as shown in the following table:

Table 4-7 Pearson correlation table

	Average star	Valid vote	Average effective vote	Total vote	Help rate
Seriousness	-0.935	0.352	0.92	0.31	0.941

As can be seen from the table, the degree of seriousness is highly negatively related to the average star rating, that is, the higher the degree of seriousness, the lower the star rating; the degree of seriousness is highly positively related to the average useful vote and help rate (0.92 and 0.941), which indicates that a user fills in The more serious the comments, the more informative you write, and the more useful votes you get, the more people will find this review helpful when they buy a product. Conversely, a comment that has little meaning does not attract the attention of other users, let alone useful. This result is consistent with common sense.

5 Analysis and Solving of Question Two

5.1 Text Processing

This section deals with user comments. Because some of the comments have a lot of content, it will take too much time to analyze them directly. Therefore, filtering out keywords in a paragraph of text and then analyzing them will make the problem much easier. The following will use the model to extract the keywords in each comment.

5.1.1 Model introduction

In order to extract the keywords in the text review, the TF-IDF algorithm is used here. In the field of natural language processing, TF-IDF refers to a statistical method used to evaluate the importance of a word in a text data set. Therefore, TF-IDF is used as a model weight in various natural language processing (NLP) tasks. In simple terms, the value of TF-IDF will increase as the frequency of keywords appearing in the text increases, and will decrease as the frequency of keywords appearing in the data set increases.

The core of the idea of TF-IDF algorithm to extract keywords is to understand two nouns. One is TF, TF refers to the number of times a word appears in a document, that is, the frequency. The other is IDF, which is also called inverse document rate, which is mainly used to measure the universality of a word. One of the main ideas of TF-IDF is: if a word appears many times in a document, it is considered to be important and meaningful to a certain extent, but the words that appear multiple times are not always true for the document. A certain meaning, such as "". Therefore, the concept of inverse document rate is proposed to filter out these words.

5.1.2 Algorithm process

In a document, term frequency (TF) refers to how often a given word appears in the document. This value needs to be normalized during processing to prevent it from biasing towards long files. Its calculation formula is as follows:

$$TF_{i,j} = \frac{n_{i,j}}{\sum k \cdot n_{k,j}}$$

Inverse document rate (IDF) is a measure of the general importance of a term. For the IDF value of a word, you can use the total number of files in the corpus to initially include the number of files of the word, and then logarithmic the result obtained:

$$DF_i = log\left(\frac{|D|}{|\{j: t_i \in d_j\}|}\right)$$

Therefore, based on the above calculations, the TF-IDF value can be calculated:

$$TF - IDF(t) = TF(t) \times IDF(t)$$

Finally, we sort the obtained TF-IDF values, and select the top K words as the algorithm's keywords for document extraction.

5.1.3 Model solving

Using the above model, you can filter out several keywords in the three product reviews, as shown in the following table:

Table 5-8 Review keywords

Product	Keywords
H	great, hot, power, works
W	use, great, new, space,
P	great, perfect, soft, price

5.2 Text semantic analysis

From the comments we can know whether the user is satisfied with the product. This section mainly analyzes the semantics of the comments. There are many methods for semantic analysis. Here we use sentiment analysis.

5.2.1 Model introduction

Sentiment analysis is a branch of the field of natural language processing, and it is a popular research direction in recent years. The sentiment analysis of products is the emotional expression of consumers on the whole product and various attributes of the products, and the sentiment words are used to show the views of the products. We will score consumers' emotional expressions, divided into positive and negative. Negative is a relatively unsatisfactory expression, and positive is a relatively satisfactory expression.

5.2.2 Algorithm flow

First, starting from the goal of selecting products through sentiment analysis, design the fields that need to be captured. Then use python to perform web crawling according to the designed crawling field, and perform text preprocessing in excel on the crawled text. Since the research in this section is based on the sentiment dictionary, the sentiment dictionary is constructed before sentiment analysis. Then it is sentiment analysis based on product reviews, including product review content extraction and sentiment value calculation and results display. The following is the specific process of sentiment analysis algorithm:

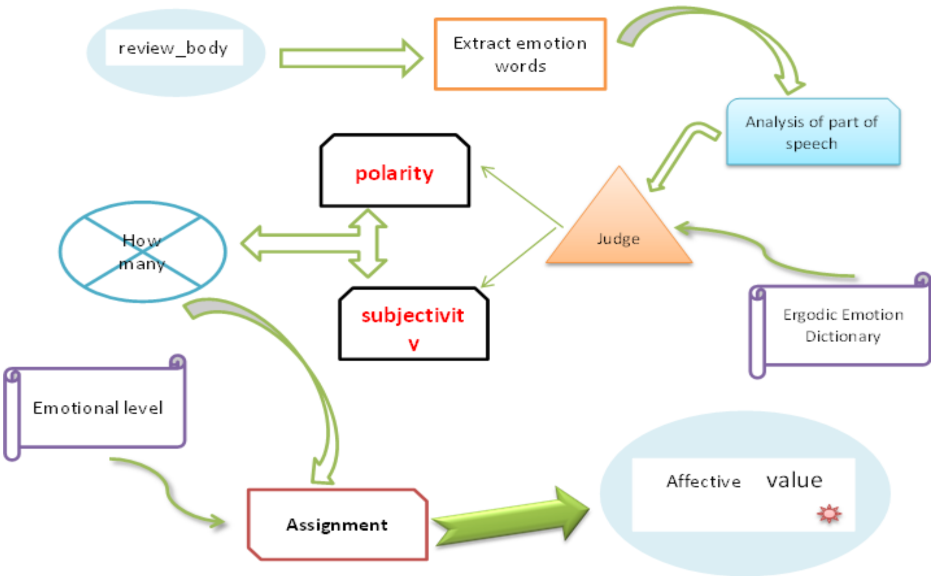

Figure 5-3 Sentiment analysis flowchart

5.2.3 Model solving

(a) Affective dictionary construction

Affective dictionary is a dictionary that judges emotional polarity based on semantics. Its quality has a direct impact on the accuracy of sentiment analysis. The construction of the emotional dictionary in this section is based on several common English emotional dictionaries, and is added by adding emotional words and network terms in the field. By consulting related dictionaries and literature, I found several common and open English sentiment dictionary resources:

1) GI (The General Inquirer): This dictionary gives very comprehensive information for each entry.

2) SentiWordNet: This dictionary performs sentiment classification on terms in WordNet, and marks the weight of each term for two categories, positive and negative.

3) MPQA Subjectivity Cues Lexicon: The dictionary contains 4912 negative emotional words and 2,718 positive emotional words.

(b) Product review sentiment analysis

Based on the information provided by the sentiment dictionary, we scored each word in each review, and then obtained the sentiment value of the review based on the weight and the sentiment of each word. The specific results are as follows (due to the huge data, only individual results are shown here):

Table 5-9 Sentiment analysis result table

comments	Great blow dryer !!!!
Segmentation weight	16.0, 'great blow dryer !!!'
Specific score	'great': 4, 'blow': 4, 'dryer': 4, '!!!': 4
Polarity and subjectivity	(polarity=1.0, subjectivity=0.75)

Note: Polarity score is between -1 and 1. The closer the score is to 1, the more satisfied the user is with the product; on the contrary, the closer the score is to -1, the less satisfied the user is with the product.

Based on this score, it is easy to filter out reviews that are satisfactory or unsatisfactory.

5.3 Product Satisfaction Evaluation

Whether you are satisfied with a product can be considered from many aspects. User reviews are one of the important manifestations of product satisfaction evaluation. Now we use fuzzy comprehensive evaluation model to evaluate the satisfaction of products. Based on the text processing in the previous section, comments can be added to the evaluation index system at this time.

5.3.1 Establishment of Fuzzy Comprehensive Evaluation Model

(a) Definition of fuzzy comprehensive evaluation model

The fuzzy comprehensive evaluation method is a kind of mathematically evaluating a class of objects under different influencing factors, giving different weights and comprehensively scoring them, and performing a common sense and practical significance evaluation. To this end, this article comprehensively evaluates the three products in combination with the factors affected by them as an evaluation index, and obtains the degree of user satisfaction with the products in the online market.

(b) Model establishment

Based on the available data, determine the set of factors for the three products of hair dryer, microwave oven and pacifier, that is, the first-level index for evaluating the product. This article selects the user rating factor, product factor, and user review factor as the first-level evaluation index of the product, and the personal rating-star rating as the second-level index of the user-rating factor; the quality, appearance, and effect of the product are the second-level indexes of the product factor, of which The quality and appearance of the product are obtained from the reviews; while the user review factor uses the number of reviews and the support of other users as secondary indicators to convert each indicator into moderate data. The product satisfaction evaluation index system constructed by it is shown in Figure 5-4:

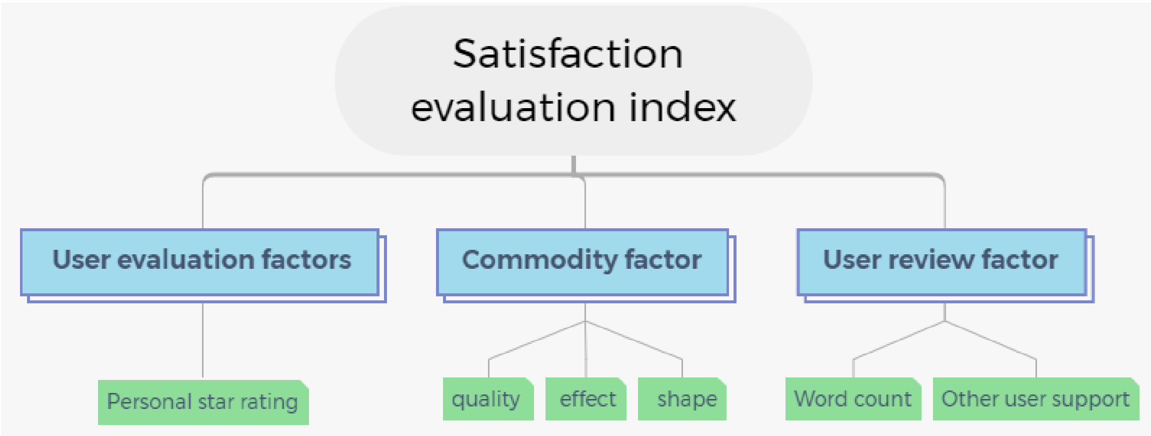

Figure 5-4 Product satisfaction index evaluation index system

(c) Model solving

Product index weights are calculated by AHP, and a relative deviation fuzzy matrix $R=(r_{ij})_{m\times n}$ is constructed, of which $0<r_{ij}<9, r_{ii}=1, r_{ji}=\frac{1}{r_{ij}}$. The summation method is used to solve the relative weight w of the evaluation factors, and the weight factor calculation formula is:

$$R_i=\frac{1}{n}\sum_{j=1}^{n}\frac{\alpha_{ij}}{\sum_{k=1}^{n}\alpha_{kj}}, i=1,2,\dots n$$

Therefore, construct a judgment matrix for the first-level indicators:

$$R=\begin{pmatrix}1 & 1/2 & 3\\ 2 & 1 & 1/2\\ 1/3 & 2 & 1\end{pmatrix}$$

Therefore, its weight is $W=(0.3698,\ 0.3323,\ 0.2979)$, and a judgment matrix is constructed for each factor of the secondary index under the determination of the primary index.

$$R_1=(1),\quad R_2=\begin{pmatrix}1 & 1/3 & 3\\ 3 & 1 & 1/2\\ 1/3 & 2 & 1\end{pmatrix},\quad R_3=\begin{pmatrix}1 & 1/4\\ 4 & 1\end{pmatrix}.$$

After the consistency test, the relative weights of the secondary indicators relative to the corresponding indicators of the upper level are: $W_1=(1)$,$W_2=(0.3325,\ 0.3678,\ 0.2997)$, $W_3=(0.2,\ 0.8)$ .The specific weights of all indicators are shown in Table 5-10:

Journal of Industrial Engineering and Applied Science
ISSN 3005-6071 (Print) | ISSN 3005-608X (Online) | Vol. 1, No. 2, 2023

Table 5-10 Index Weight

First-level indicators		Secondary indicators	
Name	Weights	Name	Weights
User evaluation factors	0.3698	Personal rating-stars	1
Product evaluation factors	0.3323	Shape	0.3325
		Quality	0.3678
		Effect	0.2997
User review factor	0.2979	Word count	0.2
		Other user support	0.8

Through statistical analysis of the given data, non-numerical data is quantified, and the rating of the reviews is divided into three levels: Y = {satisfactory, average, unsatisfactory}. It is observed that the first-level indicators of the three products of hair dryer, microwave oven and pacifier are relatively The membership matrix is shown below. Membership matrix of user rating factor, product factor and user rating factor are

$$Z1_2 = \begin{pmatrix} 0.5299 & 0.3313 & 0.1388 \\ 0.5419 & 0.3237 & 0.1344 \\ 0.3370 & 0.4811 & 0.1819 \end{pmatrix}$$

$$Z1_3 = \begin{pmatrix} 0.5501 & 0.3441 & 0.1058 \\ 0.5978 & 0.3481 & 0.0541 \end{pmatrix}$$

$$Z2_1 = (0.4130 \;\; 0.2687 \;\; 0.3182) \quad Z2_2 = \begin{pmatrix} 0.5138 & 0.2899 & 0.1963 \\ 0.4630 & 0.3013 & 0.2357 \\ 0.5415 & 0.2445 & 0.2140 \end{pmatrix}$$

$$Z2_3 = \begin{pmatrix} 0.4285 & 0.2930 & 0.2885 \\ 0.5544 & 0.2986 & 0.1470 \end{pmatrix} \quad Z3_1 = (0.6679 \;\; 0.2187 \;\; 0.1134)$$

$$Z3_2 = \begin{pmatrix} 0.4242 & 0.3462 & 0.2296 \\ 0.3879 & 0.2953 & 0.3168 \\ 0.4023 & 0.3210 & 0.2767 \end{pmatrix} \quad Z3_3 = \begin{pmatrix} 0.5659 & 0.3362 & 0.0979 \\ 0.4554 & 0.3014 & 0.2432 \end{pmatrix}$$

According to the above-mentioned established model, the user rating factors of the hair dryer satisfaction index, the product factors, and the user rating factors are comprehensively evaluated.

$$F1_1 = W_1 \cdot Z1_1 = (0.5845,\ 0.2698,\ 0.1457)$$

$$F1_2 = W_2 \cdot Z1_2 = (0.4765,\ 0.3734,\ 0.1501)$$

$$F1_3 = W_3 \cdot Z1_3 = (0.5883,\ 0.3473,\ 0.0644)$$

Calculated in the same way:

$$F2_1 = (0.4130,0.2687,0.3182) \quad F2_2 = (0.5034,0.2805,0.2161)$$

$$F2_3 = (0.5292,0.2975,0.1753) \quad F3_1 = (0.6679,0.2187,0.1134)$$

$$F3_2 = (0.4043,0.3199,0.2758) \quad F3_3 = (0.4775,0.3105,0.2141)$$

The comprehensive membership matrix of the product hair dryer: $Z_1 = \begin{pmatrix} F1_1 \\ F1_2 \\ F1_3 \end{pmatrix}$, the evaluation vector $F_1 = W_1 \cdot Z_1 = (0.5497,0.3273,0.1230)$.

Evaluation vectors for microwave ovens and pacifiers are$F_2 = (0.4777,0.2812,0.2417)$ and $F_3 = (0.5236,0.2979,0.1974)$ respectively.

According to the principle of maximum affiliation, the comprehensive evaluation of the product hair dryer, microwave oven, and pacifier are all expressed as satisfactory, and the satisfaction degree of the hair dryer is higher than that of the microwave oven and pacifier.

6 Answer questions

6.1 Processing of emotional scores and star scores

In section 6.2, the emotional words in the user's text comments have been analyzed and processed, and an emotional value has been assigned to each comment. The calculation shows that the average sentiment score of the hair-dryer is 0.264984, the average sentiment score of the microwave is 0.215447, and the average sentiment score of the paifier is 0.280245. It can be seen that the average sentiment score of paifier is the highest, that is, the text comment of paifier on the other two products is the best or the most detailed. The average star rating of the three categories of products has been given in Section 5.2: the average star rating of hair_dryer is 4.116, the average star rating of Microwave is 3.445, and the average star rating of

Journal of Industrial Engineering and Applied Science
ISSN 3005-6071 (Print) | ISSN 3005-608X (Online) | Vol. 1, No. 2, 2023

Pacifier is 4.300, combined with the review data (ie, emotional score) and the average Star rating: Of these three products, Pacifier products are the most satisfying for users.

6.2 The product's reputation change with time

Through the above-mentioned processing and analysis of the data, using python software, we can get the monthly trend, average star rating, monthly number of reviews, and average star rating change trend over time, so as to determine the change and trend of product word of mouth over time. The figure is shown in Figure 7.2-1 below.

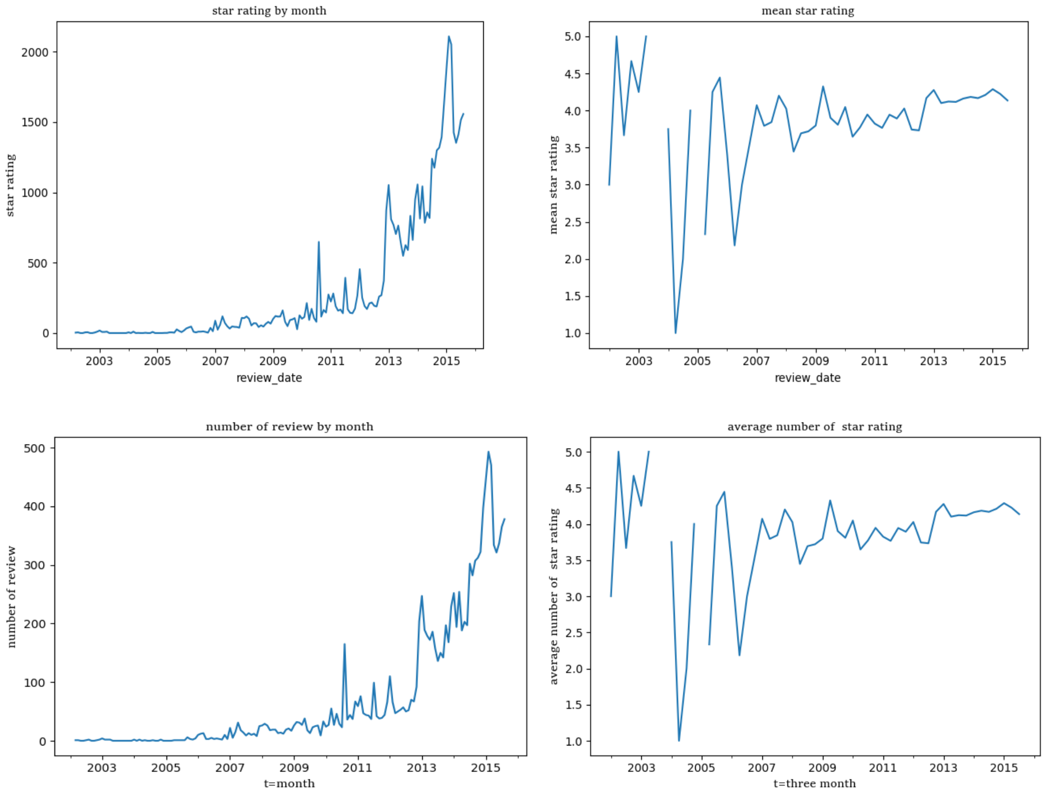

Figure6-5 Star over time trend graph

Figure star rating by month has the same trend as figure number of review by month. They were basically unchanged from 2002 to 2007. After 2007, they generally showed an upward trend, and they fluctuated regularly, that is, they have a regular pattern of time. The change in mean star rating and average number of star rating The trend is the same, with the lowest average star rating in 2004, reaching 1.0 stars. Before 2008, the annual average star fluctuation range was large, and after 2008 it tended to balance and slowly increase.

6.3 Precision marketing

In this article 6.2, the user's comments have been sentimentally analyzed. Now, based on the sentiment scores of the reviews, the reasons for good or bad product evaluations are analyzed in order to formulate a suitable marketing strategy.

6.3.1 Analysis of successful product evaluations

First, select all products with a 5-star rating, and then select products with an emotional score of 1. Then the users of these products will feel very satisfied after use. Next, browse through the customer's specific reviews in turn. It can be found that in the hair_dryer products, most of the customer comments are highly praised words such as perfect, excellent, best, etc., and several "!!!" are attached, indicating that the use of the hair dryer is excellent; In microwave products, customers also highly rated the products they purchased; in pacifier products, although customers will not buy them for their own use, it can be clearly seen from the reviews that their children like their parents to buy them very much. Pacifier.

For such very successful products, merchants can continue the current marketing model, or they can continue to promote and let more people use the excellent products they produce.

6.3.2 Analysis of failed product evaluations

First, select all products with a 1-star rating, and then select products with an emotional score less than 0. Then the users of these products will feel very dissatisfied after use. Next, browse through the customer's specific reviews in turn. It can be found that in the hair_dryer products, most of the customer reviews are words such as bad, horrible, etc., which indicates that the use of hair dryers is very bad; in microwave products, terrible, disappointed, refund, etc.

frequently appear in reviews; in Among the pacifier products, children are very hate purchased products.

In response to these very failed products, merchants must find the shortcomings of their products from customer reviews and make improvements. In addition, after-sales service must be in place. If customers complain or request, they must serve them patiently.

6.4 Analysis for the specific star rating

In order to find out whether the special comment has an impact on the follow-up, we construct a new sequence, the construction method is as follows:

(1) Find the special comment position, record it as L, L_i means the i-th special position;

(2) The evaluation values of the T evaluations after the special position is found, as the i-th sequence of the new structure, the specific formula is as follows:

$$g_i = \frac{1}{T}\sum_{k=j+1}^{j+T} f_j$$

(3) Perform mean analysis on the newly constructed series.

The product_parent number of the hair_dryer product was 732252283, and a total of 587 reviews were filtered, of which 36 were 1-star reviews and 355 were 5-star reviews. Use MATLAB soft calculation to get the star average under different conditions (source program see appendix). Therefore, when T = 8, after excluding 1-star reviews, the remaining average star rating is 4.0694; after removing 5-star reviews, the remaining average star rating is 4.2373; the overall evaluation is 4.2249. Based on the above analysis, specific star ratings and special comments will be affected when subsequent users comment on the product.

6.5 Correlation analysis between specific keywords and stars

In 6.1, the word frequency of each product review has been listed, but each word appears differently under different star reviews. In this section, we will filter out specific quality descriptors in the comments and do correlation analysis with star ratings.

After filtering the specific keywords in the five-star evaluation, find the following representative words:

Table 6-11 Hair_dryer Five Star Specific Keywords

word	great	good	fast	easy	powerful	perfect	cool	happy
frequency	2220	1065	784	634	612	583	467	400

Table 6-12Microwave Five Star Specific Keywords

word	great	fit	easy	new	good	perfect	nice
frequency	251	130	117	114	103	80	67

Table 6-13Pacifier Five Star Specific Keywords

word	love	great	cute	perfect	good	best	happy	adorable
frequency	6476	3219	1536	1303	1271	808	525	322

As can be seen from the above three tables, the most frequent keywords in five-star reviews are always positive words, which means that users are satisfied with the product. This is similar to the sentimentality of the words screened in 7.3.1.

After screening specific keywords in one-star reviews, find the following representative words:

Table 6-14Hair_dryer One Star Specific Keywords

words	hot	stopped	heat	waste	disappointed	old	broke	loud
frequency	177	110	100	74	71	68	59	51

Table 6-15Hair_dryer One Star Specific Keywords

word	heat	sharp	stopped	old	broke	bad	failed	error	poor
frequency	59	57	57	44	35	32	31	30	20

Table 6-16Hair_dryer One Star Specific Keywords

word	disappointed	waste	small	big	useless	wrong	poor	horrible	hate	heavy
frequency	95	75	64	61	31	31	29	24	23	23

As can be seen from the above three tables, the keywords that appear most frequently in one-star reviews are often negative words, which means that users are not satisfied with the product. This is similar to the sentimentality of the words screened in 7.3.2.

In summary, it can be concluded that there is a correlation between specific keywords and star ratings. The more times a positive keyword appears, the higher the evaluation star rating; conversely, the more times a negative keyword appears, the star rating is The lower the level.

7 Strengths and Weakness

7.1 Strengths

1.The advantage of emotion-based dictionary is that it is easy to use and does not require complicated algorithmic processes.

2.The fuzzy comprehensive evaluation model is based on the analytic hierarchy process, which determines the scientific weights of various factors for the analytic hierarchy process, providing a reasonable basis for the model establishment, which is helpful to reduce the application error and the accuracy of the evaluation results is higher. It can make a more scientific, reasonable, and realistic quantitative evaluation of the information that contains ambiguity; it can avoid the subjectivity inherent in target selection based on experience.

7.2 Weakness

1.The comprehensive evaluation method inherently has the characteristics of few model parameters and small fault tolerance, and it has the properties of rapid decay and increase, and its timeliness is limited, which is not suitable for long-term prediction or analysis. It has a strong dependence on historical data, and it does not consider the relationship between various factors, so its error may be large, and its relative accuracy for medium and long-term prediction is low.

2.The disadvantage of affective dictionaries is that corpora in different fields have different characteristics. Different affective words sometimes show different emotions in different fields, and may even show opposite polarity, so this method is only suitable For comparing a single fixed field. Secondly, in the face of texts with more complex semantic structure, the classification method based on sentiment dictionary cannot achieve better classification results.

8 Conclusions

By processing the data, we can calculate the average star rating, help rate, and distribution of the seriousness of reviews for each product to make a general understanding of the product situation. Secondly, we selected the best-selling products of each product as representatives and made a sales trend chart for several years. We can conclude that the sales volume of the three products has basically increased in recent years, but pacifier in 2015 There was a downward trend in the year and the decrease was obvious. By analyzing the relevance of the comments, we can know that the seriousness of the reviews is highly negatively correlated with the average star rating (-0.935), and the seriousness of the reviews is highly positively correlated with the average useful vote and help rate (0.92 and 0.941).

Using TF-DIF algorithm, keywords in text content can be extracted. Through sentiment analysis, the sentiment score of each comment is calculated. And through the emotional score, you can clearly know whether the user is satisfied with the product. In order to evaluate the satisfaction of goods, this paper uses fuzzy evaluation method. Through this model, it can be found that the comprehensive evaluation of the product hair dryer, microwave and pacifier is satisfactory, and the satisfaction degree of the hair dryer is higher than that of the microwave oven and pacifier.

After calculating the sentiment score and average score, comparing the three products, Pacifier products are the most satisfying for users. Statistics of the monthly star rating, average star rating, monthly reviews, and average star rating are performed through python software, and the trend of each indicator can be clearly seen through the image. Using the obtained emotional scores, the successful and failed products are screened separately and corresponding suggestions are put forward to the product problems to help businesses change their marketing strategies. In addition, by establishing a model, it can be concluded that specific star ratings and special reviews will be affected when subsequent users comment on the product. Finally, according to the listed keywords and their frequencies, through correlation analysis, it is concluded that there is a correlation between specific keywords and star ratings.

Acknowledgments

The authors thank the editor and anonymous reviewers for their helpful comments and valuable suggestions.

Funding

Not applicable.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

he original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Not applicable.

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