Analysis of Sales Strategies of Commodities Based on Online Comments

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Abstract: We process the correlation between reviews and star ratings to remove inconsistent data simplify the product's comprehensive rating model to get new expressions. And we propose a vector autoregressive moving average model (AVAMA) based on the attention mechanism to predict the reputation trend of a product through multiple measures at multiple time steps. We also established a combination of text-based measure (s) and ratings-based measures, which are used to indicate the degree of product success. We use a model for predicting time series, the exponential smoothing method. From the formula of the method, we can see that the closer the data is to the prediction point, the greater the effect on the prediction. Next, we use correlation analysis to correct the difference. The evaluation did a quantitative analysis. We selected the pacifier dataset with a large number of samples and used the negative evaluation (rating 1) as an indicator to organize the data. Earlier evaluation did indeed have a significant impact on subsequent evaluations. Result. We use the ngram language model. We take the pacifier dataset as an example, and map the title of the evaluation and the subject's sentiment rating through Text Blob to [0, 5]. The larger the number, the more positive the feeling, and the smaller the the more negative, the experimental results show that whether it is the title or body of the review, the level of correlation with the rating has stabilized over time, and the correlation level is relatively good. Finally, we give some suggestions.

1. Introduction

With the progress of the times, the rapid development of science and technology and the popularity of the Internet have made the online shopping platform able to rise rapidly [1]. Amazon and other network platforms have established functions such as rating and comment functions [2]. Users can express their opinions and suggestions on the products through these functions, and at the same time, the company can also take a look at all aspects of the products. Forecast the future development trend and formulate a more reasonable strategy [3].

2. Establishment and solution of model

2.1 Scoring model

2.1.1 Subjective weight calculation based on AHP

The scoring system we are going to get is influenced by many factors, including useful rating and vine impact rating star rating, comment length and vine metric evaluation; star rating, evaluation, praise rate and sales volume together determine the total product score. Different factors belong to different levels [4]. This is a three level evaluation system, so we first choose the AHP model to analyze the weight [5].

Model structure diagram

The total score is the target level; the star rating, the commentary, the rate of praise and the sales volume are taken as the criterion level; the useful rating, the vine and the comment length serve as the criterion level (indicator level) for the next level [6]. The target layer is M, the criterion level is C1, and the index level is C2.

Model construction

AHP requires the calculation of the mutual importance between elements by layer by layer. Taking the index level as an example, the weight of the relative criterion layer of each index is solved [7]. For n elements, the 22 comparison judgment matrix is constructed by combining Saaty's 1-9 scale method.

$$C=(c_{ij})_{n\times n}=\begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{bmatrix}$$

Normalize each column of matrix C:

$$a_{ij}=\frac{c_{ij}}{\sum_{i=1}^{n} c_{ij}}$$

By using the approximate solution of the eigenvector of the judgement matrix, the normalized matrix is added to the line first.

$$\overline{w}_i=\sum_{j=1}^{n} a_{ij}$$

The weight vector we can get the subjective weight of each index.

$$w_i=\frac{\overline{w}_i}{\sum_{i=1}^{n}\overline{w}_i}$$

Calculate the maximum eigenvalue max$=\frac{1}{n}\sum_{i=1}^{n}\frac{(Cw)_i}{w_i}$ among them, $(Cw)_i$ express Cw the first i component and calculate the consistency index. $CI=\frac{\lambda_{\max}-n}{n-1}$ The RI value of the random consistency index of the judgement matrix is introduced. $CR=\frac{CI}{RI}<0.1$ Is considered that the judgement matrix is consistent and the weight is valid.

Solution of model:

The weight vector of index layer is w_{1}, w_{2}, the weight vector of the criterion level is W, the corresponding judgment matrix is a.

We investigated 20 sales experts and inquired the relevant literature.

Indicator level: w_1=(0.708, 0.292), w_2=(0.4, 0.6)

Standard level: a=$\begin{bmatrix} 1 & 1/2 & 1/2 \\ 2 & 1 & 2 \\ 2 & 1/2 & 1 \end{bmatrix}$

Obtain: W= (0.1958, 0.4934, and 0.3108)

$\lambda_{\max}$=3.0536, cr=0.0462<0.1 conforms to consistency.

2.1.2 Objective weight calculation based on entropy weight method

Step1: Standardized processing of data.

Since the units of measurement of indicators are not uniform, we should first standardize them.

Because of the different meanings of positive and negative indicators, we should standardize data processing for different algorithms.

Step2: Calculation first j item index below i the data share the proportion of the index Z_{ij}.

Step3: Calculation first j entropy of item index e_j.

Step4: Calculation first j the difference coefficient of item index (information entropy redundancy)g_i.

Step5: Calculates the weights of indicators. S_j the weight equation is as follows.

$$S_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \quad (j = 1, \cdots, 4,)$$

Based on the above formula, according to the operation result of MATLAB,

Indicator level: w_1 = (0.6228, 0.3772) w_2 = (0.3150, 0.6850)

Criterion level: W= (0.1992, 0.5087, 0.2921)

2.1.3 Comprehensive weight calculation

Using AHP and entropy weight method, the weight vector is synthesized linearly. The vector obtained by AHP is w1. The vector obtained by entropy weight method is w2, and the comprehensive weight vector is W.

$$W = \alpha w1 + (1-\alpha) w2$$

Formula: α is fully reflect the objective decision-making function of passenger experience in design evaluation, it is necessary to make a trade-off between the proportion of subjective and objective weight when empowering α =0.4)

The final comprehensive weight function is W=0.4w1 +0.6w2.

In summary, the composite vector of index level is: w_1 = (0.6569, 0.3431) w_2 = (0.3490, 0.6510)

Criterion level: W= (0.1978, 0.5026, 0. 2996)

From this we get the scoring model:

$$Z=0.1978\cdot (0.6569X3+0.3431X5)\, X1+0.5026\cdot(0.3490X5+0.6510X4)X2+0.2996X6$$

2.1.4 Final model formula

$$Z= [0.1978\cdot (0.6537X3+0.3463X5)\, X1+0.5026\cdot(0.3490X5+0.6510X4)X2+0.2996X6]\cdot \ln(1+\frac{m}{M})$$

2.2 Prediction time series and correlation analysis model

We set up two models from two dimensions of qualitative and quantitative analysis.

(1) Qualitatively

In order to see whether the earlier evaluation will have a significant impact on the later evaluation, we introduce a prediction time series model, exponential smoothing method, "Holt-Winters", and the recurrence relation of the first exponential smoothing method is as follows:

$$s_i = \alpha x_i + (1-\alpha) s_{i-1}, 0 \le \alpha \le 1$$

Among them, S_i is the smoothed value on time step i, and X_i is the actual data on the time step. α As a factor between 0, 1, it controls the balance between the old and new information. It is easy to see that the exponential smoothing method is mainly aimed at the non-trend and seasonal sequence. For the assumptions made in the question, we may introduce the three exponential smoothing method to reflect the seasonal characteristics of the grading. The three exponential smoothing formula is as follows:

$$s_i = \alpha(x_i - p_{i-k}) + (1-\alpha)(s_{i-1} + t_{i-1})$$
$$t_i = \beta(s_i - s_{i-1}) + (1-\beta)t_{i-1}$$
$$p_i = \gamma(x_i - s_i) + (1-\gamma)p_{i-k}$$

It adds a trend (t_i) and a periodic part (P_i) to predict changes based on an exponential smoothing method, smoothing the three features.

We can see from the recursive formula that the closer the prediction point is, the greater the prediction effect will be, and the weight will be changed over time. α, β, Gama is also decreasing exponentially. That is to say, if the predicted image is basically consistent with the real image, we can think that the earlier rating will have a significant impact on the subsequent rating.

(2) Quantitative

We used the correlation analysis model to make a quantitative analysis of the difference. We selected the pacifier dataset with more samples and took the bad rating (rating 1) as the index.

1) Every month with transaction records (assuming a total of N months) is the starting point of data measurement, and the length of time is 12 months.

2) Accumulates the number of bad evaluations per month in monthly units, so that we can get the eigenvectors of n*1 with the vertical axis of date: [x_1, x_2, x_3...X_n]

3) Analyzes the correlation between the 12 eigenvectors and obtains the correlation matrix so as to draw a conclusion.

2.3 Rank model and NGram language model

We introduced another emotion rank model, NGram language model. For this reason, we called the Text Blob Library in Python. Text Blob is an open source text processing library written in Python. It can be used to perform many Natural Language Processing tasks, such as part of speech tagging, noun component extraction, sentiment analysis, text translation and so on.

We take the pacifier dataset as an example to map the evaluation headlines and the Text Blob's emotional classification to [0, 5]. The larger the number is, the more positive the feelings are, and the smaller the negative is.

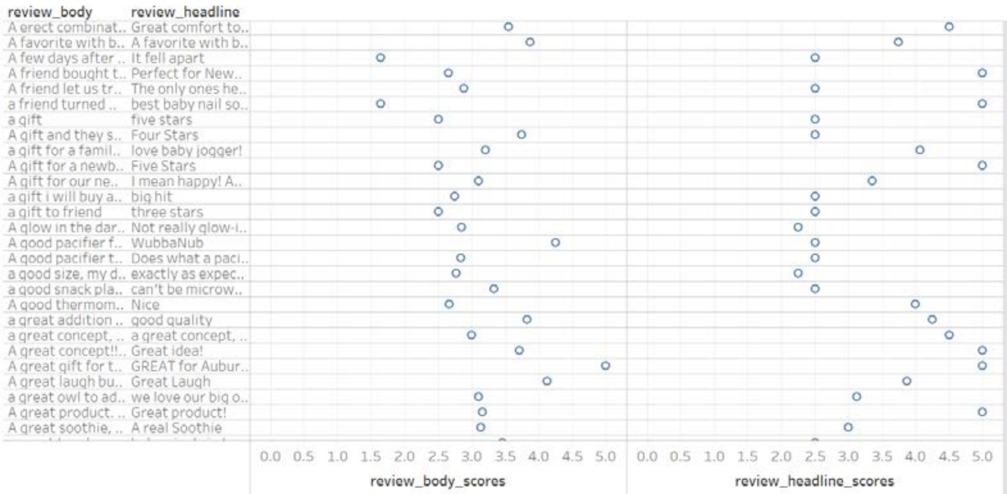

Figure 1. Emotion grading mapping

In order to verify the relationship between specific ratings and reviews, we will take time as a dimension and take three months as a cycle to measure the correlation changes over time.

3. Model testing and problem analysis

3.1 Scoring model

3.1.1 Subjective weight calculation based on AHP

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Calculate the maximum eigenvalue max=$\frac{1}{n}\sum_{i=1}^{n}\frac{(Cw)_i}{w_i}$, among them, $(Cw)_i$ express Cw first i component and calculate the consistency index. $CI=\frac{\lambda_{\max}-n}{n-1}$ The RI value of the random consistency index of the judgement matrix is introduced. $CR=\frac{CI}{RI}<0.1$ It is considered that the judgement matrix is consistent and the weight is valid.

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$$W=\alpha w^1+(1-\alpha)w^2$$

Formula: α is a proportional coefficient, i.e. the proportion of subjective and objective weights should be weighed when weighting (in order to fully reflect the objective decision-making role of passenger experience in design evaluation, experts suggest that take α =0.4)

The final comprehensive weight function is $W=0.4w^1 +0.6w^2$.

In summary, the composite vector of index level is: w_1= (0.6569, 0.3431) w_2= (0.3490, 0.6510)

Criterion level W = (0.1978, 0.5026, 0.2996)

From this we get the scoring model: Z =0.1978·(0.6569X_3+0.3431X_5) X_1+0.5026·(0.3490X_5+0.6510X_4)X_2+0.2996X_6

3.1.4 Final model formula

$$Z=[0.1978\cdot(0.6537X_3+0.3463X_5)X_1+0.5026\cdot(0.3490X_5+0.6510X_4)X_2+0.2996X_6]\cdot \ln(1+\frac{m}{M})$$

3.2 Test of vector autoregressive moving average (AVAMA) based on attention mechanism.

We use the "wubbanub infant pacifier GIRAFFE" product in the Pacifier dataset as an example to train the AVAMA model. The following figure shows the fitting results of the model on data sets of 100150250 and 500 days.

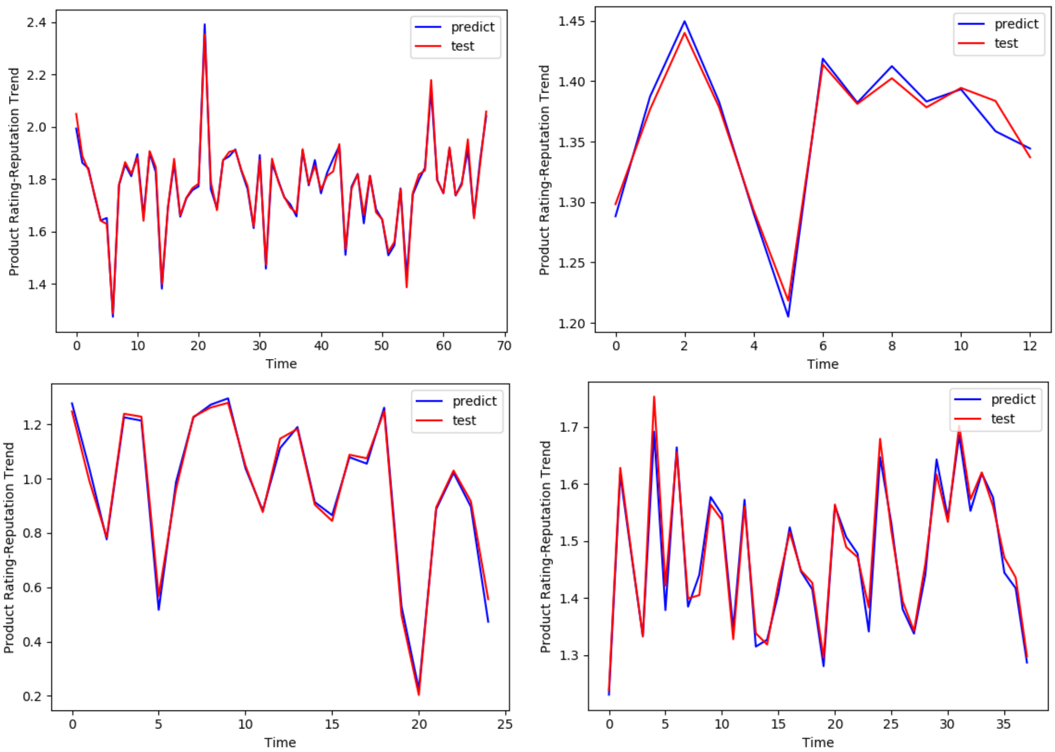

Figure 2. Fitting Results of the Model on Data Sets of 100, 150, 250 and 500 Days

The following table shows the changes of the RMSE of the model on different data sets.

Table 5. Changes in RMSE of models on different data sets

Time	100	150	250	500
RMSE	0.0451	0.0307	0.0275	0.0207

3.3 Prediction time series and correlation analysis model test

We chose a commodity with high sales volume and long time span in hair_dryer dataset, and predicted it by exponential smoothing method. We obtained the alpha =0.17, beta =0.12 and gamma =0.14 according to Bayesian adjustment, and drew the following image:

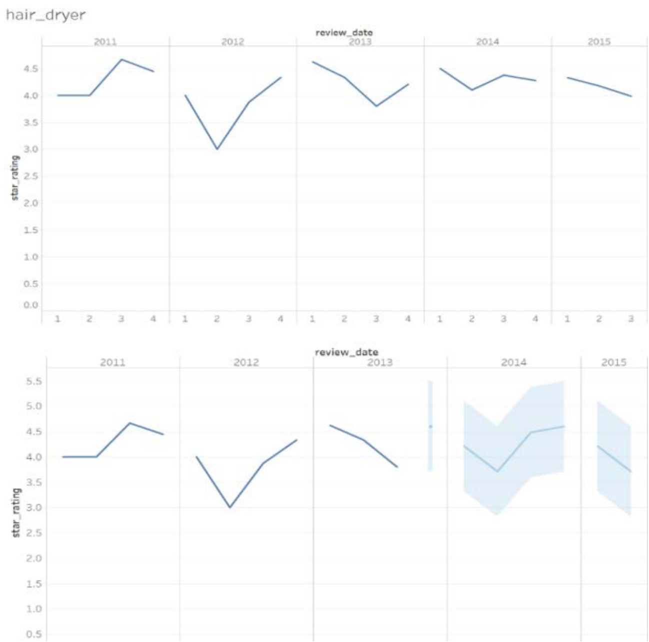

Figure 3. Hair dryer dataset predicted by exponential smoothing method according to Bayesian adjustment

We first obtained the results of the chart based on the aggregate measurement of the mean value of the commodity in five years. According to the data in the first three years, we used the exponential smoothing method to predict the change of the rating in the last two years, in which the light blue line is the predicted value while the shadow is the error range of the forecast interval at 95%.

It is easy to see that the actual and predicted image curves show a high similarity, so we can qualitatively believe that the earlier evaluation will have a significant impact on the latter evaluation.

After analyzing the correlation, we can draw the following correlation thermodynamics diagram:

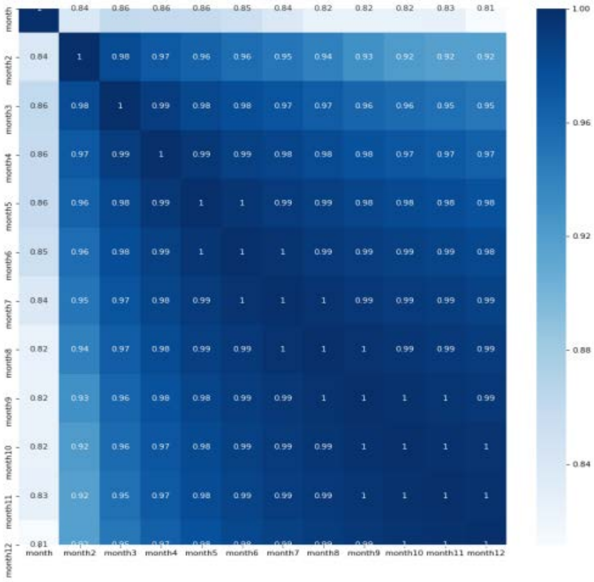

Figure 4. Correlation thermodynamic chart

We can observe the correlation size from left to right. It is not difficult to see that the correlation is generally high, indicating that the earlier evaluation did have a significant impact on the later evaluation. As time went on, the color of the color patches gradually decreased and the correlation level gradually decreased, which also conformed to our cognition of the "greater impact of the closer the time node".

3.4 Rank model and NGram language model test

In order to verify the relationship between specific ratings and reviews, we measured the correlation over time based on time dimension and three months as a cycle. We observed the correlation between ratings and reviews and the results of time varying.

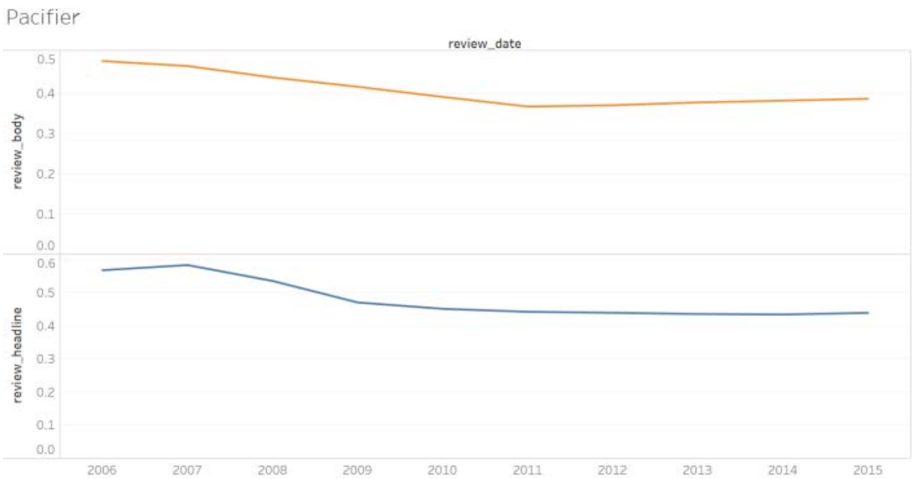

Figure 5. Results of correlation between ratings and reviews over time

As can be seen from the above figure, whether the title or body of the commentary is stable, the correlation level is relatively stable over time, that is, the correlation level is pretty good. That is to say, a specific rating actually corresponds to the word of a specific emotion, but we can also see that the correlation level has not reached a very high level, that is to say, there are some cases where ratings and commentaries do not correspond.

3.5 Analysis of grading problems

Since part of the data analysis has been done in the data preprocessing part, the relationship between grading and evaluation is mainly answered here.

Qualitative analysis: the higher the star rating, the more positive the feeling of evaluation is; the higher the useful rating is, the greater the proportion of vine is, and the higher the credibility of star rating is.

Quantitative analysis:

$$Z=[0.1978\cdot(0.6537X_3+0.3463X_5)X_1+0.5026\cdot(0.3490X_5+0.6510X_4)X_2+0.2996X_6]\cdot\ln(1+\frac{m}{M})$$

According to our scoring model, we choose the most important rating (including star rating and useful rating) and comments as the factors that affect the score. The relationship between the three is: star rating and reviews affect the product score, the higher star rating, the higher the product score, the higher the value of the comment, the higher the product score; the useful rating affects the credibility of star rating; the higher the useful rating is, the credibility of the score is higher. It can be combined with model 5.2 analysis.

Normally, the score and comment should be consistent and positive. When the score is inconsistent with the reviews, we think this is invalid data and should be deleted. Principal component analysis can be used to analyze the correlation. If the two are positive, based on the scoring model, we can easily deduce the formula of the impact of ratings and reviews on the product score.

Scoring model:

$$Z=[0.1978\cdot(0.6537X_3+0.3463X_5)X_1+0.5026\cdot(0.3490X_5+0.6510X_4)X_2+0.2996X_6]\cdot\ln(1+\frac{m}{M})$$

The influence of the useful rating on the score is 0.6537, and the useful rating can be used as the coefficient of star rating, but only the 0.6537 part of the star rating is multiplied by the useful rating. This question requires the deletion of vine factors, favorable ratings and other factors. At this time, the influence factors of star rating and comment on the total score are 0.2824 and 0.7175.

The total score is Z, star rating x_1, x_2, and the useful rating x_3, formula is:

$$Z=0.2824\cdot(0.6537X_3\cdot X_1+0.3463X_1)+0.7175X_3$$

4. Conclusion

We suggest that the product manager should analyze the comments in many aspects and grasp the customer's psychology. At the same time, we suggest that when a product continues to receive favorable comments, it should continue to increase the quantity of the product in order to obtain greater benefits, and when a product continues to receive unfavorable comments, it should reduce the quantity of the product or temporarily remove it from shelves to analyze the reasons, and then consider resuming shelves after a period of time. We need to improve the safety of products and design the appearance of products that babies like. Company's marketing department should pay attention to maintaining the balanced development of each measurement index of the product.

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