The Prediction and Evaluation of Amazon Product's Reputation Based on the Improved SSA-LSTM Model

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Abstract. **The rise of the Internet has promoted the vigorous development of online shopping. Evaluating and predicting the reputation of products is of great significance for sellers to identify the reputation trend of products and make sales plans in time. In this paper, based on the customer reviews data for hair dryer provided by Sunshine Company for Amazon Markets from August 2005 to August 2015, we propose five indexes: number of reviews, high confidence review rate, weighted average rating star, weighted average review score, and review score skewness. Then we use SSA-LSTM (Singular Spectrum Analysis-Long Short-Term Memory networks) time series method to predict the trend of product reputation. We find that the time series data processed by SSA has higher prediction accuracy than the unprocessed data, which proves that SSA processing can improve the accuracy of product reputation prediction. Moreover, we propose a product reputation evaluation method combining star rating and review data and use improved SSA-LSTM time series prediction method to predict product reputation. Overall, our results indicate that the above methods have achieved high prediction accuracy and have certain reference value for sellers' sales strategy formulation.**

Keywords: Product reputation, VADER, EWM-AHP-TOPSIS, SSA-LSTM

I. Introduction

To bring customers a better shopping experience, many shopping platforms allow customers to make online reviews and feedback on products. Then mining the value of scoring and feedback data, which has certain reference value for merchants to formulate corresponding strategies and improve sales level. At present, there are some studies on product rating and evaluation. For example, Mudamdi and Schuff 's research on What Makes a Helpful Online Review A Study of Customer Reviews on Amazon[1]. In this study, the author divided items into search products and experience products and studied the influence of review stars on review usefulness restricted by product types. Pei-yu Chen. *et.al* 's research on All Reviews are Not Created Equal shows that micro-level dynamics of product of interactions are valuable in signaling quality over-and-above the aggregate-level summary quality scores[2]. Qing Cao *et.al* used the method of text mining to study the reviews of products on basic features that affect cooperative style and grammatical features and concluded that the number of votes available for reviews is more influential than other features[3].

There are no more studies on product reputation forecasting, but other time series forecasting methods can be referred to. For example, some commonly used time series forecasting models include traditional time series forecasting models, ARIMA[4] models and machine learning models. The traditional time series forecasting method is mainly to solve the model parameters on the basis of determining the time series parameter model and use the solved model to complete the forecasting work. The deep learning model mainly includes CNN(Convolutional Neural Network), RNN(Recurrent Neural Network)[5] and LSTM(Long Short-term Memory Network)[6].

II. Theoretical Foundation and Model

A. Index explanation

We use the following indexes to evaluate the comprehensive reputation of the product in each period. The index for each product is explained as follows. C_i is the total number of reviews in the products. H_f is the amount of helpful votes. H_l is the amount of helpless votes. H_t is the amount of total votes. VP_i is the number of Vine user reviews with higher reliability. r_i is the review star rating. E_{ri} is the effective review rate, where $\boldsymbol{Er_i = H_f - H_l = 2 \times H_f - H_t}$.

$Hcrr_i$ is the high confidence review rate. The calculation formula is as follows.

$$Hcrr_i = \frac{VP_i}{C_i} \tag{1}$$

Wsr is the weighted average rating star, which reflects the customer's satisfaction with the product. The calculation formula is as follows.

$$Wsr = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} w_{1i} w_{2i} r_i}{\sum_{\mathrm{i=1}}^{\mathrm{n}} w_{1i}} \tag{2}$$

Where r_i is the star rating of that review, and w_{1i} is the weighted value depending on whether vine presents, and w_{2i} is the weighted value depending on whether the user really purchase. The weight of each review is as follows:

$$w_{1i} = \begin{cases} ln(Vr)\ , Vine \\ 1\ , \qquad Nomal \end{cases} \tag{3}$$

Where Vr *is* the ratio of common users to vine in the total number of products:

$$Vr = \frac{N_{sum} N_{vine}}{N_{vine}} \tag{4}$$

Where N_{sum} is the total number of the reviews, and N_{vine} is the reviews that the value vine is 'yes'.The weight of each review is as follows:

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$$w_{2i}=\begin{cases} 1\ , & really\ purchase \\ 0.5\ , & no\ purchase \end{cases} \tag{5}$$

Wrs is the weighted average review score which reflects the review score. The calculation formula is as follows.

$$Wrs=\frac{\sum_{i=1}^{n} w_{1i}w_{2i}w_{3i}\mathrm{Score}_i}{\sum_{i=1}^{n} w_{1i}w_{2i}w_{3i}} \tag{6}$$

Where w_{3i} is the weighted value depending on effective review indicator Er_i in question 1. $Score_i$ is the review emotionl score. And $w_{3i}=sigmoid(Er_i)=\frac{1}{1+e^{-Er_i}}$.

S_k is the review skewness. Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable. The calculation formula is as follows.

$$S_k=\frac{n}{(n-1)(n-2)}\sum_{i=1}^{n}\left[\left(\frac{X_i-\mu}{\sigma}\right)\right] \tag{7}$$

B. Reputation evaluation model construction based on EWM-AHP-TOPSIS.

EWM-AHP-TOPSIS(Technique for Order of Preference by Similarity to Ideal Solution) is a method based on the combination of entropy weight method and analytic hierarchy process[4]. On the basis of retaining the objective weighting method, it adjusts the weight that does not conform to the reality through analytic hierarchy process, so that the final weight of each index tends to be true.

In the evaluation system，The set P=[P_1,P_2,…,P_3,P_4]of the product is defined as the evaluation matrix, and $X=(x_{ij})_{m\times n}$represents the value of the review i of the product on the index j. The TOPSIS product word-of-mouth evaluation model based on EWM and AHP is constructed as follows.

Step 1 Data normalization

In order to eliminate the influence of each index dimension on the evaluation results and convert the indicators into positive indicators, the indicators need to be normalized before data analysis.

Step 2 Calculate the weight of each index based EWM

Calculate the information entropy of each index，

$$e_j=-\frac{1}{\ln n}\sum_{i=1}^{n}p_{ij}\ln(p_{ij})(j=1,2,\cdots,m) \tag{8}$$

Where p_{ij} is the index value proportion of the i th product under the j index, expressed as $p_{ij}=(1+x_{ij})/\sum_{i=1}^{1+x_{ij}}(1+x_{ij})$.

Then calculate the weight coefficient of the index

$$\mathrm{w}_j=(1-e_j)/\sum_{i=1}^{m}(1-e_j) \tag{9}$$

Where (1-e_j) is the information benefit value.

Step 3 Weight Adjustment based on Analytic Hierarchy Process

First, calculate the eigenvalues of the comparison matrix. The eigenvector of the maximum eigenvalue in the matrix is normalized as the weight vector to determine the influence weight of each evaluation index. Then, Consistency test, The consistency test should be carried out by using the analytic hierarchy process. The consistency index CI and the random consistency index RI are introduced to calculate the consistency ratio $CR=\frac{CI}{RI}$. If CR is less than 0.1, it passes the test.

Step 4TOPSIS product reputation evaluation model

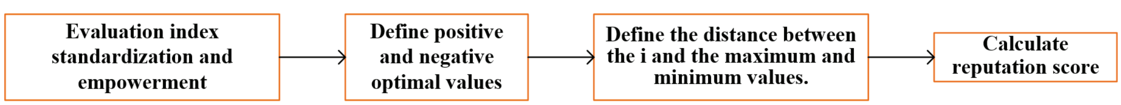

Figure 1 Flowchart of TOPSIS product reputation evaluation model

C. Product reputation prediction model based on SSA-LSTM

SSA(Singular Spectrum Analysis) is a common method to construct the trajectory matrix based on the observed time series and decompose and reconstruct the trajectory matrix[7]. So as to extract the trend, period, noise and other different components in the time series. The basic steps are as follows.

Step 1 Embedding: Transform the one-dimensional time series data Y_T=(y_1, y_2,…, y_T) into a trajectory matrix:

$$X=\begin{bmatrix} y_1 & y_2 & y_3 & y_4 & \cdots & y_{N-L+1} \\ y_2 & y_3 & y_4 & y_5 & \cdots & y_{N-L+2} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ y_L & y_{L+1} & y_{L+2} & y_{L+3} & \cdots & y_N \end{bmatrix} \tag{10}$$

Where L is the selected window length, $K=T-L+1$.

Step 2 Singular value decomposition: Calculate XX^T and perform singular value

decomposition on it to obtain L eigenvalues $\lambda_1\geq\lambda_2\geq\lambda_3\geq\lambda_L\geq 0$ and the corresponding eigenvectors U_1,U_2,…,U_L, $V_i=X_TU_i/\sqrt{\lambda_i}$, so that X can be decomposed. The formula is as follows:

$$X=\sum_{i=1}^{L}\sqrt{\lambda_i}\,(U_iVi_i^T) \tag{11}$$

Step 3 Feature grouping: According to a certain grouping principle, we divide the sub-matrix X_i into m groups.

Step 4 Diagonal homogenization processing: The sub-matrix X_i is diagonally homogenized to obtain a subsequence $\widetilde{F}_i$.

Step 5 Reconstruction: Add subsequences in m groups to get grouped subsequences.

The following is a brief introduction to the LSTM model. The formula fo the Gate is as follows :

$$g(x) = \sigma(Wx + b) \tag{12}$$

Where σ represents the sigmoid function, W is the weight vector of the gate, and b is the bias term.

The following are the basic forms of forget gate, input gate and output gate.Forget gate can be expressed as follows.

$$\mathrm{f}_t = \sigma(W_f \cdot [\mathrm{h}_{t-1}, \mathrm{x}_t] + \mathrm{b}_f) \tag{13}$$

Where W_f is the weight matrix of the forget gate, $[h_{t-1},x_t]$ is the long vector connected by two vectors, and b_f is the bias term.

Input gate can be expressed as follows :

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{14}$$

Where W_i represents the weight matrix of the input gate, and b_i is the bias term.

$$\tilde{\mathbf{c}}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{15}$$

The element state c_t at the current time is calculated as follows :

$$\mathbf{c}_t = f_t \circ \mathbf{c}_{t-1} + i_t \circ \tilde{\mathbf{c}}_t \tag{16}$$

Output gate can be expressed as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{17}$$

Thus, the final output of LSTM is determined by the output gate and the unit state :

$$h_t = o_t \circ \tanh(c_t) \tag{18}$$

III. Research Data Sources and Processing

A. Data sources

In order to understand the market and grasp the customer's satisfaction with the product, Amazon has designed a review feedback system. In this system, customers can choose a number from 1 to 5 to express their satisfaction with the product, and write any text-based information as a review, and vote freely on other reviews they think useful. The data of this study are from Sunshine Company customer reviews from August 2005 to August 2015.

B. Data processing

The data set collected by Sunshine Company is not perfect. There are some problems such as missing data, complex format, inconsistent case and data dislocation. After processing this, the basic data set that can be analyzed is obtained.

In order to obtain the sentiment represented by customer reviews, we use VADER(Valence Aware Dictionary and sEntiment Reasoner) to score each review, VADER is a lexicon and rule-based sentiment analysis tool, which is mainly aimed at text sentiment construction in social software and is also widely used in other fields. VADER processed text has four scores for evaluating emotions. We only use Compound (a score between-1~1) to represent its comprehensive score. The closer the score is to -1, the more negative the emotion is, and vice versa. We normalize the scores obtained, and the distribution of emotional scores after normalization of each review is shown in Figure 2.

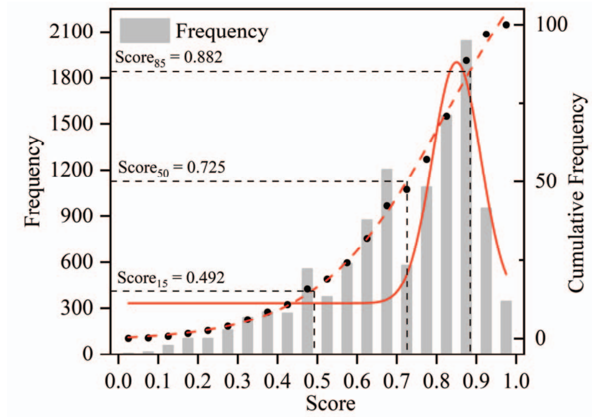

Figure 2 Review emotional score

The highest score of review emotional score is between 0.6 and 0.8. Then it shows a decreasing trend on both sides. There is a higher value between 0.3 and 0.4, and the minimum value is between 0.9 and 1.0. Taking each month as the time granularity, we integrate the monthly data of the hair dryer during the study period as the research object.

IV. Model Application

A. Index weight and product reputation calculation

Firstly, we calculate the weight of each index in the comprehensive evaluation by EWM, and then evaluate the relative importance of each index. The AHP judgment matrix is shown in Table 1, and the weight of each index calculated by EWM-AHP method is shown in Table 2.

Table 1 AHP judgment matrix

	C_i	$Hcrr_i$	Wsr	$Score_i$	S_k
C_i	1	3	1	1/7	1
$Hcrr_i$	1/3	1	1	1/9	1/2
Wsr	1	1	1	1/3	1
$Score_i$	7	9	3	1	2
S_k	1	2	1	1/2	1

The consistency calculation result of the judgment matrix is 0.063<0.1， the result is effective.

Table 2 Final weight

Method	C_i	$Hcrr_i$	*Wsr*	$Score_i$	S_k
EWM	0.543	0.212	0.106	0.114	0.025
AHP	0.131	0.071	0.124	0.521	0.153
Adjust	0.337	0.141	0.115	0.317	0.089

By using the calculation results of the weight of each index above, we can get the change of the reputation of the hair dryer with time by TOPSIS scoring.

B. Product reputation prediction based on SSA-LSTM

SSA can decompose the complete time series data into a combination of trend term, periodic term and noise term. The results of the reputation time series of the hair dryer are shown in Figure 3, where b1 is the trend term, b2-b3 is the periodic term, and b4-b6 is the noise term.

According to Figure 3, the data processed by SSA has richer details than the original data, which proves that SSA denoising can further mine the original features of time series data.

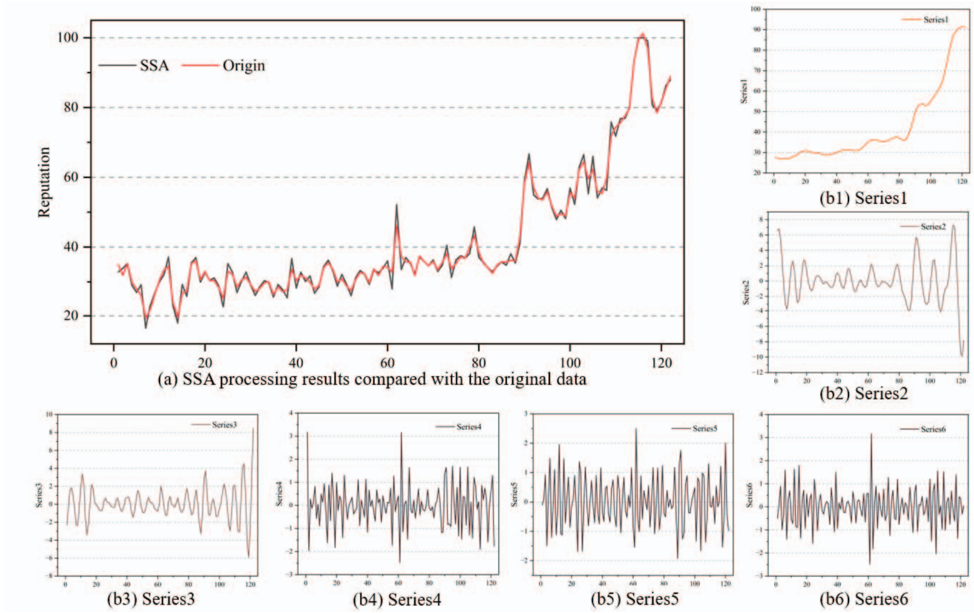

Figure 3 The result of SSA

The denoised time series data can be predicted using the LSTM algorithm. The comparison of the two prediction results whether processed by SSA is shown in Figure 4.

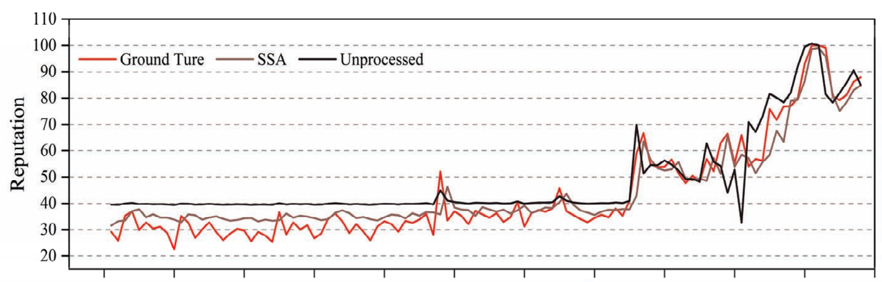

Figure 4 Comparison of LSTM prediction results

The comparison of the quality indexes of the prediction results before and after SSA treatment is shown in Table 3.

Table 3 Comparison of indexes

Processing method	MAPE	MAE	MSE	RMSE
SSA	0.10	3.82	23.25	4.82
Unprocessed	0.20	6.96	68.78	8.29

From Table 3, the prediction of time series data processed by SSA has achieved better results than unprocessed data according to the four test indexes, which has obvious advantages. It can be considered that the SSA-LSTM prediction model has better prediction results than the single LSTM model.

V. Conclusion

Based on the customer review data of Amazon market, we use EWM-AHP-TOPSIS comprehensive evaluation method to evaluate the reputation of products classified as hair dryer. Then by comparing the two prediction results of LSTM with the reputation data before and after SSA processing, we can conclude that the data after SSA processing has better prediction results due to more features obtained by removing noise.

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