Research on Star Rating based on Poisson Regression

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Abstract: Online ratings and reviews reflect consumer's real evaluation of the purchase, and contain a huge commercial value. After a preliminary understanding of the provided data, we perform sentiment analysis on the review data, fuse and replace words with consistent expressions. We use Poisson regression to explore the relationship between reviews and star ratings, and the results show that they have a positive correlation. At the same time, we utilize the Covariance Weighting method to integrate reviews and star ratings, to build a comprehensive index (RD) that quantifies the direction of consumer feedback. Considering that not every review has the same degree of confidence, we incorporate the following data into our model. Then, we combine these factors into a weighted index (RR) that reflects the reliability of the review, with the help of the propensity score weighting method. Besides, we put consumer feedback data into the model and compare their credibility. Finally, we fuse the above two models, and use the index model to make RD and RR finally generate an index (FR), which clearly shows the reputation of the product after sale. And, put time and FR into exponential smoothing model to get the trend of FR in the given data. To sum up, after making sensitivity analysis, it shows that our model is robust. Besides, our model is feasible and reasonable for solving Sunshine’s problem. Nevertheless, there are also some existing problems like any model. Yet, it will be more powerful after further extension.

1. Introduction

Online ratings and reviews reflect consumer's real evaluation of the purchase, and contain a huge commercial value [1]. Using data of other competing products, Sunshine Company hopes to gain insights into the markets, such as, when and where they participate, and the potential success of product design feature choices. Hence, based on the rich data, we are going to fulfill the tasks below.

With sentiment analysis and references, we will numerically process the given text and character data. [2] We will build a model to explore the relationship between specific description of text-based reviews and star ratings. Next, we will create a new index that integrates star ratings and reviews, Review Direction, which indicates how consumers are responding to each sold item. Then, considering some factors, such as helpful votes and so on, which affect the confidence of reviews, we will perfect our model so that it can make full use of these data. Besides, the variable, time, is included to clearly show changes in the reputation of a product. Finally, based on all we have done, we will provide Sunshine Company with sound and feasible sales strategies, and test their effectiveness.

2. Creating Review Reliability Index

Are all reviews containing high-frequency words given a certain score worthy of reference? Are all people's reviews valuable at any time? In this part, based on existing researches, we make full use of the data given to optimize our model, including review depth, whether the product was successfully purchased, whether it is a member review, helpful votes, and timeliness, so that our results are more valuable, and we can dig out some reliable sales strategies according to the results.

2.1 Data Digitization

Review length refers to the level of detail of comments on consumer psychology. Most scholars think that longer reviews usually contain more comprehensive and detailed information. However, some studies [3] have argued that overly long comments are scattered and tend to deviate from the topic, making it difficult for consumers to understand. Thus, we synthesize the two parties' views and employ the logarithmic method to get the review length.

The formula is as follows:

$$P1_i = \begin{cases} 0, L_i \le 5 \\ \dfrac{\ln(L_i - 5)}{L_i - 5}, L_i > 5 \end{cases} \tag{1}$$

Let L be review length, and let L-5 be the denominator can limit the weight of overly long reviews.

2.2 Helpful Votes

Helpful votes show how well reviews can be recognized by other consumers. Generally speaking, the higher the number of helpful votes for a review, the more detailed the user experience of the product, the stronger the authenticity and usefulness. Referring to the research of Zhang Z [5] and Zhang K [6], we use the ratio method to deal with the relationship between the number of helpful votes and total votes. The more the number of helpful votes is, the higher the weight of the review is.

The quantitative method to helpful votes is as follows:

$$P3_i = \begin{cases} \dfrac{H_i}{T_i + 1}, 0 \le H_i \le 5 \\ \dfrac{H_i}{T_i + 1} * 1.5, 5 < H_i \le 10 \\ \dfrac{H_i}{T_i + 1} * 2, 10 < H_i \end{cases} \tag{2}$$

Let H_i be the number of helpful votes for each review, and let T_i be the number of total votes for each review. Also, using parameters 1.5 and 2 to increase the weight of reviews with more helpful votes.

2.3 Purchase Result & Amazon Vine members

It is generally believed that reviews by Amazon Vine members and customers who have made a successful purchase will have greater weight, so a review that meets one of these two conditions is recorded as 0.8, otherwise 0.2:

$$P5_i = \begin{cases} 0.8, \quad verified\_purchase_i = Y \\ 0.2, \quad verified\_purchase_i = N \end{cases} \tag{3}$$

3. Exploring Changes of Final Reputation Over Time

After using the historical sales data of similar products to create the FR index, we focus on the time data. If we can find out the factors influencing the trend of the FR index, or find a good time for the new products to go on the market, we can make Sunshine Company trust our model more. Therefore, we do the following work:

We notice that there are a large number of purchase records in almost every month, since the earliest sales date in big data. So we decided to use the average of the *FR* indicator of all sales records in each month to express the feedback reputation of the product (*month_FR*):

$$month\_FR = \frac{\sum FR_i}{n_i}, \quad i = 1,2,3\cdots \tag{3}$$

In this case, FR_i refers to all sales feedback in the i-th month (the earliest sales date of the goods is the starting point), and n_i refers to the number of sales feedback in each month. After obtaining the monthly feedback reputation of the product, we visualized it: (only the hair dryer results are displayed, and the rest are put in *Appendixs.*

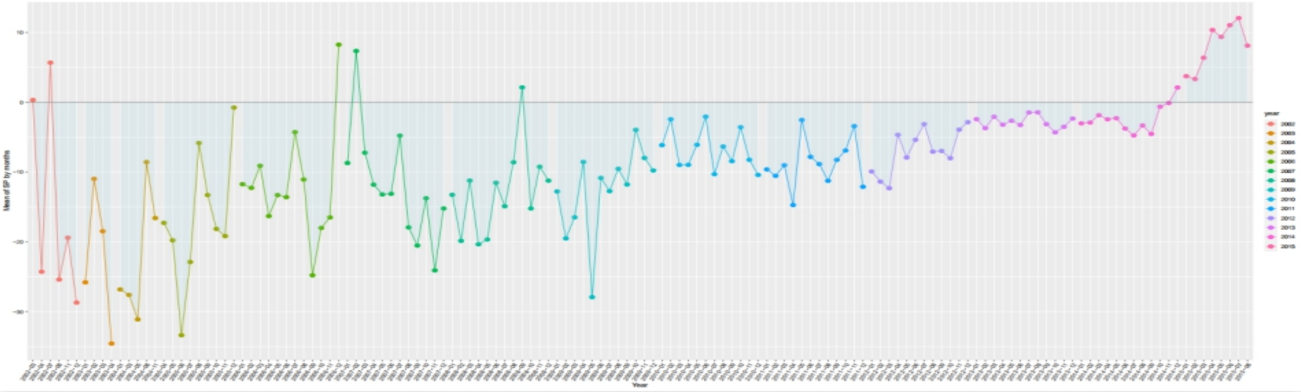

Figure 1. Changes of Final Reputation over Time (hair dryer)

From the figure 1, we can see that the sales feedback of hair dryer has been kept at a very low level until 2009, which began to tend to be positive at the beginning of 2015, and the trend is growing steadily. Therefore, we can infer that the near future is the best time to sell hair dryer.

we also provide the following suggestion for Sunshine's hair dryer products to enter the market smoothly and safely: Seize the opportunity that consumer feedback has been at a high level at present, and use the words that consumers are very concerned about (such as light, cheap, low-power, fashion, etc.) in commodity advertisements, to arouse consumers' desire to buy the hair dryer.

4. Influence of Helpful Votes

When customers purchase a product, they will vote for that review if it helps them. The more the comments help, the more influence they have, and Amazon will show the comments in turn by the number of votes it gets. Here, let's take the data of the hair dryer as an example, to explore the relationship between high-help votes and product reputation trends:

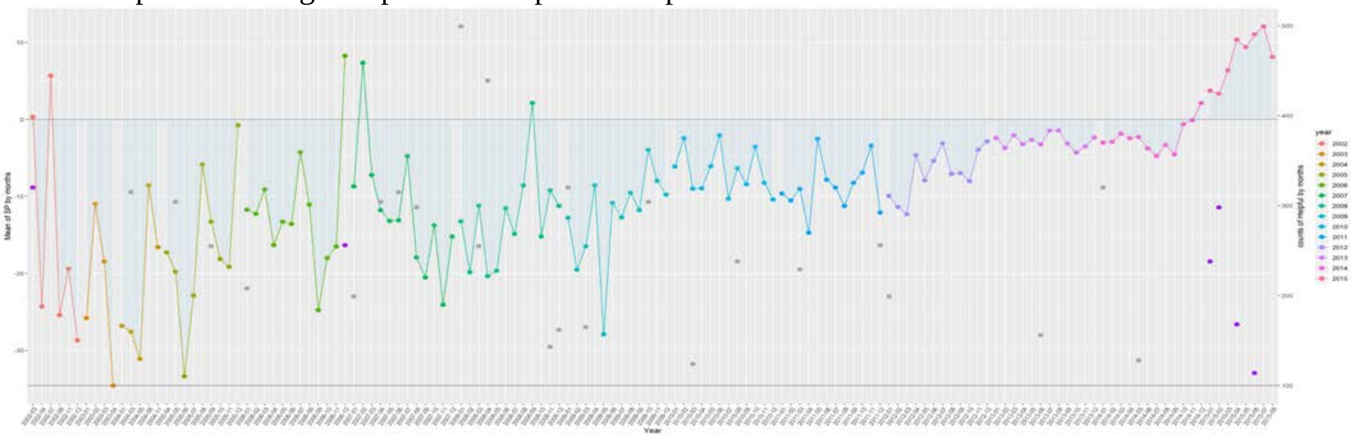

Figure 2. Trend Chart of High Helpful Votes and Final Reputation (hair dryer)

We select comments with helpful votes greater than 100 from the data, and divide them into positive and negative comments according to the FR index. Then draw them in the reputation trend chart to get the above figure.

From the Figure 2, we can conclude that most of the comments from high helpful votes are poor comments, which are just in line with the product reputation chart. And it is noted that from the end of 2014, there are four purple dots in the chart in succession, that is, at this moment, most of the high helpful comments recognized by customers are good comments, which is consistent with the trend of the product reputation turning good in this period.

Therefore, we have adequate reason to believe that comments with high helpful votes will affect customers' views on the product, and thus affect the reputation of the product.

5. Sensitivity Analysis

First, adjust the weight vector, and then draw the final reputation (FR) graph to observe its sensitivity.

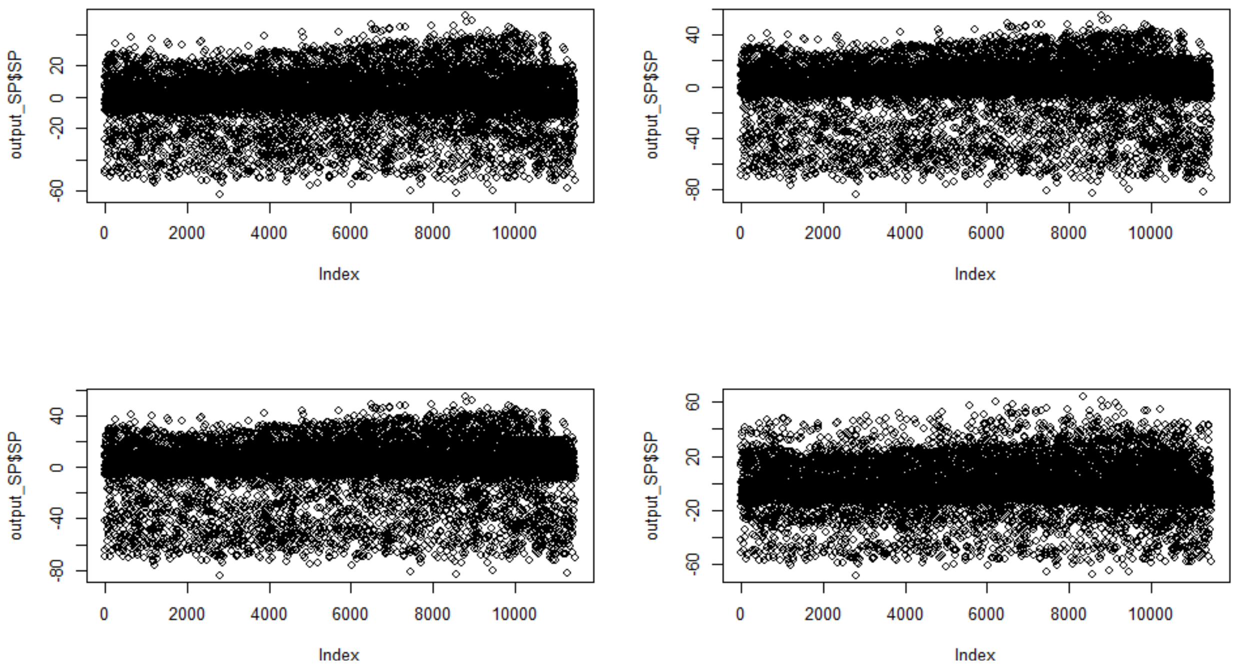

Figure 3. Sensitivity Analysis Chart

The first FR figure in the upper left corner is (1, 1, 1, 1, 1), and the rest are (1, 2, 1, 1, 1, 1), (1, 1, 2, 1, 1), (1, 1, 1, 2, 1). Due to the limit of time, we did not continue to explore other weight combinations.

From the Figure 3, we can conclude that changing the weight vector will indeed change the mean value of FR, which is consistent with the actual situation. When the weight focus is different, for example, the weight vectors combinations that focuses more on timeliness (i.e. the fifth element), its FR graph will be slightly larger later.

We usually take the weight vector of all 1, not focusing on any weight, which is the weight selection without prior information; from the figure above, we can also find that FR under different weights is different, but the mean value is around 0, which proves that our model is very robust. We can get that the change of σ has little effect on the distribution of timeliness weight, but have a greater effect on the range of timeliness weight, and a smaller σ will correspond to a larger aging weight.

It can be seen that the change of σ has little impact on the reputation trend prediction of our model that is because we set a large weight to the recent 360 day data, and the data time span is large, so most of the timeliness weight is small. Similarly, for the weight of comment length, because most of the comment length is relatively long, so that the impact of changing comment length weight on reputation prediction is similar to that of σ, which has little impact on our model.

In general, adjusting the parameters according to the actual situation can more accurately reflect the trend of product reputation, while our model is very stable, and can achieve good prediction results under different parameter settings.

This model has the following advantages: (1) Created many interpretable indicators. In order to facilitate the data onto our model, we refer to many papers to quantify the text data, which provides us with high theoretical support.

(2) Strengthen the objectivity of data. Because text data is often subjective when it comes to sentiment analysis, scoring, and weighting, we include objective data, such as vocabulary frequency

and review length, to make our results more reliable.

(3) Incorporate time dimension. We take the time factor into our model to make the model's results more timely and accurate, while many text analyses ignore it. In addition, we combine the final reputation with time, which enables us to provide effective strategies for selling and designing goods

6. Conclusion

In our paper, we have done lots of data processing work, and used quite a few models and methods such as, sentiment analysis, Poisson regression, propensity score weighting method, Covariance Weighting method and so on, to fulfill our tasks. Generally speaking, we are satisfied with our work.

Like any model, the one present above also has its strengths and weaknesses. The major points are presented below. In addition to the above, we also make the following recommendations for three products.

(1) Take incentive measures to encourage consumers to write valuable comments, and guide them to praise the comments that conform to the post consumption psychological description, so that some positive comments can have a greater impact on potential consumers;

(2) Invite some Amazon members to use our products free of charge. In exchange, they need to give our products some positive and valuable comments, which will surely set off a buying frenzy.

(3) For consumers who have given negative comments, we can sincerely apologize to them and make reasonable compensation for them to let them have a deeper understanding of our products, hoping that they can change the attitude towards this product and minimize the loss caused by low reputation.

(4) When formulating a product sales strategy, we need to focus on the reviews with high helpful votes, and improve our products according to the contents of these reviews, so that the products are more in line with user needs, reduce negative reviews gradually, and improve the reputation and competitiveness in the market.

References

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