Problem Chosen	2020 MCM/ICM Summary Sheet	Team Control Number
C		2018915

Dig and Predict: Analysis of Amazon Reviews Data

Sunshine Company is planning to release three new products in online market place: hair dryer, baby pacifier, and microwave oven. To help Sunshine company succeed in these three products, we conducted text-based, value-based, and time-based analysis of Amazon review data of three products. First, we divide the review body text into three groups corresponding to their ratings. We joined the words of these text with the Afinn list of English words to filter out words which do not have independent meanings. We then count the most frequent word within each group. We selected words with top fibe frequency of appearance and draw the word clouds to show thier count. Combining them with the sentiment grade given by NLP method and original text, we concluded customer preference and crucial product features.

We then explore the relationships between attributes of the data sets. We calculate the correlation coefficient between six factors of each product's data setlength of review text, number of vine customers, count of verified purchases, proportion of helpful votes, star rating, and proportion of high rating among all review records. With the help of data visualization, we came to conclusion that, for all products, except for length of review texts, all other factors have different levels of positive correlation with star rating and proportion of high ratings among all. Star rating and the proportion of high ratings remain highly correlated.

Some researchers have revealed that customers are more willing to buy a product that with good ratings. In this study, we use two indicators to represent whether a product is popular and will be sold well. The first indicator is the average daily star ratings. The second indicator is the average daily good ratio, which describes whether a customer would like to give a good star rating. In order to predict those two indicators, a novel deep learning model Multi-Stacked Fully Connected Bidirectional LSTM model(MSFCB-LSTM), is proposed to predict the time series data. In this work, we define stacked bidirectional LSTM with two layers as the first temporal features or information abstraction, then connect with one layer LSTM to remedy potential temporal correlation.After stacked BiLSTM and LSTM, two Dense layers added at the end, which is capable of reasonably controlling dimensions in hidden layers output, and more precisely capture non-linearity between inputs and outputs since inputs in our model are multivariate with abstract correlations.

The results shows that our proposed model could predict the average daily good ratio well. Due to the deficiency of features, we could not predict the average daily star ratings as well as we predict the average daily good ratio. But the patters of the changes of the average daily star ratings could be well described. Moreover, we find that there exists an almost linear relationship between the average daily good ratio and the average daily star ratings. We could combine those two indicators together to predict and make final decisions.

Key Words: Text Mining, MSFCB-LSTM, Time Series, NLP

Contents

1 Introduction

1.1 Background

The e-commerce market has changed the way business is transacted, especially in the retail industry. As one of the biggest platform of e-commerce, Amazon has a complete system of customer rating and reviewing, which provides both retailers and future customers sufficient information for further marketing strategies as well as buying decisions.

Recent years have seen an increasing amount of research efforts expanded in understanding the textual review resources for Business use. The existing data set contains records of the three products: hair dryer, microwave, and pacifier As a company which is going to release these new product online, Sunshine Company seeks to explore these data and identify the market factors related with sales to increase competence.

1.2 Restatement of the Problem

To develop a online strategy and identify the product features which customer value, it is necessary to combine time-based measures, text-based measures and data-based measure. We conclude specific tasks are as follows:

- The appearance of words related to product features can be calculated and categorized according to rating, thus reflecting customers' preference and requirement.
- Taking account of all the products within one kind, build a time series model to predict the products' future rating and the proportion of positive rating among all reviews. Our models consider the following factors:
  1. the number of verified reviews
  2. the number of vine customers
  3. the proportion of helpful reviews
  4. the total numbers of words in the rating text
- Evaluate the relationship between review factors and rating and proportion of positive ratings, identify the simulators for number of reviews and better rating trend.

From the above analysis, we conclude the evaluation results. Based on the measurements, we propose strategies to Sunshine company with regard to desired product feature and online marketing. We then test the accuracy of the prediction model. Finally we analyze the strength and weakness of the existing model.

1.3 Given Data

We were given three data sets which are hair dryer, microwave, and pacifier. Each data set is of the same form, consisting of product information and customer reviews within more than ten years. The data we will use are product ids, star ratings, votes, number of vine customers, verified purchases, review content and date. During different time, many product have missing information, especially during earlier years, we set the missing values to null and ignore them when calculating sum and averages.

2 Assumptions and Terminology

2.1 Assumptions

- In time series analysis part, data of products with more than 50 records are considered valid
- The average rating of the product reflect the product's level of success
- The proportion of positive ratings among all reviews also reflects products' future trend of success
- The size of market is not considered during evaluation and prediction
- Potential social and economic factors are not considered in constructing the evaluation model

2.2 Terminology

Meaning	Notation
Average star rating on time t	R_{S_t}
Average good ratio on time t	R_{G_t}
Average proportion of helpful votes on time t	p_{v_t}
Average number of words count in the review body on time t	N_{word_t}
Average number of verified purchase on time t	N_{veri_t}
Average number of vine customers on time t	N_{vine_t}

- Good ratio is proportion of good rating records among all review records, which is defined as follows:

  $$R_{G_t} = \frac{N_{G_t}}{N_{T_t}}$$

  where N_{G_t} represents the number of good star-rating (star-rating that is larger or equal to four) at time t, and N_{T_t} represents the total number number of star-rating at time t. R_{G_t} represents the ratio of people who is willing to give a good rate at time t. To predict R_{G_t}, we could conclude that whether a product is popular among customers.

- Proportion of helpful votes is number of helpful votes divided by total votes.
- Words count is number of words in the review body
- Each defined item above represents a daily average on day t.

3 Measurements and Characteristics of Review records

3.1 Data Processing

Before setting up time series model, we selected out product records which have more than 50 review records. We analyze data of all products within each date. For vine customers and verified reviews, we calculate the total count within each quarter. For the votes, we calculate the helpful vote rate by dividing helpful votes by total votes, and then calculate the average of all products.For word count of review texts and star rating, we calculate the average of all products' data within the same date. Same methods are applied to three data sets.

3.2 Text-based Analysis of Reviews

In this section, we conduct text mining on the full review text of the three data sets. We filtered the text of review body to remove any punctuation and stop words then create an individual row for each word. We then join these words with the Afinn list of English words to filter out words which do not have independent meanings. We divide texts into three parts according to their star-rating (rate 1 & 2, rate 3, rate 4 & 5). Then we count the most commonly words within each group and draw the high-frequency words in the word cloud. According to their frequency of appearance, it is able to conclude customers' preference and requirement.

3.2.1 Hair Dryer Review Analysis

We compare the word cloud of high rating group(star rating 4 & 5) and low rating group(star rating 1 & 2), and the count of appearance of words within the rating group.

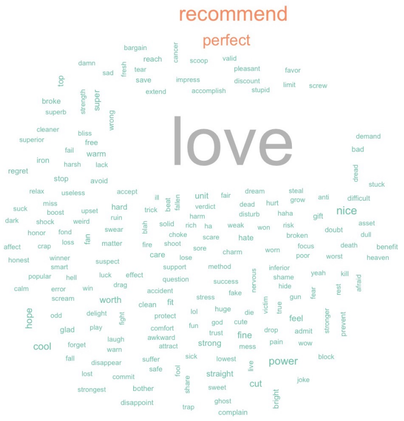


Figure 1: Cloud of high ratings

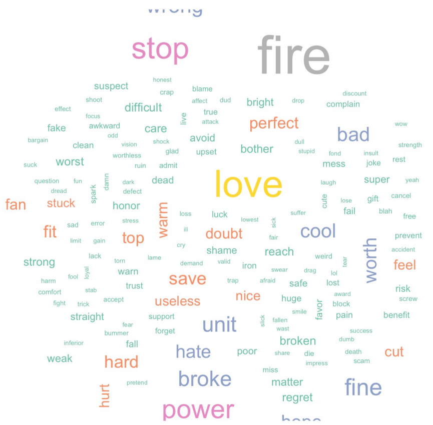


Figure 2: Cloud of low ratings

When it comes to the word count of review text within each rating group, we found that words like 'recommend', 'love' also appears a lot in low rating groups, since they are combined with words like 'not'. Thus, we adopt the Natural Language Processing package in Python to give a sentimental grade to each word, filter out the words with positive rates, and count the appearance of the rest in low rating group.

Word	Count
love	10915
recommend	2481
perfect	1584
nice	809
power	703

Table 1: Word count of high ratings

Word	Count
fire	312
stop	164
power	137
unit	106
support	91

Table 2: Word count of low ratings

From the Word Cloud and Tables, we can see that in positive ratings, words like 'love' and 'recommend' appear the most, which indicates customers tend to promote the product if they find it satisfactory. Words like 'power' also has large number of appearance, which indicates the power of hair dryer plays a large role in customers' preference. In negative ratings, the most frequent words indicates common problems within the functions of hairdryer. The detailed result will be discussed in the Result section.

3.2.2 Microwave Review Analysis

We then adopt the same method to Microwave products:

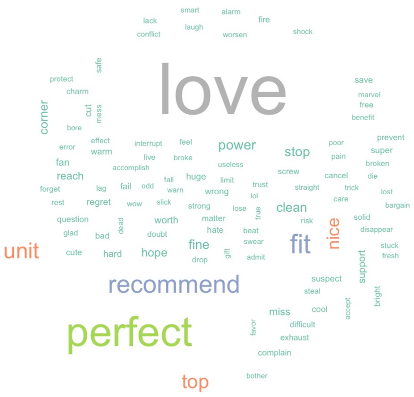


Figure 3: Cloud of high ratings

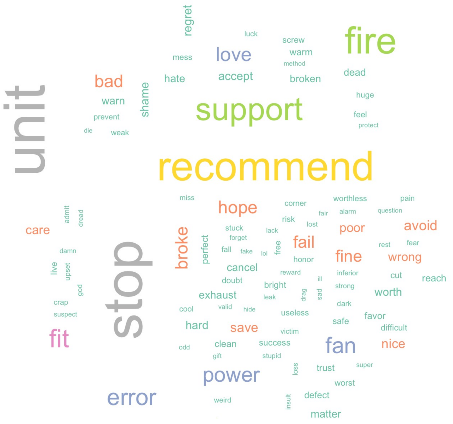


Figure 4: Cloud of low ratings

The following is the word count in high rating group and low rating group:

Word	Count
love	775
perfect	411
fit	238
recommend	216
unit	181

Table 3: Word count of high ratings

Word	Count
unit	205
stop	188
fire	126
top	120
support	105

Table 4: Word count of low ratings

From the above result, we can see that, except for words like ’love’ and ’perfect’, words like ’fit’ also indicates customers’ preference point toward microwave product. In negative rating group, ’stop’, ’fire’, ’support’ indicates common problems of existing microwave products.

3.2.3 Pacifier Review Analysis

Finally adopt the same method to product of pacifier:

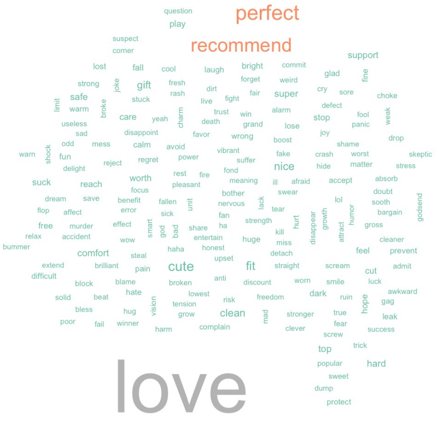


Figure 5: Cloud of high ratings

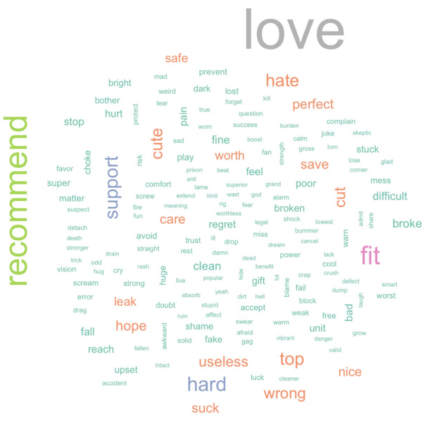


Figure 6: Cloud of low ratings

The following is the word count in high rating group and low rating group: From the above analysis,

Word	Count
love	17730
recommend	3168
cute	1680
fit	1256
nice	1009

Table 5: Word count of high ratings

Word	Count
fit	230
hard	166
support	154
hate	136
cut	114

Table 6: Word count of low ratings

in high rating group, apart from common words like ’love’, ’cute’, ’fit’, ’nice’ also have a large number of appearance, indicates customer pay attention to these features when they judge a product of pacifier. In low rating group, words with most appearance also shows problems pacifier may have, which Sunshine Company should try to avoid.

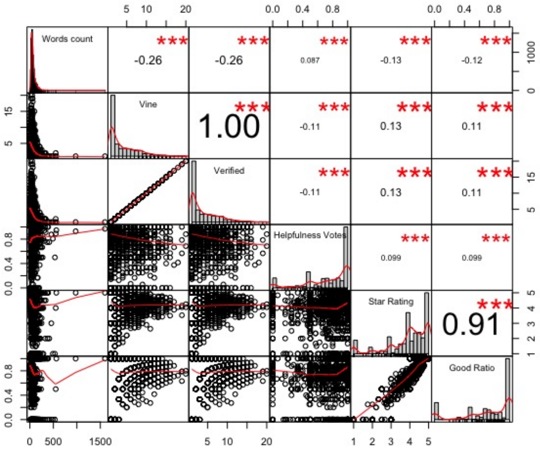
3.3 Relationship Within Review Factors

In this section, we analyze the relationship between the review factors, to see whether the change of one sector will result in customers’ differnt review reactions. We calculate the correlation coefficient between some attributes of the product data set by:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

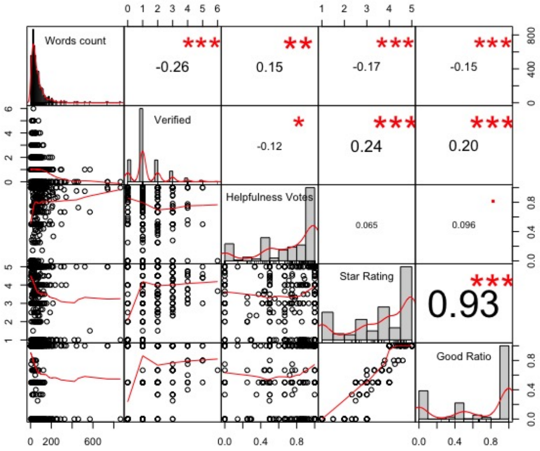
where r_{xy} is the correlation between attribute x and attribute y. The attributes we take into consideration are: the length of review body(denoted as Word count); the number of vine users; the number of verified records; the proportion of helpful votes; the star ratings; and the proportion of high ratings among all the reviews(denoted as good ratio). The data are processed at at daily base.

Figure 7: Correlation between attributes of hair dryer data



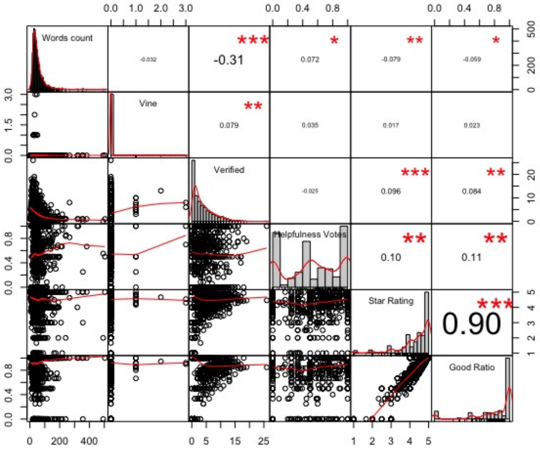
From Figure.7, in the market of hair dryer, we can see the length of review text have negative relationship with all attributes except helpfulness of votes. This indicates customers tend to write longer reviews for low-rating products, and there is fewer vine customers and verified purchases. Number of vine customers have a linear relationship, they both have positive correlation with star rating and good ratio. Helpful votes also have positive relationship with star rating and good ratio, while it has a slightly negative relationship with number of vine customers and verified purchases. One thing worth noticing is that, in hair dryer market, star rating and good ratio have nearly linear relationship.

Figure 8: Correlation between attributes of microwave data



From Figure.8 generated by data from microwave product, correlations are similar from that within the hair dryer. The length of review body still maintain negative relationship with all attributes except helpfulness of vote. Helpful votes has positive relationship with star rating and good ratio while have negative relationship with number of verified purchase. Star rating and good ratio still maintain a nearly linear correlation in market of microwave products.

Figure 9: Correlation between attributes of pacifier data



Similar plot Figure.9 is generated for pacifier's data. In this case, the number of vine customers and verified purchases only have weak correlation. Helpful votes have positive relationship with number of vine customers while have weak negative correlation with number of verified purchases. Except for length of review body, all the other attributes remain positive correlation with star rating and good ratio. Star rating and good ratio keep maintaining a strong positive correlation in market of pacifier.

Based on the correlation analysis of the market data of these three products, some common conclusions can be drawn: Low product ratings often incite reviewers to write longer comments, which includes the problems of the product, while reviews with high ratings tend to short, and longer reviews tend to be more helpful; Products with more verified purchases, vine customers, tend to have higher star rating; In the three product cases, star rating and good ratio all have a strong correlation which is almost linear, thus, in the following section of constructing time series model, we define good ratio as the indicator of the products' selling situation.

3.4 Time Series of Model of Rating and Good Ratio

Recurrent Neural Network (RNN) has exhibited the power on analyzing time series data prediction. Each node at a time step takes an input from previous node and this can be indicated using a feedback loop.

Even though RNN indicates a strong ability to analyze the correlation in time series data, it has disadvantages in solving long term time series data, which means to understand the context at time step $t + 1$, it may require information representing at time 0 and 1. To capturer the high dependency in time series,the Long Short Term Memory(LSTM) is invented by Hochreiter and Schmidhuber[2]. Based on typical RNN structure, each cell is indicated by a more complex inner network with the crucial components, gates. Comparing with a single neural layer in RNN, there are four interacting gates, input gate, forget gate, update gate, and output gate. The gated structure, especially crucial forget gate and the update gate, supports LSTM to remember information in the long term time series optionally, and decides vital information to update to the cell state. It has proved that the bidirectional networks [3] are sincerely better than the traditional LSTM in many fields capturing time-series information.

In this work, we define stacked bidirectional LSTM with two layers as the first temporal features or information abstraction, then connect with one layer LSTM to remedy potential temporal correlation. After stacked BiLSTM and LSTM, two Dense layers added at the end, which is capable of reasonably controlling dimensions in hidden layers output, and more precisely capture nonlinearity between inputs and outputs since inputs in our model are multivariate with abstract correlations.

In this study, we use features R_G, P_v, n_{word}, n_{veri} and n_{vine} to predict R_S since there exists correlation among Average star rating and other factors. Similarly, we also use features R_S, P_v, n_{word}, n_{veri} and n_{vine} to predict R_G. Each data point represents the daily average on day t. For example, when we predict the average daily good ratio of pacifier on day t, R_G, we use features from two historical time steps(two days), t2 to t 1, to predict. The input can be characterized as an input features matrix:

$$X_t = \begin{bmatrix} R_{G,t-2} & R_{S,t-2} & N_{word,t-2} & N_{veri,t-2} & N_{vine,t-2} & P_{v,t-2} \\ \\ R_{G,t-1} & R_{S,t-1} & N_{word,t-1} & N_{veri,t-1} & N_{vine,t-1} & P_{v,t-1} \end{bmatrix}$$

where

- $R_{S,t-2}$ = Average daily star rating at historical time segment $t - 2$
- $N_{word,t-2}$ = Average daily words count at historical time segment $t - 2$
- $P_{v,t-2}$ = Average daily helpfulness votes at historical time segment $t - 2$

Similar meanings for all other notations in the input matrix X_t.

3.5 Test of Model Accuracy

Final prediction results using evaluation metrics RMSE, which is defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{1}$$

where $\hat{y}_i$ is a predicted value, y_i is the corresponding true value and n is the number of predicted values.

3.5.1 Hair Dryer

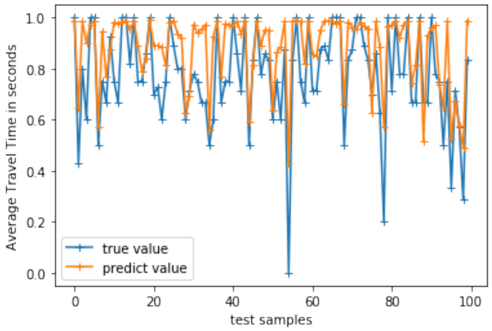


Figure 10: Hairdryer Average Good Ratio Prediction

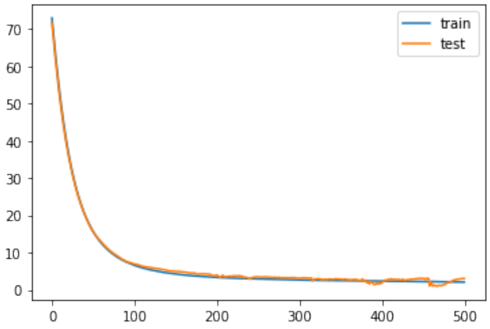


Figure 11: Loss Function of Hairdryer Average Good Ratio Predtion

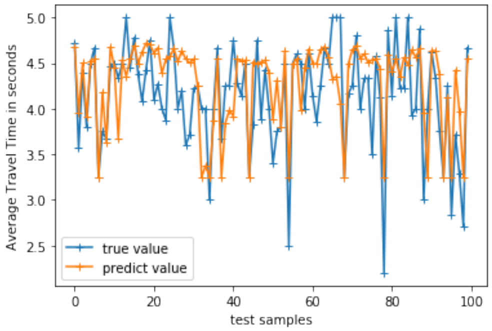


Figure 12: Hair Dryer Average Star Rating Prediction

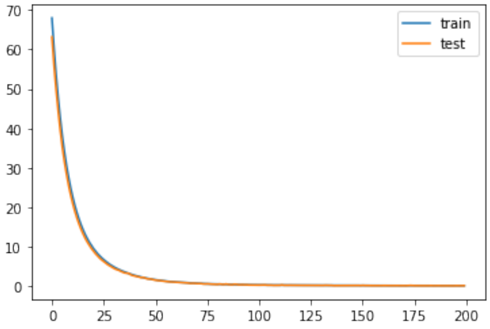


Figure 13: Loss Function of Hairdryer Average Star Rating

Figure(10-12) shows the results of the prediction of the average daily good ratio R_G at time t and the prediction of the average daily star rating R_S at time t, respectively. Figure(11-13) shows the loss function of training and testing. The RMSE, which is defined in Equation(1), of predicting R_G at time t is 0.131 and of predicting R_S at time t is 0.528.

3.5.2 Microwave

Figure(14-16) shows the results of the prediction of the average daily good ratio R_G at time t and the prediction of the average daily star rating R_S at time t, respectively. Figure(15-17) shows the loss function of training and testing. The RMSE, which is defined in Equation(1), of predicting R_G at time t is 0.177 and of predicting R_S at time t is 1.211.

3.5.3 Pacifier

Figure(18-20) shows the results of the prediction of average daily good ratio R_G at time t and the prediction of average daily star rating R_S at time t, respectively. Figure(19-21) shows the loss function of training and testing. The RMSE, which is defined in Equation(1), of predicting R_G at time t is 0.095 and of predicting R_S at time t is 0.935.

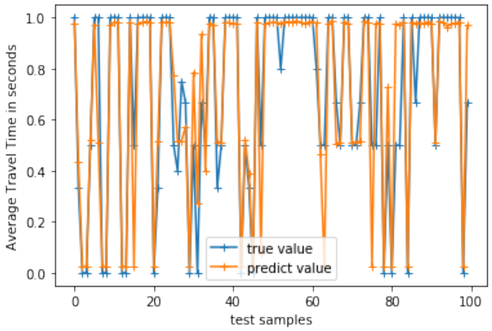


Figure 14: Microwave Average Good Ratio Prediction

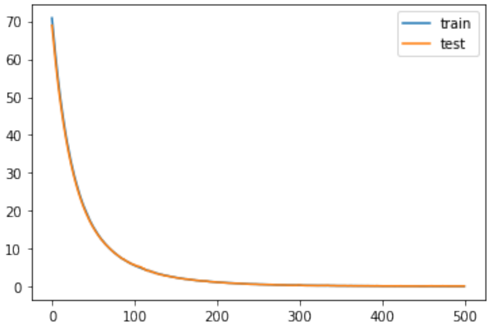


Figure 15: Loss Function of Microwave Average Good Ratio

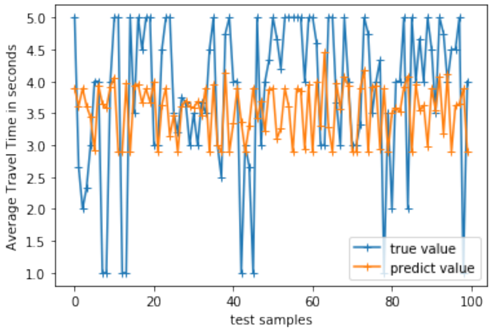


Figure 16: Microwave Average Star Rating Prediction

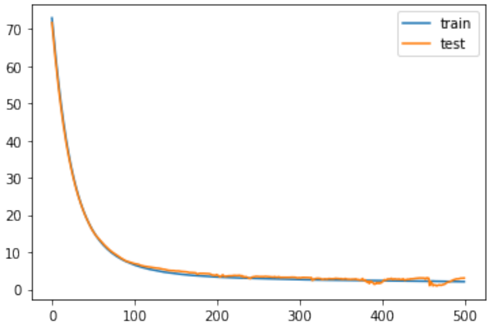


Figure 17: Loss Function of Microwave Average Star Rating

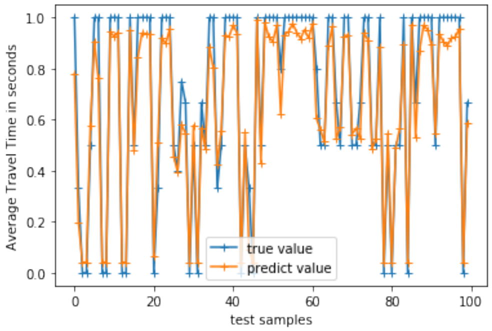


Figure 18: Pacifier Average Good Ratio Predtion

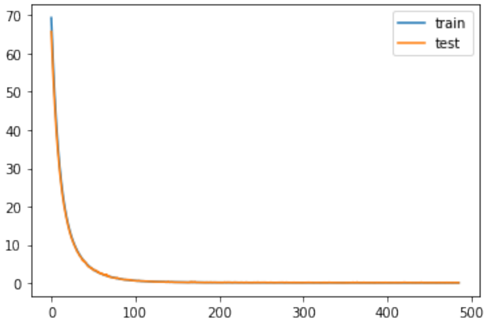


Figure 19: Loss Function of Pacifier Average Good Ratio

3.5.4 Conclusion of the Time Series Model

From the results of the prediction of the average daily good ratio R_G at time t and the prediction of the average daily star rating R_S at time t, we could conclude that the good ratio, which depicts the trend of a customer to give a product a high star rate, could be well predicted using the information of the previous two time segments using our proposed Multi-Stacked Fully Connected Bidirectional LSTM model(MSFCB-LSTM). Nevertheless, we could use our proposed model to predict the star rate at time t, the results of the prediction are not all accurate due to the reasons that the deficiency of information.

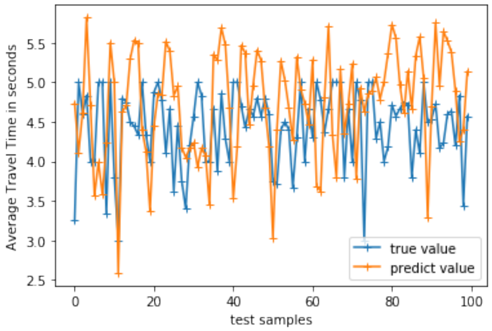


Figure 20: Pacifier Average Star Rating Predtion

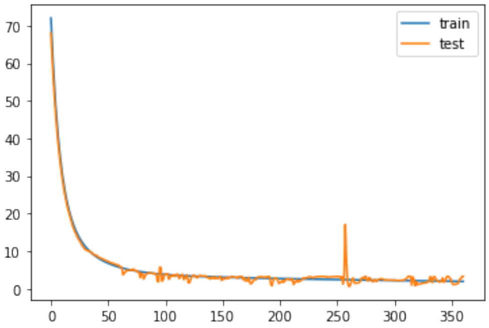


Figure 21: Loss Function of Pacifier Average Star Rating

But the patterns of changes of star rating could be well described. Thus, we could combine the results of the prediction of average daily good ratio R_G at time t and average daily star rating R_S at time t together to make decisions.

4 Results

4.1 Identification of Crucial Product Features

In this section, we will analyze what Sunshine Company should focus on improving their upcoming product, based on the previous text mining results. Apart from filtering out the most common words within each range of rating, we also referred to the complete text of review records containing these words.

4.1.1 Hair Dryer

Among positive ratings, besides common phrasing words, word count shows that customers favor most about the machines' power when they give good ratings. Sunshine company should also keep high quality of machines' power, since many other brands are doing good.

Among negative ratings, we first go through complete review texts of frequent words which have positive sentimental grade(Given by NLP method). By going through reviews containing word 'recommend', in which customers expressed they wouldn't recommend, problems with other hair dryer includes short battery life, coming out cold air, and loud noise. Among negative reviews containing 'unit', customers complained about the short life of the product, poor quality of material, insufficient power, and bad design.

Combine these results with word 'fire', 'power', 'stop', we can see that in existing market, the common problems with hair dryer such as : battery life, inappropriate temperature, loud noise, short lifespan, bad design, are the points Sunshine Company should focus on improving their current product before putting them to the market and thus increase its competence.

4.1.2 Microwave

Among positive ratings, apart from common words like ’love’, the frequent appearance of ’fit’ indicates the size of microwave product plays a important role in customers’ preference.

Among negative ratings, we go through the complete review record of words which have positive sentimental grade. In text containing ’recommend’, customers don’t recommend a product due to inappropriate size, bad function, short lifespan. Complains including word ’unit’ mainly due to customer support, bad function, power problems.

Combining the above analysis with other frequent words ’stop’, ’fire’, we can conclude that Sunshine Company should focus on improving its’ microwave product’s heating function, design more appropriate size by doing more customer survey, also pay more attention to improve customer service, and thus increase competence in existing market.

4.1.3 Pacifier

Among the positive ratings of pacifiers, we can see that ’cute’ and ’fit’ indicate customers pay more attention to pacifiers’ appearance and size when judging. Thus Sunshine Company should keep the appearance of their product cute and design pacifiers with appropriate size to keep competence.

Among negative ratings’ records, we first analyze frequent words with positive NLP grade. Based on complete review text, customers don’t recommend products due to: making loud noise, useless to keep babies quiet, bad material, and bad function. Bad reviews containing ’support’ mostly due to no customer service support, product doesn’t work well with other devices.

Combining the results above and other words appear frequently in negative reviews: ’hard’, ’fit’, we can conclude that, to compete with existing pacifier products, Sunshine Company should focus on improving the pacifiers’ function, material, reducing the noise, and improve its size design to fit with the other corresponding devices like bottles.

4.2 Indicators for Sales Tracking

Some researchers have revealed that customers are more willing to buy a product that with good ratings. In this study, we use two indicators to represent whether a product is popular and will be sold well. The first indicator is the average daily star ratings, R_{S_t}. The second indicator is the average daily good ratio, R_{G_t}, which describes whether a customer would like to give a good star rating.

To predict the two indicators above, five more features are used:

- N_{vine_t}: Average number of vine customers on time t
- N_{veri_t}: Average number of verified purchase on time t
- N_{word_t}: Average number of words count in the review body on time t.
- P_{v_t}: Average proportion of helpful votes on time t.

Besides, we also use NLP to dig the words with high priority, find the sentences with those words to see what disadvantages a product owns. We could summary those negative reviews to improve our products.

5 Strength and Weakness

5.1 Strengths

- We applied various data visualization techniques including word cloud and combined image of correlation to demonstrate the word count distribution intuitively.
- We took multiple factors into consideration when constructing the time series model and ...
- We adopt method of natural language processing to identify the words expressing customer feelings, and explored the full text consisting these words to draw conclusion.
- Our model has high level of accuracy at predicting the future proportion of positive ratings among total reviews.

5.2 Weakness

- For time series analysis, took average of data of all products within each date, more product related factors should be considered in future research.
- Made an assumption of ignoring market size factor, which has an effect on product's future success.
- In text analysis, we only considered words with top five occurrence, some information might be lost.

6 Letter to Market Director of Sunshine Company

Date: March 8, 2020
To: Market Director of Sunshine Company
From: MCM Team # 2018915
Subject: Market Analysis and Strategy Recommendation

Dear Director,

Hope you are doing well. After conducting a through analysis of the Amazon data of the three type of product Sunshine Company is going to release. Due to the large amount of available products, the current online market has quite intensive competitions. We are writing to provide some advice Sunshine Company might find useful.

We analyzed the words, sentiments in customers review text and come up with following suggestions for pre-release stage of products.

- For hair dryer, according to customers' review, to compete with other similar products, Sunshine may consider to enhance in products' material quality, power capacity, longer lifespan. Also the noise the machine made and appropriate temperature are also concerns of customers;

- For microwave oven, customers pay more attention to the machines' heat function, size, and power capacity. Sunshine may also need to focus on improving customer support for this kind of electronic appliance;

- For pacifier, Sunshine can put more attention on the material, size, and also finding ways to reduce noise will be a good strategy to improve competence. Designing cute products will also help since it's for babies.

After the products are released, it might be useful to track some factors and predict future selling. According to our analysis, having more vine customers and verified purchase, encouraging helpful votes for existing reviews will bring positive effect to the success of the product. Also, it may be a good idea to pay more attention to long reviews, since they possibly contain more information to help improve the product.

We understand that releasing new products into market is a very long and complicated process. We believe Sunshine Company has made sufficient preparation for the moment.Due to lack of data, we ignored some challenges in real market, we also didn't put enough weight on analyzing specific products. There will be some information missing in our advice. Doing more customer survey as time goes by is a more sufficient way to keep track of customer opinions. But we sincerely hope our advice can help. We will try to provide more sufficient and accurate information in future cooperation.

Best Regards,

MCM Team 2018915
03/09/2020

References

[1] M. A. Maddah-Ali, and U. Niesen, “Fundamental Limits of Caching", in *IEEE Trans. Inform. Theory*, vol. 60, no. 5, pp. 2856-2867, May 2014.

[2] S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[3] M. Schuster and K. Paliwal, “Bidirectional recurrent neural networks,” IEEE Transactions on Signal Processing, vol. 45, no. 11, pp. 2673–2681, 1997.

7 Appendices

7.1 Code (R)

```
# To plot the correlation plot
Data <- read.csv(’hraw.csv’)
d = as.data.frame(cbind( Data$Average.of.word_counts,
                   Data$Count.of.verified_purchase,
                      Data$Average.of.helpful_rate,
                   Data$Average.of.star_rating,Data$good_ratio))
colnames(d) <- c(’Words count’,’Verified’,’Helpfulness Votes’,’Star
   Rating’,’Good Ratio’)
cor_matr <- rcorr(as.matrix(d))$r
corrplot(cor_matr, type="upper", order="hclust", tl.col="black",
   tl.srt=45)
chart.Correlation(d,histogram = TRUE,pch=19)
col = colorRampPalette(c("blue", "white", "red"))(20)

hair_dryer<-as.data.frame(fread(’hair_dryer.tsv’))
hair_dryer12 <- hair_dryer[which((hair_dryer$star_rating == 1) |
   (hair_dryer$star_rating == 2)),]

words <- hair_dryer12 %>%
  select(c("review_id", "star_rating", "review_body")) %>%
  unnest_tokens(word, review_body) %>%
  filter(!word %in% stop_words$word, str_detect(word, "^[a-z’]+$"))

afinn <- get_sentiments("afinn") %>% mutate(word = wordStem(word))
reviews.afinn <- words %>%
  inner_join(afinn, by = "word")
head(reviews.afinn)

word_summary <- reviews.afinn %>%
  group_by(word) %>%
  summarise(count_word = n()) %>%
  arrange(desc(count_word))

datatable(head(word_summary))
wordcloud(words = word_summary$word, freq = word_summary$count_word,
   scale=c(5,.5), max.words=200, colors=brewer.pal(8, "Set2"))
wordrate1 <- word_summary[which(word_summary$count_word >= 50),]
wordrate1 <-cbind(wordrate1$word,wordrate1$count_word)
colnames(wordrate1) <- c(’word’,’count’)
write.csv(Data,file="hwordrate1.csv",row.names = F)
```

7.2 Code (Python)

```
# Data Preparation
hair_dryer = pd.read_csv('50.csv')
key = list(hair_dryer.keys())
new = hair_dryer[['marketplace','customer_id','review_id','product_id',
              'product_parent','product_title','product_category',
              'star_rating','helpful_vote','total_votes','review_head',
              'review_body','review_date']]

# To handle with the features
h_body = list(hair_dryer['review_body'])
words_count = []
# Add word counts of the review body
for text in h_body:
   blob = TextBlob(text)
   token = blob.words
   words_count.append(len(token))
words_count = pd.DataFrame(words_count)
vine = list(hair_dryer['vine'])
veri = list(hair_dryer['verified_purchase'])
# Convert Vine and Verified Purchased into numerical
for i in range(len(vine)):
   v = vine[i]
   if v == 'N':
      vine[i] = 0
   else:
      vine[i] = 1
for i in range(len(veri)):
   v = veri[i]
   if v == 'N':
      veri[i] = 0
   else:
      veri[i] = 1
vine = pd.DataFrame(vine)
veri = pd.DataFrame(veri)
tosave = pd.concat([new,vine,veri,words_count],axis = 1)
tosave.columns =
   ['marketplace','customer_id','review_id','product_id','product_parent',
              'product_title','product_category','star_rating','helpful_vote',
              'total_votes','review_head',
              'review_body','review_date','vine','veri','word']
tosave.to_csv('hairdryer50.csv')
# To find the Good Ratio and combine them with the original data set
data = pd.read_csv('hairdryer50.csv')
data = data[data.columns[1:]]
date = list(set(data['review_date']))
```

```
date_dict = {}
for d in date:
   date_dict[d] = []

info = np.array(data)
for i in range(len(info)):
   rate = info[i][6]
   da = info[i][13]
   date_dict[da].append(rate)

keys = sorted(list(date_dict.keys()))
count = []
for k in keys:
   j = date_dict[k]
   length = len(j)
   c = len([1 for i in j if i >= 4])
   count.append(c/length)
count = pd.DataFrame(count)
hraw = pd.read_csv('hairdryer.csv')
a = pd.concat([hraw,count],axis = 1)
a.columns = ['Date','Average of word_counts','Average of helpful_rate',
           'Count of verified_purchase', 'Count of vine','Average of
              star_rating','good_ratio']
a.to_csv('hraw.csv')

# Words Grading and Sentences Collection
nltk.download('punkt')
review = pd.read_csv('hrate1.csv')['review_body']
cols = pd.read_csv('hwordrate1.csv').columns
word = pd.read_csv('hwordrate1.csv')[cols[0]]
count = pd.read_csv('hwordrate1.csv')[cols[1]]

# To find the grate of the words that appear more than 50 times in the
   review body
grade = []
for w in word:
   blob = TextBlob(w)
   for sentence in blob.sentences:
      print(sentence + '------>'+ str(sentence.sentiment.polarity))
      grade.append(sentence.sentiment.polarity)
grade = pd.DataFrame(grade)
a = pd.concat([word,count,grade],axis = 1)
a.columns = ['word','count','grade']
a.to_csv('hwordrate1.csv')

# To find the sentences that contains words with non-positive grade
from textblob import TextBlob
```

```
check_word = word[12]
sentence_list = []

for i in range(len(review)):
   text = review[i]
   blob = TextBlob(text)
   for sentence in blob.sentences:
      if check_word in sentence:
         sentence_list.append(str(sentence))
sentence_list = pd.DataFrame(sentence_list)
sentence_list.columns = [check_word]
sentence_list.to_csv('hairdryer_%s.csv'%(check_word))

# MSFCB-LSTM
def series_to_supervised(data, n_in=1, n_out=1, dropnan=True):
   n_vars = 1 if type(data) is list else data.shape[1]
   df = pd.DataFrame(data)
   cols, names = list(), list()
   # input sequence (t-n, ... t-1)
   for i in range(n_in, 0, -1):
      cols.append(df.shift(i))
      names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
   # forecast sequence (t, t+1, ... t+n)
   for i in range(0, n_out):
      cols.append(df.shift(-i))
      if i == 0:
         names += [('var%d(t)' % (j+1)) for j in range(n_vars)]
      else:
         names += [('var%d(t+%d)' % (j+1, i)) for j in range(n_vars)]
   # put it all together
   agg = pd.concat(cols, axis=1)
   agg.columns = names
   # drop rows with NaN values
   if dropnan:
      agg.dropna(inplace=True)
   return agg

def Bnorm(model):
   model.add(BatchNormalization(axis=1, momentum=0.99, epsilon=0.001))

def get_lr_metric(optimizer):
   def lr(y_true, y_pred):
      return optimizer.lr
   return lr

dataset = pd.read_csv('praw.csv',index_col = 0)
a = dataset.columns
```

```
dataset = dataset[a[1:]]
dataset.columns =
   ['word','helpful_rate','veri','vine','star_rating','good_ratio']
dataset['word'].fillna(0, inplace=True)
dataset['vine'].fillna(0, inplace=True)
dataset['veri'].fillna(0, inplace=True)
dataset['helpful_rate'].fillna(0, inplace=True)
dataset['star_rating'].fillna(0, inplace=True)
dataset['good_ratio'].fillna(0, inplace=True)
values = dataset.values
# ensure all data is float
values = values.astype('float32')
# normalize features
scaler = MinMaxScaler(feature_range=(0, 1))
scaled = scaler.fit_transform(values)
# frame as supervised learning
reframed = series_to_supervised(values, 1, 1)
# To choose the index of the predictors
var = [0,1,2,3,4,6,7,8]
# split into train and test sets
values = reframed.values
n_obs = int(len(values)*0.7)
train = values[:n_obs, :]
test = values[n_obs:, :]
# split into input and outputs
train_X, train_y = train[:, var], train[:, -1]
test_X, test_y = test[:, var], test[:, -1]
# reshape input to be 3D [samples, timesteps, features]
train_X = train_X.reshape((train_X.shape[0], 1, train_X.shape[1]))
test_X = test_X.reshape((test_X.shape[0], 1, test_X.shape[1]))
print(train_X.shape, train_y.shape, test_X.shape, test_y.shape)

# set GPU
os.environ["CUDA_VISIBLE_DEVICES"]="1"
config = tf.ConfigProto()
# config.gpu_options.per_process_gpu_memory_fraction = 0.6
session = tf.Session(config=config)
KTF.set_session(session )

lr = 0.001
masking_func = lambda inputs, previous_mask: previous_mask[:, N:]
# Batch_Size=1
model = Sequential()
model.add(Bidirectional(LSTM(50,return_sequences=True,
                      input_shape=(train_X.shape[1],train_X.shape[2]),
                      kernel_initializer='he_normal',
                      #kernel_regularizer=regularizers.l2(0.05)
                      dropout=0.02,recurrent_dropout = 0.02,
                      kernel_regularizer=regularizers.l2(0.03))))
Bnorm(model)

model.add(Dense(output_dim=100,activation= ’relu’))##
Bnorm(model)

model.add(Bidirectional(LSTM(50,return_sequences=True,
                      kernel_initializer=’he_normal’,
                      #kernel_regularizer=regularizers.l2(0.05)
                      dropout=0.02,recurrent_dropout = 0.02,
                     kernel_regularizer=regularizers.l2(0.03))))
Bnorm(model)


model.add(Bidirectional(LSTM(30,return_sequences=True,
                     kernel_initializer=’he_normal’,
                      #kernel_regularizer=regularizers.l2(0.05)
                      dropout=0.02,recurrent_dropout = 0.02,
                     kernel_regularizer=regularizers.l2(0.03))))
Bnorm(model)
model.add(Dense(output_dim=50,activation= ’relu’))##
Bnorm(model)
model.add(LSTM(50, return_sequences=False,kernel_initializer=’he_normal’,
           dropout=0.01,recurrent_dropout = 0.01,
            kernel_regularizer=regularizers.l2(0.02)))
Bnorm(model)
model.add(Dense(output_dim=100, activation= ’relu’))
Bnorm(model)
model.add(Dense(output_dim=100,activation = ’relu’))
Bnorm(model)
model.add(Dense(output_dim=100,activation = ’relu’))
Bnorm(model)
model.add(Dense(output_dim=1))
model.add(Activation(’relu’))
Bnorm(model)

adam=Adam(lr,decay=0.0005)
model.compile(loss=’mae’, optimizer=adam)
from keras.callbacks import EarlyStopping

early_stopping=EarlyStopping(monitor=’val_loss’, min_delta=0,
                       patience=100, verbose=0, mode=’auto’,
                       baseline = None, restore_best_weights = True)

history = model.fit(train_X, train_y, epochs=500, ##
               batch_size=80, validation_split=0.05, shuffle=False,
               callbacks=[early_stopping])

#### Test Ratio with word count
pyplot.plot(history.history[’loss’], label=’train’)
pyplot.plot(history.history[’val_loss’], label=’test’)
pyplot.legend()
pyplot.show()
plt.figure()
yhat = model.predict(test_X)
test_y = test_y.reshape((len(test_y), 1))
# To print the first 100 predictions in the test data set.
plt.plot([x for x in range(len(test_y[0:100])) ],test_y[0:100],[x for x
   in range(len(test_y[0:100])) ],yhat[0:100],marker=’+’, linestyle=’-’)
plt.xlabel(’test samples’)
plt.ylabel(’Average Travel Time in seconds’)
plt.legend([’true value’, ’predict value’])
rmse = sqrt(mean_squared_error(test_y, yhat))
print(’Test RMSE: %.3f’ % rmse)
```