Information Retrieval Baseline Results

"Aspect Based Product Review Mining"

Group No. 9

Authors *:* *Bhaswanth Gudimella, MT22025* *Kushagra Mittal, MT22108*
Vamshi Krishna Vannekala, MT22086 *Vaibhav Nauriyal, MT22129*
Ujjwal Garg, MT22085 *Shreeyash Khalate, MT22069*

1. Updated Problem Formulation:

What is the problem identified in the project?

The objective of the project is to develop a system that analyzes large volumes of generalized customer reviews on Amazon products of various categories and extracts the different aspects/features mentioned in the reviews like quality, design, usability, durability. The dynamic extraction of aspects can lead to extracting everything that is labelled as 'NOUN' by the NLTK POS tagging technique. Thus an external interference is needed to determine which of the retrieved aspects are product features and which are not. All aspects that correspond to product features can then be evaluated with their opinion reviews to calculate a particular rating for each aspect.

The goal of our proposed system remains to provide more detailed evaluation of a product's performance with respect to its different features.

2. Updated Literature Review:

Is there any related work?
<Research paper references given below>

The research paper[1] in this area, propose methodologies to classify a review as positive and negative, where they come up with two key innovations : metadata substitutions and variable length features. They also Coupled the product name substitution with the best substring algorithm yielded 85.3 percent accuracy, higher than the 84.6 percent accuracy of bigrams in classification. Another research paper[2] introduces OPINE, an unsupervised information extraction system which mines reviews in order to build a model of important product features, their evaluation by reviewers, and their relative quality across products. OPINE solves the opinion mining tasks outlined above and outputs a set of product features, each accompanied by a list of associated opinions which are ranked based on strength. Another proposed technique[3] is an aspect-based product recommendation model that identifies aspects and sentiments from user reviews and incorporates them into a collaborative filtering approach to improve the accuracy of recommendations.

Analysing the importance of aspects review for any product, a user gives their opinion on a particular product may it be positive or negative, and the authors call the analysis of these opinions as 'Sentimental analysis'. There are two machine learning techniques to perform this analysis, they are Lexicon based and SVM. The existing system uses only unigram Lexicon system where only words like 'nice', 'bad', 'great', etc. are taken into account. But this method fails to include the inverted words like 'not'. When the review is 'not bad' and if the word 'not' is excluded then the review becomes

negative, to overcome this a bi-gram Lexicon system is proposed. Also previous proposed systems fail to compute the rating of individual features of a product just based on the customer review. Some platforms like Flipkart have implemented a similar approach but only for limited products. We will be implementing this for large group of products from different categories like electronics, books, dvds, and clothing.

Thus through our survey, we get an overview of the aspect-based opinion mining field, including tasks such as aspect extraction and sentiment classification, methods for addressing these tasks, and applications in various domains.

3. Baseline Results:

Techniques used and retrieved results

1. Data Preprocessing:

The first step in the project majorly involved data pre-processing steps like collecting the scattered data of different product categories and merging them into one single dataset,

Using NLTK to lowercase the categorical columns in the dataset, removing stopwords, removing punctuations and non-alphabetic symbols, etc.

Then we calculated the initial sentiment behind every product review based on the user rating.

2. *Sentiment Analysis:*

We computed the compound sentiment score of each review using SentimentIntensityAnalyzer() and 'vader_lexicon'. A new rating and corresponding sentiment for each product is calculated based on this compound sentiment score.

This can further include computing polarity, subjectivity of the text in order to assign an aspect score to each aspect of a particular product.

3. *Aspect-Opinion Extraction and Aspect-Rating Calculation:*

This step further included more data preprocessing steps. First we remove the relative pronouns (that, which, who, whom, whose, etc.). So the statement like ‘it is that good’ becomes ‘it is good’. Then we remove adverbs so they are not detected as aspects further. We then join the related nouns so the phrase ‘battery life’ is detected as one single aspect ‘battery_life’.

We also handle negated words in the text like ‘not good’ by replacing them with their closest antonym. Thus ‘not good’ becomes ‘bad’ and ‘not terrible’ may become ‘okay’ and so on.

Further we extract Nouns and their related Adjectives from each review. Thus Nouns are our aspects and their corresponding adjectives become the description(opinion) of that aspect. Based on the description of each aspect of the product, a corresponding sentiment score is calculated using AFINN tool between -5 and +5. Based on this calculated sentiment score, a new rating is assigned to each aspect of the product out of 5.

For each of the aspect extracted from the text, a sentiment score is assigned to their respected descriptions (adjectives). Based on this sentiment score a rating (out of 5) is assigned to each aspect. The new rating for the product will be the average of ratings of all aspects extracted from that product review.

Example, The text 'The battery life of the phone is good but the camera quality is not that good.' gives the following output –

{'battery_life': 'good', 'camera_quality': 'bad'}
{'battery_life': 3.0, 'camera_quality': -3.0} (Sentiment Score between -5 to +5)
{'battery_life': 4, 'camera_quality': 2} (rating out of 5)
Sentient Score by Aspects: 0.0 (-1 to +1)
Rating by Aspect Sentiment Score: 3.0 (out of 5)

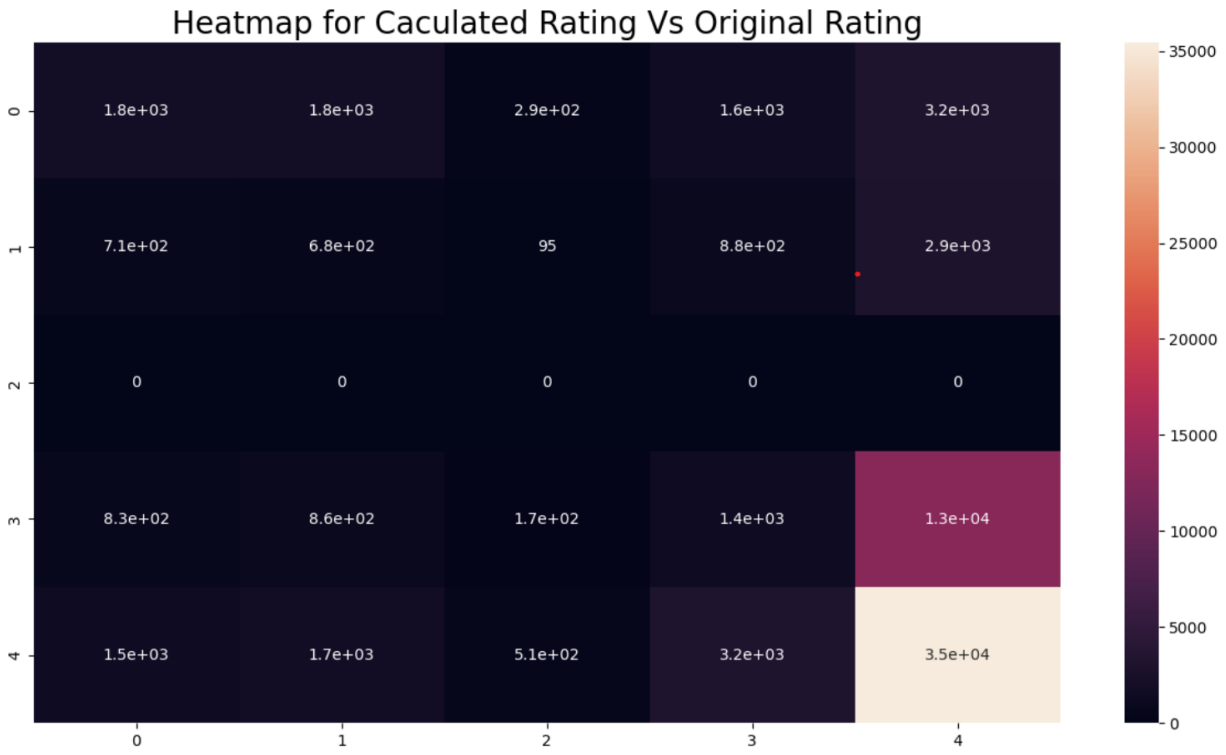
4. *Results:*

We were successful in extracting the aspects and their corresponding adjectives in the review text. All the negated words in the text were handled. We were able to eliminate all adverbs and relative pronouns and were able to join related nouns in the sentence.

The initial accuracy received for the sentiment detection is 80%

```
Calculated Sentiment Accuracy  0.800848040970291
```

The confusion matrix for calculated rating Vs original rating is –



The Classification Report for new rating vs original rating is –

```
Classification report:
              precision    recall  f1-score   support

         1.0       0.38      0.21      0.27      8647
         2.0       0.13      0.13      0.13      5304
         3.0       0.00      0.00      0.00         0
         4.0       0.20      0.09      0.12     16415
         5.0       0.65      0.84      0.73     42272

    accuracy                           0.54     72638
   macro avg       0.27      0.25      0.25     72638
weighted avg       0.48      0.54      0.49     72638
```

5. ***Output:***

   The final retrieved output for an input text like “The battery life of the phone is good but the camera quality is not that good.” is –

```
Original Text :  The battery life of the phone is good but the camera quality is not that good.


After Removing Pronouns :  The battery life of the phone is good but the camera quality is not good .
After Removing Adverbs(but keeping negations) :  The battery life of the phone is good but the camera quality is not good .
After Joining Related Words :  The battery_life of the phone is good but the camera_quality is not good .
Negated words in the text are :  ['good']


Aspects: ['battery_life', 'camera_quality']
Adjectives: ['good', 'bad']
Aspects With Description: {'battery_life': 'good', 'camera_quality': 'bad'}
Aspects With Sentiment Scores (-5 to +5):  {'battery_life': 3.0, 'camera_quality': -3.0}
Aspects With Ratings (Out of 5):  {'battery_life': 4, 'camera_quality': 2}


Normal Sentiment Score  0.7003
Rating by Normal Sentiment Score:  5
Sentient Score by Aspects:  0.0
Rating by Aspect Sentiment Score:  3.0
```

The first 5 rows of final dataframe after extracting aspects and calculating ratings is –

	product_name	review_text	rating	initial_sentiment	normal_sentiment_score	normal_sentiment	rating_by_normal_sentiment	aspect_ratings
0	sphere: books: michael crichton	sphere michael crichton excellant novel certai...	5.0	positive	0.9231	positive	5	{'novel': 3, 'misssion': 3, 'mile': 3, 'spacec...
1	healing from the heart: a leading surgeon comb...	dr oz accomplished heart surgeon field cardiac...	4.0	positive	0.93	positive	5	{'transplantation': 4, 'epilogue': 4, 'medicin...
2	mythology: dc comics art of alex ross 2007 cal...	gorgeous artwork comic books contains extraord...	5.0	positive	0.9118	positive	5	{'books': 4, 'artwork': 3}
3	pegasus descending: a dave robicheaux novel (d...	book lovers robicheaux demons seem put rest re...	4.0	positive	-0.8442	negative	1	{'mayhem': 2, 'shortcomings': 3}
4	guns, germs, and steel: the fates of human soc...	going short sweet review many others commented...	5.0	positive	0.9912	positive	5	{'review': 4, 'others': 2, 'value': 3, 'though...

4. Conclusion:

The accuracy of the system still needs to be improved, and the aspects extracted need to be examined for each product for their correlation with the actual product features and unnecessary aspects for each product need to be eliminated. A static set of aspects need to be determined for each product category to eliminate unnecessary aspects. The accuracy of the system can further be improved by using neural networks rather than just depending on NLTK POS tagging methodology.

5. References:

[1] *"Mining the Peanut Gallery: Opinion Extraction and Semantic Classification of Product Reviews", Kushal Dave, Steve Lawrence, David M. Pennock; 12th international conference on World Wide Web, May 2003*

[2] *"Extracting Product Features and Opinions from Reviews", Ana-Maria Popescu and Oren Etzioni, Department of Computer Science and Engineering, University of Washington Seattle, WA 98195-2350*

[3] *"Aspect-Based Product Recommendation: Identifying Aspects and Sentiments of User Reviews" by Jisun An, Sungchul Kim, and Jeonghee Yi (2019)*

[4] *"A Survey of Aspect-Based Opinion Mining: Tasks, Methods, and Applications" by Bing Liu (2012)*

[5] *"Aspect Based Sentiment Analysis on Product Reviews," A. P. Rodrigues and N. N. Chiplunkar, 2018 Fourteenth International Conference on Information Processing (ICINPRO), Bangalore, India*