Aspect-based Sentiment Analysis on Dynamic Reviews

Tushar Agarwal
Department of Information Technology
JSS Academy of Technical Education
Noida, India
tagarwal698@gmail..com

Tushar Agrawal
Department of Information Technology
JSS Academy of Technical Education
Noida, India
tusharag432@gmail.com

Utkarsh Dixit
Department of Information Technology
JSS Academy of Technical Education
Noida, India
utkarshdixit9598@gmail.com

Utkarsh Agrawal
Department of Information Technology
JSS Academy of Technical Education
Noida, India
utkarshaug31@gmail.com

***Abstract*—The reviews of users mentioned on the website are necessary and do provide a good insight into what the other customers experience. Different aspects of the reviews affect his decision-making, like their requirements, budget, etc. Aspect Based Sentiment analysis identifies and extracts subjective information about various aspects of a given sentence. We can determine the sentiment and polarity of an aspect that can be used by businesses to improve in certain aspects.**

In this paper, we proposed an aspect-based product performance analyzer for dynamic reviews, which exploits the information conveyed by users' reviews to provide a multi-faceted representation of users' interests. To this end, we developed a model for aspect-based sentiment analysis, which extracts relevant aspects and sentiment scores from users' reviews. Aspect extraction is performed using LDA and fasttext to identify the best aspect and a neural network is trained with an accuracy of 94% to find the aspects' sentiment.

A dynamic review processing system is developed which analyses the performance of the product for the current week. These results are then compared with that of previous weeks to visualize insights into variations in product performance.

Keywords—Aspect Term Extraction; Polarity Detection; Dynamic Review; Aspect Sentiment

I. INTRODUCTION

The reviews posted by customers are the globally trusted source of genuine content for other users. Customer feedback serves as the third-party validation tool to build user trust in the brand. For understanding this customer feedback on an entity, sentiment analysis is becoming an augmenting tool for any organization.

Aspect-Based Sentiment Analysis (ABSA) is the task of determining the sentiment of a text with respect to a specific aspect. Traditional sentiment analysis methods treat a text as a whole and assign it a single sentiment label (e.g., positive, negative, or neutral). This is adequate for many tasks, but there are also many situations where it would be useful to know the sentiment of a text with respect to a specific aspect.

For example, let's say you're reading a review about a phone. The review might mention several aspects such as camera, delivery, processor, and battery. Each of these aspects could have a positive or negative sentiment associated with them. ABSA is a technique that can automatically identify and extract these aspects and sentiments from the text.

LDA is most commonly used to discover a user-specified number of topics shared by documents within a text corpus. Here each observation is a document, the features are the presence (or occurrence count) of each word, and the categories are the topics. Since the method is unsupervised, the topics are not specified up front, and are not guaranteed to align with how a human may naturally categorize documents. The topics are learned as a probability distribution over the words that occur in each document. Each document, in turn, is described as a mixture of topics.

The objectives of the proposed method are as follows:

- Develop an LDA model for aspect extraction.
- To detect the sentiment of the extracted aspect
- Develop an ELT pipeline to get dynamic reviews
- To provide visual insights into the product performance by processing reviews over several weeks.

The use of pre pre-defined data set for sentiment analysis has already been done so we came up with the idea to use dynamic reviews which are real-world responses and comments from the actual users.

Our analysis will keep up with the fast-changing dynamics of the market as we will run an ELT pipeline to get the data and pre-process it after a specified period of time. Moreover, if we go a step ahead, we might make it an event-driven system as well where each review is considered as an event and each event is processed in real-time. However, for this, we need to consider times of high traffic.

II. RELATED WORK

Aspect Based Sentiment Analysis (ABSA) aims to analyze and understand people's opinions at the aspect level. Various taxonomies are provided for ABSA which organizes existing studies from the axes of concerned sentiment elements, with an emphasis on recent advances in compound ABSA tasks.

Aspect-based sentiment analysis (ABSA) has received increasing attention recently. Most existing work tackles ABSA in a discriminatory manner, designing various task-specific networks for the prediction. Various works propose to tackle various ABSA tasks in a unified generative framework. The proposed framework can be easily adapted to arbitrary ABSA tasks without additional specific model design.

The model used in [1] takes into consideration the user's weighted specific sentiments on different aspects of products. MCNN model has been used for aspect-based opinion mining. Moreover, a recommender system using the tensor factorization (TF) technique has been implemented. In [2], the author has implemented a recommendation algorithm based on CF techniques and Sentiment Aspect-Based Retrieval Engine (CoreNLP and AFINN-based). The model is able to extract relevant aspects from the review and extracts sub-aspects related to the main aspect. Automatic text summarization can be useful to identify the most relevant aspects of the items and support the suggestions generated by a recommendation algorithm. It is thoroughly discussed in [3] where the model evaluated transparency, persuasiveness, engagement, and trust of the recommendation as the average score collected through the user questionnaires. The model discussed in [4] gives a better understanding as to which of the aspects of the hotel under study are better than the others as per the user comments and on which of these aspects more improvement needs to be done. The analysis of the reviews, providing the hidden topics and frequent words can be of further importance for finding out valuable information.

The author in [5] has used a technique that helped in combining aspect extraction and aspect sentiment classification, which were considered separate before. It accounts for multi-word aspect terms and grammatical aspects of the sentence. It builds an Aspect Based sentiment analysis (ABSA) that empowers syntactical correlation between aspect terms and the context words. The modeling schemes are designed in such a way that they ensure the training process by formulating each Abstract based Sentiment Analysis task as a text generation problem (discussed in [6]). This also ensures strong generality of the framework proposed and it can be adapted to arbitrary ABSA tasks without any further model specification. A ternary classification groups the dependent, or 'target' variable into three groups. There are many different models that can perform this operation though they sometimes differ slightly from binary problems. Ternary classifications, as well as any model that has more than two targets, are considered multinomial problems. In [7], it is discussed in detail. Transfer learning models along with ternary classifications provide a neutral facet of the reviews. As a result, 98.30% of the maximum accuracy is obtained using ALBERT mode. Opinion mining has been used in the analysis of restaurant reviews and using binary and ternary classifications. Opinion mining has been used in the analysis of restaurant reviews and using binary and ternary classifications. The author in [8] has introduced various tasks for analyzing different sentiment elements and their relations, including the aspect term, aspect category, opinion term, and sentiment polarity.

III. SYSTEM ARCHITECTURE

This section provides the interpretation of our methodology for aspect-based sentiment analysis. The system architecture of the proposed model is represented in Fig. 1. Datasets are taken from Flipkart mobile reviews. This data is preprocessed to make it suitable for training.

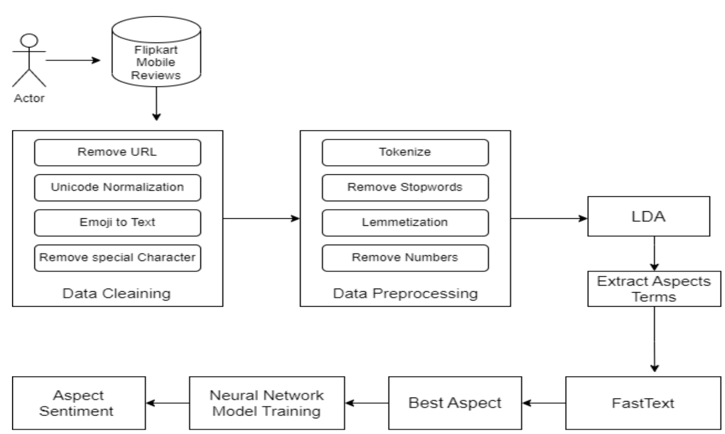

Fig 1: ABSA Training System Archutecture

After pre-processing the datasets, LDA is used for extracting various aspect terms. Fasttext library is used for finding the best aspect. A Neural Network is then trained to determine the sentiments of reviews.

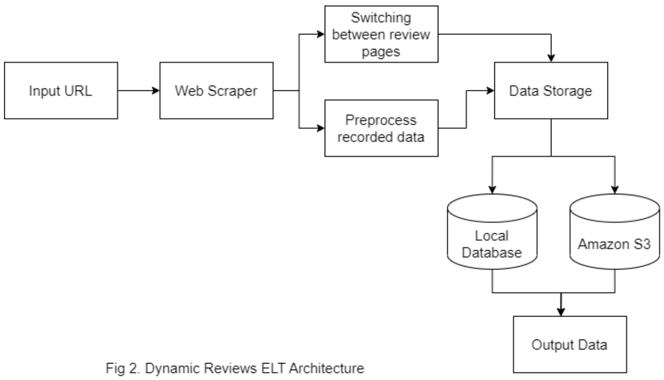

Fig 2. Dynamic Reviews ELT Architecture

An ELT pipeline is developed to dynamically obtain reviews of a product weekly from Amazon. Fasttext identifies the best aspect after preprocessing the reviews. A trained neural network identifies the sentiment of the obtained aspect.

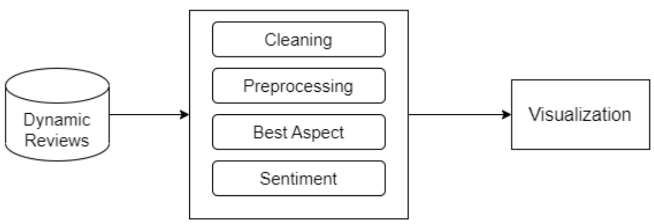

Fig 3: ABSA on Dynamic Reviews

Visual insights are then provided for product performance using graphs over several weeks.

IV. PROPOSED WORK

In order to perform Aspect Based Sentiment Analysis on dynamic reviews, a model is initially trained on mobile reviews from Flipkart as training data. Cleaning and preprocessing methods are performed to prepare for LDA which extracts top aspect terms. Fasttext then gives the best aspect in a review out of identified aspect terms. A neural network is then trained to identify the sentiment of the aspect.

The dynamic reviews are extracted using an ELT pipeline which is then preprocessed to obtain the best aspect and its sentiment using the model developed. The obtained results are visualized using graphs that represent variations in the performance of various product aspects over weeks.

A. Data Collections

Data collected from the Kaggle for Flipkart mobile reviews is used as training and testing the performance of aspect term extraction. The various tables in DB format are compiled to organize in a data frame.

The statistics of the data collected are shown in Table I.

Review Count	53493
Columns	Review, Rating

B. Data Preparation

Steps involved in preparing data include handling missing values to avoid errors and data augmentation.

Data augmentation is performed to eliminate skewness in data i.e., a small proportion of negative reviews.

C. Cleaning and Preprocessing of data

The Cleaning of data involves removing URLs, Unicode Normalisation, handling emojis by converting them into text, and removing special characters. The preprocessing steps include - Removing stopwords, tokenization, and lemmatization.

D. Visualization of Data

The top 100 words and their frequency is visualized using a bar graph and a word cloud of the given reviews is displayed for a better understanding of the Data. The sentiments of the entire review are also extracted and presented as a comparison of positive and negative reviews.

E. Aspect terms Extraction

Latent Dirichlet Allocation(LDA) is a topic modeling technique that takes word frequency into consideration to identify topics and their weightage in a sentence.

LDA is used to identify top aspect terms that are common in most reviews.

F. Best Aspect in a Review

Gensim FastText module allows training word embeddings from a training corpus with the additional ability to obtain word vectors for out-of-vocabulary words.

FastText is used to identify the best aspect in a review i.e., the aspect having the highest similarity with a sentence.

G. Identification of Aspect Sentiment - NN model

A neural network model is trained to identify the sentiment of the best aspect of the review. The Neural Network is based on LSTM and the model is cross-validation 5-fold using the k-fold cross-validation technique which gives a validation accuracy of 94%.

H. Performance Analysis

An accuracy score is calculated for evaluating the performance of the model to identify the sentiment of a review. A sample of 50 reviews was annotated manually and compared against the model's prediction. The accuracy achieved is 84%.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

I. An ELT Pipeline for Dynamic Reviews

An ELT Pipeline is developed by scraping data from Amazon using BeautifulSoup. The input requires a URL of the product on Amazon. The Output is a list of reviews in S3 and the database. The Network Connection in S3 is Maintained using the Boto3 library of Python

J. Processing Dynamic Reviews

Dynamic reviews are obtained in raw form with review text only. These reviews are prepared by cleaning and preprocessing. FastText technique is used for finding the best aspect term of each review. A trained neural network predicts the sentiment of the best aspect of a review.
The data for the current week is organized in a data frame to store the performances of a product in various aspects over weeks.

K. Visualization of Change in Sentiment Score

The product aspect performance over a period of several weeks is visualized in the form of bar and line graphs which essentially represent the change in the sentiment score of an aspect of the product over a given time period.

V. RESULT

The following section represents the results of various models and methodologies used. The top aspect terms identified using LDA are shown in Fig 4. Where each row represents a review and its topics.

```
(2,
 '0.046*"phone" + 0.034*"good" + 0.033*"camera" + 0.019*"battery" + '
 '0.017*"awesome" + 0.015*"mobile" + 0.014*"flipkart" + 0.013*"performance" + '
 '0.013*"great" + 0.012*"price"'),
(3,
 '0.065*"phone" + 0.038*"bad" + 0.032*"evil" + 0.028*"camera" + 0.021*"price" '
 '+ 0.019*"battery" + 0.016*"flipkart" + 0.014*"awesome" + '
 '0.014*"performance" + 0.014*"redmi"'),
(4,
 '0.061*"phone" + 0.024*"good" + 0.021*"battery" + 0.019*"nice" + '
 '0.018*"camera" + 0.014*"price" + 0.011*"flipkart" + 0.011*"redmi" + '
 '0.011*"great" + 0.010*"best"'),
```

Fig 4. Aspect Extraction Using LDA

The performance of the neural network is compared against VADER which calculates sentence sentiment as shown in Fig 5.

	clean_review2	Sentence_Sentiment	Aspect_Sentiment
0	great phone budget pubg performance rough came...	Negative	negative
1	best smartphone mi range born r confuse samsun...	Negative	negative
2	bad smooth phone back camera quality evil rear...	Negative	negative
3	thise nice mobile like much delivery also fast...	Positive	positive
4	meagerly dissatisfy thumb section r superb del...	Positive	negative

Fig 5: VADER vs ABSA model

A sample of 50 reviews was used to compare the results of predicted vs actual Aspects and Sentiment. An accuracy score of 72% is achieved in Aspect and 82% in Sentiment prediction as shown in Fig-6.

Review	Aspect	Sentiment	Predicted_Aspect	Predicted_Sentiment
phone's great b...	Battery	positive	battery	positive
evil processor	processor	negative	processor	negative
amazing battery	battery	positive	battery	positive
best camera	camera	positive	camera	positive
worst phone	Phone	negative	phone	negative

Fig 6. Aspect and its sentiment Prediction

Fig 7 represents the weekly results of aspect terms and their sentiments. A high score represents a positive sentiment of an aspect for that week.

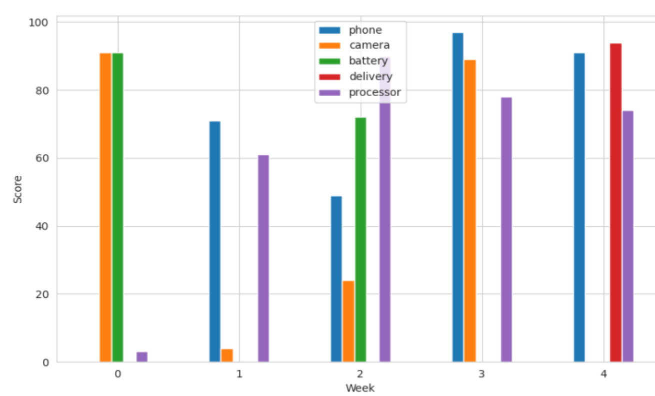

Fig 7. Weekly aspect score of a product

We have used the weekly aspect performance of a product to provide visual insights into the performance of products over a period of time as shown in Fig 8.

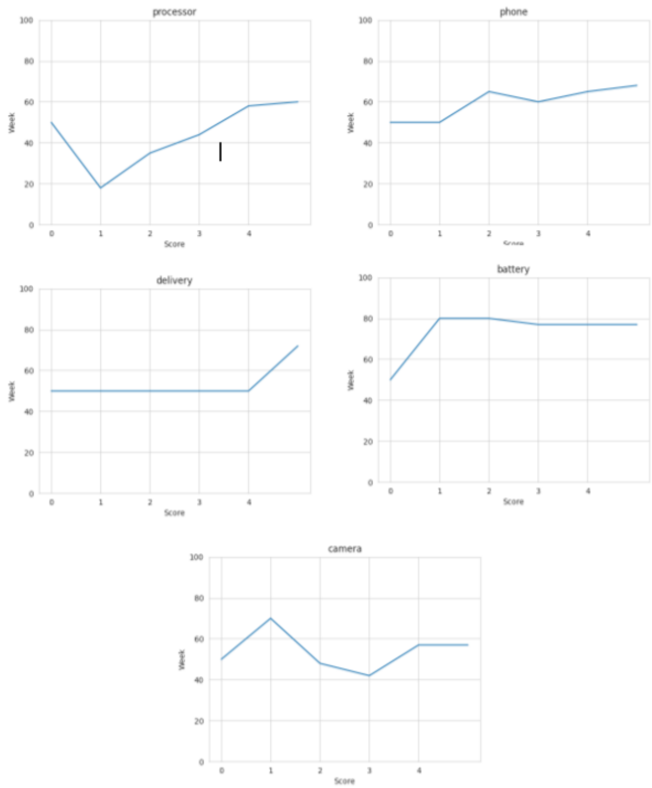

Fig 8. Variation in product performation based on each aspect

VI. CONCLUSION

The proposed method is to use LDA for the task of extraction of aspect terms and further use fasttext to compare and get the best aspect of the chosen aspect terms in a particular review obtained using LDA. The model performs well with dynamic reviews and is a major advancement in the field of Aspect-Based Sentiment Analysis. The aspect terms are chosen with the help of most weighted words, specifically nouns in the dataset. A Neural Network is then configured and trained to get the sentiment of the aspect. This model is further cross-validated using the K-fold Technique. Our analysis will keep up with the fast-changing dynamics of the market as we will run an ELT pipeline to get the data and pre-process it after a specified period of time.

In the future, as a step ahead, make it an event-driven system as well where each review is considered as an event and each event is processed in real-time. It can be built as a highly interactive User Interface that helps us input the URL of a specific product which will trigger the ELT pipeline.
Further, other aspect extraction models and techniques such as Gensim can be explored. Integration of aspect categorization and multi-language models to expand the scope of the paper can be considered.

VII. REFERENCES

[1] Da'u, A., Salim, N., Rabiu, I., & Osman, A. (2020). Weighted aspect-based opinion mining using deep learning for recommender systems. Expert Systems with Applications, 140, 112871.

[2] Musto, C., de Gemmis, M., Semeraro, G., & Lops, P. (2017, August). A multi-criteria recommender system exploiting aspect-based sentiment analysis of users' reviews. In Proceedings of the eleventh ACM conference on recommender systems (pp. 321-325).

[3] Musto, C., Rossiello, G., de Gemmis, M., Lops, P., & Semeraro, G. (2019, September). Combining text summarization and aspect-based sentiment analysis of users' reviews to justify recommendations. In Proceedings of the 13th ACM conference on recommender systems (pp. 383-387).

[4] Akhtar, N., Zubair, N., Kumar, A., & Ahmad, T. (2017). Aspect-based sentiment-oriented summarization of hotel reviews. Procedia computer science, 115, 563-571.

[5] Phan, M. H., & Ogunbona, P. O. (2020, July). Modeling context and syntactical features for aspect-based sentiment analysis. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (pp. 3211-3220).

[6] Zhang, W., Li, X., Deng, Y., Bing, L., & Lam, W. (2021, August). Towards generative aspect-based sentiment analysis. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers) (pp. 504-510).

[7] Alamoudi, E. S., & Alghamdi, N. S. (2021). Sentiment classification and aspect-based sentiment analysis on Yelp reviews using deep learning and word embeddings. Journal of Decision Systems, 30(2-3), 259-281.

[8] Zhang, W., Li, X., Deng, Y., Bing, L., & Lam, W. (2022). A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges. arXiv preprint arXiv:2203.01054.

[9] M. Gupta, A. Mishra, G. Manral and G. Ansari, "Aspect-category based Sentiment Analysis on Dynamic Reviews," 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA), Greater Noida, India, 2020, pp. 492-496, doi: 10.1109/ICCCA49541.2020.9250914.

[10] Ankit Gupta, "Flipkart Cell Phone Reviews" kaggle.org. https://www.kaggle.com/datasets/nkitgupta/flipkart-cell-phone-reviews.

[11] Zhang, K., Zhang, K., Zhang, M., Zhao, H., Liu, Q., Wu, W., & Chen, E. (2022). Incorporating Dynamic Semantics into Pre-Trained Language Model for Aspect-based Sentiment Analysis. ArXiv. https://doi.org/10.18653/v1/2022.findings-acl.285