Aspect based Sentiment Analysis

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***Abstract*—The increase in online marketing platform usage has given an opportunity to express one's thoughts and ideas about products, and organizations to everyone. These reviews can be used as a medium for determining one's sentimental behavior. Suppose someone is sharing posts that are of negative sentiment then by determining the sentiment we can understand the mental condition of the person. Analysis of sentiment can be done into 3 parts: analyzing sentiment of the whole document, analyzing sentiment of text, and analyzing sentiment of the aspect level [Hu and Liu, 2004]. In our pattern recognition project, we are using a deep learning model "LSTM"(Long Short-Term Memory) to analyze the sentiment of aspect of sentence.**

***Index Terms*—Sentiment Analysis, Aspect, LSTM**

I. INTRODUCTION

At present, with the advancement of the internet, social media platforms have become very popular for sharing ideas and thoughts of individuals. As the realm of digital data expands exponentially, individuals and organizations are increasingly captivated by the potential of mining this vast source of subjective information. Online customers share their experiences about different products, organizations, and services on the web [Yoo and Gretzel, 2008] and these reviews help other customers to take decisions [Chevalier and Mayzlin, 2006]. At the forefront of computer sciences, sentiment analysis emerges as a prolific research area, driven by the relentless pursuit to identify and extract user opinions. This captivating field holds the key to unraveling the intricate tapestry of human sentiment, opening doors to invaluable insights and empowering decision-making in the ever-evolving digital landscape. [Do et al., 2019]

Sentiment analysis offers valuable insights at multiple levels: document, sentence, and entity/aspect. While focusing on the document or sentence level assumes a single topic, real-world situations often involve multiple topics. To achieve a comprehensive analysis, it becomes essential to delve deeper into the entity and aspect level. This entails identifying specific entities and their related aspects, enabling the classification of sentiments associated with each entity and aspect. By exploring sentiments at this granular level, we unlock a more profound understanding of the nuances and complexities within the data, empowering us to extract richer insights.

Within the realm of sentiment analysis, a diverse array of entities come into play. These entities encompass a broad spectrum of subjects, ranging from products and services to topics, issues, persons, organizations, and events [Zafra et al., 2017]. Each entity, brimming with its unique characteristics and attributes, holds within it a multitude of aspects to explore. By recognizing and examining these various aspects, we gain a comprehensive understanding of the multifaceted nature of the entities under analysis. Through this holistic approach, we unveil the rich tapestry of sentiments associated with each entity, unraveling profound insights that contribute to a deeper comprehension of the intricate web of human experiences and interactions.
One example of aspect sentiment analysis is shown below in figure 1 [Do et al., 2019].

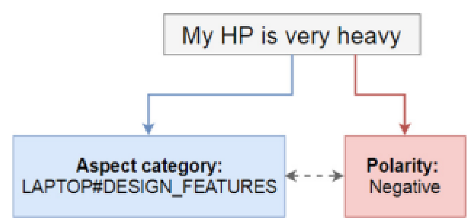


Fig. 1. Aspect sentiment analysis [Pontiki et al., 2014]

II. LITERATURE REVIEW

Aspect-based sentiment analysis is not a recent concern. [Thet et al., 2010] paper looks at how people express their feelings about movies on discussion boards. Instead of just looking at overall opinions, the researchers wanted to understand people's thoughts about specific aspects of the movies. They used a linguistic approach of computing the sentiment of a clause to analyze the written comments and figure out which parts of the movies people were talking about. They also looked at whether people had positive or negative feelings towards those aspects. The results showed that their approach was successful in identifying the specific aspects and understanding people's opinions about them. This information can be useful for understanding what aspects of movies people like or dislike based on their discussions online. Different deep learning-based models have been used for aspect-based sentiment analysis.

This paper [Ma et al., 2018] presents a methodology for targeted aspect-based sentiment analysis using an attentive LSTM (Long Short-Term Memory) model that incorporates commonsense knowledge. The approach involves training the model on large datasets of movie reviews and their corresponding sentiment labels. The model uses word embeddings to capture semantic information and attention mechanisms to focus on relevant aspects of the reviews. Additionally, commonsense knowledge is integrated into the model to enhance its understanding of the relationships between aspects and sentiments. Experimental results demonstrate that the proposed approach outperforms other baseline methods in accurately identifying targeted aspects and predicting sentiment polarity. The incorporation of commonsense knowledge improves the model's overall performance and provides more nuanced sentiment analysis results.

Paper [Liu et al., 2018] proposed a novel content attention based aspect based sentiment classification model, which has two attention enhancing mechanisms, one is sentence-level content attention mechanism that is capable of capturing the important information about given aspects from a global perspective, the second one is the context attention mechanism that is responsible for simultaneously taking the order of the words and their correlations into account, by embedding them into a series of customized memories. The model was trained on a large set of examples where people expressed their opinions, and it learned to predict the sentiment, whether positive or negative, related to each aspect.

Different kinds of tasks related to aspect based sentiment analysis have been asked to solve in SemEval. This paper [Kirange et al., 2014] proposes a solution of SemEval 2014 task 4. It discusses various techniques employed in the SemEval-2014 Task 4, which focuses on aspect-based sentiment analysis. The techniques include feature-based approaches, which extract and utilize specific linguistic features, such as n-grams and part-of-speech tags, to identify aspects and sentiments. Another technique is the use of machine learning algorithms, such as Support Vector Machines (SVM) and Conditional Random Fields (CRF), to classify the sentiment polarity of aspects. Additionally, the paper explores the use of domain-specific resources, such as sentiment lexicons and WordNet, to enhance the analysis. Overall, the paper presents a comprehensive overview of the different techniques employed in aspect-based sentiment analysis for the given task.

Another task related to aspect based sentiment analysis was asked in task 12 of SemEval 2015 [Pontiki et al., 2015]. The task called SemEval-2015 Task 12 builds upon the previous SemEval-2014 Task 4. It encourages researchers to go beyond just classifying sentiments at the sentence or text level and focus on Aspect Based Sentiment Analysis. The main objective is to identify opinions that people express about particular things (like laptops) and their specific features (like price). In simpler terms, the goal is to understand what people think about different aspects of something, rather than just looking at overall sentiments.

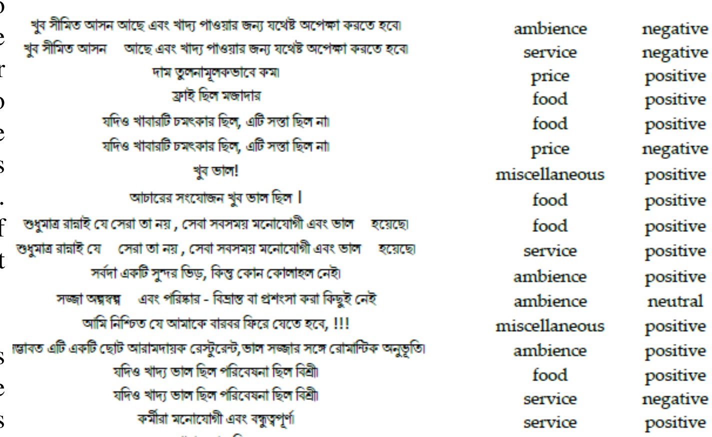
The solution of this task 12 was proposed by [Saias, 2015]. This paper discusses the methodology used in the Sentiue system for the SemEval-2015 Task 12, which focuses on target and aspect-based sentiment analysis. The researchers propose a three-step approach: target extraction, aspect extraction, and sentiment classification. They utilize machine learning techniques such as Support Vector Machines (SVM) and Conditional Random Fields (CRF) to identify the target (the entity being discussed), extract the aspects (specific features or attributes), and classify the sentiment associated with each aspect. The Sentiue system achieves competitive performance in the task, demonstrating the effectiveness of their methodology in analyzing sentiments towards specific targets and aspects in textual data.

III. Proposed Methodology

This section contains the development of our proposal for this pattern recognition project. This follows data acquisition, data pre-processing and the proposed method accordingly.

A. Data acquisition

For this task, we have used a publicly available dataset [Rahman and Kumar Dey, 2018] to train our model. This dataset contains 2 different types of dataset. We have used only one of them, restaurant dataset for our task. To create this dataset they have took help from an english dataset [Pontiki et al., 2014] that contains restaurant dataset as a sub dataset. They just translated the original dataset. This dataset contains 2800 samples for restaurant reviews. This dataset consists of four different polarity labels: positive, negative, neutral, and conflict. Figure 2 shows a snapshot of the dataset. This dataset



খুব সীমিত আসন আছে এবং খাদ্য পাওয়ার জন্য যথেষ্ট অপেক্ষা করতে হবে।	ambience	negative
খুব সীমিত আসন আছে এবং খাদ্য পাওয়ার জন্য যথেষ্ট অপেক্ষা করতে হবে।	service	negative
দাম তুলনামূলকভাবে কম।	price	positive
ফ্রাই ছিল মজাদার	food	positive
যদিও খাবারটি চমৎকার ছিল, এটি সস্তা ছিল না।	food	positive
যদিও খাবারটি চমৎকার ছিল, এটি সস্তা ছিল না।	price	negative
খুব ভাল!	miscellaneous	positive
আচারের সংযোজন খুব ভাল ছিল।	food	positive
শুধুমাত্র রান্নাই যে সেরা তা নয়, সেবা সবসময় মনোযোগী এবং ভাল হয়েছে।	food	positive
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সর্বদা একটি সুন্দর ভিড়, কিন্তু কোন কোলাহল নেই।	ambience	positive
সজ্জা অম্লবম্ল এবং পরিষ্কার - বিভ্রান্ত বা প্রশংসা করা কিছুই নেই	ambience	neutral
আমি নিশ্চিত যে আমাকে বারবর ফিরে যেতে হবে, !!!	miscellaneous	positive
ভাবত এটি একটি ছোট আরামদায়ক রেস্টুরেন্ট,ভাল সজ্জার সঙ্গে রোমান্টিক অনুভূতি।	ambience	positive
যদিও খাদ্য ভাল ছিল পরিবেষনা ছিল বিশ্রী।	food	positive
যদিও খাদ্য ভাল ছিল পরিবেষনা ছিল বিশ্রী।	service	negative
কর্মীরা মনোযোগী এবং বন্ধুত্বপূর্ণ।	service	positive

Fig. 2. Sample of the dataset

contains different aspects such as food, price, services and so on.
The following figure 3 shows the statistics of the dataset.

Category	Polarity			Total
	Positive	Negative	Neutral	
Food	500	126	87	713
Price	102	60	16	178
Service	186	118	32	336
Ambiance	138	53	43	234
Miscellaneous	300	120	193	613

Fig. 3. Statistics of the dataset

B. Data Pre-processing

To feed the data into a model we need to pre-process the data. We referred to the original restaurant dataset [Pontiki et al., 2014] and plotted the word cloud for that dataset to see which words are most frequent. The below figure 4 represents the word cloud of the most frequent words in the dataset.

Fig. 4. Word cloud of the dataset

We then changed the polarity labels to integers for the training phase. After that, we dropped the columns which were useless. We dropped the entries whose polarities were conflicting. Now dataset only contains 3 polarities: negative, positive, and neutral. The following chart 8 shows the histogram of each polarity.
Here, 0 = negative polarity
1 = positive polarity
2 = neutral polarity

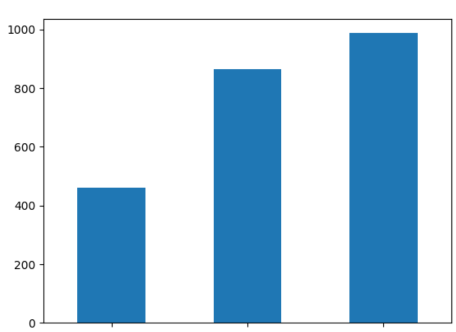

Fig. 5. Histogram of polarity

As we have used bangla dataset, we need to use bangla embedding which does not come by default. So we downloaded a bangla glove file and then by using it we created bangla embedding for each of the word.

We then tokenized each of the texts, before tokenizing we lowered the texts and then removed punctuations and alpha-numeric characters.

C. proposed method

We have used Long Short-Term Memory (LSTM) model to accomplish our task. We added attention to LSTM, we embedded aspect terms as well. The design flow of our proposed method is:

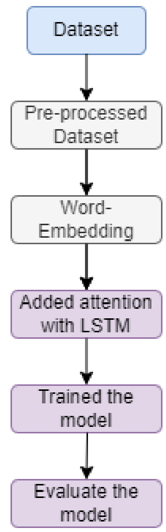

Fig. 6. Design flow of proposed work

Our model uses Tanh activation function.

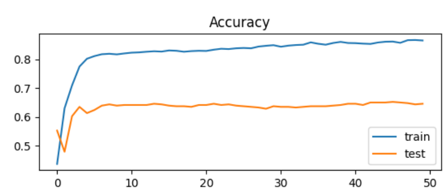

Fig. 7. History of model

IV. Experiment and Result

We have trained and tested our model using google colab, an online platform. We used Testal T4 GPU, Cuda version is 12.00 for training our model. To train our model,

#of epochs = 50,
Loss function = sparse_categorical_crossentropy,
Optimizer = Adam,
Learning_rate = ReduceLROnPlateau, which reduces the learning rate when loss does not decrease.
Validation accuracy = **65.23%**

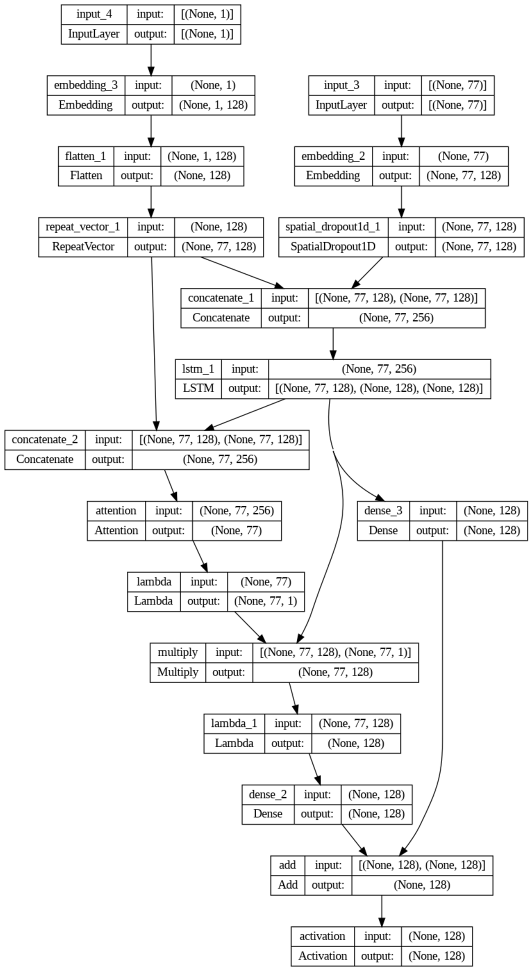

Fig. 8. Histogram of polarity

Test accuracy = **64.58%**.

V. Conclusion

There are many works on aspect-based sentiment analysis but we could not find any of them in bangla. We used attention-based LSTM model to do aspect-based sentiment analysis in bangla.

There are only 2 publicly available dataset on bangla aspect-based sentiment analysis, one of them is the translated version of an original english dataset. So we want to propose a dataset in this field in future. We also want to use common knowledge with LSTM to see if this helps to achieve more accuracy with the same dataset.

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