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Aspect Extraction from Bangla Reviews using Convolutional Neural Network

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***Abstract*—The extensive customer reviews in web assist customers for purchase-decision-making as well as providers for business planning. Summarization of reviews is desirable as reading all reviews is not feasible to evaluate properly. To find aspect categories from reviews is a sub-task of summarization known as Aspect Based Sentiment Analysis (ABSA). In this paper, we present two Bangla datasets to perform ABSA task. We collected user comments on cricket game and annotated manually. The other dataset consists of consumer reviews of restaurants. A model to extract aspect category based on Convo-lutional Neural Network (CNN) is presented. The model shows the convincing performance of the proposed datasets compared to the conventional classifiers.**

Keywords. Bangla Aspect Based Sentiment Analysis, Bangla Dataset of ABSA, Aspect Extraction in Bangla.

I. Introduction

People rely on human judgment more than conventional advertising. For example, customers are used to asking for a recommendation and suggestion from others before important purchase decisions. Word of Mouth (WOM) has always been important to make such decisions for customers. On the other hand, WOM carries great significance for providers. It has a stronger effect on new customer acquisition than traditional forms of marketing [1].

Sharing experience has become very frequent these days with the help of internet. Social media like Twitter and Facebook have made it easy to exchange judgment about product, service or brand. This extended form of word of mouth is Electronic Word of Mouth (eWOM). For example, E-commerce like Amazon and Alibaba have a large number of reviews of their products and services shared by consumers. These reviews are more admissible for consumers than the various form of marketing information [2]. On the other hand, companies are eager to mine all these activities and interactions to understand how the majority are feeling about a particular brand or product. It would help them to develop their business strategy in this competitive world.

Our involvement with social media is rapidly growing day by day. We share our views and opinions on every aspect of life. Therefore, it is necessary to automatically analyze all these data to produce such useful information that helps both companies and consumers. Aspect based sentiment analysis is a major technique to obtain such convenient information.

Sentiment analysis, also known as opinion mining, is a process to determine if the expression is favorable, unfavorable, or neutral. Sentiment analysis has three levels to analyze [3]: document level, sentence level, and aspect level. The document level analyzes a piece of text and determines whether the text has a positive or negative sentiment. Sentence level identifies the polarity of each sentence. These two levels of analysis do not reveal what exactly people liked and did not like. Aspect level is known as Aspect Based Sentiment Analysis (ABSA) identifies the aspects of a given document and the sentiment expressed towards each aspect. ABSA is the most detailed version of sentiment analysis that discovers desired information from a document.

There are two major tasks to perform aspect based sentiment analysis. 1) extract the particular areas mentioned in a given review. 2) classify the polarity into positive, negative or neutral for every aspect. For example, a review of a restaurant is:

"The place was relaxed and stylish but the food was not good."

Here, this review reveals two aspects: 'ambience' and 'food'. The 'ambience' aspect category indicates 'positive' sentiment and the 'food' aspect category indicates 'negative' sentiment. In the review, aspect categories are mentioned explicitly. People can share their opinion implicitly such as,
"All the money went into the interior decoration, none of it went to the chefs."
here, it carries the same aspects 'ambience' and 'food' without directly mentioned.

In the NLP domain, SemEval (Semantic Evaluation) is a reputed workshop. It introduces a dataset [4] for ABSA task in English. Later they extend this work by adding more domains with several languages. To perform Aspect Based Sentiment Analysis (ABSA), the datasets of different languages like French [5], Czech [6] and Arabic [7] have been created.

Previous works [8], [9], [10] attempt to detect aspects in opinion mining task. Most of them use Latent Dirichlet Allocation (LDA) as topic modeling. [11] presents the first deep learning approach for aspect extraction where deep convolutional neural network (CNN) is applied. In Bangla language, sentiment analysis [12] [13] [14] has been performed. They identify the polarity (positive or negative) from Bangla text.

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Aiming to work with ABSA in Bangla, the contributions of this paper in the following.

- We propose two Bangla datasets in the field of Aspect Based Sentiment Analysis (ABSA). These datasets were collected and annotated manually.
- We present a model to extract aspect category that shows convincing performance than the other popular machine learning models.

One of the presented datasets is collected from Facebook on the topic of cricket. The other dataset on the restaurant is collected from English benchmark dataset [4] by abstract translation. The collection and annotation processes of the datasets are described in section IV. These datasets are publicly available [1]. Using these datasets, we present a CNN model and perform aspect category extraction which is a subtask of ABSA.

The structure of the paper is as follows. Section II discusses the related works in the field of ABSA. We present our methodology in Section III. In Section IV, we present the experimental results. In this section, we discuss the dataset collection and annotation process. Finally, the conclusion is presented in Section V.

II. Related Work

To improve rating predictions, [15] provides a restaurant review dataset that introduces aspect category. They categorize a review into six aspects and a general polarity. They didn't prepare complete ABSA dataset as aspect category is present but the polarity for those identified aspect category is absent. For example, a review like "Burger was appetizing but a little expensive." have two aspect categories: 'food' and 'price'. They annotate the polarity on an overall review that is 'positive'.

SemEval 2014 evaluation campaign [4] extends their dataset adding more three fields with aspect category. Datasets of several languages are published in semeval 2016 workshop [16], these are English, French, Russian, Arabic, Turkish, Dutch, Spanish and Chinese. They also introduce different domains like mobile phone, restaurant, digital camera, laptop, hotel, museum and telecommunication. In [6], an IT product review dataset is created in Czech language for ABSA task in which total 2200 reviews are contained. In Arabic language, another dataset of book reviews is provided by [7]. They classify book reviews into 14 categories and 4 types of polarities.

To perform ABSA, common approaches include topic modeling where Latent Dirichlet Allocation (LDA) is the most popular method to discover aspects. A weakly supervised topic modeling approach is proposed in [17]. It uses word co-occurrence information to capture latent topics in the corpus and four different topic models are introduced where local LDA gives the highest accuracy. Sentence-LDA [18], a probabilistic generative model, assumes all words in a single sentence are generated from one aspect which is a limitation of their work. Recently common-sense knowledge SenticNet [19] is incorporated in LDA to improve the performance of aspect extraction [20].

Association rule mining is the major technique in [21] that utilize co-occurrence frequency of words. They propose both a supervised and an unsupervised method based on co-occurrence frequencies. Using double propagation (DP), an unsupervised method for opinion aspect extraction is presented in [22]. Double propagation provides recommendations that are based on aspect similarity and aspect association. Semantic similarity uses word vectors for similarity comparison that incorporate synonymous aspects of DP.

Recently one new dimension is integrated to ABSA named 'target' in [23]. It detects the aspects and classify the sentiment polarity given a target in the document. This work is extended in [24] that uses SenticNet as commonsense knowledge to improve the accuracy. They propose 'Sentic LSTM' as an extension of LSTM to leverage SenticNet efficiently.

Convolutional neural network (CNN) is successfully used for text classification in [25]. They propose a new CNN architecture for sentence classification and provide a series of experiments with pretrained word vectors. [26] apply similar CNN model in ABSA. They perform aspect category identification, extraction of opinion target expression and polarity identification. [11] includes part of speech tags with word vectors in word embedding and uses CNN to extract aspects. In their experiment, they utilize a set of linguistic patterns and result shows that a little bit improvement in accuracy. Recurrent neural network (RNN) is also successfully applied in aspect identification. Several important RNN architectures are experimented in [27]. They initialize RNN models with popular pretrained word vectors.

In Bangla language, many researchers perform only sentiment analysis from Bangla text. [12] identifies the overall polarity from Bangla microblog posts as either positive or negative. Semi-supervised bootstrapping approach is applied to develop a training corpus. They use Support Vector Machine (SVM) and Maximum Entropy (MaxEnt) to classify the polarity. [13] detects polarity (positive, negative or neutral) using contextual valence analysis. They use the WordNet to get the senses of each word according to its parts of speech. SentiWordNet is also used to get the prior valence (i.e. polarity) of each Bangla word. A dataset of Bangla text is proposed in [28] for sentiment analysis task. Long Short Term Memory (LSTM) of deep recurrent model is applied on their dataset. Only 850 Bangla comments are collected in [29] and Convolutional Neural Network (CNN) is used to classify the comments either positive or negative sentiment.

III. Methodology

The architecture of our CNN model for aspect extraction is shown in Figure 1. The network is consist of a single convolutional layer followed by a non-linearity, max-pooling and finally a fully connected layer as output. In the following, we provide a concise interpretation of the major components of our network: review matrix, convolutional, pooling and output layer. We also describe regularization to prevent overfitting.

[1] https://github.com/AtikRahman/Bangla_Datasets_ABSA

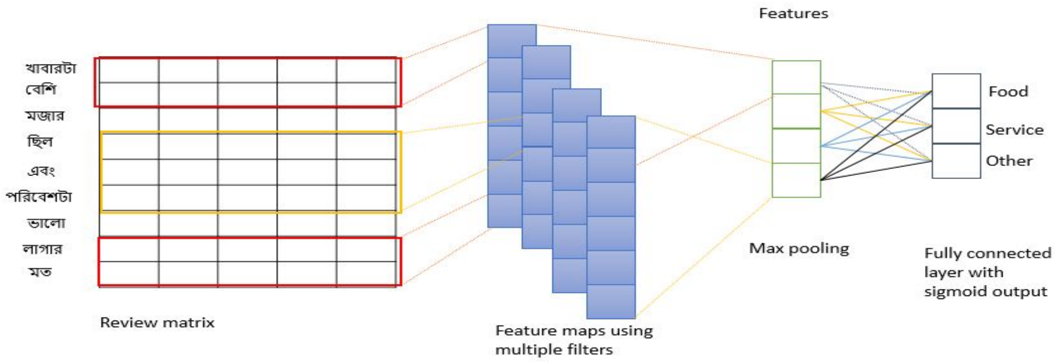

Figure 1. The CNN architecture for aspect extraction from Bangla review

A. *Review matrix*

Each review is treated as a sequence of words where each word represents a vector of fixed size. These vectors are initialized randomly. Let a word x_i is initialized randomly with q-dimensional vector. If n is the number of maximum words of reviews, a review (padded with n length if needed) is represented as,

$$x_{1:n} = (x_1 \oplus x_2 \oplus \cdots \oplus x_n) \tag{1}$$

where $\oplus$ is the concatenation operator. It produces a matrix for one review. For each review R, we build a review matrix $R \in \mathbb{R}^{x \times q}$ where each row i represent a word embedding x_i of the i-th word in the review. To extract features of individual words from a given review, the neural network applies conversions to the input review matrix R using convolution and pooling operations which are explained in the next.

B. *Convolution*

The convolutional operation between an input matrix R and a filter $W \in \mathbb{R}^{p \times q}$ of p words window results in a vector $C \in \mathbb{R}^{n-p+1}$, where each component is computed as follows:

$$C_i = f(R_{i:i+p-1} \otimes W + b) \tag{2}$$

Here $\otimes$ is the element-wise multiplication, $b \in \mathbb{R}$ is a bias term and f is a non-linear function such as rectified linear units (ReLUs). As shown in Figure 1, an element-wise multiplication between a row slice of R and a filter matrix W is performed and then summed to a single value which is the outcome of one component C_i . It is noted that the convolution filter is of the same dimensionality q to capture a entire word vector of the input matrix. One feature map M can be represented as,

$$M_i = [C_1, C_2, \cdots, C_{n-p+1}] \tag{3}$$

The above procedure construct only one feature map. To build a developed representation of the input, a set of filters with varying window size are used which produce a stack of feature maps (Figure 1). A non-linear activation function is used in each convolutional layer. We apply rectified linear (ReLU) as an activation function in our model.

C. *Pooling*

The output, produced from the convolutional layer, is proceeded to the pooling layer. This layer aggregate the information and reduce the dimensionality of feature maps. The result of the pooling operation is,

$$M_{pool} = [M_1, M_2, \cdots, M_j] \tag{4}$$

Here j is the number of total filters used in convolutional layers. The most popular methods for reduction are max pooling and average pooling. Max pooling has demonstrated faster convergence and better performance compared to the average pooling. The max pooling is used in our model which return the maximum value of every feature map.

D. *Output layer*

The eventual features, produced from the penultimate pooling layer, are passed to a fully connected layer that generate outputs over each aspect. We determine a threshold f and choose all aspects whose predicted value exceed the threshold. We use binary cross entropy loss where output y is defined as $y_i = 1$ when the review has aspect i, otherwise $y_i = 0$.

Aspect extraction is a multi-label classification problem. One review might carry multiple aspects. Previous works [26] use softmax as activation function in the output layer. In softmax function, when the score for one is increased, all others are decreased as it's a probability distribution and then a threshold would be hard to find. Sigmoid activation function is used in our output layer. This non-linear function computes the probability over aspects equally that exists between 0 to 1 which would solve the threshold finding complication.

E. *Regularization*

Multiple non-linear hidden layers are contained in deep neural networks that assist to learn very complicated relationships between inputs and outputs. Overfitting happens when these networks learn limited training data too well that negatively impact the performance on test data. To mitigate the ovefitting issue, we employ dropout [30] on the penultimate layer. Dropout prevents units from co-adapting too much by setting to zero of a portion of hidden units.

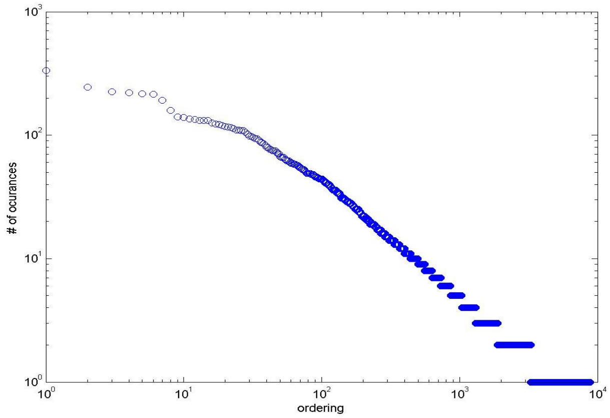

Figure 2. Word frequency of Bangla Cricket dataset using Zipf's law.

টেস্টে সিনিয়র খেলাওয়ারের বিকল্প নেই	other	neutral
বাংলাদেশের ব্যাটিং ভরসার নাম একমাত্র তামিম ইকবাল	batting	positive
মিরপুরে ২য় ইনিংসে পরে ব্যাটিং করা কঠিন আর দলে মোসাদ্দেককে না নেয়াটা বোধহয় ঠিক হয়নি	batting	negative
মিরপুরে ২য় ইনিংসে পরে ব্যাটিং করা কঠিন আর দলে মোসাদ্দেককে না নেয়াটা বোধহয় ঠিক হয়নি	team	negative
সাত জন স্পিনার দিয়ে মাঠে বোতল টানানো যায় ম্যাচ জেতা যায় না	bowling	negative
শুভকামনা টাইগারদের জন্য।	team	positive
টারনিং পিচ বানিয়ে ওষুধ খুজে লাভ কি বাউন্সি পিচ বানালেই হয় ।	team management	negative
এটা পুরা দমে ফিক্সিং একটা খেলা হইসে।	team	negative
জয় শুধু সময়ের অপেক্ষা	other	positive

Figure 3. A portion from cricket dataset

IV. Experiments

This section is divided into two parts: data collection and result discussion. Data collection includes the process of collecting and annotating our proposed datasets. In the next subsection, the result and discussion of our model on the datasets are presented.

A. *Data Collection*

We created two datasets from two different domains named cricket dataset and restaurant dataset. Nowadays the cricket is the most popular game in Bangladesh. People share their opinions in Bangla on cricket more than other issues. Therefore we choose to collect opinions of people from cricket domain. On the other hand, English restaurant dataset is the benchmark dataset which is used by almost all researchers in the field of aspect based sentiment analysis. The collection and annotation process of the datasets are presented in the following.

*1) **Cricket Dataset**:* We collected Bangla user comments manually on the topic of cricket from two popular facebook pages [2]. People usually comments in Bangla under a cricket related post. Only Bangla comments were collect from those post. However, English comments and Bangla sentences written in English alphabet are also found. Again, some comments contain only emoticons. These kind of comments are not considered for our dataset. We applied Zipf's law [31] on the Cricket dataset. Figure 2 shows that our cricket dataset follows Zipf's law.

After completing the collection process, the dataset was annotated individually by the authors and a group of undergraduate students from IIT in University of Dhaka. Five aspect categories were selected which are bowling, batting, team, team management and other. The polarity is divided into three classes i.e, positive, negative and neutral. Every comment was annotated by each participant. We calculated the majority voting to choose the final aspect category and the polarity of a comment. A part of the cricket dataset is given in Figure 3. The summary of the Cricket dataset are mentioned in table I.

[2]https://www.facebook.com/BBCBengaliService and https://www.facebook.com/DailyProthomAlo

আমি এটা পছন্দ করি এবং শীঘ্রই ফিরে আসতে হবে	miscellaneous	positive
সর্বদা একটি সুন্দর ভিড়, কিন্তু কোন কোলাহল নেই।	ambience	positive
আমার বার্গার মোটেই রান্না করা হয়নি, আমার বন্ধুর চিকেনটা সম্পূর্ণরূপে কাঁচা ছিল।	food	negative
এই সেবাটি সুন্দর, কখনও কখনও সত্যিই বন্ধুত্বপূর্ণ	service	positive
সজ্জা অল্পস্বল্প এবং পরিষ্কার - প্রশংসনীয়	ambience	positive
তার পানীয় খুব উদ্ভাবনী শক্তিসম্পন্ন , সুস্বাদু এবং উত্কৃষ্ট।	food	positive
অত্যন্ত ভাল খাদ্য, তবে মূল্য বেশি।	food	positive
অত্যন্ত ভাল খাদ্য, তবে মূল্য বেশি।	price	negative
এটা আপনার এলাকার খাবারের মত গ্রহণযোগ্য নয়।	miscellaneous	neutral
মজাদার পিজা বিশেষ করে মার্গারিটা স্লাইস	food	positive

Figure 4. A portion from restaurant dataset

TABLE I
The summary of Cricket Dataset

Aspect Category	Polarity			Total
	Positive	Negative	Neutral	
Bowling	150	144	33	327
Batting	136	385	55	576
Team	165	490	66	721
Team Management	24	290	15	329
Other	89	820	96	1005
Total Comments				2958

*2) **Restaurant Dataset**:* We created Bangla restaurant dataset from the English benchmark dataset [4] by abstract translation. The same participants were engaged to translate of this dataset. The same annotation process has been con-sidered in which 5 types of aspect categories i.e, food, price, service, ambiance and miscellaneous. There were four types of polarities in the original dataset i.e., positive, negative, neutral and conflict. We merged the conflict category with neutral in our translated Bangla dataset. A part of the restaurant dataset is given in Figure 4. Both cricket and restaurant datasets are provided in xlsx file format. The summary of the restaurant dataset is presented in table II

Some popular machine learning models are applied to compare with our proposed model. After removing punctuations and stop words, a TF-IDF (Term Frequency – Inverse Document Frequency) feature matrix has been created to learn the following models:

1) Support Vector Machine (SVM)
2) Random Forest (RF)
3) K-Nearest Neighbor (KNN)

TABLE II
THE SUMMARY OF RESTAURANT DATASET

Aspect Category	Polarity			Total
	Positive	Negative	Neutral	
Food	495	125	87	707
Price	98	60	16	174
Ambiance	135	53	43	231
Service	185	115	32	332
Miscellaneous	298	118	193	609
Total Reviews				2053

TABLE III
THE EXPERIMENTED RESULT USING OUR DATASETS

Dataset	Model	Precision	Recall	F1-score
Cricket	Proposed-CNN	0.54	**0.48**	**0.51**
	SVM	**0.71**	0.22	0.34
	RF	0.60	0.27	0.37
	KNN	0.45	0.21	0.35
Restaurant	Proposed-CNN	0.67	**0.61**	**0.64**
	SVM	**0.77**	0.30	0.38
	RF	0.69	0.31	0.38
	KNN	0.54	0.34	0.42

B. *Result and Discussion*

Table III shows the experimental results on our created datasets using the proposed CNN model along with other conventional approaches. Our model shows significant recall and F1 score for both datasets. Though precision rate is higher in SVM, the proposed CNN shows the highest recall rate by big margin for both datasets. Recall rate indicates the higher learning rate for CNN than other approaches. From the result, we can say that our model identifies more aspect categories than popular machine learning approaches. It is clear from Table III that for most of the cases the precision and recall rate shows different results. For this reason, we calculated F1 score which is the harmonic mean of precision and recall. The proposed CNN achieved the highest F1 score in both datasets. Cricket dataset show 51% F1-scores whereas Restaurant dataset shows 64% scores.

Figure 5 shows the overall accuracy on both datasets. Proposed CNN model shows the significant level of accuracy for both datasets. For Cricket dataset we got 81% accuracy whereas classification using SVM, RF and KNN shows only 19%, 25% and 22% respectively. Again Restaurant dataset shows 83% accuracy using the proposed CNN whereas SVM, RF and KNN shows only 29%, 30% and 32% accuracy respectively. So, in terms of accuracy we can say that use of Convolutional Neural Network in aspect extraction is the best option for these two proposed Bangla datasets.

We can see from the result that the performances of the models are lower in both datasets. Different people think differently as well as they share their opinion from numerous dimension. Therefore, too much diversity of opinion might be the reason behind lower performance. On the other hand,

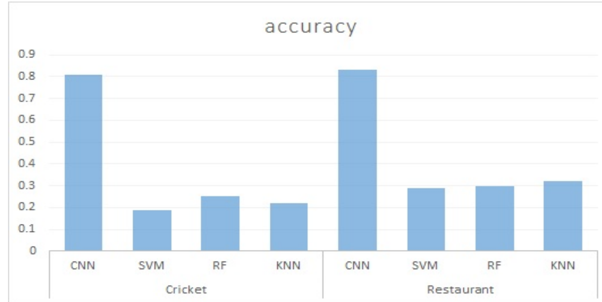

Figure 5. The comparison using accuracy measurement

One's review or comment might have multiple aspect categories. Some of those aspect categories are missed by the conventional classifiers.

One of our dataset named cricket dataset is collected from user comments in Facebook pages. In cricket related posts, some user share their comments about out of cricket domain i.e. about politics or personal matter of cricket players. These kind of comments can't be categorized properly within selected five aspect categories. These comments are included in our dataset as 'other' aspect category which may reduce the quality of the dataset.

V. CONCLUSION AND FUTURE WORK

In Bangla language, we provided two datasets in the field of Aspect Based Sentiment Analysis (ABSA). The first dataset named cricket dataset is created with user comments from cricket related post in Facebook pages. The second dataset consists of restaurant reviews which is collected from English benchmark dataset. These datasets are intended to perform two task which are extraction of aspect category and identification of polarity.

We proposed a model for aspect category extraction based on CNN architecture. we initilized random numbers to generate matrix for convolutional layer in the CNN model. We compared our model with popular machine learning approaches using our proposed datasets. Our experimental result shows convincing performance compared to other models.

Use of pretrained word vectors instead of random initialization might enhance the performance of our model. We are working on Bangla word embeddings for better initialization in the CNN model. As future work, we aim to connect sentiments with the corresponding aspects to complete the objective of Aspect Based Sentiment Analysis.

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