Aspect Based Sentiment Analysis in Bangla Dataset Based on Aspect Term Extraction

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Abstract. Recent years have seen rapid growth of research on sentiment analysis. In aspect-based sentiment analysis, the idea is to take sentiment analysis a step further and find out what exactly someone is talking about, and then measuring the sentiment if she or he likes or dislikes it. Sentiment analysis in Bengali language is progressing and is considered as an important research interest. Due to scarcity of resources like proper annotated dataset, corpora, lexicon such as part of speech tagger etc. aspect-based sentiment analysis hardly has been done in Bengali language. In this paper, we have conducted our experiments based on a recent work from 2018 using conventional supervised machine learning algorithms (RF, SVM, KNN) to perform one of the ABSA's tasks - aspect category extraction. The work is done on two datasets named – *Cricket* and *Restaurant*. We then compared our results with the existing work. We used two traditional steps to clean data and found that less preprocessing leads to better F1 Score. For Cricket dataset, SVM and KNN performed better, resulting F1 score of 37% and 27%. For Restaurant dataset, RF and SVM achieved improved score of 35% and 39% respectively. Additionally, we selected two more algorithms LR and NB, LR achieved best F1 score (43%) for Restaurant dataset among all.

Keywords: Supervised machine learning · Sentiment analysis · Aspect Based Sentiment Analysis (ABSA) · ABSA dataset in Bangla · Aspect category extraction

1 Introduction

We are in the age of internet where every day we generate over 2.5 quintillion of data [1] and sentiment analysis has become one of the key tools for making sense of these user generated data. Sentiment Analysis (SA) (or Opinion Mining) is a field regarding NLP (Natural Language Processing) that builds systems which generally tries to extract

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opinions within text in natural language understanding [2]. Even SA has occupied a wide area in the real-world applications and both business importance and academic interest [3]. The typical sentiment analysis generally focuses on predicting the overall polarity (positive or negative or neutral) of the given sentence.

If we imagine having a large dataset that contains feedbacks of customers from various sources like social media, online reviews or customer's online surveys. e.g. "Food is decent but service is so bad", it is evident that the sentiment towards food is positive however contains a powerful negative sentiment towards facet service. So, after classifying the overall sentiment, existence of a strong negative sentiment would neglect the positive fact that food was actually good [3]. But to make the information more helpful and get a complete picture, the nitty-gritty of each feedback must be retrieved. To solve this issue Aspect Based Sentiment Analysis (ABSA) comes up being an advanced tool to make it possible to analyze these reviews and predict opinions not only for an overall feedback, but also on an aspect-level [4].

ABSA task has been added since 2014 in the annual SemEval (Semantic Evaluation, a reputed workshop in the NLP domain) competition [3]. SemEval has introduced a complete dataset in English for the ABSA task and later they expanded it in multi-lingual datasets in which eight languages over seven domains were included [5]. Datasets of several languages, such as Arabic, Czech, and French were created to perform ABSA. Moreover, there are plenty of powerful libraries like NLTK, Textblob and Spacy that have become major part while performing SA or ABSA. Also, they've published benchmark datasets Restaurant and Laptop [6] with gold annotations.

In SemEval 2014 [7] ABSA's task was divided into four subtasks-

Aspect term Extraction - An aspect term refers to a particular aspect of the target entity [8]. Aspect term extraction is returning a list containing all distinct aspect terms from a set of sentences with pre-identified entities (E) e.g., (restaurants; laptop) by identifying the aspect terms e.g. (delicious; hard-disk).

Aspect Term Polarity - From a given set of aspect terms within a sentence, determining whether the polarity of each aspect term is positive, negative, neutral or conflict [8].

Aspect Category Detection - From a predefined set of aspect categories e.g. (food, display), identifying the aspect categories discussed in a given sentence [8]. Aspect categories are typically crude comparing with the aspect terms of and they do not necessarily occur as terms in the given sentence.

Aspect Category Polarity - From a set of pre-identified aspect categories e.g. (food; display), determine the polarity (positive, negative, neutral or conflict) of each aspect [8].

While performing ABSA, it involves around two crucial tasks – 1) extracting the specific areas or aspects, 2) identifying the polarity for every aspect. As one sentence or review might contain different polarities [5], an overall decision will not be beneficial every time. Aspect extraction is necessary to first deconstruct sentences into product features and after the task is done only then assign a separate polarity value to each of these features. There are several approaches in previous studies that has already been developed to perform ABSA in English and some other languages that includes supervised, semi supervised, unsupervised approaches, rule-based approaches and more. Most of the approaches were machine learning centric [3, 9].

In early 2010 ABSA was introduced as a framework titled "aspect-based sentiment analysis" [10] address the problem of getting only the overall sentiment from a sentence where aspect refers to a component or attribute of an entity.

One of the first studies for both explicit and implicit aspects extraction from product reviews, proposed a rule-based approach [11]. Two popular review datasets (Restaurant and Laptop) were used for evaluating the system where the proposed framework achieved highest precision of 94.15% among their five kind of review categories.

In SemEval 2014 ABSA's task is divided into before mentioned four subtasks [7]. Also, they've published benchmark datasets Restaurant and Laptop with gold annotation [6]. With continuation of SemEval 2014, in 2015 an aspect category extraction was modeled as a multiclass classification problem with features based on n-grams, parsing, and word clusters. SVM with a linear kernel was trained for category extraction [4]. The highest F-1 scores in both datasets are 50.86% and 62.68% respectively.

In another work CNN has been adopted in work of Wang's aspect-based sentiment analysis [3]. They have introduced a combined model with aspect prediction and sentiment prediction that left behind the highest scores achieved by the wining team in SemEval 2015. There F1 score was 51.3%.

Above discussed reviews are done regarding English language. If we highlight some other languages for ABSA then language, Arabic [12], Czech [13], French [14], Hindi [15] can be mentioned. Czech language is progressing very successfully in ABSA and several label corpora has been built both for supervise and unsupervised training, morphological tools and lexicons. For aspect term extraction both rule-based and machine learning algorithms were applied on the new dataset that consists of segments from user reviews of IT products [13]. 65.70% and 30.27% F1 score were achieved for short-term and long-term reviews. In another work the authors introduced two new corpora in Czech language to attempt ABSA for both supervised and unsupervised training [16]. The four subtasks of ABSA have been done where word clusters are created and used as features. F1 score came out of 71.4% and 71.7% for aspect term and aspect category extraction.

Regarding Hindi language a new dataset has introduced that includes several domains [15]. CRF and SVM are used for aspect term extraction and sentiment analysis. The average F1-score is 41.07% for aspect term extraction and accuracy is 54.05% for sentiment classification.

Bengali is the 7th most spoken languages in the world [17]. People are using it frequently over the social media for expressing reviews, sentiments or feedbacks. But there is no proper dataset available and very few works have been done regarding ABSA. Very recently in 2018, an annotated dataset to perform ABSA has been published in Bengali language where the authors have "extracted aspects", one of the SemEval 2014 tasks [5, 7]. The dataset contains two domains - Cricket and Restaurant. SVM, RF and KNN classifiers has been used and highest F1 score of 34% and 42% has been achieved from Cricket and Restaurant domains. Bengali language is far behind and remains un-explored due to very less availability and lack of various resources and tools such as annotated corpora, lexicons, Part-of-Speech (PoS) tagger etc. that plays vital role while performing ABSA. Therefore, the concentration of this paper is to use the annotated dataset from [5] and perform ABSA's aspect extraction task to take ahead the possibilities of ABSA's aspect category extraction in Bengali language. We have used supervised machine learning algorithms SVM, RF, KNN, LR, and NB. We have also compared our results with the previous work by [5] (Table 1).

Table 1. Example of aspect based sentiment analysis (cricket & restaurant dataset)

	Review Text	Aspect Category	Polarity
Original Text	বোলাররা যে পরিমানে শর্ট বল দিচ্ছে তাতে রান কত বেশি হয় সেটাই দেখার বিষয়	**Bowling**	**Negative**
Translated	It is a matter of watching how much runs the bowler is making in the short ball	**Bowling**	**Negative**
Original Text	যদিও খাদ্য ভালো ছিল পরিবেশনা ছিল বিশ্রী	**Service**	**Negative**
Translated	Although the food was good, the serving was awkward	**Service**	**Negative**

Rest of the paper is organised as follows: Sect. 2 presents the proposed model, Sect. 3 depicts the experimental results and discusses on the major findings based on the experimental results. Finally, Sect. 4 concludes the paper with future research leads with some future indications.

2 Methodology

The methodology proposed on this paper is divided into following sections: data collection, data preprocessing, data analysis and visualizing the outcome. The proposed model of this research is shown in Fig. 1 where the steps are introduced respectively.

2.1 Dataset Collection

We have used the datasets created for ABSA and specially designed for aspect term and polarity extraction for the first time in Bengali [5] by Md. A.R and Emon K.D, 2018 (https://github.com/AtikRahman/Bangla_ABSA_Datasets). The two different datasets, are named, Cricket dataset and Restaurant dataset.

Cricket dataset consists of human-annotated user comments with five different aspect categories - bowling, batting, team, team management, and other. On the other hand, Restaurant dataset is an abstractly translated in Bengali form of the SemEval 2014's

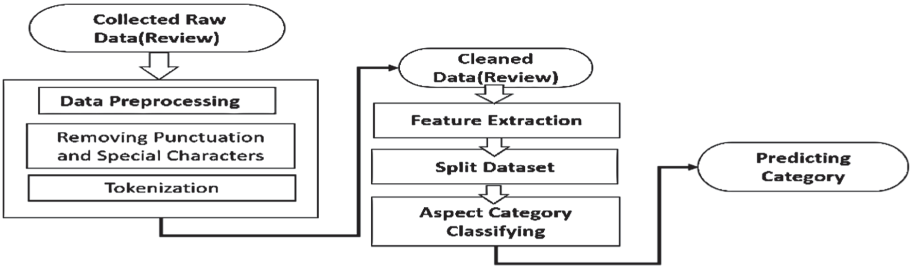

Fig. 1. Proposed model for aspect based sentiment analysis

English dataset [4], consisting five aspect categories-Food, Price, Service, Ambiance, and Miscellaneous. To make the overall of understanding of the datasets (Cricket and Restaurant) a complete statistic has been presented in Table 2.

Table 2. Overall statistics of both datasets

Dataset	No. of reviews	Aspect category	Polarity
Cricket	2979	Batting Bowling Team management Other	Positive (19%) Negative (72%) Conflict (9%)
Restaurant	2059	Food Price Service Ambiance Miscellaneous	Positive (59%) Negative (23%) Conflict (12%) Neutral (6%)

2.2 Data Preprocessing

Data preprocessing plays a vital role on text analysis to make the model understand the data. Text data contains a lot of noise and as a result, it's a challenge to clean the texts. Data pre-processing reduces the size of the input text documents significantly and is done by various steps:

1) ***Removing special characters:*** Removed the special characters as they sometime create confusion, we feel in these kind of Bengali datasets special characters will lead to complexity for classification.
2) ***Removing punctuations:*** One of the very popular and often applied preprocessing is removing punctuations. Even the full-stop "." in Bengali language refers to "।" sign. So, we have removed punctuations.

2.3 Feature Extraction

We have represented reviews (texts) into numeric form to use them as features. The process is stated here:

BOW - For training the statistical algorithms using machine learning, the dataset should be in numeric form. We have first converted the texts into numbers in order to make these statistical algorithms work. Bag of words is one of the approaches that helps to do so. It is a representation of text that reflects the occurrence of words within a document [18].

TF-IDF - It is almost a similar approach like BOW but has little different idea behind it. It is evident that it has two terms, where TF (Term Frequency) refers to the number of times a word occurs in a document and IDF (Inverse Document Frequency) refers to how important the word is in the document [19]. The equation for TF and IDF given bellow-

$$\mathbf{TF}(\mathbf{t}) = (\text{Number of times term t appears in a document}) \big/ (\text{Total number of terms in the document})$$

$$\mathbf{IDF}(\mathbf{t}) = \text{log\_e (Total number of documents} \big/ \text{Number of documents with term t in it)}.$$

We have used sklearn library [20] that contains the TFiDfVectorizer class which has been used to convert the features into TF-IDF feature vectors. We have set the limitation of maximum features to 2500. It only uses the 2500 most frequently occurring words to create BOW feature vector. For classification we have passed the known label corresponding to the review (Table 3).

Table 3. Sample Bengali pre-processed data

Original Review	সময় বাংলাদেশের ভাগ্য ড্র রেখেছে, নাহয় হার চাড়া উপায় ছিলোনা.!!
Processed Review	সময় বাংলাদেশের ভাগ্য ড্র রেখেছে নাহয় হার চাড়া উপায় ছিলোনা
Tokenization	‘সময়’ ‘বাংলাদেশের’ ‘ভাগ্য’ ‘ড্র’ ‘রেখেছে’ ‘নাহয়’ ‘হার’ ‘চাড়া’ ‘উপায়’ ‘ছিলোনা’
Uni-gram	সময়’ ‘বাংলাদেশের’.‘ভাগ্য’ ‘ড্র’ ‘রেখেছে’ ‘নাহয়’ ‘হার’ ‘চাড়া’ ‘উপায়’ ‘ছিলোনা’

2.4 Fitting Algorithm to Train

Finding a well-performing machine learning algorithm for a particular dataset is a challenging task. We went through "Trial and Error" process to determine a sufficient list of algorithms that works on these datasets. We studied several algorithms that has been using for ABSA [5, 7, 21–23]. Finally, we have selected frequently used following algorithms for classifying-

1. As we want to compare result with [5] we used same algorithms SVM (Support vector machine), RF (Random Forest) and KNN (K-Nearest Neighbor)
2. Algorithms not used in [5], LR (Logistic Regression) and NB (Naïve Bayes).

Logistic Regression (LR) is an appropriate regression analysis to act on dichotomous variable (binary variable). To describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal even interval level independent variables we have used logistic regression [24].

On the contrary, Naive Bayes classifier is surprisingly a powerful algorithm for predictive modeling. We selected NB as it has often been used in sentiment analysis as it remains less affected by data scarcity and text classification tasks [25, 26].

2.5 Languages and Tools

The system is implemented using Python 3 (Jupyter NoteBook) in Anaconda. The Python modules skLearn - which provides a set of modules for machine learning and data mining [16] is used. For NLP tasks NLTK (A leading platform for building Python programs and rich with libraries to perform NLP tasks [27]) has been used.

3 Results and Discussion

3.1 Split Dataset

Working with supervised machine learning requires the dataset to be split into two parts, training set and testing set. In this work the data split has been done by a split function named Train_test_split function which is imported from scikit-learn library [16]. We used 80% of dataset for training and 20% for testing.

3.2 Aspect Category Classifying

We have provided the experimental average results of precision, recall, and F1 score for the classification task using supervised machine learning algorithms SVM, RF, KNN, LR and NB, calculating from both of the dataset's different aspect categories, in Table 4. To represent the results, precision, recall and F1-score terms have been used and the measurements are done using four parameters - true positive (tp), true negative (tn), false positive (fp) and false negative (fn).

Table 4 denotes the overall confusion matrix of the experimental results for aspect category extraction using RF, SVM, KNN, LR and NB for both Cricket and Restaurant

Table 4. Results experiments using RF, SVM, KNN, LR & NB

Dataset	Algorithm	Precision	Recall	F1 score
Cricket	RF	0.39	0.36	**0.37**
	SVM	0.40	0.35	0.35
	KNN	0.27	0.27	0.27
	LR	0.41	0.34	0.34
	NB	0.23	0.27	0.18
Restaurant	RF	0.70	0.27	0.35
	SVM	0.79	0.30	0.39
	KNN	0.39	0.38	0.38
	LR	0.42	0.43	**0.43**
	NB	0.25	0.26	0.17

datasets. From this the experimental results can be depicted from five algorithms performed on Cricket and Restaurant dataset. For Cricket dataset, the precision rate from Logistic regression is highest, which is 41%, and the recall rate from Random Forest is highest, 36%. As in this particular problem for aspect category extraction, both precision and recall are important, thus, we can see Random Forest has given the highest F-1 score, 37%.

Similarly, for the Restaurant dataset, both Logistic Regression provided the highest precision score, 42% and recall score 43% resulting highest F-1 score of 43%. The other algorithms such as RF, SVM and KNN also performed well with F1-Score of 35%, 39% and 38%.

For both of the Cricket and Restaurant dataset, NB algorithm performed significantly low with the F1-Score of 18% and 17%.

It is apparent that in Cricket dataset the scores for RF, LR and SVM are comparatively better in overall. KNN and NB performed less comparative to other algorithms.

Conversely, in the case of Restaurant dataset results, SVM, and LR provided the highest result for the Restaurant dataset.

Table 5 and Table 6 shows the comparison among our experimental results and the results achieved from [5] for both cricket and restaurant dataset on different algorithms. For Cricket dataset, the F1 score from our experiment is 35% from SVM and 27% from KNN resulting higher score than [5], where the previous results for both algorithms were 34% and 25% respectively. However, RF provided same result as [5], which is 37%.

From Table 5, the results for restaurant dataset can be outlined. SVM and RF algorithms has given better F1 Score than previous one, 39% and 35%, where the previous results were 38% and 33% for these algorithms. In this case, KNN performed less than the previous one resulting F1 score of 38%, lower than 42%.

From the experimental results and discussions we can conclude that our experiments have provided improved results than the previous work [5] and we have eliminated some preprocessing steps. As a result this less preprocessing leads to better F1 score in both dataset. Aspect category extraction is a multi-label classification problem [5] where one opinion might carry several categories. Hence, our supervised classifiers might skip some

Table 5. Model performance comparison of cricket dataset

Model	Precision (previous result)	Precision (our result)	Recall (previous result)	Recall (our result)	F1 score (previous result)	F1 score (our result)
SVM	.71	.40	0.22	0.35	0.34	0.35
KNN	.45	.27	0.21	0.27	0.25	0.27
RF	.60	.39	0.27	0.36	0.37	0.37

Table 6. Model performance comparison for restaurant dataset

Model	Precision (previous result)	Precision (our result)	Recall (previous result)	Recall (our result)	F1 score (previous result)	F1 score (our result)
SVM	0.77	0.79	0.30	0.30	0.38	0.39
KNN	0.54	0.39	0.34	0.38	0.42	0.38
RF	0.64	0.70	0.26	0.27	0.33	0.35

of these aspect categories. Better results can be attained, if we can train the datasets in more advanced way using POS tagging.

4 Conclusions and Recommendations

In this study we have used conventional supervised aspect category model of machine learning with less preprocessing. We used two traditional steps to clean data and achieved better results comparing ABSA Bangla dataset's paper for both of the dataset. The advanced researchers use better and detailed dataset for ABSA these days which results high accuracy. More detailed annotated dataset like SemEval for Bengali language can lead to impressive results.

Moreover, sentiment analysis is getting popular for spam review/comment detection and fraud app detection these days. So, increasing research with more non-English languages and aspects can lead to more precise notion about users and their reviews that can help to make better business decision as well as improve cyber security.

Besides, unsupervised approaches have been seen to build good enough impact on ABSA even in different language like Czech. However, in this trend, very effective deep learning powerful neural networks model can lead to more satisfying work and results in ABSA proven in the paper comparing with SemEval 2015 task. In future, we would like to explore more advanced techniques of deep learning (CNN) applied in NLP for ABSA for both aspect category and sentiment analysis extraction. Also, we would like to use Bangla POS tagger to train model in aspect term extraction and train classifier with more preprocessing steps.

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