

Toward a multitask aspect-based sentiment analysis model using deep learning

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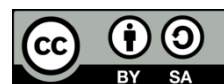
Part-of-speech tag

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ABSTRACT

Sentiment analysis or opinion mining is used to understand the community's opinions on a particular product. This is a system of selection and classification of opinions on sentences or documents. At a more detailed level, aspect-based sentiment analysis makes an effort to extract and categorize sentiments on aspects of entities in opinion text. In this paper, we propose a novel supervised learning approach using deep learning techniques for a multitasking aspect-based opinion mining system that supports four main subtasks: extract opinion target, classify aspect, classify entity (category) and estimate opinion polarity (positive, neutral, negative) on each extracted aspect of the entity. We have used a part-of-speech (POS) layer to define the words' morphological features integrated with GloVe word embedding in the previous layer and fed to the convolutional neural network_bidirectional long-short term memory (CNN_BiLSTM) stacked construction to improve the model's accuracy in the opinion classification process and related tasks. Our multitasking aspect-based sentiment analysis experiments on the dataset of SemEval 2016 showed that our proposed models have obtained and categorized core tasks mentioned above simultaneously and attained considerably better accurateness than the advanced researches.

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1. INTRODUCTION

Collecting customer feedback is a great way for businesses to understand the strengths and weaknesses of their products and services and quickly grasp the psychology and needs of customers to bring them the most perfect products and services. This collection requires an automatic opinion understanding, exploration, and analysis system. Traditional opinion mining systems mainly focus on identifying opinions in sentences or entire documents. This leads to a drawback: the defined sentiment polarity is general to the whole text. However, in some cases, users will express their personal views on each aspect of the entity mentioned rather than stating their opinions on the whole text. Aspect-based sentiment analysis (ABSA) with the target to categorize opinion represented on each extracted aspect of the entity in opinion text is an efficient resolution for this trouble. Most recent sentiment analysis researches have focused on one of two main approaches [1]: (i) based on lexicon and (ii) based on machine learning.

In (i) measures are used to estimate the text's sentiment orientation based on the words' sentiment tendency identified on the degree of correlation between opinion words in the opinion corpus and the data. Some of the studies illustrate this approach. Khan *et al.* [2], [3] applied WordNet and SentiWordNet to calculate semantic scores of words in the sentences. Estimating the adjectives' opinion orientation based upon seed word lists was exploited by [4], [5]. Likewise, [6] identified the opinion of review sentences through the average opinion tendency of word phrases in opinion text with pointwise mutual information (PMI) and latent semantic analysis (LSA) stood on the association with positive or negative seed word lists. A thesaurus was created by [7] to build the sentiment polarity specified system to opinion text. The syntactic interrelation between sentiment and target word with sentiment seed word list in [8] was applied to obtain sentiments and target words simultaneously. According [9] extracted aspect and detected the opinion orientation by using mutual information measurement and Naive Bayes.

Opinion mining formed on (ii) was as well attracted at a recent time. In this approach, a set of techniques for classification are applied for categorizing opinion documents, detecting sentiment with a supervised learning mechanism on the two labeled datasets: training and testing set or unsupervised learning mechanism on the unlabeled data. In [10] used hidden markov model (HMM) for learning patterns to extricate aspects and opinion phrases in web opinion mining. In [11] extracted opinion target words in the document by using the conditional random field (CRF) technique. In [12] also applied the same CRF with two integrated modifications for obtaining and classifying aspects and opinions. Support vector machine (SVM) technique was used in [13] to extract opinion target words and classify the opinion polarity corresponding to each aspect. The three deep learning techniques recursive neural network, matrix-vector recursive neural network, and recursive neural tensor network were combined in one graded groundwork in [14] for extracting aspects and sentiment. A recursive neural network expansion in [15] with the received syntactical material from diagrams of dependency and component in opinion sentence was applied to classify the opinion of each aspect in text. In [16] used convolutional neural network (CNN) and the two variant models of CNN: parameterized filters for CNN and parameterized gated CNN to effectively achieve aspect-specific features for enhancing the accuracy of their model. In [17] used a recurrent neural network (RNN) variant to identify the opinion depended on target and context word in the sentence. Also with this context-based approach, evaluated the valuable level of context word aimed at their aspect-based sentiment analysis based on a neural attention architecture [18]. A method of continuous word embedding was used by [19] with the extraneural layer in their model to extract features and sentiments simultaneously. In [20] made use of the combination of RNN and CRF to identify aspects and sentiments. In [21], [22] applied effective attention techniques for aspect-based sentiment analysis (ABSA) but [21] focused on the content while [22] used a model of long short-term memory (LSTM) that based attention technique for putting mind to capture semantic and syntactic material to get the aspect's necessary information for sentiment analysis. In [23] also used LSTM accompanying attention mechanism for taking the vital portions related to aspects in the sentence help to classify the opinion in ABSA. In [24] found the sentiment of each aspect in opinion text employing multiple attention control mechanisms on memory in a recurrent attention network. Our previous approaches in [25], [26] recommended the two models with the integration of CRF and RNN variants: gated recurrent unit (GRU) and IndyLSTM. We made the best use of the two-way mechanism for BiGRU and Bi-IndyLSTM to classify aspects proficiently. The incorporation of convolutional layers in CNN and the independent operation structure of gates was used in [27] and got good results in ABSA.

Within the scope of this research, we offer to utilize the deep learning approach with the combined construction of CNN and bidirectional long-short term memory (BiLSTM) for multitasking ABSA model to extract and classify opinion target, aspect, entity and sentiment polarity concurrently. We decide to develop this model because of the subsequent details: CNN is capable of extracting local features based on convolutional kernel architecture with different sizes. Besides, LSTM has the capability to maintain memory in the long-term cycle and resolve the gradient vanishing and exploding concern to well handle long sequences. Through experimentation, the results obtained from our proposed ABSA model exhibit superior performance compared to previous models on the same dataset. Specifically, our approach has reached enhanced exactness on (i) two measures F1 and accuracy in terms of opinion target extraction task and (ii) four measures F1, accuracy, precision and recall on the aspect, category and sentiment classification task.

We set up the layout of this paper for the rest in such a way. Section 2 illustrates our proposed approach with the two models: deep CNN_IJOB2 model for extracting opinion target and MABSA model for classifying the remaining aspect, entity and sentiment polarity components. Our experimentations and argument about obtained products are shown in section 3. In summary, section 4 emphasizes our assumption and potential study tendency.

2. METHOD

We propose two combined models: a Deep CNN-IOB2 and a MABSA model supported to main subtasks in ABSA. Our use of the CNN [28], [29] in combination with BiLSTM aims to take advantage of both CNN's good local feature extraction proficiency and BiLSTM's ability to learn long-distance representations in both dimensions for better mastering the sentence context. LSTM [17] is a better version of RNN with the ability to learn long-term dependencies without having problems with vanishing and exploding gradients [30] like RNN. Additionally, using softmax at the last layer in the model acts as a classifier to identify components concurrently. This incorporated method works for rising model correctness in multitasking accomplishment: opinion target, category, aspect and sentiment classification.

2.1. Convolutional neural network (CNN) and bidirectional long short-term memory (BiLSTM)

Convolutional neural network (CNN) [29] has recently been exploited in natural language processing and triumphed notable successes. In the process of operating with sequences, convolutions take advantage of the competence to mine local features round each token. Each review with length L (n_1, n_2, \dots, n_L) after passing through GloVe word embedding layer and the POS word morphological determination layer is fed to the CNN to extract high-level features

One of the two variants of RNN is LSTM [17] which is suitable for sequential data and solves problems of vanishing and exploding gradients encountered by RNN. With a mechanism of using three gates f_t , i_t , o_t respectively forget, input and output gate, LSTM can filter and decide which information should be forgotten, updated, and outputted. In this paper, we utilized a bidirectional LSTM network to make use of the ability to learn far representations from the current token in both directions. This capability of BiLSTM helps to understand sentence context more clearly and removes information vagueness compared to the unidirectional nature of LSTM.

2.2. Data preprocessing

Data cleaning: some data cleaning operations are performed before word embedding. We detach emojis, uncommon characters, numbers and null sentences; change text to lower-case letter; find and substitute lingo or condensation with replacement (i.e. 'vs.' -> 'versus'); lemmatize words in the sentence into their base form (i.e. 'caring', 'cared' -> 'care'); word embedding: we use pre-trained word vectors from GloVe [31], an unsupervised learning technology, for learning word representation; part-of-speech (POS) tags: to identify the parts of speech of words in the input text, we use the stanford POS tagger; IOB2 tags: to obtain the opinion target word, we use IOB2 tags at the last layer of our Deep CNN-IOB2 model. Labeling B/I/O to each token in input sentence must comply with subsequent instructions: (i) the first word in the phrase is labeled 'B-' or 'O', not 'I-'; (ii) valid label formats must be 'O B-label' or 'B I-label', not 'O I-label'; (iii) each opinion target that can be a word or a phrase will have the first label 'B-' not 'I-'.

2.3. Proposed multitask aspect-based sentiment analysis model

2.3.1. Deep CNN-IOB2 (DCI) model

The GloVe word embedding layer was applied at the first position of our DCI model for encoding the semantically and syntactically related properties of a word in an input sentence with a 300-dimension feature vector. By concatenating with the POS tagger vector in the next layer to determine the parts of speech of the word, we get the 333-dimension feature vector and feed for the next CNN layer. In this paper, we used the three-layer CNN to extract high-level abstract features. The IOB2 architecture in the final layer position was superimposed on CNN layers in Figure 1 to assign B, I, or O to each token for the purpose of achieving the task of opinion target extraction. The labeling process pursues the following rules: B and I are labeled for the opinion target word at the beginning and inner location of the phrase, correspondingly, and O is labeled for the outer word.

2.3.2. Multitask aspect-based sentiment analysis (MABSA) model

Words in input review after being cleaned in the data preprocessing step will be provided to the word embedding and the POS tagger layer to encode into the 333-dimension feature vectors. In this model that can be shown in Figure 2, we still apply the three-layer deep CNN in the next layer for extracting local features around the token under consideration like our DCI model. A BiLSTM used in the succeeding layer supports the ability to learn information from both previous and subsequent directions at long steps away from the current token. Applying the average pooling layer on top of the BiLSTM aims to decrease the dimensionality of word vectors. In the last layer, we exploit a dense with softmax function for computing probability distribution over the possible categories to extract what we are looking for: the category, aspect, and sentiment simultaneously. Both of our models has reached outstanding correctness compared with earlier advanced researches.

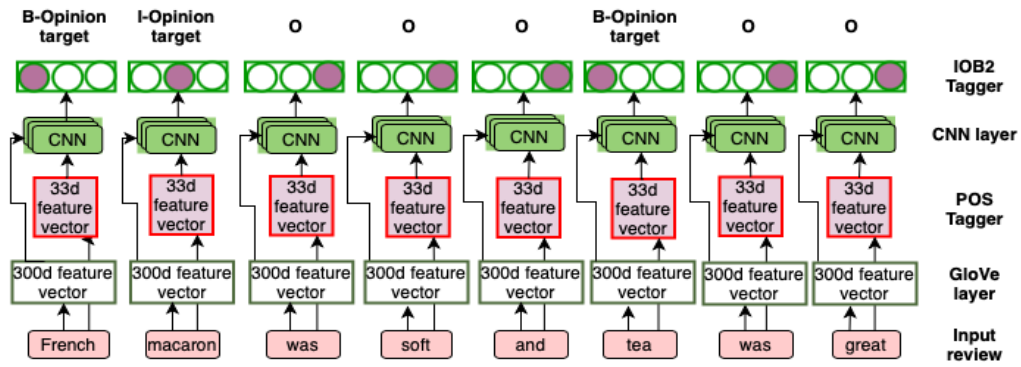


Figure 1. DCI model for extracting opinion target

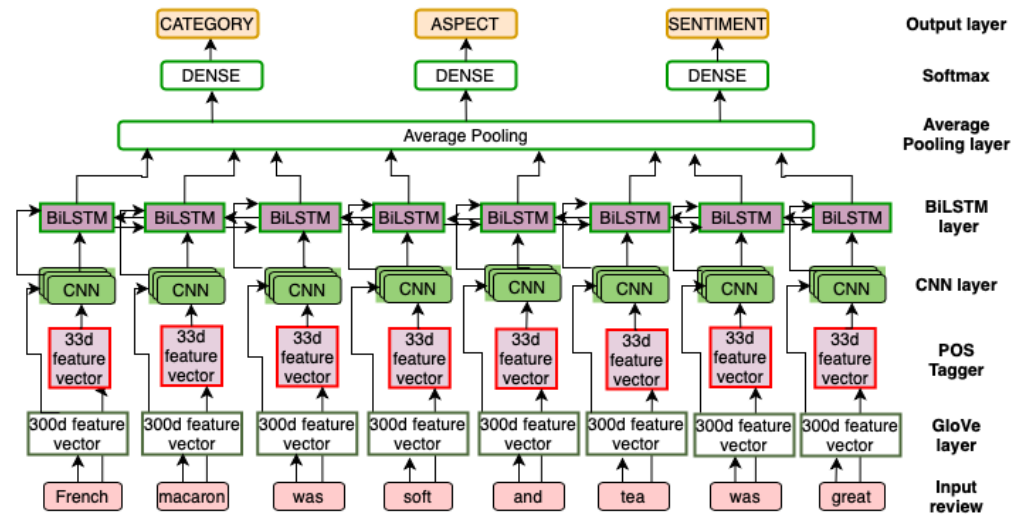


Figure 2. MABSA model for extracting and classifying aspect, category and sentiment

3. RESULTS AND DISCUSSION

We use the SemEval2016 Task 5 benchmark dataset as a corpus for training and evaluation. Our DCI and MABSA models have been experimentalized on the restaurant domain that can be shown in Table 1 and provided significant performance. F1 and Accuracy are the two measures used in our experiments to evaluate the performance of proposed models compared with previous models also experimentalized on the restaurant domain of the SemEval 2016. Each concatenation vector of 300-dimensional GloVe feature vector and POS tagger vector of 33 dimensions corresponding to each word in the input sentence is fed to the next CNN layer.

Table 1. Restaurant domain

Restaurant domain	Sentence	Opinion target
Training	2000	1743
Testing	676	622

CNN will perform the task of extracting high-level features and fed to the next layer of BiLSTM. We use the rmsprop optimizer with a learning rate of 0.001, dropout 0.25, and a batch size of 128 in both DCI and MABSA models. Tables 2 and 3 describe our experimental results on the two proposed models. Our proposed DCI model for extracting opinion target words or phrases of input reviews is evaluated through comparison with the following baseline models also experimentalized on the same benchmark dataset_the SemEval 2016, restaurant domain. Besides, our MABSA model of classifying the remaining subtasks such as category, aspect, and sentiment polarity also achieved remarkable results.

Table 2. Compare the experimental results of our DCI model with baseline models in F1_score and Accuracy_score on the restaurant domain of the SemEval 2016 dataset

Model	Opinion target extraction	
	<i>F1_score</i>	<i>Accuracy_score</i>
NLANGP(U) [32]		
CRF [33]	72.34	-
AUEB [34]	66.54	-
MIN [35]	70.44	-
DE-CNN [36]	73.44	-
THA&STN [37]	74.37	-
BiDTreeCRF [38]	73.61	-
Our DCI model	74.49	-

As can be seen obviously from Table 2, with the task of extracting opinion target words, the DCI model has surpassed the former researches and reached superior performance on both F1 and Accuracy.

- F1_score: Our DCI model achieves 27.62%, 33.42%, 29.52%, 26.52%, 25.59%, 26.35%, 25.47% higher accuracy than previous NLANGP(U), CRF, AUEB, MIN, DE-CNN, THA&STN, BiDTreeCRF models respectively on the same Restaurant domain.
- Accuracy_score: Our model achieves a pretty high result of 99.93%.

The graph from Figure 3 depicts our opinion target extraction model's validation F1, accuracy measure, and loss. Viewing the loss chart from Figure 3, we see that after a drastic decrease for the first five epochs and a slower decline over the next 35 epochs, the loss has been on a stable downward trend since the 40th epoch and reached a steady-state between 100th and 120th epoch. From Figure 4, it is clear that our deep CNN-IOB2 model attains superior results in the two measures F1 and accuracy compared to previous methods.

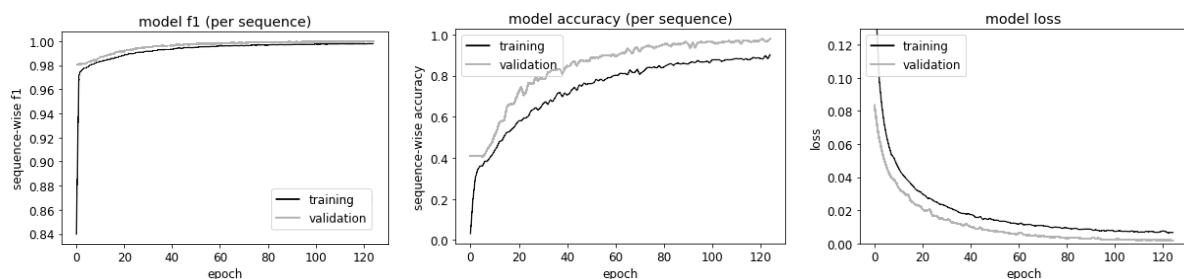


Figure 3. F1, accuracy score and training loss of our deep CNN-IOB2 model

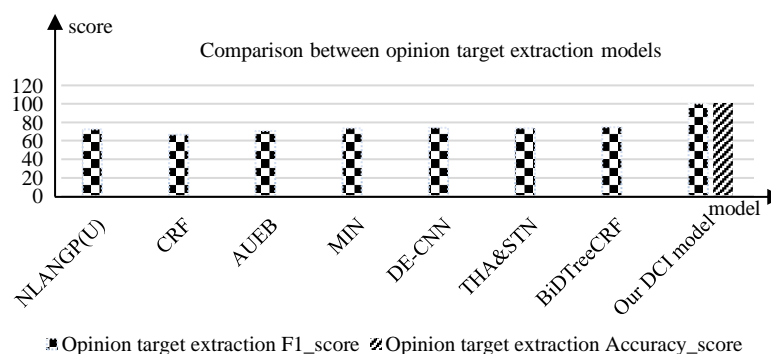


Figure 4. F1, accuracy of previous models and our deep CNN-IOB2 model in opinion target extraction

Similar to the DCI model above for extracting opinion target words, the MABSA model for classifying aspect, category and sentiment has also achieved outstanding results. Specifically, in Table 3, the model's results for category and sentiment classification are really high in the range of 96.58% to nearly 98% on accuracy, precision, recall, and F1. The experiment results of our model for aspect extraction are also relatively high, reaching over 92% on all measures.

Table 3. Experimental results of our MABSA model in accuracy, precision, recall, F1_score on the domain of restaurant

Our MABSA model	Category classification	Aspect extraction	Sentiment polarity classification
<i>Accuracy</i>	97.83	92.39	96.58
<i>Precision</i>	97.97	92.52	97.19
<i>Recall</i>	97.67	92.24	96.58
<i>F1</i>	97.82	92.38	96.88

Figure 5 depicts the performance evaluation of the model in terms of two measures F1 and accuracy. In addition, the last three charts in the group of descriptive charts describe the model's loss. In the category loss chart, after a drastic drop in the first 50 epochs and a stable downward trend from the 50th epoch to the 150th epoch, the loss tends to be steady from the 150th epoch to the last 300th epoch. A similar downtrend is also shown in the aspect loss chart with a sharp decrease in the initial 20 epochs. The downturn will be lighter between the 20th epoch and 120th epoch. From the 120th epoch on, the chart shows a very trivial decrease until the 200th epoch and gradually stabilizes in the last interval. The ultimate chart for polarity loss has a slight difference from the prior two with a deep drop from the 50th epoch to 125th epoch after the first 50 epochs with a negligible decrease. During the period from the 125th to the 175th epoch, the chart tends to decrease slightly, repeat as at the beginning and stabilizes after the 200th epoch. As is illustrated by the chart in Figure 6, our MABSA model for the remaining tasks achieves high performance in the four measures of precision, recall, F1, and accuracy.

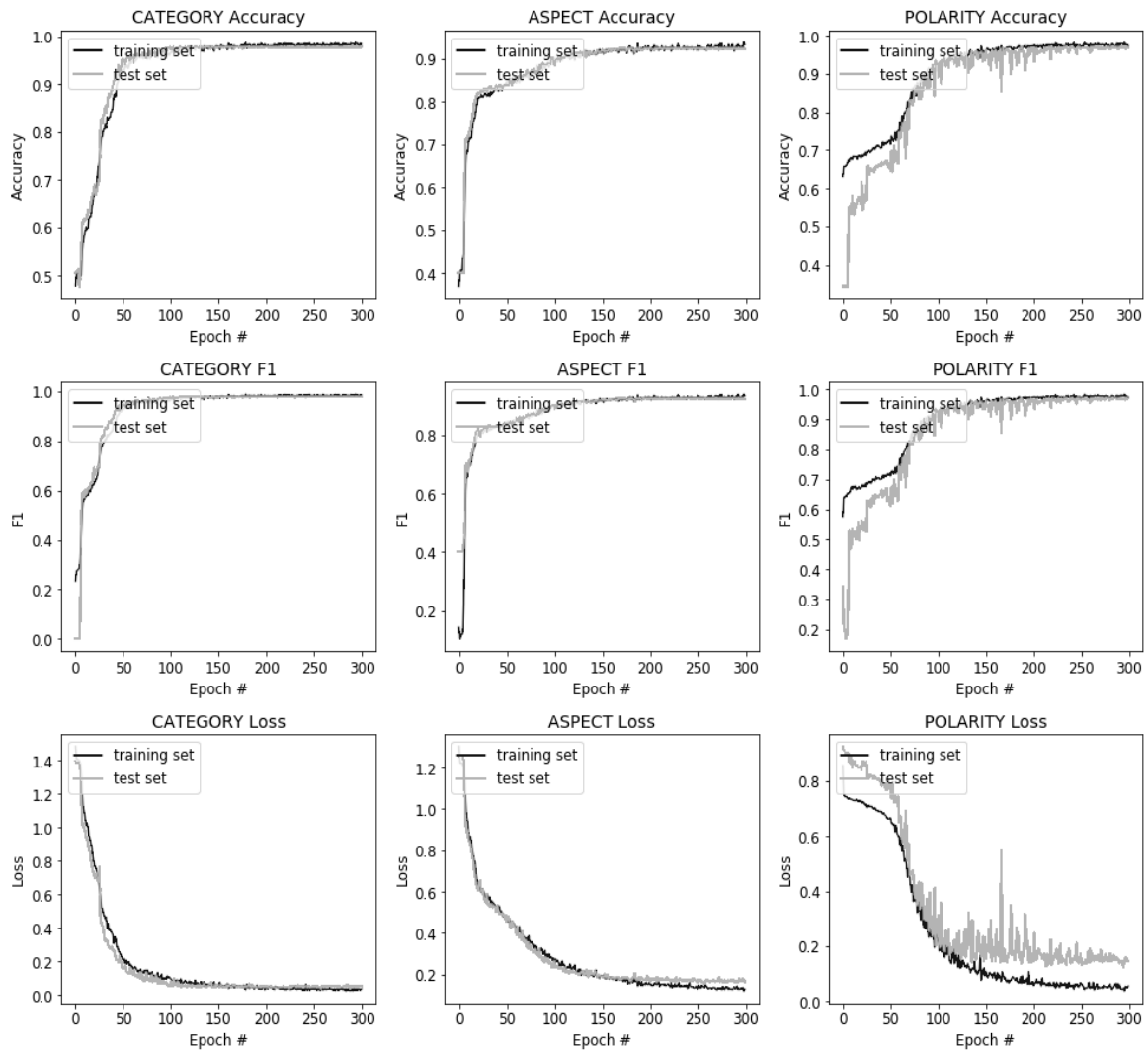


Figure 5. Accuracy, F1 score and loss of our MABSA model

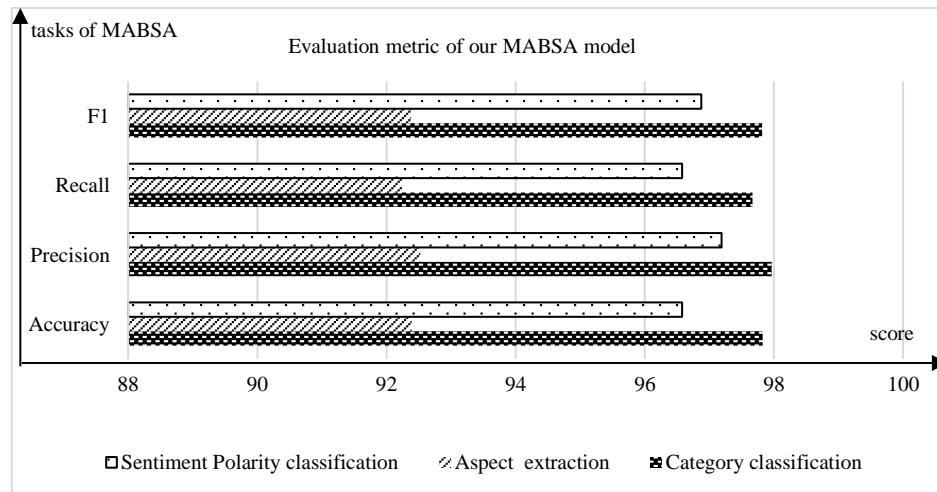


Figure 6. Precision, recall, F1 and accuracy score of our MABSA model

4. CONCLUSION

Within the scope of this study, we have suggested an approach of deep learning for multitasking ABSA that completes opinion target, category, aspect, and sentiment polarity classification tasks simultaneously with two models DCI and MABSA. On both models, we used a deep 3-layer CNN design with feature vectors derived from the previous GloVe combined with the POS tagger layer to enable high-level abstraction feature extraction. For the DCI model that supports the opinion target, we implemented an IOB2 layer at the end of the model right on top of the CNN layer to label each word with one of three B/I/O labels. Deployment of a BiLSTM layer on top of the CNN in our second model based on the advantage of long-distance learning in both directions integrated with a fully connected layer and a softmax at the top layer of the model contributed to making a classifier for aspect, category, and sentiment. Our proposed approach has significantly succeeded on the same experiment domain of the benchmark dataset over the preceding baseline models. In upcoming research, we plan to deploy our models on a multidomain dataset to increase the utility and friendliness of the models.




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