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# An Unsupervised Multiple Word-Embedding Method with Attention Model for Cross Domain Aspect Term Extraction

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***Abstract*— Aspect-based sentiment analysis is mainly a domain-dependent problem. In recent years, the existing approaches have the problem of domain adaptation for the poor performance when the domain on which the model is applied is other than the one on which the aspect extraction model is trained. However, a large sample corpus for all domains is required to train an accurate model to extract the most relevant domain-specific aspects. Furthermore, the manual annotation of large labels for the supervised model for the different domain is expensive and time-consuming. In this paper, first, we used an unsupervised method using multiple word embeddings to extract domain-specific aspects belonging to different aspects and then use these aspects as label data to train an attention-based cross-domain model for better prediction. The proposed method is evaluated on SemEval-14 and SemEval-16 datasets and competitive results are shown for baseline and most recent approaches.**

**Indexed Terms— Attention Model, Deep Learning, Multi-domain sentiment analysis, Word-Embedding.**

## I. Introduction

In the last decade, online portals have become one the primary source for users and industries to evaluate, compare different products and services. The processing of vast user-generated unstructured text is infeasible and time-consuming. Moreover, the analysis of the data is fine-grained level requires deep understating of the text. Sentiment analysis plays a crucial role in automatically analyzing these data and extract the opinion of the users from the review[1]. Nowadays, it is very important to extract important features about which opinions are provided in the text. However, aspect-based sentiment analysis(ABSA) will be very useful for both customers and providers to take the decision on the basis of overall sentiments about different aspects of the products [2], [3]. Fig. 1. shows an example to explain aspects, aspect category, polarity, and entity of any sentence. Furthermore, ABSA has touched different domains like education[4], hotels, government policies, YouTube video ranking[5], Medical etc. The existing ABSA models suffer from the domain adaptation problem[6], however, perform well if domains of both the training and testing datasets are the same. Best performing deep learning models for aspect extraction task use manually labeled data for training for a particular domain. In different domains users use different words to express their views. Sometimes, the similar or same expression might convey different opinions for different domains[7], [12]. In the review, "the plot of the movie is predictable", the "predictable" is a negative word. However, in the review, "The steering of the car is predictable", the word "predictable" holds the negative sentiment. On the other side, the domain difference between training and the testing dataset is a problem for aspect terms as the most relevant and most frequent opinion word of one domain may not as frequent and relevant for the other domain[8]. In our experiments, we have used SemEval-16 and SemEval-14 datasets of two different domains: Restaurant and Laptop. The ideal solution to the problem is to train a unique model for every domain[9]. However, it is very costly to manually annotate a large number of labeled data from each domain[8]. Furthermore, the accuracy of aspect extraction from poorly trained models with fewer samples will be quite challenging[10]. The reviewers may use some general opinion words ( good, excellent, nice, bad etc.) as well as domain-specific words (large, long, small, unpredictable etc.) to express their opinions [8], [11].

In recent years, domain adaptation has been an interesting research area among researchers and business communities[12]. Rule-based supervised learning and deep learning-based methods had improved the performance of cross-domain aspect-level sentiment analysis but the results are not competitive enough. The rule-based methods are unsupervised in nature which doesn't require labeled samples but they are unable to capture high-level linguistics to extract valid aspects in different domains[6], [9], [13]. Supervised learning out-performs rule-based methods (double propagation), however, the supervised approaches required training sample thus it is very costly and require more time to evaluate the model.

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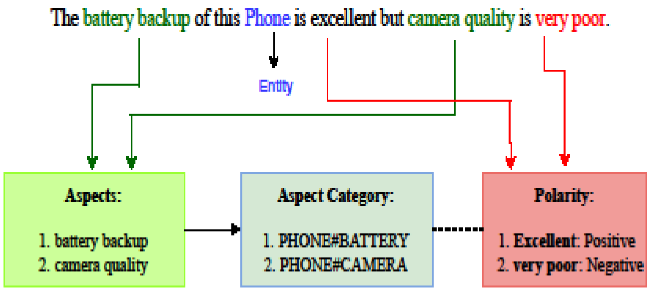

Fig. 1. An Example for Aspects, Aspect Category and Polarity

The deep learning-based methods (Recurrent Neural Networks and its variants) are very effective but they also degrade the performance of the aspect extraction when the domain is changed [9], [14]. In our experiments, we found that some best performing most recent aspect extraction models face the accuracy drop when the testing domain is different from the training domain[15], [16].

In this paper, an unsupervised method for multi-domain ABSA is used which further extended to prune most relevant domain-specific aspect terms using multiple word embeddings[17]. Next, the extracted aspects are used as labels to train an attention-based deep learning model. The attention method have shown great results in recent aspect extraction tasks[18]. The representation of the domain is used as attention to extracting the most appropriate domain features for every domain[12]. The main motivation behind the proposed work is to take advantage of the attention mechanisms with supervised recurrent neural network and unsupervised methods to prepare a model to achieve higher performance for multi-domain aspect term extraction[9], [19].

The rest of the paper is structured as follows, in section II a related work for a single domain and cross-domain aspect term extraction is presented. In section III attention based proposed approach for cross-domain aspect extraction is explained. Then, in section IV experimental results are discussed. Section V concludes the work.

## II. RELATED WORK

A domain is basically a collection of documents in which the same topics are discussed [7]. The ample cross-domain corpus about which similar opinion is conveyed for all the domains has created the opportunity for new research[20]. The existing aspect extraction approaches [21], [22] are broadly categorized into rule-based [23], [24], [25], supervised learning, and deep learning approaches. Further, reasonable research has done for domain-specific aspect term extraction, however, most of the methods extract most relevant aspects from the same domain [8], [26]. Furthermore, the existing best deep learning models for aspect extraction tasks perform well for in-domain as compared to cross-domain which means any model may perform excellently in one domain, however, it is not necessary to perform similarly for another domain [6], [27], [28].

In the SemEval-14 and SemEval-16 datasets, the performance of the restaurant dataset is better than the laptop dataset. The same model gives higher precision and recalls when the dataset of the restaurant is considered, whereas, lower precision and recall for laptop dataset. There are some researches done on laptop domain for aspect extraction but the performance is very lower as compared to the restaurant domain. Researchers have trained models in a specific domain and tried to exploit the model to explore the aspects of another domain. A rule-based unsupervised method is used to create auxiliary labels and then these used as labels for a recurrent neural network for cross-domain sentiment analysis[9]. [29] and [30] have used hand-crafted domain-independent features for multi-domain aspect extraction. [31] have used domain similarity matrices to guide for appropriate selection of training data. The pre-trained word embedding is also used to overcome the domain adaptation problems [32]. If word embedding is prepared from an opinion based corpus than general-one domain adaption will be more effective [7]. They proposed a neural word embedding approach for cross-domain analysis. W2VLDA, a topic modeling based unsupervised method was proposed for multiple domain aspect extraction[33]. A hybrid unsupervised method was proposed to improve the cross-domain sentiment analysis. Yuan, Wu has proposed a domain attention model for multi-domain sentiment analysis[12], [40], [41], [42].

The existing cross-domain approaches suffer from the limitations of domain adaptation which in-turn produces low accuracy. However, we have used an unsupervised approach where the linguistic rules are free from domain-specific knowledge to extract valid aspect terms[9], [36], [37]. In continuation, we have used multiple word embedding models to prune most relevant aspect terms based on the similarity of the particular domain[8], [34], [35]. These extracted aspects are then used as labels to train an attention-based deep learning model[14]. The proposed model is capable to handle the datasets that are different from the one used for training the model[38], [39].

## III. PROPOSED UNSUPERVISED APPROACH

In our approach, we used unsupervised method to extract potential aspects which further pruned using multiple word embeddings. Next, we combined the attention mechanism which allows the network to select the most relevant features for the desired domain as given in Fig. 2.

### *A. Unsupervised methods for potential aspects using Multiple Word Embeddings*

Initially, dependency parser and part of speech(POS) tagger is used on each sentence of the review to find all the noun and noun phrases. Based on Qui et al. work, we used the rules while extracting nouns and noun phrases as potential aspects. The extracted potential aspects are domain-independent because they are extracted using unsupervised methods. The POS tagger has tagged each word and dependency parser has established a relation between the noun or noun phrase; and its associated opinion word. However, this approach extracts potential aspects independent of the specific domain. Next, all the potential aspects are not relevant to the domain for which the task is performed. In our experiment, Word2Vec word-embedding, Glove word embedding and one-hot character vector of the given domain have generated and then all the vectors are concatenated to generate a global domain vector. We have used this global vector of the task domain and find the cosine similarity with all the non-frequent words from the potential aspect set. In Eq. 1 $we(n_i)$ represent embedded weight for word $w_i$ and $we(D)$ is pre-embedded weight for task domain.

$$cos\_similarity(we(n_i), we(D)) = \frac{\sum_{j=1}^{m} n_{ij} \cdot D_j}{\sqrt{\sum_{j=1}^{m} n_{ij}^2}\sqrt{\sum_{j=1}^{m} D_j^2}} \tag{1}$$

The domain-specific aspect identified using the above method is not competitive because this method cannot cover all the aspects due to limitations of the rules.

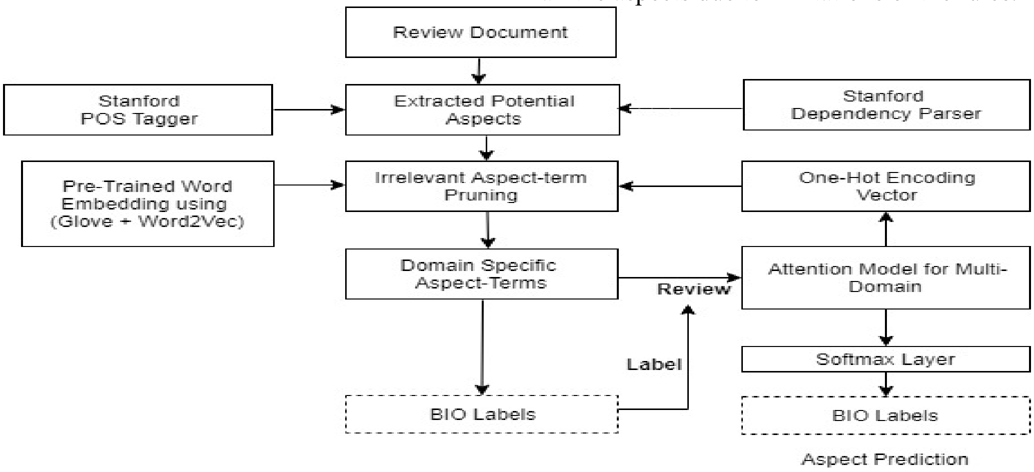


Fig. 2. Proposed Model for cross-domain aspect extraction

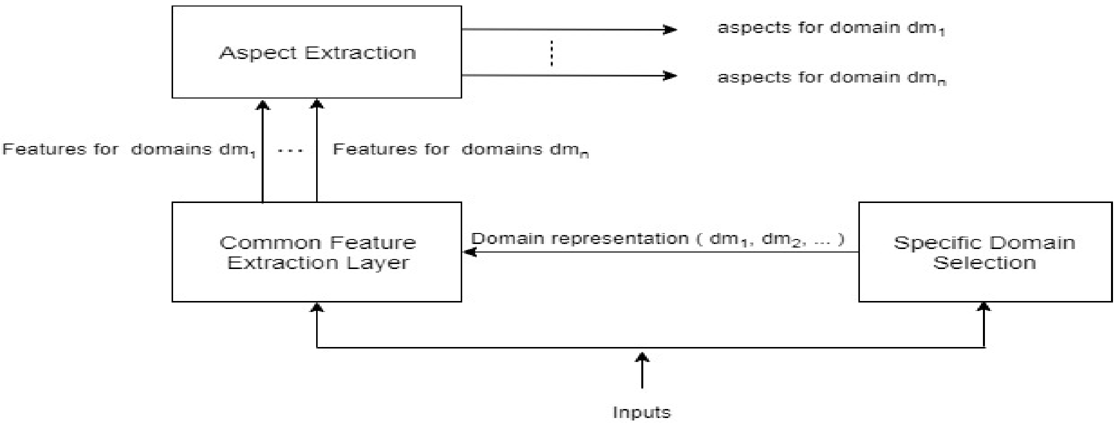


Fig. 3. Attention model for cross-domain aspect extraction

However, we have combined an attention-based deep learning model for the cross-domain aspect extraction task.

*B. Attention mechanism for cross-domain aspect extraction*

Deep Neural Network approaches for Natural language processing tasks are divided into 3 steps: (1) dense word embedding; (2) multiple hidden layers; and (3) output units. Multiple word embedding is used to generate the global vectors as dense embedding layer [6]. Bi-LSTM based attention model is used as a hidden layer. The third step, output units; represents the distributed probability over all classes or labels. Let's consider, there are $k$ classes and the final layer is $z$ then the probability obtained using softmax function for the label $i$ is as below (Eq. 2):

$$y_i = softmax(z_i) = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}} \tag{2}$$

In the ATE task, the label whose probability distribution is highest represents the predicted aspect term. The aspect extracted in *section A* is used as a label for the network. The standard BIO notation is used for sequence labeling tasks. *B* represents *BEGINNING*, *I* represents *INSIDE* and *O* represents *OUTSIDE* of the opinioned target. POS tags and global word vector generated from multiple word embedding ( Word2Vec, Glove, and one-hot vector) are used as features for the aspect extraction task. The main concept of attention is that it allows the network to revisit every part of the sentence for the decision.

It is assumed that if the knowledge of data distribution is in advance then better aspect extraction can be achieved. In the proposed model, a common feature extraction layer is shared with all the domains to extract the most domain-specific aspects. A domain of knowledge based representation is used as attention to further extract domain-specific features[12]. The extracted features that are related to domain includes all the general features that contain the same polarity in all domain as well as domain-specific features that shift the polarity in different domains. The broad illustration of our model is as shown in Fig. 3. In Fig. 4, the domain-specific aspect extraction part a good domain aspect representation by using domain aspect extraction task. The domain representation is given as input into common aspect extraction layer to apply the attention process. The most domain-related aspects are thus automatically extracted for every domain.

In our network, we follow the attention mechanism for bi-directional LSTM model as given by [43]. We also applied dropout (0.5) on embedding layers to avoid overfitting. Suppose, given the input sentence $S=\{X_1, X_2, \ldots X_T\}$ at a time $t$, the output $y_t$ depends on decoder state $s_t$ and the set of encoder states $H=\{h_1, h_2, \ldots, h_T\}$. The computation of $s_t$ (Eq. 3) is:

$$s_t = f(s_{t-1}, y_{t-1}, c_t) \tag{3}$$

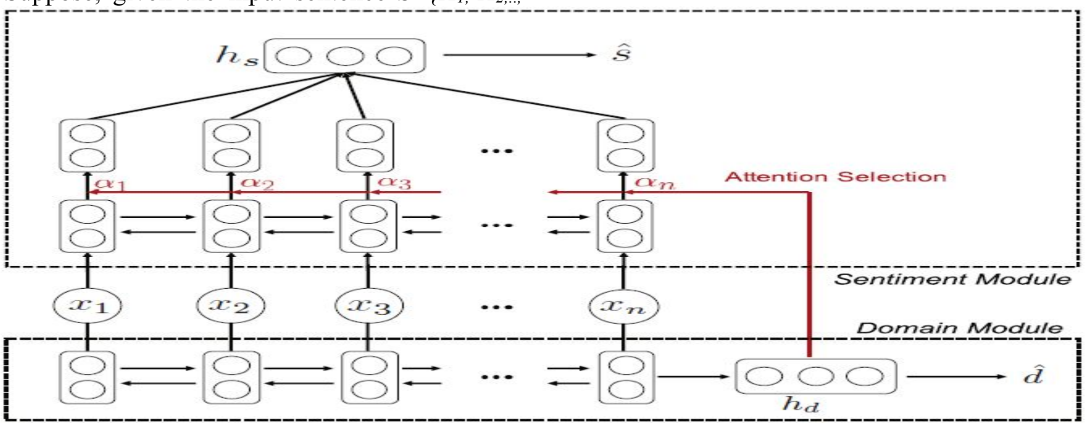


Fig. 4. Attention model for cross-domain aspect extraction

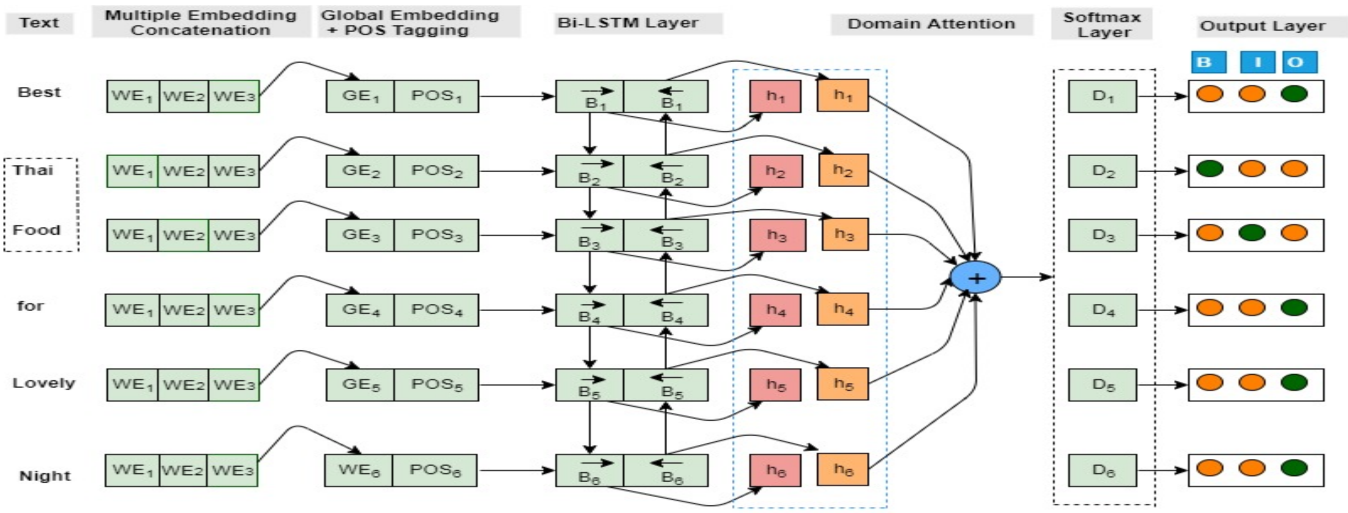


Fig. 5. Architecture of proposed deep learning network

The context vector ($c_t$ ) will be calculated as (Eq. 4) using attention weight

$$c_t = \sum_{i=1}^{T} \alpha_{ti} h_i \tag{4}$$

Categorical cross-entropy loss is used to tag each word as an aspect. Finally, the softmax function is used to find the attention weight $\alpha_{ti}$ as (Eq. 5):

$$\alpha_{ti} = softmax(e_{ti}) = \frac{\exp(e_{ti})}{\sum_{j=1}^{T} \exp(e_{tj})} \tag{5}$$

where $e_{ti} = a(s_{t-1}, h_i)$ represent attention energies

The architecture of attention mechanism based bi-directional LSTM network used in our model is shown in Fig. 5. In this model $WE_1$ is word embedding for word2vec, $WE_2$ is word embedding for Globe, and $WE_3$ is a hot-encoding vector.

The Global vector($GE$) and POs tag of each word is given as input to the attention network.

## IV. EXPERIMENTAL RESULT ANALYSIS

### A. Dataset Description

For research purpose, the used datasets is SemEval-16 on Restaurant and Laptop domain. The restaurant domain

contains 2000 sentences and the laptop domain contains 2500 sentences. The laptop dataset have more domain-specific aspects as compared to laptop one. These datasets are used majorly in the recent researches on cross-domain aspect extraction. The precision (Eq. 6), recall (Eq. 7), and F-score (Eq. 8) are used as metrics for evaluation. The formula for precision is calculated as below:

$$P = TP / (TP + FP) \tag{6}$$

Similarly recall and F-score has formulated as eq.7 and eq.8

$$R = TP / (TP + FN) \quad (7)$$

$$F = 2*P*R / (P+R) \quad (8)$$

The results are compared with the original results of Ding, Yu, and Jiang [9], Pablos[33], Chuhan Wu and Huang[14]. Table I shows the statistics of the SemEval-16 dataset for restaurant and laptop domains.

*B. Experiments*

The main aim of the experiments is to evaluate the role of attention mechanism and to compare the performance for in-domain and cross-domain aspect extraction. Table II and Table III show the precision and recall in cross-domain aspect extraction. The result of our system has increased precision for the restaurant to 8% and 11% for the laptop as compared to the most recent cross-domain aspect retrieval task. It is clear that our approach has out-performed the exiting approaches. The performance or laptop dataset is improved better because reviews of laptop contain more domain specific noun/noun phrase. Further, in Table IV in-domain and cross-domain aspect extraction performance is measured. The results show that the performance of our model when the model is trained in the restaurant domain and tested on a dataset of laptop domain gives quite competitive results when both training and testing datasets are in the same domain. The proposed unsupervised results have out-performed the unsupervised rule-based and deep learning approach as shown in Table III and Table IV. The precision (Fig. 6) and recall (Fig. 7) for the restaurant domain is higher than laptop reviews. The difference of precision and recall for in-domain and cross-domain performance of restaurant and laptop domain is 19% and 12% respectively. Our proposed cross domain aspect extraction approach produces low precision for cross domain aspect extraction as compared to in-domain approach of Pablos et al. [33], however, it gives better results as compared to state-of-art and most recent cross-domain aspect extraction approaches as shown in Table IV.

Moreover, proposed cross-domain approach produces the recall as compatible to recent in-domain aspect extraction approach Chuhan Wu et al.[14] and better than state-of-art aspect extraction approaches as shown in Table III. The proposed Unsupervised Multiple Word-Embedding Method with Attention Model for Cross Domain Aspect Term Extraction resolves the problem of domain adaptation when the domain on which the model is applied is other than the one on which the aspect extraction model is trained.

TABLE I. STATISTICS OF SEMEVAL-16 DATASET

| Criteria | Restaurant | | | Laptop | | |
|---|---|---|---|---|---|---|
| | Training data | Testing data | Total | Training data | Testing data | Total |
| Reviews | 395 | 91 | 486 | 451 | 80 | 531 |
| Sentences | 2000 | 676 | 2676 | 2500 | 800 | 3300 |
| Aspect Category | 12 | 12 | 12 | 81 | 68 | 88 |

TABLE II. PRECISION OF PROPOSED APPROACH

| Model | Restaurant | Laptop |
|---|---|---|
| CRF | 48.52 | 42.87 |
| DP | 39.68 | 46.56 |
| Ding et al. [9] | 46.0 | 38.0 |
| Pablos et al. [33] | 77.0 | 72.0 |
| Chuhan Wu et al. [14] | 55.86 | 47.44 |
| **Our System** | 63.42 | 58.68 |

TABLE III. RECALL OF PROPOSED APPROACH

| Model | Restaurant | Laptop |
|---|---|---|
| CRF | 76.64 | 68.96 |
| DP | 58.41 | 72.44 |
| Ding et al. [9] | 56.0 | 52.0 |
| Pablos et al. [33] | 62.0 | 58.0 |
| Chuhan Wu et al. [14] | 84.58 | 76.52 |
| **Our System** | 74.20 | 78.34 |

TABLE IV. IN-DOMAIN AND CROSS-DOMAIN PERFORMANCE

| Model | Restaurant | Laptop |
|---|---|---|
| In-Domain Precision | 82.22 | 73.66 |
| Cross-Domain Precision | 63.42 | 58.68 |
| In-Domain Recall | 86.84 | 66.24 |
| Cross-Domain Recall | 74.42 | 62.42 |

## V. CONCLUSION

In this paper, an unsupervised method has been used to extract potential aspect terms, moreover, global word embedding is used to prune irrelevant aspects to identify domain-specific aspect terms. Further, domain-specific extracted aspects are used as a label to trained the deep learning model using attention to improve the cross-domain aspect extraction task. The proposed Unsupervised Multiple Word-Embedding Method with Attention Model for Cross Domain Aspect Term Extraction resolves the problem of domain adaptation when the domain on which the model is applied is other than the one on which the aspect extraction model is trained. The performance of identifying cross-domain nouns/noun phrases has been improved by multiple word embedding and attention mechanism.

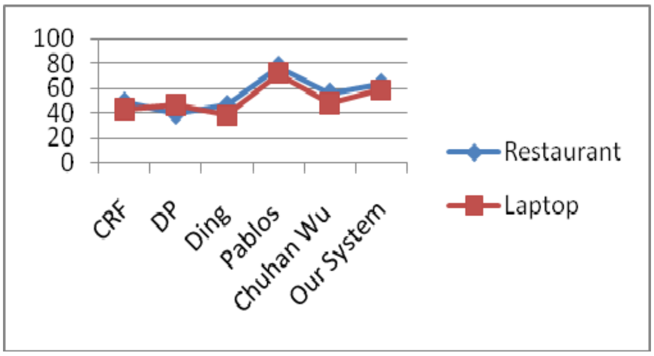


Fig. 6. Precision of proposed model with related approaches

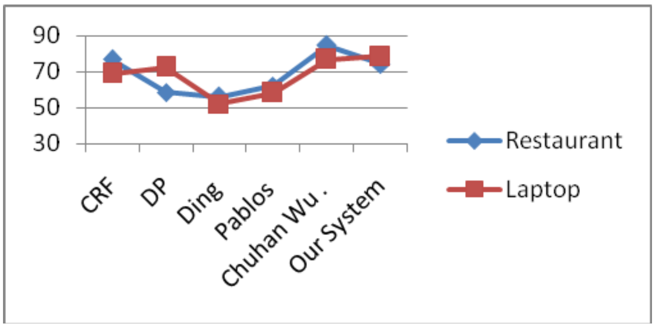


Fig. 7. Recall Comparison of proposed model with related approaches

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