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An efficient LSTM based cross domain aspect based sentiment analysis (CD-ABSA)

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K E Y W O R D S

Aspect Extraction

Sentiment Analysis

ABSA

Cross Domain

Aspect Identification

LSTM

A B S T R A C T

This research study focuses the cross-domain aspect-based sentiment analysis (CD-ABSA) for existing source domain annotation data. The CD-ABSA tries to use the valuable information in a source domain to extract aspect terms and evaluate their sentiment polarities in a target domain. It can considerably increase the usage of the source domain annotation resources while also reducing the workload of newer domain data annotation. one of the main components of the CD-ABSA is aspect extraction. In this paper, we utilized the most common topic modelling techniques: LDA and LSA to extract aspects from the reviews as it does not require labelled data. The topics are extracted from the education domain of the Course and Teacher Performance Evaluation (CTPE) dataset. In this paper, we also evaluated the different hyper-parameters on the CD-ABSA model and selected the best and optimal combination. The proposed methodology train on domain-dependent and independent word embedding that achieves CD-ABSA, in particularly end-to-end fashion. The experiment carries out on Academica dataset, which consists of students' comments/feedback and SemEval-2014 dataset, which includes laptops and restaurants reviews. The evaluation metrics such as (precision, recall, F1 score and validation Accuracy) is considered while judging the LSTM classifier performance for CD-ABSA as a result.

1. Introduction

Now a days, the different natural language processing (NLP) techniques are used for sentiment analysis (SA), which is these are also known as opinion mining that has drawn a lot of significant research [1]. The sentimental tendencies of the SA extract texts. According to multiple research findings, there are three levels of sentiment analysis: document, phrase, and aspect levels. Studies on sentiment at the sentence and document levels assume that there is merely one significant subject. However, when considering useful opinion mining in user reviews of goods or services, a more precise analytical approach is required when one or more entities are mentioned in a single sentence and their evaluation may vary varies. Moreover, by using the NLP method known as opinion mining, we will examine the attitudes and feelings expressed by the customers. Opinion mining analyses customer opinions by considering people's emotions, perceptions, sentiments, and attitudes [2-4]. Inspecting and identifying the sentiment polarity of various elements or aspects in a single text is the focus of aspect-level sentiment analysis that is gradually rising the stage [5].Previously, it was believed that Aspect extraction and sentiment polarity clarification (SPC), was one of the processes or subtasks that made up the task known as "aspect-based sentiment analysis" (ABSA) that comprises aspect categories identification (ASD) and opinion target extraction (OTE). In summary, just one or two subtasks were primarily considered when building models. Techniques have been developed to find out the emotions and aspect term extraction (OTE) [6–9]. It takes a lot of domain expertise to perform SA. Sentiment characteristics of data from diverse domains vary slightly. The sentiment prediction model typically cannot be applied quickly to data from another domain. For building an effective model for sentiment prediction, it is essential to manually classify the data in a new domain. However, the cost of obtaining human-labelled data in high quality is a substantial task. It would be a tragedy to neglect the tagged sentiment data that some fields of inquiry have accumulated in the meantime. One of the major challenges in NLP work has always been the categorization of cross-domain text sentiment has been a study focus and issue in both academia and business. To create a trustworthy model to forecast unlabelled data in the target domain with different sample distributions, transfer learning uses labelled training samples in the source domain. According to multiple existing research studies, one of the best techniques for managing cross-domain text sentiment classification is transfer learning. Several researchers have carried out exploratory research on this topic and have drawn some results [10–12]. To offer cross-domain text with fine-grained sentiment analysis and effectively execute cross-domain text sentiment classification, this work suggests an aspect-level sentiment analysis algorithm based on BERT. The method uses an enhanced convolutional neural network for local feature extraction after first extracting aspect-level and sentence-level representation vectors using the BERT structure. Constructing a sequence of sentences, combines the aspect-level and sentence-level corpora. The method then makes use of an adversarial neural network for the domain to increase the degree of indistinguishability between feature representations extracted from different domains, or the similarity between the features retrieved target and source domain. As a result of the sentiment classifier training on a dataset containing sentiment labels from the source domain, aspect and sentence-level sentiment classification are both possible and perform well in both the target and source domains. The domain adversary and the sentiment classifier error pooled values are simultaneously back propagated to update and optimise the model parameters and enable cross-domain analysis. As a result, a model that can analyse sentiment across several domains can be trained effectively. By leveraging Bert and domain-dependent embeddings, this study will build on the CD-ABSA trend that offers a fresh approach. The suggested framework CD-ABSA includes a parameter generation module along with the main network comprising the aspect-based layer and the word embedding layer. The F1 and Accuracy values are used as evaluation indicators in the study, which uses the SemEval-2014 and MOOC datasets. The outcomes illustrate the superior performance of our suggested hierarchy. The CD-ABSA is comprised of different layers of the LSTM model, such as (i) aspect extraction and (ii) sentiment classification. The first layer classifies a comment/review of sentences in one of the top five aspects as shown in Fig 2, such as Course, Teacher, Assessment, Resource, and General and SemEval-14 dataset aspects. The experiment is carried out on academic (CTPE) and SemEval-2014 datasets; accuracy and F1 value are used as evaluation indicators. the results show that our proposed algorithm performs far better. However, the main contribution and motivation of this paper are discussed as follows.

- Different features or domains can be simply adapted to the suggested strategy.
- To Extract aspects from review/comment by utilizing topic modelling techniques LDA and LSA, we have suggested an unsupervised model that covers the major tasks needed in an opinion mining system.
- LSTM is first initiated into transferrable CD ABSA with a complex structure and learn domain-related knowledge to comprehends various domains.
- In the experiment, the performance CD-ABSA model was also tested with various hyperparameters such as regularization, optimization, and dropout values.

The remaining sections of this paper are organized as follows: The relevant work of aspect and domain-based sentiment analysis discussion mentioned in Section II. And Section III presents the detailed working environment and methodology for CD aspect extraction and sentiment classification. Section IV shows the simulation results and explains the efficiency obtained with various hyperparameters. The article is concluded in Section VII.

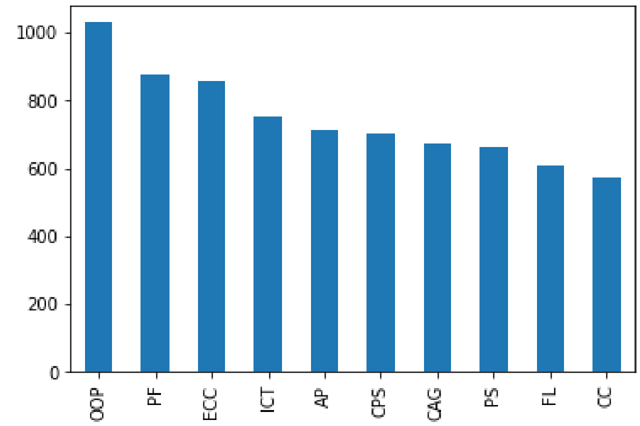

Fig. 1. Academic Reviews of Top (10) Courses

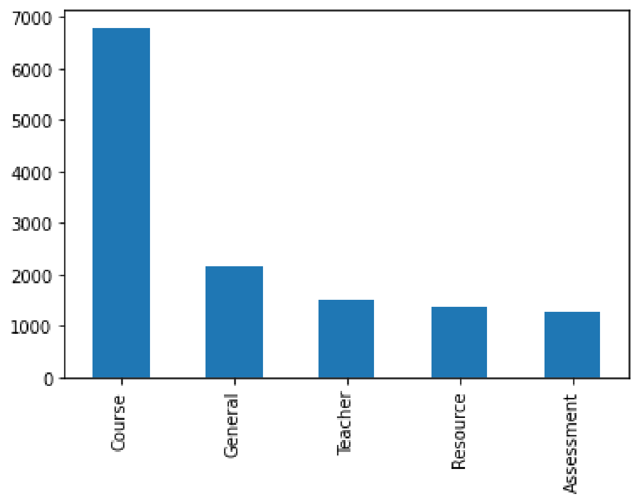

Fig. 2. Academic Reviews of Top (5) Aspects

2. Related Work

2.1 Aspect-Based Sentiment Analysis

Aspect-level sentiment analysis (ALSA), a task in sentiment analysis, is used to categorize sentiment in a more specific manner. The Neural networks with attention [16, 17] or classifiers [15] were used for SPC, while topic modelling [14], rule-based [13], and CRF as traditional sequence labelling models [15] were utilized for ACD and OTE. For instance, ILWAANet [18] uses a variety of attentions to extract features from both lexicon and data to help with a more thorough collection of characteristics. Target-based opinion mining was given a unified approach because [19–20] a more comprehensive strategy can lead to better results in fine-grained sentiment analysis. It promotes further research from many perspectives and aids ABSA's expansion. CD-ABSA was first used to explore modelling and labelling methodologies by fusing the unified model with the Bert-trained model. It also Introduces a DOER cross-shared unit, through which aspect sentiment and aspect phrase extraction categorization are connected and uses joint labels [21]. Furthermore, Hu et al. [22] made the case that the pipeline technique can outperform the span-based labelling technique for open-domain targeted opinion mining. For ASD and SPC tasks, Zeng et al. [23] developed an end-to-end joint learning neural network. The unified model was improved by Peng et al. [24] utilizing modelling techniques to fulfill the subtask they offer dubbed aspect sentiment triplet extraction (ASTE). To improve the CDABSA, further machine-learning methods have also been applied. Recently, the unified approach also included open-domain learning [25]. The fundamental distinctions between the models previously mentioned and CD-ABSA are the incorporation of adaptation of domain and the accomplishment of fine-grained sentiment analysis cross-domain based on the creation of end-to-end sentiment analysis.

2.2 Transfer Learning (TL) in ABSA

The TL permits the fine-tuning of existing model methodologies for usage with new domains or functionalities. The usage of combine ABSA and TL can lead knowledge transfer between different ABSA subtasks. The TL is a method that encourages computers to learn on their own from data and use that knowledge to complete new tasks. Feature-based transfer learning involves bridging the distance between the target and source domains before transferring features to classifiers. According to Pan and Yang [26], the four categories are feature-based, sample-based, relation-based transfer learning, and model-based, which can be used to distinguish between the basic transfer learning methodologies. When model-based and feature-based learning is combined, the fine-grained sentiment analysis is more result-oriented. Moreover, Xu et al. [27] completed the ABSA task by using the Bert technique to acquire domain knowledge. Hu et al [28] developed a model that focuses on distilling domain-invariant features to achieve aspect-based sentiment analysis. Besides this, model-based transfer learning assumes that data to the target domain from the source domain may include certain model parameters in common. in advance, the researchers have directly applied pre-trained models to attempt and the ABSA model's capacity for learning will be enhanced through task transfer learning [29]. Furthermore, the coarse-to-fine task was used by Li et al. [30] to transfer information from ASD with plenty of resources to OTE. Additionally, Selective adversarial learning (SAL) was added to the unified model as a domain adaptation strategy by Li et al. [31], addition to this, Liang et al [32] developed cross-domain ABSA with combined sentiment-related knowledge and domain-specific transfer among aspect-level sentiment analysis subtasks utilizing IKTN. But most of them did not consider aspect-level sentiment analysis to be a thorough method of problem solutions and did not incorporate relevant data into feature generation to help with ensuing tasks. Cross-domain ABSA will be handled as an entire system by CD-E2EABSA, which will also investigate model-based transfer learning that makes use of network-learned domain expertise.

2.3 Sentiment Analysis and Domain Embeddings

To facilitate the transfer of domain knowledge in cross-domain ABSA, most of the earlier work focused on extracting domain-invariant features [34]. While Hu et al. [28] used a more straightforward method to distil features of domain-invariant by considering domain-dependent and domain-independent features as orthogonal information, Liang et al. [32] used an adversarial multitask learning framework to distinguish between domain-invariant and domain-dependent embeddings. In addition to this, some ABSA models are employs multidomain sentence-level sentiment analysis with domain-dependent embeddings. For instance, domain-aware embeddings [33] were developed and improved the effectiveness of sentence-level sentiment analysis by combining word embeddings and domain-dependent features. Furthermore, Liu et al [34] developed a domain embedding to address the issue of varied sentiment terms for various domains in sentence-level multi-domain sentiment analysis. In contrast to using an attention method, the CD-E2EABSA technique focused on ALSA and learned domain representation through hyperparameter network generation. By training hyperparameter, the model learns effective domain features and representation Besides this, the model tries to extract representations for sentiment analysis that are domain-specific and frequently employs the multitask learning technique. The designed CD-ABSA was used for a multi-task approach. The capacity of the model to perform well and generalize across tasks is enhanced by the multitask learning technique, which enables concurrent learning of several related tasks. The unified model for CD-ABSA has also been enhanced with an interactive multitask learning network [35], which prepares for sentiment analysis at the document and aspect levels at the same time.

3. Experimental Setup

This section explains the system architecture of the proposed cross-domain aspect-based sentiment analysis model (CD-ABSA), it holds 5 key components, 1) design and development of academic dataset and utilization of well-known SemEval-14 dataset, and 2) understanding of the domain ,3) Pre-processing and 4) aspect extraction of an individual domain. 5) proper utilization of word embedding and transfer learning for each domain for aspects and reviews and finally, Aspect based sentiment classification. Fig 5 depicts an overview of the architecture of the proposed CD-ABSA Model.

a. Datasets

In this paper, we used academic and SemEval-14 datasets to evaluate the performance of our model, the academic dataset was self-created by the Faculty of Information technology of the two public sector universities of Karachi, in the academic dataset contains (1500) students tagged comments about teaching, course and so on. The feedback is collected around 30 different courses of (1-8) first to eight semesters of students, we used our constructed 6k students' tagged comments categorized by aspect to perform CD ABSA tasks. Specifically, we are transferred knowledge of restaurant domain to laptop domain and vice versa the transfer of expertise between fields boosted SA competences in the target domain, which will enable more accurate analysis of reviews and comments, and improved ABSA model performance. Table 1 depicts some statistics of Course Evaluation and SemEval-14) and Fig 2 shows the top ten courses in the CTPE dataset, which has large volume or size samples in reviews. To analyze the insight of data, we have also used word cloud to show the most significant words of the comment/review of the CTPE dataset, the larger size font size found on the word cloud describes the importance of comment, However, in Fig 3, we can see the words with large font sizes such as ‘Course,’ ‘Teacher,’ ‘Instructor,’ ‘student’ and users are contributing to the more information about the course and teacher performance evaluation (CTPE).

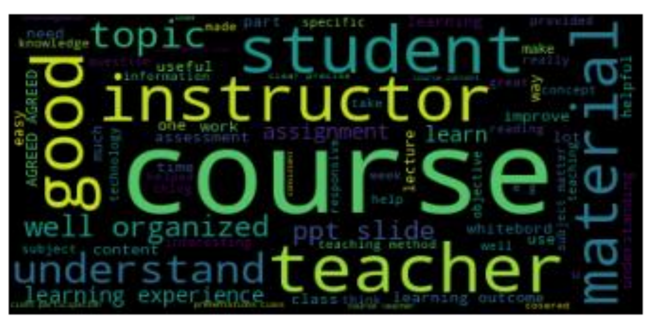

Fig. 3. Top words in Academic dataset

Table 1

Academic Domain and SemEval-14 Dataset Statistics

	Academic	Restaurant	Laptop
No of Reviews	10776	3841	3845
No of Aspects	5	1212	954
No of Sentences	27660	-	-
No of Orientation categories	3	4	4

Table 2

Domain wise no of reviews each category in Semeval-14 and CTFE dataset.

Domain	Aspect	No of Reviews	P(%)
Education Reviews	Course	6772	62.8%
	Teacher	1494	13.8%
	Assessment	1285	11.9%
	Resources	328	3.0%
	General	898	8.3%

Table 3

No of reviews each aspect category CTFE dataset.

Domain	Polarity	No of Reviews	P(%)
Education Reviews	Positive	4794	44.4%
	Negative	4659	43.2%
	Natural	1323	12.2%
Restaurant Reviews	Positive	2164	58.5%
	Negative	805	21.7%
	Natural	633	17.1%
	Conflict	91	2.4%
Laptops Reviews	Positive	987	41.8%
	Negative	868	36.7%
	Natural	460	36.7%
	Conflict	45	1.90%

The polarity of the aspect opinion can be either neutral (NEU)or negative (N) and positive (P). Table 2 displays the review distribution by polarity category. Table 3 displays the breakdown of reviews into aspect categories. The table shows that there is a significant disparity in the number of reviews for each aspect category. For instance, the category for the aspect of content has 10776 reviews, whilst the category for the aspect of structure has only 6772 reviews.

b. Preparation and understanding of domain

The process of extracting, structuring, and organizing domain knowledge from subject-matter specialists into a program is known as knowledge acquisition. This is necessary to understand the fundamental characteristics or criteria of a teacher that management considered while evaluating faculty teaching performance to select the categories of labeling for our domain data of academic gathering. We need the results of subject matter specialists for our project, particularly those assigned to various administrative roles in academia. Since they are the ones with the most experience to provide regarding the various criteria used to evaluate teaching performance. We created a structured google form based on 20 questions that had been approved by two public sector universities' Quality Enhancement Cell (QEC) to get their responses. In the appendix, subject-based questions are listed. A 20-minute time limit was set for the fill this form. We have opted for an electronic questionnaire that utilizes written responses to a series of questions to evaluate the performance of faculty and courses.

c. Pre-processing

We used a few pre-processing techniques before training classifiers, primarily eliminating HTML tags (Many comments were quoted directly from online sources.), lowercasing everything, and removing punctuation. Additionally, it used an English language filter at the word level to eliminate all non-English words. Additionally, we eliminated stop words, which are rather common and unhelpful for creating word vectors. Since some of the comments in the dataset were duplicates, we eliminated them. We used stemming text normalization as the final step in the preparation procedure. The exact same pre-processing procedures were used in all the trials carried out for this investigation. The repetition of words in a text collection is referred to as "tokens" in this paper, whereas the collection's unique words (vocabulary size) are simply referred to as "words."

d. Aspects extraction

We extract aspects from the academic CTPE dataset using Latent Semantic analysis (LSA) and Latent Dirichlet Analysis (LDA) topic modeling methods. They presumptively believe that each document is composed of several subjects and that the words within each topic are dispersed probabilistically. It establishes a method for building documents probabilistically, consider that Di represents how the themes are distributed throughout the new document, and each word in the paper was given a topic that relates to Di. The next step is to choose a word from the topic. We are extracting topics from the collection of documents in our work utilizing topic models. A multinomial distribution over words describes each component. The correlated words that express the same or similar features can be conveniently grouped under one aspect. In this study, we extract aspects and use multi-class classifiers to categorize these aspects using the LDA and LSA models. The LDA modeling approach is probabilistic. It is based on the idea that each document depicts a distribution of themes using statistics and displays a distribution of terms for each topic using statistics. The interactive visual display shown in Fig 6 contains words. LDA creates a model of a document by performing the actions listed below: 1) Determines the document's word count. 2) Using a document having a range of themes, a predetermined selection of topics is chosen. 3) A multinomial distribution of documents is utilized to select a topic.

e. Word embedding layer

Word embedding is essential for portraying words because it preserves the contextual and semantic information of each word. where each word is represented as an actual value-filled vector. And these single dimensional vectors are trained using deep learning-based networks (ANN, CNN), By evaluating contextual similarity using cosine similarity distance, this method enables us to capture the syntactic and semantic links between words. and it converts words from texts to vectors, which makes ABSA possible. These embeddings are fed into the succeeding neural network. Traditional word vector sets, which can be difficult to handle when reprocessing data for the lexicon, were employed in previous ABSA solutions. The use of aspect-sensitive word embeddings allows for the introduction of word-level, aspect-sensitive features that consider the possibility that the same word can convey sentiments with varying polarities towards various aspects. Apiece word in a phrase is improved using the associated aspect-sensitive features before the LSTM-based component is used to get contextual word representations through the compositionality of word embeddings. Some words might not have pre-trained embeddings and require separate initialization. the Contextual data and text mining model efficacy can be considered while applying Bert, a potent word embedding layer, for ABSA. Bert considers the context by building token-level representations with utterances as input. A contextualised representation, denoted as Hl, is produced, and passed on to subsequent tasks after the refining of token-level features utilising various transformer layers, which contain token embeddings, position embeddings, and segment embeddings. It's important to note that both texts from the source domain and those from the destination domain use the same word embedding layer.

f. LSTM model

We now go over the operation of our suggested LSTM model, which we employed in both the opinion orientation and the aspect extraction processes, as depicted in Fig 5. In contrast to earlier studies, we simply employed a data file with tags in which we manually sorted reviews according to their relevant label categories instead of modelling this challenge is modelled as a task of sequence labelling with the data first labelled by various labelling techniques such as IOB2.To categorize a review, our suggested model uses an LSTM neural network. The unique RNN variation that circumvents the vanishing gradient issue is the LSTM [35, 36]. It has superior control over what is stored and discarded and can store a longer memory. Additionally, a control system for regulating data flow inside the LSTM cell. These gates include the input gate, forget gate, and output gate, each designated by the letters fgt, igt, and ogt. The pointwise multiplication and the sigmoid neural network layer operation make up each of these gates. This sigmoid layer's output ranges from 0 to 1. The letter ct stands for the current cell state of the LSTM at timestamp t.

Table 4

Summary of network

Layer (Type)	Output Shape	Connected to
Input_2	[(none,1)]	[]
Input_1	[(none,1111)]	[]
Embedding_1	[(none,1,256)]	[]
Embedding_1	(none, 1223,256)	["input_2[][]"]
Flatten	(none, 256)	["input_1[][]"]
Spatial_droupoutID	(none, 1223,256)	["embedding_2[][]"]
Repeat vector	(None, 1223, 256)	['flatten_7[0][0]']
concatenate_7	(None, 1223, 512)	['spatial_dropout1d_7[0][0]', 'repeat_vector[0][0]']
lstm_7	(None, 256)	['concatenate [0][0]']
dense_1	(None, 128)	['lstm[0][0]']
dense_2	(None, 3)	['dense[0][0]']

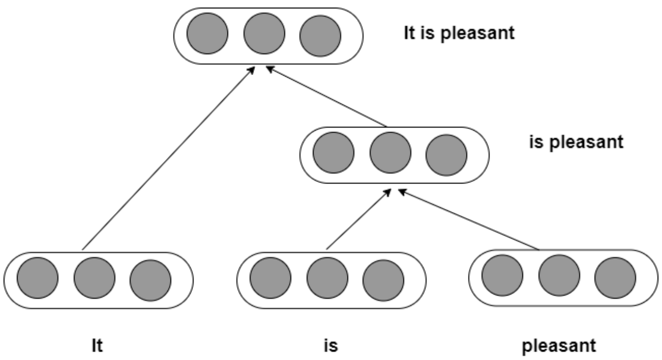

Fig. 4. LSTM Layers

Updates to gates and memory cells depend more on the states of a node's children than they do on the states of the words that came before them. To selectively incorporate input from each child, Tree-LSTM unit comprises one forget gate for each child in instead of a single forget gate as shown Fig 4. We used sparse categorical cross entropy on dense layers to classify the polarity and aspects, H(X) truth labels are integer encoded for

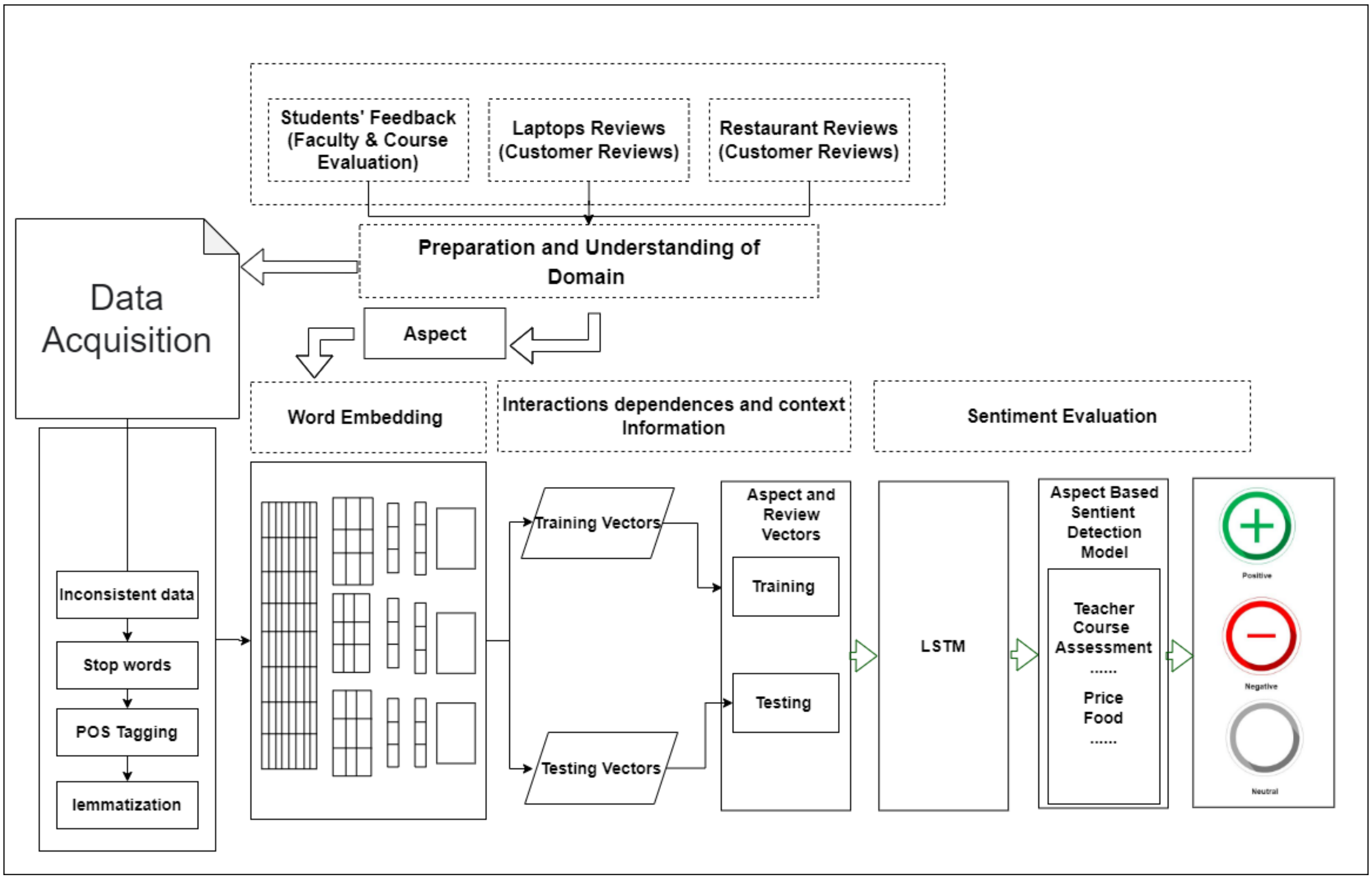

Fig. 5. The architecture of proposed CD-ABSA Model

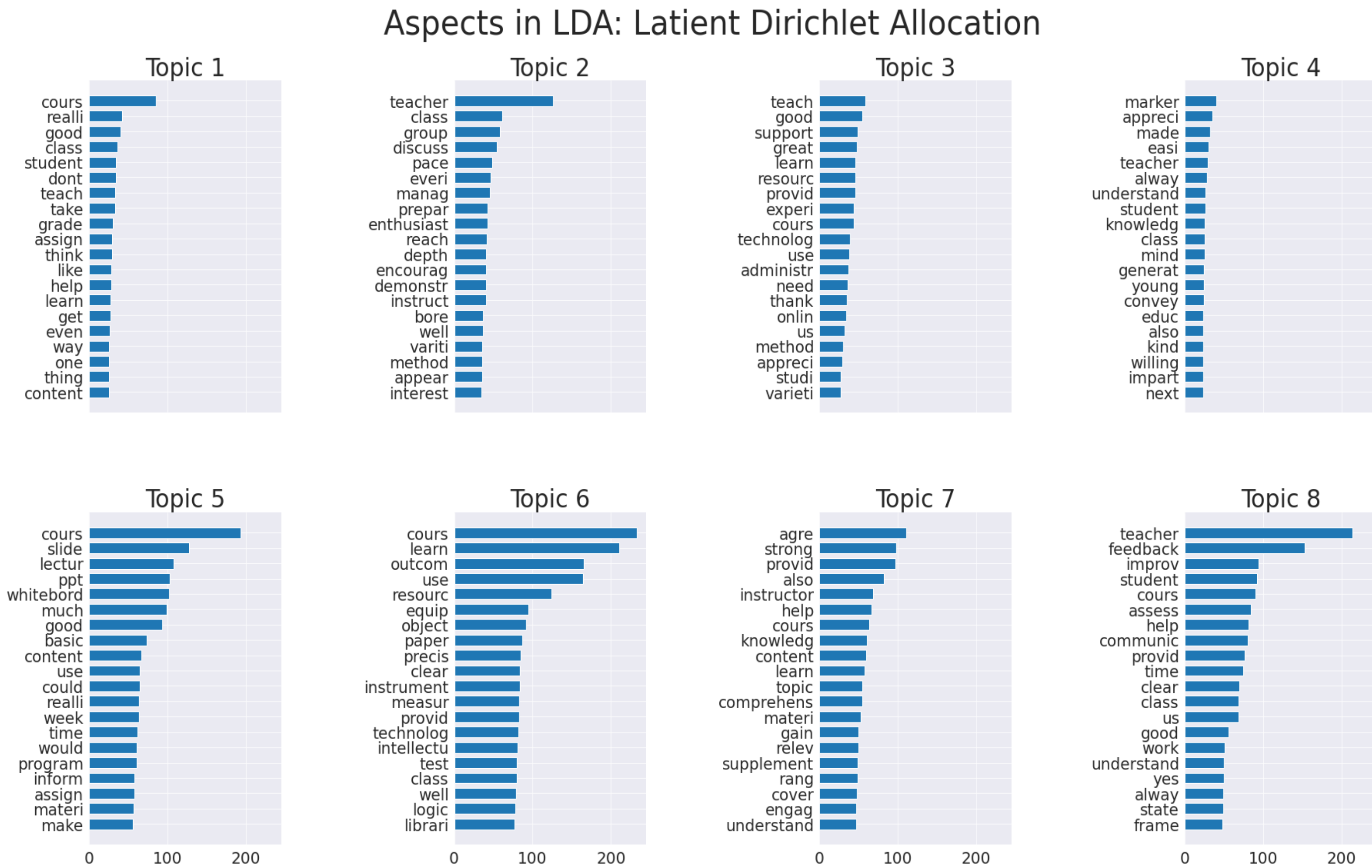

Fig. 6. Interactive visual display of LDA model results for Academic domain

4. Result and Discussion

In this section, the performance and effectives of proposed CD-ABSA model analysed based on experiments. we conducted experiment on popular publicly available SemEval-14 and self-created academic CTFE datasets. We configured a two-layer LSTM system, where each layer performed for its specific purpose, we choose four metrics (Precision, Recall, F1 Score, and Accuracy) that are often used in the ABSA domain to assess the model's performance. Equation (2-5) is utilized to calculate these metrics. First, we ran experiments with our model utilizing various word embedding dimensions, such as (300,600) and word embeddings produced from the academic dataset and SemEval-14. The outcome of aspect extraction and classification is shown in Fig. 8, where a diagonal graphical representation demonstrates the correct prediction concerning the true and predicted labels. The table 5, presents evaluation metrics for Aspect extraction, where F1-Score (0.94%), and precision (0.94%) and recall (0.95%.). respectively, we have shown the outcomes for each category. Due to the low number of training instances for assessment and resource, which made it difficult for LSTM to learn about this aspect label category, we received a poor F1 score in the assessment and resource category. Therefore, the score can be raised if we supply additional training cases for this category. The model's second layer performance in detecting sentiment orientation showed different levels of precision and recall for the targeted category. table 5 provides the details. The average F1 value was 0.96, with values ranging from 0.79 to 0.96. Aspect extraction and orientation detection are the two subtasks that make up the proposed system, as was previously discussed. We used 13% of the data for model validation and testing and 70% of the data for model training in our experiment. The two-layered LSTM network utilized was trained using stochastic gradient descent. For 20 epochs, we begin our model training with a learning rate of 1. (50 iterations over all samples in mini batches of 16 samples). On the validation data, we simultaneously focused our attention on loss and accuracy. As shown in Fig. 12–13, with each passing epoch, the training accuracy was rising, and the training loss was declining. Both the accuracy and the loss appear to peak at the fifth epoch, and the model then restarted its optimization process using the training data. In this instance, we trained a brand-new network from scratch for nine epochs to avoid such overfitting, and then we assessed it using test data. Equation illustrates how we employed sparse categorical cross-entropy as a loss eq (1).

$$H(X) = \sum_{i=1}^{n} yi.logyi \quad (1)$$

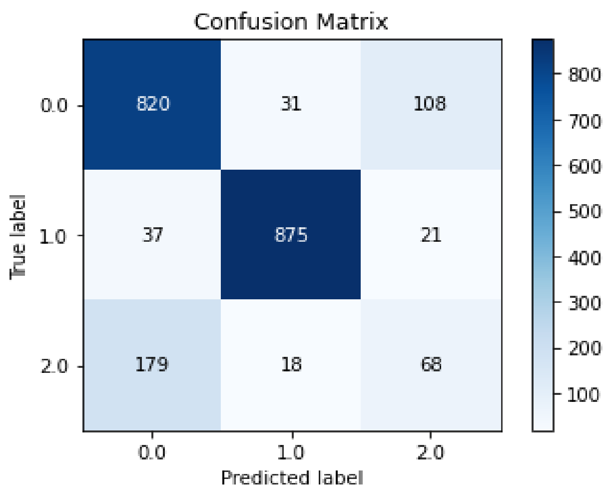

Fig. 7. Polarity based true and false predication of CD-ABSA model

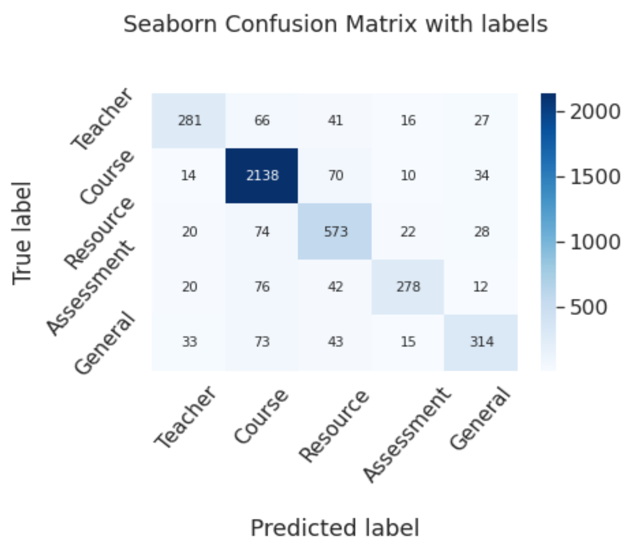

Fig. 8. Aspect wise true and false predication of CD-ABSA model

Table 5

Performance Proposed Model with various aspects.

Domain	Aspect	P	R	F1
Education Reviews	Positive	0.95	0.94	0.94
	Negative	0.79	0.86	0.82
	Neutral	0.35	0.26	0.29
Restaurant Reviews	Positive	0.59	0.51	0.55
	Negative	0.79	0.80	0.79
	Neutral	0.41	0.46	0.43
Laptop Reviews	Positive	0.72	0.66	0.49
	Negative	0.74	0.66	0.46
	Neutral	0.73	0.66	0.47

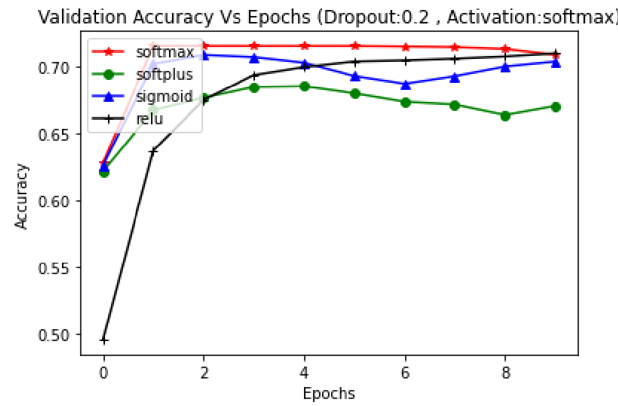

Fig. 9. The training loss curve of the proposed CD-ABSA with activations functions

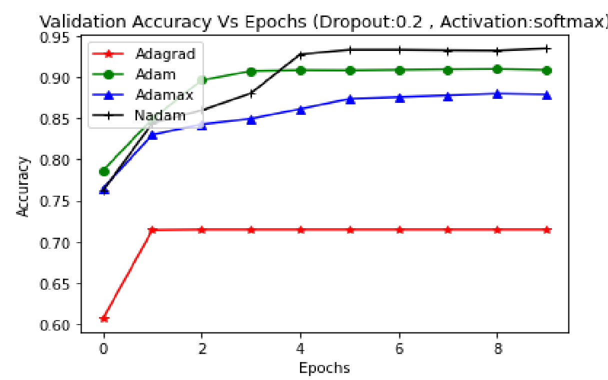

Fig. 10. The training loss curve of the proposed CD-ABSA with optimization functions

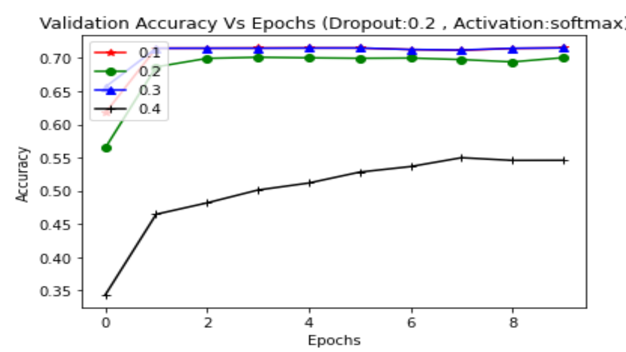

Fig. 11. The training loss curve of the proposed CD-ABSA with dropouts' values

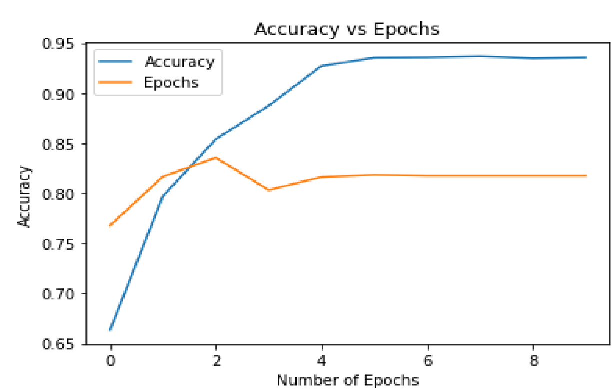

Fig. 12. The training and testing accuracy curve of the proposed CD-ABSA

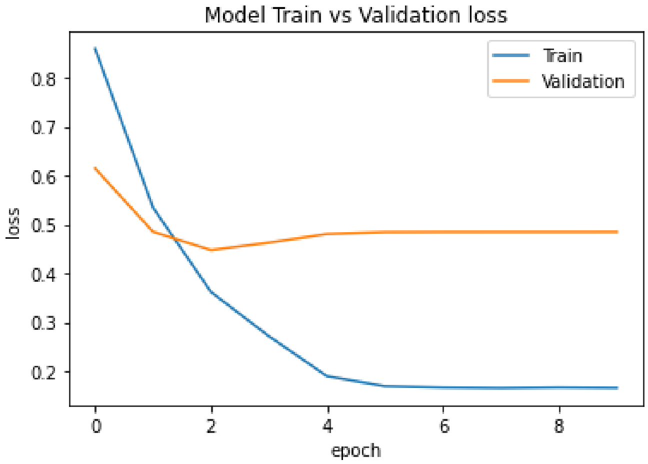

Fig. 6. The training loss curve of the proposed CD-ABSA

Table 7

Comparison of proposed CD-ABSA with other State-of-the-Art Approaches

Approach	P	R	F1	Acc
Supervised SVM [37]	-	-	-	78.7%
OSA [38]	-	-	-	0.80%
Lexicon+ Naïve Bayes [39]	-	-	-	0.80%
Naïve Bayes [37]	-	-	-	0.79%
Proposed Model	0.80%	0.82%	0.81%	0.82%

The expected and forecast probability for label l is represented by y and y 0, respectively. In both layers, the softmax function serves as an activation function. The softmax function is used because it produces a wide range of probability values as an output. We have also evaluated the performance of hyper-parameter such as activation, optimization, and dropout values (0.2) in Fig 9-11. Fig 9 showed that the model has a significant impact on a combination of (Adam, softmax, and dropout). As indicated in Table 8, we have contrasted the performance of our model with the results of the academic baseline investigations. As demonstrated, our model performed better in both tests of sentiment orientation detection than the standard approaches.

$$ACC(p) = \frac{TP_p + TN_p}{TP_p + FN_p + TN_p + FP_p} \tag{2}$$

$$PR\ (p) = \frac{TP_p}{TP_p + FP_p} \tag{3}$$

$$RE\ (p) = \frac{TP_p}{TP_p + FN_p} \tag{4}$$

$$FS(p) = \frac{2 * PR(p) * RE(p)}{PR(p) * RE(p)} \tag{5}$$

APPENDIX A: Interview Questions

1. The objectives and learning outcomes for each part of the course clear, precise, and specific.
2. The course was well organized, logical, and consistent.
3. The course was intellectually challenging.
4. The required tests, assignments, presentations, class participations, projects and papers measured my attainment of these learning outcomes.
5. The instruments used in course were useful for my learning.
6. Teacher was prepared and organized every class.
7. Teacher appeared enthusiastic and interested.
8. Teacher encouraged the discussion and participation.
9. Teacher demonstrated the depth knowledge about the course.
10. Teacher used a Varity of instructional methods to reach the course objectives (e.g., Student presentation, group actives or group discussion).
11. Teacher managed the class time and pace well.
12. Teacher was clearly communicated about assessment about course.
13. Teacher was provided feedback with stated time frame.
14. Teacher Feedback showed how to improve my work (e.g corrections or suggestions including in comments)
15. The course was supported by adequate library resources.
16. The provided technology and equipment were useful course (e.g whiteboard, projector, audio-visual, lab and PowerPoint)
17. The teacher shared platforms where you find related resources.
18. Any further suggestion or comments

4. Conclusion

This research study presented a CD-ABSA model for investigate course evaluation and SemEval-14 datasets. The CD-ABSA system has two main objectives in the first stage, the extract of the aspects from reviews and comments corpus, then analysis of the polarity of extracted opinion words from cross-domain. The LSA and LDA combined methods are used for analysing the aspects from the education domain dataset, and ABSA process, the LSTM network employed with word embedding produces contextual representations of words. The LDA outperforms as compared to LSA for aspects extraction. Moreover, for sentiment classification, CD-ABSA uses LSTM for TL multi domain learning. domain embeddings are also added along with a parameter generation network. From an experimental standpoint, we showed the value and efficiency of each component in the cross-domain ABSA task. The research study demonstrates how the proposed model recognizes domain knowledge. When compared to existing in-domain aspect-based sentiment analysis models, CD-ABSA can get the second-best results following cross-domain training. This study has limitations in data, machines, and so on. In the future, this study should be explored with bidirectional encoder representations for capturing more contextual and aspects information, and moreover, it would be also tested with various configurations of (Batch Size, Epochs, embedding, and LSTM units).

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