Reinforcement Learning-based Aspect Term Extraction using Dilated Convolutions and Differential Equation Initialization

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***Abstract*—Aspect term extraction is a crucial subtask in aspect-based sentiment analysis that aims to discover the aspect terms presented in a text. In this paper, a method for ATE is proposed that employs dilated convolution layers to extract feature vectors in parallel, which are then concatenated for classification downstream. Reinforcement learning is used to save the ATE model from imbalance classification, in which the training procedure is posed as a sequential decision-making process. The samples are the states; the network, and the agent; and the agent gets a more significant reward/penalty for correct/incorrect classification of the minority class compared with the majority class. The training phase, which typically employs gradient-based approaches, including back-propagation for the learning process, is tackled. Thus, it suffers from some drawbacks, including sensitivity to initialization. A novel differential equation (DE) approach that uses a clustering-based mutation operator to initiate the BP process is presented. Here, a winning cluster is identified for the current DE population, and a new updating strategy is used to generate candidate solutions. The BERT model is employed as word embedding, which can be included in a downstream task and fine-tuned as a model, while BERT can capture various linguistic properties. The proposed method is evaluated on two English datasets (Restaurant and Laptop) and has achieved outstanding results, surpassing other deep models (Restaurant: Precision 85.44%, F1-score 87.35%; Laptop: Precision 80.88%, F1-score 80.78%).**

Keywords—Aspect term extraction; sentiment analysis; differential evolution; reinforcement learning; BERT

I. Introduction

Sentiment analysis (SA) [1] is a challenging task in NLP that aims to extract overall sentiment from a single sentence or document. However, sentence-level SA doesn't reflect specific features or attributes that a user likes or dislikes. Aspect-based sentiment analysis (ABSA) provides a solution by specifying sentiment at a fine-granular level, giving sentiment to each phrase property. Aspect term extraction (ATE) is a component of ABSA that identifies every particular characteristic or aspect of the good or service being addressed. AT is a textual entity, a sequence of tokens within a sentence that must be referred to explicitly within the text. Such data is vital and frequently mandates an educated decision-making procedure [2].

From the literature, the ATE approaches can be categorized as lexicon-based methods [3], machine learning methods [4], and deep learning approaches [5]. Traditional ATE approaches mainly use feature engineering methods, including part-of-speech [6] and bag-of-words [7], to train machine learning classifiers, including SVM and Naïve Bayesian. Generally, traditional approaches have two shortcomings. First, they mainly do not utilize semantic information in keywords, rules, or features, forcing them not to regard relationships between sentences. Second, handmade rules and feature extraction are not flexible, resulting in inferior generalization ability [8]. DNNs have earned significant success in numerous industries since the introduction of neural networks in recent years [9-12]. ATE works have moved from feature engineering approaches to DNN approaches. Deep learning-based approaches for ATE typically hire RNN [13, 14], CNN [15-17], RecNN [18], and Memory Networks [19]. Besides the direct uses of various DNNs, the attention mechanism coupled with DNNs is increasingly popular. Other kinds of ATE approaches include embedding techniques and transfer learning. The BERT model [20, 21] is the language model, superior to other language models, which captured the benefit of the statement proposed in transformers [22], which is being applied extensively and utilized in NLP studies [23, 24]. Deep learning-based ATE approaches have shown promising results in identifying and extracting aspect terms from textual data. However, the performance of these models is greatly affected by the imbalance of the datasets. Imbalanced datasets are common in the ATE task, as the number of aspect terms in a sentence is typically small compared to the number of non-aspect terms. This can lead to biased models that are unable to capture the underlying distribution of the data. Another challenge faced by deep learning-based ATE approaches is the sensitivity to initialization during the training phase. The quality of the initial weights of a neural network greatly affects its ability to learn meaningful representations from the input data. Poor initialization can lead to suboptimal performance, and in some cases, the model may fail to converge.

Data imbalance is a significant challenge in ATE, as it can lead to a drop in performance. There are two methods to tackle class imbalance: algorithm-level and data-level [25]. The data-level approach involves under-sampling or over-sampling methods, or both, to counteract the negative impact of class imbalance. SMOTE [26] and NearMiss [27] are examples of under-sampling and over-sampling methods, respectively. Algorithm-level approaches raise the weight of the minority class through decision threshold adjustment [28], ensemble learning [29], and cost-sensitive learning [30]. Deep-learning approaches have also been proposed to address imbalanced classification. Research has focused on understanding the discriminative characteristics of imbalanced data while maintaining inter-class and inter-cluster margins, and developing a method based on the bootstrapping algorithm that balances data in convolutional networks per mini-batch [31]. Deep reinforcement learning (DRL) has been used in various domains to improve classification performance by eliminating noisy data and discovering better features. However, there have been few studies that apply DRL to classify imbalanced data, despite its suitability for this task. DRL's learning approach, which employs a reward function that discriminates between classes by imposing penalties on minority classes or rewarding them with greater rewards, makes it particularly well-suited for imbalanced data classification.

In the field of neural network methods, gradient-based algorithms like back-propagation have traditionally been used to find the optimal weights [32]. However, these methods can be limited by issues like initialization of parameters and getting stuck in local optima [33, 34]. A potential solution to these problems is to use meta-heuristic algorithms like DE [9], which have been successfully adapted to various optimization problems. DE operates through three main steps: mutation, crossover, and selection, with the mutation operator being particularly significant. By utilizing DE to optimize the learning process, it may be possible to overcome the limitations of gradient-based algorithms and achieve better model performance.

This paper suggests a framework for ATE founded on BERT word embedding, a clustering-based DE algorithm, and a reinforcement learning-based training algorithm. The suggested ATE model contains three dilated convolution layers, aiming to extract rich features in parallel, then concatenated for final classification. The ATE model should classify every word in three classes $\{B, I, O\}$, where B, I show the beginning and non-beginning words of an aspect term, and O means non-aspect terms. Since the number of members in class O is more significant than those in the remaining classes (B and I), the classifier assigns the majority of members to class O, resulting in an unbalanced classification that dramatically reduces system efficiency. Reinforcement learning is used to solve this issue, and design ATE as a guessing game with sequential decision-making steps. At each stage, the agent uses a training instance to represent the environmental state and then, guided by a policy, performs a three-class classification operation. The classifier will accept a positive reward if the operation is completed; otherwise, it will get a negative reward. The minority class receives higher compensation than the majority class. During the sequential decision-making process, the agent's objective is to classify the samples as precisely as possible in order to collect the maximum number of cumulative rewards. An enhanced DE technique is presented based on clustering for weight initialization in order to identify a favorable region in the search space from which to launch the BP algorithm in all networks. Here, the best candidate solution in the best cluster is chosen as the starting solution in the mutation operator, and a new updating technique is used to generate candidate solutions. The proposed technique is assessed using two English benchmark datasets (Restaurant + Laptop), the experimental findings of which show that the suggested model outperforms its competitors.

Following is a summary of the model's contributions:

- An ensemble of dilated convolutions is provided for the ATE model, enabling the model to extract valuable features from text to make a better decision for classification.
- The proposed model uses BERT word embedding to automatically learn and extract complicated and meaningful text representation from the input data.
- A reinforcement learning architecture is provided for the ATE problem in order to address imbalanced classification.
- As an alternative to random weight systems for model weights, an encoding method is created, and a starting value is computed using an enhanced DE algorithm.

The article's body has the following structure: In Section II, a review of the literature on ATE works is presented. In Section III, further depth into the suggested approach is delved. Section IV provides the experimental results and necessary analyses. Section V represents the conclusion of this article.

II. Related Works

To date, numerous domains have seen the proposal of a wide range of approaches for SA [35-37]. The majority of current tasks focus on detecting sentiments within single sentences or documents. Due to the limited availability of labeled datasets, supervised learning methods are commonly used, with few exceptions such as the unsupervised clustering method [38, 39]. Turney [40] suggested the utilization of an unsupervised learning method. To do this, the phrases containing adverbs or adjectives are initially evaluated for their semantic direction. Then, by examining the correlation between the average semantic orientation scores, the review can be classified as "recommended" or "not recommended." Pang and Lee [40] introduced a supervised machine learning technique to categorize the sentiment of movie reviews. They employed various linguistic features, such as part-of-speech tags, the presence of adjectives, unigrams, bigrams, etc., and trained them on machine learning classifiers such as Maximum Entropy and Naive Bayes. Pang et al. [35] proposed using a star rating system for movie reviews and argued that the labels derived from it were not independent. They suggested that the system should assign equal ratings to comparable reviews, and submitted a meta-algorithm that uses the connection among labels to improve the multi-class categorization outcome. Meanwhile, Kim and Hovy [41] used a probabilistic technique to identify a paragraph's comment and comment owner and employed the WordNet resource to determine word-level sentiments for sentiment categorization in a sentence. Lastly, Ganu et al. [42] conducted aspect category sentiment categorization in restaurant reviews by identifying six primary restaurant categories and classifying the reviews into one of four sentiment categories. Moreover, they showed that the review's textual content is a superior signal to the other meta-information. Go et al. [43] adopted a sentiment classifier by comparing PoS tags and N-grams with emoticon data. However, their suggested model does not use the data provided by emoticons. They remove emoticons from the tweet, so if the testing data has an emoticon, it does not impact the classifier because there was no emoticon in the training data.

According to the literature, ABSA has recently garnered the interest of scholars worldwide. [44, 45]. In 2014, the first dataset, SemEval-2014 [46], was shared, addressed ABSA's challenges, and provided a particular benchmark configuration. For additional improvement of the issues, two more datasets, SemEval-2015 [47] and SemEval2016 [47], on ABSA were. These datasets introduced the ABSA problem in multiple fields, including laptops, restaurants, hotels, cameras, and languages such as Arabic, English, Chinese, and Dutch.

The task of ATE which is a crucial part of ABSA has captured the attention of many researchers. Liu et al. [48] presented a solution to the ATE problem through the application of RNNs in their research. They discovered that the LSTM-RNN technique was more effective than the Conditional Random Field with many features (CRF) method, which relied on a multitude of features. Majumder et al. [49] integrated positional-based account data from other ATs in their research to classify aspect terms. The aim was to enable the method to recognize the position of other parts-of-speech words and their associated sentiment-carrying phrases, thus avoiding being sidetracked by them. Their modifications led to better performance and introduced a new approach for the laptop and restaurant domains. Yin et al. [50] employed word embeddings in the dependency path to acquire word representations. Xu et al. [51] proposed the DE-CNN model, which incorporates a dual embedding mechanism consisting of domain-specific and general-purpose embeddings. Xu et al. [52] fine-tuned BERT [53] on a specialized dataset to obtain advanced word embeddings. Yin et al. [54] created a word embedding approach that exploits positional dependence to take into account both positional setting and reliance correlations. They utilized assorted neural network architectures to capture diverse factors of the mission, such as illustrating the association between a unit and its appropriate sentiment term in a sequence identification system [55], and transfiguring the task into a Seq2Seq problem to grab the all-purpose objective of the entire sentence for identifying the part with more crucial contextual data [56]. Since annotating every component of an expression can be a time-intensive task, unsupervised ATE models have been widely advocated by analysts [57]. He et al. [58] put forward an autoencoder design for neural network-powered methods that diminishes insignificant terms to amplify the consistency of extracted features. By employing this approach, Luo et al. [59] coerced sememes to enhance lexical semantics during the creation of phrase representations. Tulkens and Cranenburgh [60] offered a solution named CAt, which uses a POS tagger and in-domain word representations to find component terms. The POS tagger discovers nouns as candidate features before using a contrastive attention technique to choose features. Shi et al. [61] formulated the ATE problem as a self-supervised contrastive learning task to discover feature representations that are more precise.

III. Method

A. Word Embedding

BERT [20] is a word embedding model often fine-tuned from a layer for various classification tasks and trained on huge datasets, like Wikipedia, to produce contextual word representations. Fine-tuning enables the use of the problem-specific meaning with a trained generic meaning and trains it for classification tasks. The general BERT architecture is shown in Fig. 1. In BERT, representations are jointly conditional on the left and proper context in all layers thanks to a bi-directional transformer. In contrast to Word2Vec and GloVe models, which create an embedding in one direction to disregard contextual differences, BERT produces an embedding in both directions.

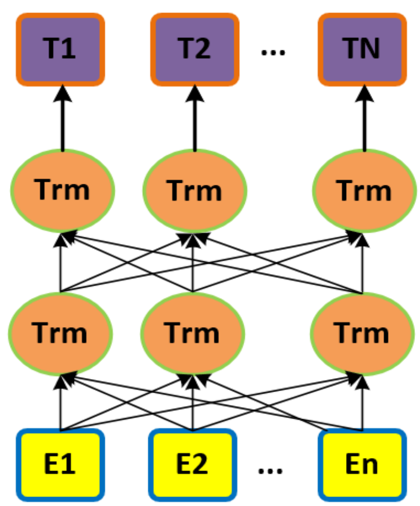

Fig. 1. Structure of the BERT model.

B. Prediction

Fig. 2 depicts the structure of the suggested ATE model. The model receives a sentence $s = [w_1, w_2, \dots, w_n]$ as input, where w_i are the words, and n is the maximum number of words in a sentence and passes it to the BERT model. The output of the DistilBERT model is the embedding matrix $M = [e_1; e_2; \dots; e_n]$, where e_i is the embedding of the word w_i. Three dilated convolution layers are employed on the matrix M working in parallel. Each of the three branches independently extracts a feature vector from the sentence. After obtaining text features by convolution, the rich features are extracted by max pooling to simplify the network's computational complexity. Finally, the connection obtained from the Maxpooling layers enters the MLP network for classification. The output of MLP is a vector whose length is $3 \times n$, as every word w_i should be classified into three classes $\{B, I, O\}$, where B, I show the beginning and non-beginning words of an aspect phrase, and O shows non-aspect words.

As most words from a sentence are in class O than two other classes, the classifier faces the problem of imbalanced classification, which drastically decreases system performance. A sequential decision issue is created using the imbalanced classification Markov decision process (ICMDP) to solve this.

The neural network weights are initialized in Step 0 through pre-training with the enhanced DE algorithm. In Step 1, a sample (s_t) is randomly selected from the dataset, which is part of the RL environment. The network processes the sample in Step 2. In Step 3, the network's prediction (action at) is returned to the environment to obtain the next sample (s_{t+1}) and its corresponding reward r_t in Step 4. The transition $\{s_t, a_t, r_t, s_{t+1}\}$ is then stored in the replay memory in Step 5. Multiple transitions are stored in the replay memory until a minibatch of transitions can be randomly drawn for updating the network weights in Step 7, after being drawn in Step 6. This process is repeated until the network is capable of correctly classifying the input sample. The algorithm stops when the number of episodes has been reached.

C. Pre-Training

At this stage, the weights of the proposed model are initialized. For this, an enhanced differential evolution method boosted by a clustering scheme and a novel fitness function is introduced.

a) Clustering-based Differential Evolution: The enhanced DE algorithm employs a clustering-based mutation and updating technique to improve the optimization performance.

The proposed mutation operator, which draws inspiration from [62], pinpoints a potential area in the search space. The k-means algorithm is used to partition the current population P into k clusters, each of which covers a distinct area of the search space. The number of clusters is chosen at random from the range $[2, \sqrt{N}]$. After clustering, the best cluster is identified as the lowest mean fitness of its samples. An illustration of this procedure for a toy problem with 19 potential solutions separated into three clusters is shown in Fig. 3.

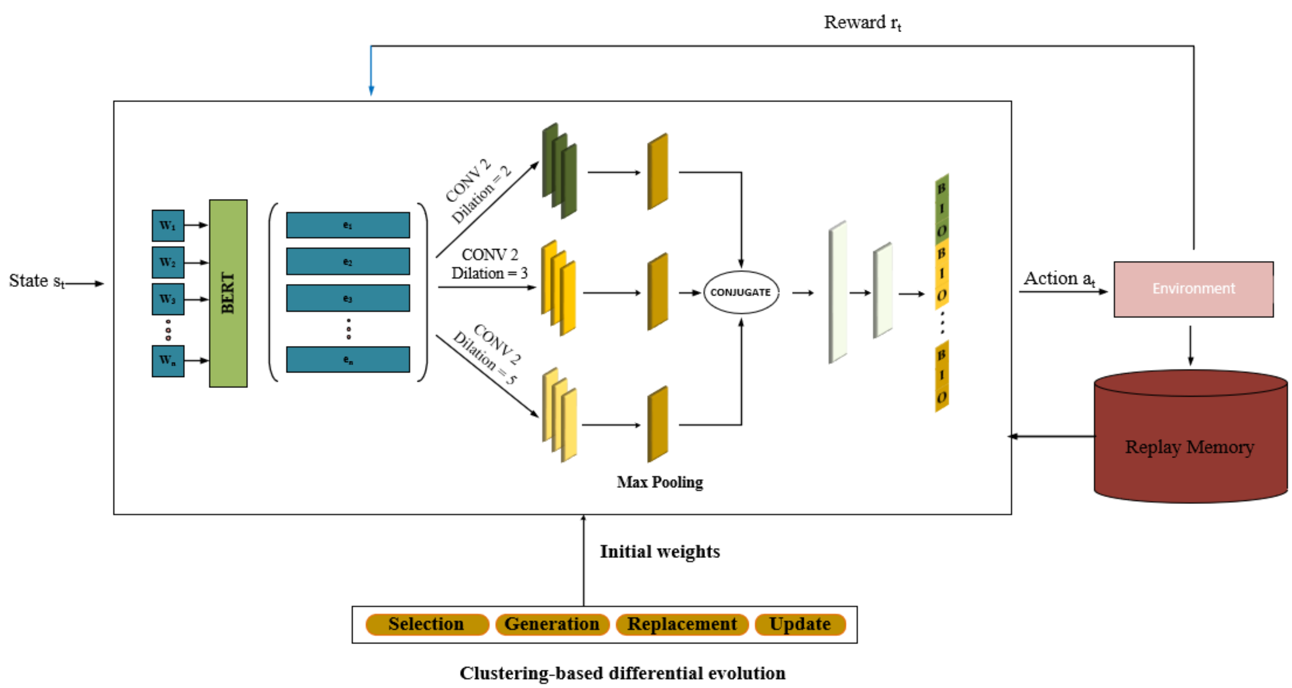

Fig. 2. Overview of the proposed ATE model.

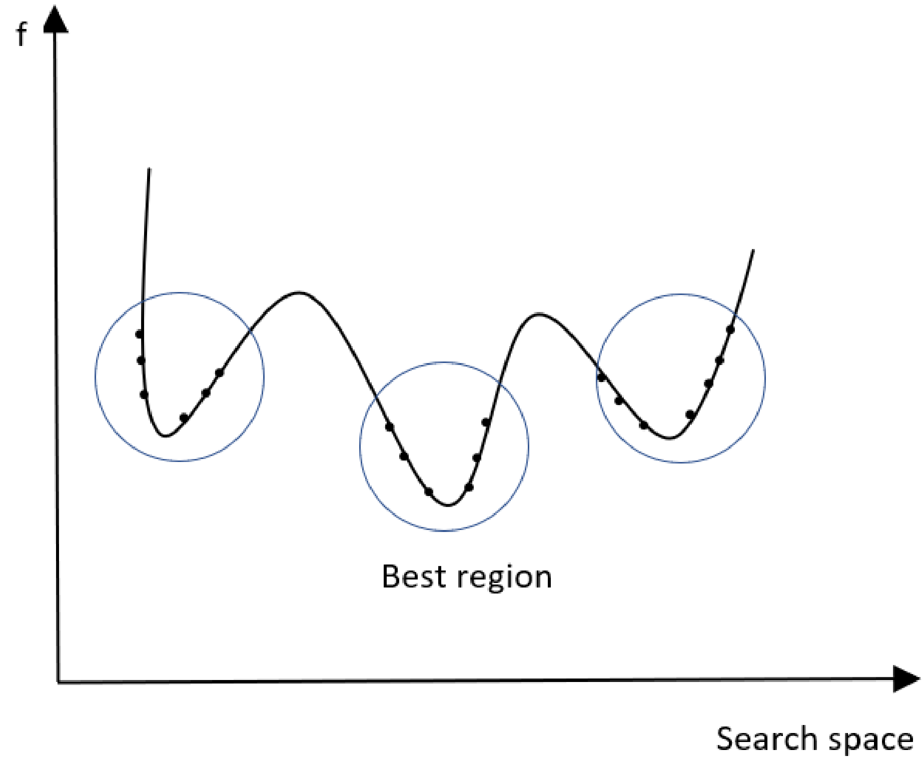

Fig. 3. Population clustering in search space to find the optimal region.

The proposed clustering-based mutation is defined as

$$\overrightarrow{v_i^{clu}} = \overrightarrow{win_g} + F(\overrightarrow{x_{r_1}} - \overrightarrow{x_{r_2}}) \quad (1)$$

where $\overrightarrow{x_{r_1}}$ and $\overrightarrow{x_{r_2}}$ are two randomly chosen candidate solutions from the current population, and $\overrightarrow{win_g}$ is the best solution in the promising region. Note that $\overrightarrow{win_g}$ is not necessarily the best solution for the population.

After generating M new solutions by clustering-based mutation, the current population is updated based on GPBA [63]; proceedings are as follows:

1) Selection: Create k individuals randomly to serve as the algorithm's initial seeds.

2) Generation: generate M solutions with clustering-based mutation as set v^{clu}.

3) Replacement: Select M solutions randomly from the existing population to comprise set B.Update: Select the top M solutions from v^{clu} □ B as set B'. The new population is found by $(P - B)$ □ B'.

b) Encoding Strategy: The primary structure of the proposed model includes three convolutional layers and a feed-forward network. As illustrated in Fig. 4, all weights and bias terms are arranged into a vector to form a candidate solution in the proposed DE algorithm.

c) Fitness Function: To calculate the quality of a candidate solution, the fitness function is defined as

$$F = \frac{1}{\sum_{i=1}^{N}(y_i - y'_i)^2} \quad (2)$$

where N shows the number of training examples, y_i and y'_i are the i-th target and output predicted by the model, respectively.

D. Deep Q-Network Training

This article employs RL to tackle ATE. Each sentence in the training set represents a state of the environment, and the network serves as the agent that executes a series of classifications on all sentences. When the agent predicts the class label of a sentence, it takes action, where the sentence observed at the t^{th} time-step is the state s_t, and the classification performed is a_t. In return, the environment offers a reward, r_t, to guide the agent. The rewards are assigned such that classifying a sample from the majority class yields a lower absolute value than the minority class. The reward function can be expressed as:

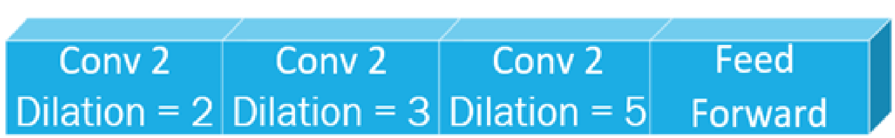

Fig. 4. Encoding strategy in the proposed algorithm.

$$r_t(s_t, a_t, y_t) = \frac{1}{n} \times \sum_{i=1}^{n} r_{w_i} \quad (3)$$

where r_{w_i} is the reward received for classifying the word w_i, which is described as:

$$r_{w_i} = \begin{cases} +1, \hat{y}_{w_i} = y_{w_i} \; and \; y_{w_i} \in \{D_B \cup D_I\} \\ -1, \hat{y}_{w_i} \neq y_{w_i} \; and \; y_{w_i} \in \{D_B \cup D_I\} \\ \lambda, \hat{y}_{w_i} = y_{w_i} \; and \; y_{w_i} \in D_O \\ -\lambda, \hat{y}_{w_i} \neq y_{w_i} \; and \; y_{w_i} \in D_O \end{cases} \quad (4)$$

where D_B and D_I represent the larger class and D_O denotes the smaller class. Properly/improperly classifying a sample from the larger class results in a reward of $+\lambda/-\lambda$, where $0 < \lambda < 1$. In the deep Q-learning approach, the agent's aim is to choose actions that maximize the predicted future rewards. The future rewards are discounted by a factor of γ at each subsequent time step, where

$$R_t \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'} \quad (5)$$

where T shows the last time-step of the episode. An episode ends when all the samples have been classified or the agent misclassifies a sample from the minority class. Q values, measures of state-action quality, are defined as the expected return of the following strategy π, after seeing state s and taking action a:

$$Q^{\pi}(s, a) = E[R_t | s_t = s, a_t = a, \pi] \quad (6)$$

The optimal action-value function equals the maximum expected reward overall strategies after seeing state s and taking action a:

$$Q^{*}(s, a) = max_{\pi} \; E[R_t | s_t = s, a_t = a, \pi] \quad (7)$$

This function satisfies the Bellman equation, which asserts that the optimal expected return for a given action is equal to the sum of the rewards from the current action and the maximum expected return from future actions at the following time:

$$Q^{*}(s, a) = E[r + \gamma \; max_{a'} Q^{*}(s', a') | s_t = s, a_t = a] \quad (8)$$

The Bellman equation is used as an iterative update to estimate the optimal action-value function:

$$Q_{i+1}(s, a) = E[r + \gamma \; max_{a'} Q_i(s', a') | s_t = s, a_t = a] \quad (9)$$

During training, after a state s is shown to the network, the network outputs an action a for that state while the environment returns a reward r, and the next state becomes s'. These parameters are embodied in a tuple (s, a, r, s') that is saved into the replay memory, M. Minibatches B of these tuples are selected from the replay memory to perform gradient descent. The loss function is denoted as:

$$L_i(\theta_i) = \sum_{(s,a,r,s') \in B} (y - Q(s, a; \theta_i))^2 \quad (10)$$

where θ represents the model weights, and y, is the estimated target for the Q function. The latter is equal to the reward for the state-action combination plus the discounted maximum future Q value:

$$yr + \gamma \; max_{a'} Q(s', a'; \; \theta_{k-1}) \quad (11)$$

Of note, the Q value for the terminal state equals zero. The gradient of the loss function at step i is calculated as:

$$\nabla_{\theta_i} L(\theta_i) = -2 \; \sum_{(s,a,r,s') \in B} (y - Q(s, a; \theta_i)) \nabla_{\theta_i} Q(s, a; \theta_i) \quad (12)$$

By performing a gradient descent step on the loss function, the model weights will be updated so as to minimize the error:

$$\theta_{i+1} = \theta_i + \alpha \nabla_{\theta_i} Q(s, a; \theta_i) \quad (13)$$

where α represents the learning rate of the network.

IV. Empirical Evaluation

The SemEval-2014 English dataset is employed to analyze the proposed method [46]. The SemEval-2014 dataset is a collection of text data designed for the task of sentiment analysis and opinion mining. This dataset was part of the 8th International Workshop on Semantic Evaluation (SemEval-2014), a shared task initiative that aimed to promote research and development in natural language processing and computational linguistics. The SemEval-2014 dataset contains various subtasks, including aspect-based sentiment analysis, sentiment classification, and sentiment polarity detection. The dataset is composed of two parts, the first of which is the Laptop dataset. This dataset contains a total of 2,186 laptop reviews, each labeled with the corresponding aspect terms, aspect categories, and sentiment polarity. The aspect terms are the specific aspects of the laptop that the reviewer is commenting on, such as keyboard, battery life, or screen. The aspect categories are the broader categories that these aspects fall under, such as design features, performance, or usability. The sentiment polarity is the overall sentiment expressed by the reviewer towards the aspect, which can be positive, negative, or neutral. The second part of the SemEval-2014 dataset is the Restaurant dataset. This dataset contains a total of 3,851 restaurant reviews, each labeled with the corresponding aspect terms, aspect categories, and sentiment polarity. Similar to the Laptop dataset, the aspect terms represent specific aspects of the restaurant that the reviewer is commenting on, such as service, food quality, or atmosphere. The aspect categories are the broader categories that these aspects fall under, such as food, service, or ambience. The sentiment polarity is the overall sentiment expressed by the reviewer towards the aspect, which can be positive, negative, or neutral.

In the first experiment, ten deep learning-based approaches are compared to the algorithm, namely Baseline, System [64], DLIREC [65], IHS_RD [66], PSO-EN [67], MTNA [68], RNCRF [55], CMLA [69], E2E [2].

Table I displays the quantitative outcomes of the proposed model for two datasets. In addition to comparing the suggested method with cutting-edge algorithms, the ATE without RL method is used to assess the efficacy of the RL component on the model ATE. For the Restaurant dataset, the suggested ATE model outperformed competing models, including E2E, resulting in an error reduction of more than 40% and 24% in the F1-score and accuracy criterion, respectively. The suggested model reduces the error rate by roughly 51% compared to ATE without RL, demonstrating the significance of the RL technique. For the Laptop dataset, the approach outperformed E2E and PSO-EN algorithms in terms of F1-

score and accuracy, so for the F1-score and accuracy criteria, the error improving rates are roughly 30.13% and 21.00%, respectively.

A. Comparison with other Metaheuristics

The improved DE algorithm is compared with a number of metaheuristic optimization algorithms. Different metaheuristics are used to obtain the initial model parameters while keeping the other model components. Seven different algorithms are used, namely standard DE [70], BA [71], COA [72], ABC [73], GWO [74], WOA [75], and SSA [76]. Table II contains the obtained results for the Restaurant and Laptop datasets. For the Restaurant dataset, the proposed model reduces error by about 31% compared to the standard DE. It clearly shows that the model has a substantial ability compared to the standard one. Also, DE offers more acceptable results than other algorithms, including ABC, GWO, and BAT. There is a minor improvement for the laptop dataset, so the error rate is reduced by around 17.17%.

B. Word Embeddings

Word embedding is a critical component of deep learning models, as incorrect embeddings can mislead the model. In this study, BERT, one of the latest embedding models, was utilized as the word embedding. Five other word embeddings, including One-Hot encoding [77] , CBOW, Skip-gram [78], GloVe [79] , and FastText [80], were employed to compare various word embeddings with the model. One-Hot encoding is a vital step in converting the collected data variables into binary features, which improves the accuracy of predictions and classifications. A binary feature is generated for each class, and each sample's feature is assigned a value of 1 corresponding to its original class. The Skip-gram and CBOW algorithms use neural networks to convert a word to its word embedding vector. GloVe is a technique for aggregating global word-word co-occurrence data from a corpus. The FastText word embedding technique expands on the Skip-gram paradigm by encoding each word as an n-gram of letters instead of learning word vectors. The results of this study are presented in Table III. As anticipated, One-Hot encoding is the least effective among the others. Therefore, the proposed model's improvement rate is around 53.72% and 61.95% for the Restaurant and Laptop datasets, respectively. Due to their similar design, Skip-gram and CBOW perform almost equally across all datasets, and both outperform the GloVe word embedding. Compared to the FastText model, BERT reduces errors by 14% and 10% for the Restaurant and Laptop datasets, respectively.

TABLE I. EVALUATIONS OF THE DEEP LEARNING-BASED SYSTEMS

Model	Restaurant			Laptop		
	Precision	Recall	F1	Precision	Recall	F1
Baseline	44.69	50.49	47.26	31.40	38.05	35.64
System	78.62	82.09	81.91	68.44	74.11	72.42
DLIREC	82.15	85.12	83.11	71.50	74.53	73.59
IHS_RD	79.18	81.16	80.49	72.82	76.12	74.55
PSO-FS	80.49	86.53	83.11	71.00	74.46	72.78
PSO-EN	80.14	87.06	84.52	73.01	76.25	74.93
MTNA	82.49	84.10	83.67	74.46	76.09	75.45
RNCRF	83.02	85.78	84.05	74.09	79.36	76.83
RNCRF+F	83.02	85.98	84.90	76.26	79.56	78.42
CMLA	81.86	88.42	85.34	75.36	79.06	77.80
E2E	82.52	84.18	83.36	74.59	79.46	78.57
ATE without RL	79.10	82.19	81.16	70.09	76.15	73.84
Proposed	85.44	89.14	87.35	80.88	82.48	80.78

TABLE II. EVALUATIONS OF METAHEURISTIC ALGORITHMS

Model	Restaurant			Laptop		
	Precision	Recall	F1	Precision	Recall	F1
DE	84.41	81.10	82.20	75.69	80.12	77.90
BA	73/85	63/24	70/47	67/49	72/69	68/45
COA	68/52	61/89	64/23	59/14	68/48	63/40
ABC	78.10	70.26	75.81	69.01	75.56	72.30
GWO	49/80	50/47	49/85	32/58	40/15	37/96
WOA	67/00	55/86	60/55	52/40	61/86	57/23
SSA	65/10	53/20	60/25	50/48	58/47	54/00

TABLE III. EVALUATIONS OF VARIOUS WORD EMBEDDINGS

Model	Restaurant			Laptop		
	Precision	Recall	F1	Precision	Recall	F1
One-Hot encoding	45.20	49.46	47.23	33.96	37.20	35.64
CBOW	79.02	83.16	81.94	69.13	74.29	72.42
Skip-gram	79.14	82.13	80.15	69.29	74.82	72.79
GloVe	82.14	86.19	84.06	72.46	75.93	74.55
FastText	83.59	87.23	85.11	74.63	78.20	76.78

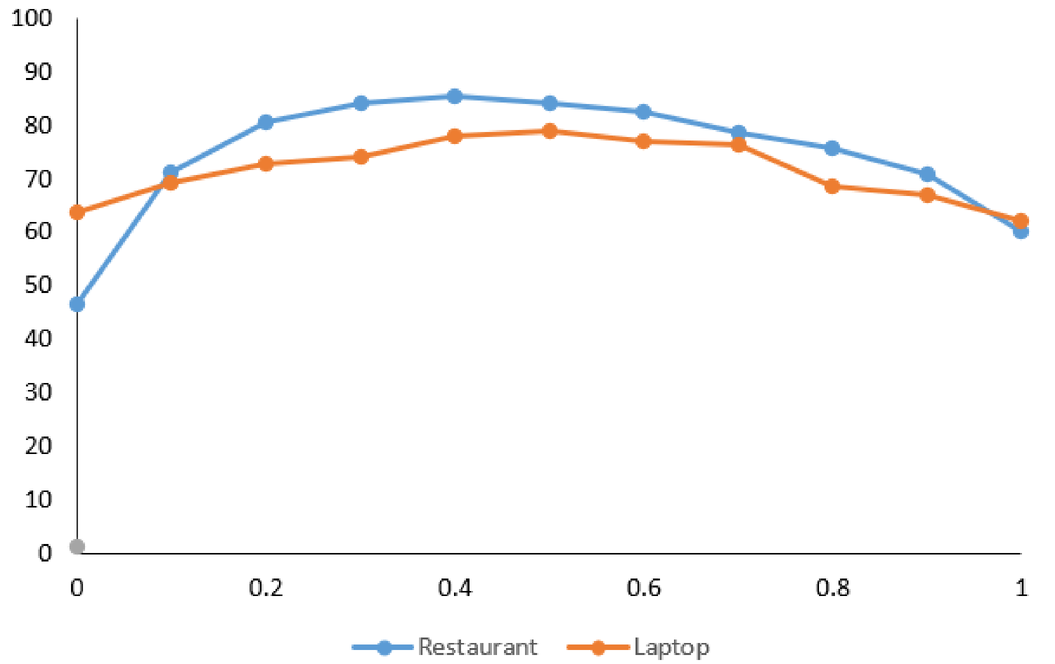

Fig. 5. The procedure of altering the criteria for each dataset by changing the value of λ.

Without RL	With RL	Real
I have to say they have one of the fastest delivery times in the city.	I have to say they have one of the fastest **delivery times** in the city.	delivery, times
Certainly not the best sushi in New York, however, it is always fresh, and the place is very clean, sterile.	Certainly not the best **sushi** in New York, however, it is always fresh, and the **place** is very clean, sterile.	sushi, place
We enjoyed ourselves **thoroughly** and will be **going** back for the desserts.	We enjoyed ourselves thoroughly and will be **going** back for the **desserts**.	desserts
Most importantly, it is reasonably priced.	Most importantly, it is reasonably **priced**.	priced
The unattractive lighting made me want to gag, the **food** was overpriced, there was the most awful disco pop **duo** performing - and my escargot looked like it might crawl off the plate.	The unattractive **lighting** made me want to gag, the **food** was overpriced, there was the most awful **disco pop duo** performing - and my **escargot** looked like it might crawl off the plate.	lighting, food, disco, pop, duo, escargot

Fig. 6. Examples of ATE output with and without reinforcement learning.

C. Impact of the Reward Function

In the suggested ATE design, appropriate rewards of +1/-1 and +λ/-λ are assigned for the accurate/inaccurate identification of the dominant and subordinate classes, respectively. The value of λ is reliant on the relative proportions of the majority to minority samples, and it should decrease as the ratio increases. To evaluate the effect of λ, the ATE model's performance was assessed by initiating λ with incremental values from the set {0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}, while holding the majority class bonus constant (Fig. 5). At λ = 0, the influence of the majority class is eliminated, and at λ = 1, both majority and minority classes have equivalent impacts. Across all metrics, model performance peaks at a λ value of 0.4 (increasing from 0 to 0.4; decreasing from 0.4 to 1). As a result, while λ needs to be adjusted to weaken the impact of the majority class, a too-low value can impair the overall model performance.

D. Case Study

To evaluate the effectiveness of RL in the proposed ATE model, five samples were randomly selected from the SemEval-2014 dataset. The results are illustrated in Fig. 6, where the first column shows the model's output without RL, the second column represents the model's output with RL, and the third column displays the actual aspect term. The results reveal that the model without RL tends to assign a higher score to class O. On the other hand, the model with RL generates the maximum number of scores for correctly classifying classes B and I.

E. Discussion

The use of artificial intelligence in natural language processing has seen significant progress in recent years. The paper presents an approach for ATE that employs dilated convolution layers and reinforcement learning to address the problem of imbalance classification. A novel DE approach is proposed to initiate the BP process and use the BERT model as word embedding. The experimental results on two English datasets show that the suggested ATE model outperforms other systems.

However, there are some limitations that need to be addressed in future works. Firstly, the proposed method was only evaluated on two English datasets. The method's performance on other languages or domains needs to be explored to demonstrate its generalizability. Secondly, the BERT model is used, which is computationally expensive due to its large number of parameters. Although they suggest using other BERT extensions, such as the DistilBERT language model, for reducing the computing costs, it would be interesting to investigate other lightweight and efficient models for word embedding. Finally, no analysis of the extracted aspect terms, such as their relevance or coherence with the context was provided, which could have been a valuable addition to the evaluation metrics.

In addition to the aforementioned limitations, another area that could be explored in future works is the effectiveness of the proposed method on long texts. The ATE task becomes more challenging when dealing with longer texts, as there may be multiple aspects mentioned in the same text, and identifying the relevant aspects requires a more sophisticated approach. Therefore, it would be beneficial to investigate how the proposed method performs on longer texts and whether any modifications or adaptations are necessary to improve its performance. Another potential avenue for future work is to explore the interpretability of the ATE model. While the proposed approach achieved high accuracy in extracting aspect terms, it is not clear how the model makes its predictions. Understanding the reasoning behind the model's decision-making process could help to identify any biases or errors in the model and improve its performance. Furthermore, it would be interesting to investigate the impact of different hyperparameters on the performance of the proposed method. a specific set of hyperparameters was used for the experiments, and it is not clear whether these hyperparameters are optimal for all scenarios. A more thorough analysis of the impact of different hyperparameters on the model's performance could help to identify the most effective settings for different use cases.

V. Conclusion

In this article, the problem of ATE was handled, which was constructed from three dilated convolution layers deployed to extract feature vectors in parallel, concatenated for downstream classification. An improved DE algorithm is used for pre-training the model networks. The improved DE algorithm clusters the current population to find a suitable region in the search space and implements a new updating technique. Moreover, Reinforcement learning, which presents the training process as a sequential decision-making process, was applied to shield the ATE model from imbalanced classification. At each stage, the agent receives samples and classifies them. The environment rewards the agent for each categorization act in which the minority class gets a greater reward than the majority class. Finally, with the help of a particular reward function and a conducive learning environment, the agent reveals the optimal strategy. The proposed models are evaluated using the Restaurant and Laptop datasets. The experimental results showed that the suggested ATE model outperformed other systems.

The BERT model typically comprises millions of parameters, increasing the computing costs associated with these models' environmental scaling. This problem can be solved using other BERT extensions, like the DistilBERT language model. The other language models with fewer parameters will be used for the following work.

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