EPiDA: An Easy Plug-in Data Augmentation Framework for High Performance Text Classification

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Abstract

Recent works have empirically shown the effectiveness of data augmentation (DA) for NLP tasks, especially for those suffering from data scarcity. Intuitively, given the size of generated data, their diversity and quality are crucial to the performance of targeted tasks. However, to the best of our knowledge, most existing methods consider only either the diversity or the quality of augmented data, thus cannot fully tap the potential of DA for NLP. In this paper, we present an easy and plug-in data augmentation framework EPiDA to support effective text classification. EPiDA employs two mechanisms: relative entropy maximization (REM) and conditional entropy minimization (CEM) to control data generation, where REM is designed to enhance the diversity of augmented data while CEM is exploited to ensure their semantic consistency. EPiDA can support efficient and continuous data generation for effective classifier training. Extensive experiments show that EPiDA outperforms existing SOTA methods in most cases, though not using any agent network or pre-trained generation network, and it works well with various DA algorithms and classification models. Code is available at https://github.com/zhaominyiz/EPiDA.

1 Introduction

Data augmentation (DA) is widely-used in classification tasks (Shorten and Khoshgoftaar, 2019; Feng et al., 2021; Zhang et al., 2021). In computer vision (CV), (Krizhevsky et al., 2012; Chatfield et al., 2014; Szegedy et al., 2015) adopt strategies like flipping, cropping, tilting to perform DA. In natural language processing (NLP), (Xie et al., 2017; Coulombe, 2018; Niu and Bansal, 2018; Wei and Zou, 2019) find that native augmentation skills such as spelling errors, synonym replacement, deleting and swapping, can bring considerable performance improvement. All these methods use various transformations for data augmentation, but they do not achieve equal success in different NLP tasks (Yang et al., 2020). Sometimes, they fail to guarantee semantic consistency, and may even bring semantic errors that are harmful to classification. The reason lies in that data augmentation for NLP is in discrete space, so it can easily incur large deviation of semantics (e.g. in sentiment classification task, deleting emotional words from a sentence will make its meaning completely different).

Generally, given the size of generated data, their diversity and quality are crucial to the performance of targeted tasks (Ash et al., 2019). Recent works have begun to emphasize the diversity or quality of augmented data. For example, in CV, AA (Cubuk et al., 2019), Fast-AA (Lim et al., 2019) and LTA (Luo et al., 2020) employ agent networks to learn how to enhance diversity. In NLP, language models are widely used to control generation quality, including Back-translation (Sennrich et al., 2016; Yu et al., 2018), Seq2seq models (Kobayashi, 2018; Kumar et al., 2019; Yang et al., 2020), GPT-2 (Radford et al., 2019; Anaby-Tavor et al., 2020; Quteineh et al., 2020; Liu et al., 2020) and T5 (Dong et al., 2021). In addition, some works (Morris et al., 2020) in NLP utilize adversarial augmentation to enrich the diversity of the samples. However, to the best of our knowledge, most existing works consider only either the quality or the diversity of augmented data, so cannot fully exploit the potential of data augmentation for NLP tasks. Besides, recent existing DA methods for NLP tasks usually resort to pre-trained language models, are extremely inefficient due to huge model complexity and tedious finetuning, which limits the scope of their applications.

In this paper, we propose a new data augmentation framework for text classification. This framework is called EPiDA (the abbreviation of Easy Plug-in Data Augmentation), which employs two mechanisms to control the diversity and quality
The main contributions of this paper are as follows:

1. We propose an easy plug-in data augmentation framework EPiDA for text classification. EPiDA can work with various existing DA algorithms and classification models, it is general, efficient, and easy-to-deploy.

2. We design two mechanisms relative entropy maximization (REM) and conditional entropy minimization (CEM) to boost the diversity and quality of augmented data simultaneously in an explicit and controllable way.

3. We conduct extensive experiments to evaluate EPiDA. Experimental results show that EPiDA outperforms existing DA methods, and works well with different DA algorithms and classification models.

The rest of this paper is organized as follows: Sec. 2 reviews related work and highlights the differences between our work and major existing methods. Sec. 3 introduce our method in details. Sec. 4 presents the results of performance evaluation, and Sec. 5 concludes the paper.
Table 1: A qualitative comparison between EPiDA and major existing methods from four aspects: whether controlling the diversity and quality of the augmented data, whether using language model or agent network and whether using the feedback of the classifier.

| Method               | Div | Qua | LM | FB |
|----------------------|-----|-----|----|----|
| AA (Cubuk et al., 2019) | ✓  | ×   | ✓  | ✓  |
| EDA (Wei and Zou, 2019) | ✓  | ×   | ×  | ×  |
| DataBoost (Liu et al., 2020) | ×  | ✓   | ✓  | ✓  |
| LearnDA (Zuo et al., 2021) | ✓  | ✓   | ✓  | ×  |
| VDA (Zhou et al., 2021)   | ✓  | ✓   | ×  | ✓  |
| Ours EPiDA              | ✓  | ✓   | ×  | ✓  |

Table 1, our method EPiDA differs from LearnDA in at least three other aspects: 1) LearnDA employs perplexity score (PPL) and cosine similarity to measure diversity and quality respectively, while EPiDA adopts two mechanisms relative entropy maximization (REM) and conditional entropy minimization (CEM) to control diversity and quality, which is theoretically more rational and solid. 2) LearnDA is for event causality identification, while EPiDA is mainly for text classification. 3) LearnDA needs knowledge guidance, while EPiDA does not. These make it difficult to evaluate LearnDA in our experimental settings. Thus, we do not conduct performance comparison between EPiDA and LearnDA. Nevertheless, in our ablation study, we replace REM and CEM with PPL and cosine similarity in EPiDA, and our experimental results show that EPiDA with REM and CEM performs better than that with PPL and cosine similarity. Besides, comparing with VDA that requires PLM to provide substitution probability, EPiDA is free of PLMs, and is more effective, efficient and practical.

3 Method

As shown in Fig. 1, EPiDA consists of three components: a DA algorithm $T$, a classifier or classification model $C$, and a Sample Evaluation and Selection (SEAS) module that is the core component of EPiDA. Generally, the DA algorithm and the classifier can be any of existing DA algorithms and classifiers. With the feedback of the classifier, SEAS evaluates candidate samples generated by the DA algorithm in terms of diversity and quality via the Relative Entropy Maximization (REM) mechanism and the Conditional Entropy Minimization (CEM) mechanism, and outputs the qualified samples to further train the classifier. So EPiDA can serve as a plug-in component to boost existing DA algorithms for training better target models.

3.1 The Rationale to Control DA

Consider a classification task with a dataset $X$ of $n$ samples: $X = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$. Here, $x_i$ is a sample, $y_i$ is its label. The loss function is

$$L_\omega(\omega) = \frac{1}{n} \sum_{i=1}^{n} l(\omega^T \phi(x_i); y_i). \tag{1}$$

where $\phi : \mathbb{R}^d \rightarrow \mathbb{R}^D$ is a finite-dimensional feature map, $\omega \in \mathbb{R}^D$ means learnable parameters, and $l$...
can be a common loss function like cross-entropy.

Now we employ a DA algorithm \( T \) to conduct augmentation for each sample in \( X \). Let \( t_i^j \) be the \( j \)-th sample generated by \( T \) with \( x_i \) as input, and \( m \) samples are generated from \( x_i \), the loss function for the generated samples can be written as

\[
L_g(\omega) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{m} \sum_{j=1}^{m} l(\omega^\top \phi(t_i^j); y_i). \tag{2}
\]

Here, we assume 1) \( t_i^j \) and \( x_i \) have the same label \( y_i \), so we can use \( y_i \) to optimize the new loss function; 2) Data augmentation does not significantly change the feature map \( \phi \), that is, augmentation can maintain semantic consistency of the sample space. Now we combine the augmented samples into the original samples, thus the total loss function of EPiDA can be written as follows:

\[
L(\omega) = L_o(\omega) + L_g(\omega). \tag{3}
\]

Recall that we use the feedback of the classifier \( C \) to select samples. Specifically, we use the original training samples \( X \) to pre-train the classifier \( C \), and for each generated sample \( t_i^j \), the feedback signal about \( t_i^j \) from the classifier is used for evaluating \( t_i^j \). When the generation process is over, all generated samples \( \{t_i^j\} \) are used to train \( C \) again.

First, we consider how to generate samples of high diversity. Intuitively, generated samples should be different from the original samples. Recall that the classifier \( C \) is pretrained by \( X \), so for generated sample \( t_i^j \), its loss \( l(\omega^\top \phi(t_i^j); y_i) \) should be large. In this sense, given the classifier \( C \) (\( \omega \) is fixed), we select samples that meet the following objective function:

\[
\max_{t_i^j} L_g(\omega, \phi(t_i^j)), \tag{4}
\]

which means that we are to generate “hard” samples for the classifier to cope with.

Second, we consider how to control the quality of augmented data. Recall that we assume for each augmented sample \( t_i^j \), its label \( y_i \) keeps unchanged, so we can use the original label to evaluate the loss function. However, due to the discrete nature of language, it is nontrivial for augmented samples to meet this assumption. Taking the sentiment analysis task for example, suppose we use EDA (Wei and Zou, 2019) to augment \( x_i = “you’ll probably love it” \), EDA may delete the word “love”. Obviously, the resulting sentence breaks the semantic consistency. To guarantee semantic consistency, we limit the semantic deviation of \( \phi(t_i^j) \) from \( \phi(x_i) \). Let \( M \) and \( \rho \) be a metric function to measure semantic difference between samples and a threshold respectively, we impose the following constraint on \( \phi(t_i^j) \):

\[
|M(\omega^\top \phi(t_i^j), \omega^\top \phi(x_i))| \leq \rho. \tag{5}
\]

Thus, we can enhance data diversity by optimizing Eq. (4), and improve data quality using Eq. (5). The problem turns to solve Eq. (4) and Eq. (5).

### 3.2 Relative Entropy Maximization

We rewrite the objective function in Eq. (4) via:

\[
L_g(\omega, \phi(t_i^j)) = \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} l(\omega^\top \phi(t_i^j); y_i)
= \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} D(p(\omega^\top \phi(t_i^j)), p(y_i)) + H(p(y_i)), \tag{6}
\]

where \( p, H, D \) indicate probability distribution, Shannon entropy, and relative entropy respectively, and actually \( H(p(y_i)) = 0 \) since \( p(y_i) \) is a one-hot vector. According to Eq. (6), we try to augment samples with large relative entropy under the given labels. Thus, we call this method relative entropy maximization (REM) mechanism. As relative entropy measures the difference between the two distributions \( p(\omega^\top \phi(t_i^j)) \) and \( p(y_i) \), the larger the difference is, the more diverse the augmented sample is. Therefore, we define the diversity score \( s_{div}^{ij} \) of augmented sample \( t_i^j \) as follows:

\[
s_{div}^{ij} = D(p(\omega^\top \phi(t_i^j)), p(y_i)). \tag{7}
\]

### 3.3 Conditional Entropy Minimization

We use conditional entropy as the metric function in Eq. (5) to constrain the semantic deviation of \( \phi(t_i^j) \) from \( \phi(x_i) \), i.e., \( M(\cdot, \cdot) := H(\cdot|\cdot) \). Then, Eq. (5) can be rewritten to

\[
H(p(\omega^\top \phi(t_i^j)|p(\omega^\top \phi(x_i))) \leq \rho. \tag{8}
\]

where \( H(\cdot, \cdot) \) is conditional entropy. Furthermore, to meet Eq. (8), we select samples \( \{t_i^j\} \) by solving the following optimization problem:

\[
\min_{t_i^j} H(p(\omega^\top \phi(t_i^j)|p(\omega^\top \phi(x_i))). \tag{9}
\]

We call this conditional entropy minimization (CEM) mechanism. The smallest value of
$H(p(\omega^T \phi(t^i_j))|p(\omega^T \phi(x_i)))$ is 0, indicating that given $p(\omega^T \phi(x_i))$, $p(\omega^T \phi(t^i_j))$ is exactly predictable. Eq. (9) can also be expanded to the difference between Shannon entropy $H$ and mutual information $I$, i.e., $H(X|Y) = H(X) - I(X,Y)$. In other words, CEM minimizes the entropy of the selected sample $t^i_j$ and maximizes the mutual information between $t^i_j$ and the original sample $x_i$, which means that CEM tries to augment samples of high prediction probability and high similarity with the original sample. As in REM, we define the quality score $s_{qua}^{ij}$ of augmented sample $t^i_j$ as

$$s_{qua}^{ij} = -H(p(\omega^T \phi(t^i_j))|p(\omega^T \phi(x_i))). \quad (10)$$

### Algorithm 1: EPiDA Data Augmentation.

**Input:** Classification model $\omega$, input sample $x_i$ and its label $y_i$, DA algorithm $T$, augmentation number $m$ and amplification factor $K$.

**Output:** $m$ augmented samples.

// assign the set $T(x_i)$ of $mK$ candidates to array $\hat{t}_i$ 
$t^i_1 \leftarrow T(x_i)$; 
$s_{div}, s_{qua}, s_{tot} = \mathbb{R}^{K*m}, \mathbb{R}^{K*m}, \mathbb{R}^{K*m}$; 
for $j = 1, 2, \ldots, K * m$ do 
  Calculate $s_{div}^{ij}$ via Eq. (7); 
  Calculate $s_{qua}^{ij}$ via Eq. (10); 
end 
Take Min_Max_Norm for $s_{div}$ and $s_{qua}$; 
$s_{tot} = s_{div} + s_{qua}$; 
// find the subscripts of the top $m$ small elements 
$id = \text{argtopm}(-s_{tot})$; 
Return $\hat{t}_i[id]$;

### 3.4 Algorithm and Implementation

The procedure of EPiDA is presented in Alg. 1. For each input sample $x_i$, EPiDA outputs $m$ augmented samples. First, we employ $T$ to generate $K * m$ candidate augmented samples for $x_i$, where $K$ is a hyperparameter to amplify the number of candidate samples, which is called amplification factor. Then, for each augmented sample, we use REM and CEM to evaluate its diversity score ($s_{div}$) and quality score ($s_{qua}$), respectively. Next, we adopt Min_Max_Norm to make $s_{div}$ and $s_{qua}$ fall in $[0,1]$. After that, we add them together as the overall score of the sample, and sort all the augmented samples in descending order according to their scores. Finally, we take the top $m$ samples from all the $K * m$ candidate samples as the output, and utilize them to train the classifier.

By nature, the goals of REM and CEM are conflicting, i.e., a sample of high diversity is more probably of low quality, and vice versa. We give an example in Tab. 2 to demonstrate this point. REM encourages to change salient words, which is prone to break the semantic consistency (see the 3rd row, “excited” is changed to “mad”, leading to large diversity score but small quality score). However, CEM tends to make the augmented samples keep semantic consistency, i.e., has large quality score but small diversity score (see the 4th row, “comes” is deleted). By jointly considering REM and CEM, satisfactory samples with balanced diversity and quality can be found (see the 5th row).

Besides, the calculation of $s_{div}$ and $s_{qua}$ requires the feedback of the classifier, so we first pre-train the classifier using the original samples, then with EPiDA we can generate samples of high diversity and quality for the classifier continuously.

### 4 Performance Evaluation

In this section, we conduct extensive experiments to evaluate EPiDA, including performance comparison with SOTA methods, performance evaluation when working with different DA algorithms and classification models, ablation study, and qualitative visualization of samples augmented by EPiDA.

#### 4.1 Datasets and Settings

Datasets for five different tasks are used in our experiments: Question Classification (Li and Roth, 2002) (TREC, $N=5,452$), News Classification (Zhang et al., 2015) (AGNews, $N=120,000$), Tweets Sentiment Analysis (Rosenthal et al., 2017)
| Method                                | Sentiment 10% | Sentiment 40% | Irony 10% | Irony 40% | Offense 10% | Offense 40% | PPL 10% | PPL 40% | PPL 10% | PPL 40% | PPL 10% | PPL 40% |
|--------------------------------------|---------------|---------------|-----------|-----------|-------------|-------------|---------|---------|---------|---------|---------|---------|
| EDA                                  | 0.560         | 0.608         | 41.22     | 0.530     | 0.515       | 76.07       | 0.637   | 0.629   | 37.37   |
| Contextual Word Embs Aug.            | 0.610         | 0.627         | 1043.18   | 0.518     | 0.593       | 1146.40     | 0.663   | 0.713   | 1729.62 |
| Back-translation Aug.                | 0.617         | 0.620         | 474.29    | 0.520     | 0.541       | 423.32      | 0.655   | 0.724   | 345.23   |
| Data Boost                           | 0.591         | 0.642         | 56.23     | 0.591     | 0.639       | 77.40       | 0.695   | 0.784   | 35.18   |
| Ours EPiDA: REM only                 | 0.619         | 0.650         | 66.86     | 0.624     | 0.665       | 77.09       | 0.652   | 0.673   | 81.13   |
| Ours EPiDA: CEM only                 | 0.629         | 0.659         | **8.10**  | 0.629     | 0.666       | **12.11**   | 0.668   | 0.670   | **8.57** |
| Ours EPiDA: REM+CEM                  | **0.639**     | **0.659**     | **25.40** | **0.651** | **0.687**   | **53.17**   | 0.680   | 0.687   | **32.56** |

Table 3: Performance comparison with existing augmentation methods. 10%: 10% original data + 30% augmented data \((m = 3)\); 40%: 40% original data + 40% augmented data \((m = 1)\). We report the F1 score of the BERT classifier averaged over five repeated experiments on each dataset. We also report the perplexity score (PPL) of 10,000 randomly sampled data augmented by each method, where PPL is evaluated by the kenLM language model trained on the training data of each task.

(Sentiment, \(N=20,631\), Tweets Irony Classification (Van Hee et al., 2018) (Irony, \(N=3,817\)) and Tweets Offense Detection (Founta et al., 2018) (Offense, \(N=99,603\)), where \(N\) is the number of training samples. To fully demonstrate the performance of data augmentation, we use only part of each dataset. In the following experiments, the percentage (%) that follows the task name means the ratio of training data used from each dataset, e.g. Irony 1% means that 1% of the dataset is used. Macro-F1 (F1 for binary tasks) is used as performance metric, and all the experiments are repeated five times. The amplification factor \(K\) is set to 3.

4.2 Comparing with SOTA Methods

Here we carry out performance comparison with major SOTA methods to show the superiority of EPiDA on three datasets: Sentiment, Irony and Offense. For a fair comparison, we strictly follow the experimental setting of DataBoost (Liu et al., 2020): we do only one round of augmentation to ensure that the number of samples of our method is consistent with that of the other methods, and use BERT as the classifier. We use the widely used EDA as the DA algorithm of EPiDA. We do not use DataBoost because it is not yet open-sourced. The experimental results are presented in Tab. 3.

From Tab. 3, we can see that 1) with the help of EPiDA, the performance of EDA is greatly improved. In particular, comparing with the original EDA, EPiDA gets performance improvement of 14.1%, 8.39%, 22.83%, 33.40%, 6.75% and 9.22% in six task settings, respectively. 2) Our method outperforms DataBoost in four settings. In particular, EPiDA+EDA gets performance improvement of 8.12%, 2.65%, 10.15% and 6.99% in various settings of the Sentiment and Irony tasks. 3) The variants of EPiDA that utilize only REM or CEM to enhance diversity or quality are inferior to using both, which demonstrates the effectiveness of joint enhancement. 4) DataBoost performs better in the Offense task, the reason lies in that DataBoost can create novel sentences from Offense (a relatively huge corpus) via GPT-2, while EDA only conducts word-level augmentation, which limits EPiDA’s performance. 5) We also present PPL as an auxiliary metric to measure the generation perplexity. Our method outperforms the others due to the high quality of data generation. We also provide experimental comparisons with other DA approaches (SUB and VDA) and generation speed results in the supplementary file. In conclusion, EPiDA is a powerful and efficient technique.
Table 4: Performance comparison with different DA algorithms and classification models on five classification tasks.

| Method          | TREC 1% | AGNews 1% | Sentiment 1% | Irony 1% | Offense 1% |
|-----------------|---------|-----------|--------------|----------|------------|
| CNN             | 0.722   | 0.806     | 0.745        | 0.826    | 0.446      |
| +EPiDA with EDA | 0.745   | 0.814     | 0.806        | 0.829    | 0.520      |
| +EPiDA with CWE | 0.737   | 0.817     | 0.806        | 0.826    | 0.524      |
| +EPiDA with TextAttack | 0.723 | 0.838     | 0.819        | 0.829    | 0.527      |
| BERT            | 0.769   | 0.914     | 0.759        | 0.820    | 0.507      |
| +EPiDA with EDA | 0.786   | 0.931     | 0.813        | 0.832    | 0.538      |
| +EPiDA with CWE | 0.780   | 0.922     | 0.821        | 0.834    | 0.546      |
| +EPiDA with TextAttack | 0.762 | 0.930     | 0.816        | 0.839    | 0.551      |
| XLNet           | 0.746   | 0.904     | 0.749        | 0.776    | 0.563      |
| +EPiDA with EDA | 0.756   | 0.906     | 0.768        | 0.790    | 0.556      |
| +EPiDA with CWE | 0.750   | 0.894     | 0.779        | 0.795    | 0.554      |
| +EPiDA with TextAttack | 0.758 | 0.909     | 0.790        | 0.798    | 0.555      |

Table 5: Ablation study on TREC 1% and Irony 1%.

| ID | DA | REM | CEM | OA | PT | TREC 1% | Irony 1% |
|----|----|-----|-----|----|----|---------|----------|
| 1  | -  | -   | -   | -  | -  | 0.722   | 0.534    |
| 2  | ✓  | -   | -   | -  | -  | 0.736   | 0.474    |
| 3  | ✓  | -   | -   | ✓  | -  | 0.723   | 0.550    |
| 4  | ✓  | ✓   | -   | ✓  | -  | 0.729   | 0.557    |
| 5  | ✓  | ✓   | ✓   | ✓  | -  | 0.723   | 0.559    |
| 6  | ✓  | ✓   | ✓   | ✓  | -  | 0.734   | 0.548    |
| 7  | ✓  | ✓   | ✓   | ✓  | -  | 0.739   | 0.575    |
| 8  | ✓  | ✓   | ✓   | ✓  | ✓  | 0.740   | 0.576    |
| 9  | ✓  | ✓   | ✓   | ✓  | ✓  | 0.745   | 0.579    |

4.3 Performance with Different DA Algorithms and Classifiers

EPiDA is a plug-in component that can work with different DA algorithms and classifiers. Here, to check how EPiDA performs with different DA algorithms and classifiers, we consider three frequently-used DA algorithms: rule-based EDA (Wei and Zou, 2019), model-based CWE (Kobayashi, 2018) and Attack-based TextAttack (Morris et al., 2020), and three different classifiers: CNN (Kim, 2014), BERT (Devlin et al., 2019) and XLNet (Yang et al., 2019). And to show that EPiDA can cope with different NLP classification tasks, we present the results on five different tasks: TREC, AGNews, Sentiment, Irony and Offense. In order to fully evaluate the performance of DA algorithms, we use only a small part of the training data. The experimental results are presented in Tab. 4. Here, we remove the restriction of only one time augmentation so that EPiDA can continuously generate qualified samples. We call this online augmentation, to differentiate it from one-time augmentation. As shown in Tab. 4, EPiDA is applicable to various NLP classification tasks. Although these tasks have different forms of data (questions or tweets) and different degrees of classification difficulty, EPiDA boosts performance on these tasks in almost all cases. More details on how EPiDA controls the generation quality are discussed in ablation study. Besides, we can also see that EPiDA works well with the three DA algorithms EDA, CWE and TextAttack. All achieve improved performance in most cases. For the three different classification models: CNN, BERT and XLNet, with the help of EPiDA, they all but XLNet on Sentiment get classification performance improvement, which shows that EPiDA is insensitive to classification models.

4.4 Ablation Study

Here we conduct ablation study to check the effectiveness of different EPiDA configurations. We take CNN as the classifier, EDA as the DA algorithm and report the Macro-F1 score over five repeated experiments on TREC 1% and Irony 1%. Tab. 5 shows the experimental results.

**Effect of REM and CEM.** The 4th and 5th rows show the results with only REM and CEM, respectively. Both of them perform better than the baseline (1st row), but not as good as the combined case.
(the 8th row). On TREC (relatively simple task), REM outperforms CEM (0.729 vs. 0.723), while on Irony (relatively hard task), CEM outperforms REM (0.559 vs. 0.557). Using only REM can limitedly boost performance since REM promotes the generation of high diversity samples, which may have wrong labels. And using only CEM is also not enough to fully tap the performance as REM tends to generate redundant samples.

We also compare our ‘REM + CEM’ with ‘PPL + cosine similarity’ used in LDA (Zuo et al., 2021). Our method achieves the performance of 0.740 and 0.576 on TREC 1% and Irony 1%, while the latter achieves 0.730 and 0.562. This shows that our ‘REM + CEM’ is more effective.

**Effect of online augmentation.** Comparing the results of the 2nd and the 3rd rows, the 6th and the 7th rows, the 8th and the 9th rows, we can see that generally online augmentation can boost performance, as online augmentation can generate sufficient qualified samples to train the model.

**Effect of pre-training** As REM and CEM use the feedback of the classifier, a pre-trained classification model should be beneficial to REM and CEM. By comparing the results of the 6th and the 8th rows, the 7th and the 9th rows, it is obvious that pre-training can improve performance.

**Effect of normalization.** In Alg. 1, we normalize $s_{div}$ and $s_{qua}$. Here, we check the effect of normalization. With the same experimental settings, the performance results on TREC 1% and Irony 1% without normalization are 0.732 and 0.568, lower than the normalized results 0.740 and 0.576. This shows that normalization is effective.

**How to combine REM and CEM?** How to combine REM and CEM is actually how to combine the values of $s_{div}$ and $s_{qua}$. We consider three simple schemes: addition ($s_{tot} = s_{div} + s_{qua}$), multiplication ($s_{tot} = s_{div} * s_{qua}$) and weighted addition ($s_{tot} = \alpha s_{div} + (1 - \alpha)s_{qua}$, $\alpha$ is a hyperparameter to tradeoff REM and CEM). Note that for multiplication, there is possibly an extreme situation: after normalization, $s_{div}$ or $s_{qua}$ may be very small and even approaches 0, then the multiplication result is very small or even zero, which means that REM and CEM do not take effect in sample generation. In our experiments, the multiplication scheme achieves performance of 0.725 and 0.572 on TREC 1% and Irony 1%, lower than the addition scheme 0.740 and 0.576. As for weighted addition, we find that setting $\alpha = 0.5$ can achieve satisfactory results (see the supplementary file). This is actually equal to the addition scheme. Therefore, in our experiments, we use only the addition scheme.

**Quality and diversity metrics.** Here, we provide another two metrics to verify EPiDA from the perspective of quality and diversity. For quality, we use the augmentation error rate. As for diversity, we calculate the average distance of samples before and after augmentation (ignoring wrong samples). From the perspective of quality and diversity, a good DA should has a small error rate but a large distance. Experimental results are given in Tab. 6. We can see that EPiDA gets better trade-off between error rate and distance.

**Effect of the amplification factor $K$.** The amplification factor $K$ determines the size $Km$ of candidate samples from which $m$ samples are chosen. On the one hand, with a large $K$, we have more choices, which seems beneficial to diversity. On the other hand, more candidate samples make the selected samples more homogenous, not good for diversity. By grid search, we set $K$ to 3 in our experiments, the experimental results are shown in the supplementary file.
4.5 Visualization Effect of EPiDA

Above we give comprehensive quantitative performance evaluation of EPiDA, here to intuitively illustrate the effectiveness of EPiDA, we visualize some augmented samples of EPiDA, and compare them with that of EDA. Specifically, we utilize BERT as the classifier and visualize its hidden state on the sentiment analysis task via t-SNE (Van der Maaten and Hinton, 2008). Fig. 2 shows the results. In terms of data quality, we find that two negative samples generated by EDA are located in Neural and Positive classes, while samples generated by EPiDA are generally properly located. And in the point of view of diversity, samples generated by EPiDA extend the distributed areas of the original data, while samples generated by EDA are mainly located in the areas of the original samples. This shows that samples generated by EPiDA are more diverse than those generated by EDA.

5 Conclusion

In this paper, we present an easy plug-in data augmentation technique EPiDA to control augmented data diversity and quality via two mechanisms: relative entropy maximization and conditional entropy minimization. Through extensive experiments, we show that EPiDA outperforms existing methods, and can work well with different DA algorithms and classification models. EPiDA is general, effective, efficient, and easy-to-deploy. In the future, more verification of our method is expected to be conducted on other classification tasks.

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