

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

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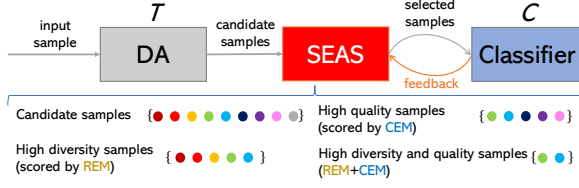


Figure 1: The pipeline of EPiDA. EPiDA first evaluates the candidate samples from the perspectives of diversity and quality, then takes the samples of high diversity and quality as training samples. It can work with various DA algorithms and classification models.

of augmented data: *relative entropy maximization* (REM) and *conditional entropy minimization* (CEM), where the former is for boosting diversity while the latter for ensuring quality. Fig. 1 shows the pipeline of EPiDA. EPiDA consists of a DA algorithm, a classifier, and a *Sample Evaluation And Selection* (SEAS) module. SEAS works with the DA algorithm and the classifier, and evaluates the candidate samples with the feedback of the classifier. With REM and CEM, SEAS can select samples of high diversity and quality to train the classifier continuously until the model converges.

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.

2 Related Work

In this section, we first review the related work of DA for NLP, then expound the differences between our method and the major existing ones. According to the methodology of data generation, existing methods can be categorized into three types: rule-based, interpolation-based, and model-based, respectively.

2.1 Rule-Based Methods

These works use easy and predetermined transformations without model components. (Kolomiyets et al., 2011; Zhang et al., 2015; Wang and Yang, 2015) use synonyms to replace words. EDA (Wei and Zou, 2019) and AEDA (Karimi et al., 2021) introduce random insertions, swaps, and deletions. Xie et al. (2017) employed spelling errors to augment sentences. Şahin and Steedman (2018) conducted sentence rotating via dependency tree morphing. Wei et al. (2021) proposed a multi-task view of DA. SUB² (Shi et al., 2021) generates new examples by substituting substructures via constituency parse trees. Although these methods are easy to implement, they do not consider controlling data quality and diversity.

2.2 Interpolation-Based Methods

MIXUP (Zhang et al., 2017) pioneers this type of works by interpolating the input and labels of two or more real examples. Recently, many MIXUP strategies (Verma et al., 2019; Yun et al., 2019) were proposed in CV. Due to the discrete nature of inputs of NLP tasks, such methods can be applied to NLP tasks only via padding and mixing embeddings or higher hidden layers (Chen et al., 2020; Si et al., 2021).

2.3 Model-Based Methods

Seq2seq and language models have been used to generate high quality samples. Among these approaches, Back-translation (Sennrich et al., 2016; Yu et al., 2018) translates sentences into another language and then translates it back to the original language. RNNs and transformers are used to reconstruct sub-parts of real data with contextual information (Kobayashi, 2018; Gao et al., 2019; Yang et al., 2020). Recently, we have witnessed the great success of large-scale pre-trained language models (PLMs) such as BERT (Devlin et al., 2019), XLNet (Yang et al., 2019), GPT-2 (Radford et al., 2019) in NLP tasks. These state-of-the-art PLMs

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: 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.

are also widely used to augment samples (Ng et al., 2020; Nie et al., 2020; Anaby-Tavor et al., 2020; Quteineh et al., 2020; Liu et al., 2020; Dong et al., 2021). For example, DataBoost (Liu et al., 2020) develops a reinforcement learning strategy to guide the conditional generation without changing the architecture of GPT-2. Besides, adversarial augmentation (*i.e.*, attack, GANs) are also used to enrich the diversity of the generated samples (Morris et al., 2020; Simoncini and Spanakis, 2021). Although model-based methods can control generation quality well via PLMs, they are computationally inefficient, which limits their applications.

2.4 Differences between EPiDA and Existing Methods

To expound the differences between EPiDA and typical existing methods, in Tab. 1 we present a qualitative comparison from four dimensions: whether controlling the diversity and quality of the augmented data, whether using pre-trained model (language model or agent network), and whether using the feedback from the classifier.

As shown in Tab. 1, among the existing methods, most control only either diversity (*e.g.* AA and EDA) or quality (*e.g.* DataBoost) of augmented data, thus cannot completely leverage the potential of data augmentation. And most use language model or agent network, which is beneficial to data quality but also inefficient. Only the recent LearnDA (Zuo et al., 2021) and VDA (Zhou et al., 2021) consider both diversity and quality, and only AA uses feedback of the classifier. Our EPiDA addresses both diversity and quality of augmented data via the feedback of the classifier in an explicit and controllable way, without the help of any additional model components, which makes it not only more effective but also more efficient.

Note that in addition to the differences listed in Tab. 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: $X = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$. Here, x_i is a sample, y_i is its label. The loss function is

$$L_o(\omega) = \frac{1}{n} \sum_{i=1}^n l(\omega^\top \phi(x_i); y_i). \quad (1)$$

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

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

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 ϕ , 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:

$$L(\omega) = L_o(\omega) + L_g(\omega). \quad (3)$$

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. Recalling 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 (ω is fixed), we select samples that meet the following objective function:

$$\max_{t_i^j} L_g(\omega, \phi(t_i^j)), \quad (4)$$

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 ρ be a metric function to measure semantic difference between samples and a threshold respectively, we impose the following constraint on $\phi(t_i^j)$:

$$|M(\omega^\top \phi(t_i^j), \omega^\top \phi(x_i))| \leq \rho. \quad (5)$$

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:

$$\begin{aligned} L_g(\omega, \phi(t_i^j)) &= \frac{1}{nm} \sum_{i=1}^n \sum_{j=1}^m l(\omega^\top \phi(t_i^j); y_i) \\ &= \frac{1}{nm} \sum_{i=1}^n \sum_{j=1}^m D(p(\omega^\top \phi(t_i^j)), p(y_i)) + H(p(y_i)), \end{aligned} \quad (6)$$

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:

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

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

$$H(p(\omega^\top \phi(t_i^j))|p(\omega^\top \phi(x_i))) \leq \rho. \quad (8)$$

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

$$\min_{t_i^j} H(p(\omega^\top \phi(t_i^j))|p(\omega^\top \phi(x_i))). \quad (9)$$

We call this *conditional entropy minimization* (CEM) mechanism. The smallest value of

$H(p(\omega^\top \phi(t_i^j))|p(\omega^\top \phi(x_i)))$ is 0, indicating that given $p(\omega^\top \phi(x_i))$, $p(\omega^\top \phi(t_i^j))$ 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

$$s_{qua}^{ij} = -H(p(\omega^\top \phi(t_i^j))|p(\omega^\top \phi(x_i))). \quad (10)$$

Algorithm 1: EPiDA Data Augmentation.

Input: Classification model ω , 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

$\hat{t}_i \leftarrow T(x_i)$;

$s_{div}, s_{qua}, s_{tot} = \mathbb{R}^{K*m}, \mathbb{R}^{K*m}, \mathbb{R}^{K*m}$;

for $j = 1, 2, \dots, K * m$ **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

Sentence	s_{div}	s_{qua}	s_{tot}
Go Set a Watchman comes out Tuesday and I'm really <u>excited</u> for it	0.00	1.00	1.00
Go Set a Watchman comes out Tuesday and I'm really <u>mad</u> for it	0.96	0.03	0.99
Go Set a Watchman out Tuesday and I'm really <u>excited</u> for it	0.05	0.92	0.97
Go Set a security guard comes out Tuesday and I'm really <u>excited</u> for it	0.86	0.15	1.01

Table 2: An example from the sentiment analysis task to demonstrate the effect of REM and CEM. The first row is the original sample, the rest are the augmented samples. Underlined are salient words.

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. 13 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			Irony			Offense		
	10%	40%	PPL	10%	40%	PPL	10%	40%	PPL
EDA (randomly delete, swap etc.)	0.560	0.608	41.22	0.530	0.515	76.07	0.637	0.629	37.37
Contextual Word Embs Aug. (insert, replace using Bi-RNN LM)	0.610	0.627	1043.18	0.518	0.593	1146.40	0.663	0.713	1729.62
Back-translation Aug. (Eng. → Fr. → Eng. as aug. text)	0.617	0.620	474.29	0.520	0.541	423.32	0.655	0.724	345.23
Data Boost (RL-guided conditional generation)	0.591	0.642	56.23	0.591	0.639	77.40	0.695	0.784	35.18
Ours EPiDA: REM only (EDA as the DA algorithm)	0.619	0.650	66.86	0.624	0.665	77.09	0.662	0.673	81.13
Ours EPiDA: CEM only (EDA as the DA algorithm)	0.629	0.659	8.10	0.629	0.666	12.11	0.668	0.670	8.57
Ours EPiDA: REM+CEM (EDA as the DA algorithm)	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 (SUB² and VDA) and generation speed results in the supplementary file. In conclusion, EPiDA is a powerful and efficient technique.

Method	TREC		AGNews		Sentiment		Irony		Offense	
	1%	10%	0.05%	0.1%	1%	10%	1%	10%	0.1%	1%
CNN	0.722	0.806	0.745	0.826	0.446	0.584	0.534	0.616	0.479	0.548
+EPiDA with EDA	0.745	0.814	0.806	0.829	0.520	0.598	0.579	0.621	0.493	0.551
+EPiDA with CWE	0.737	0.817	0.806	0.826	0.524	0.598	0.578	0.623	0.488	0.556
+EPiDA with TextAttack	0.723	0.838	0.819	0.829	0.527	0.600	0.568	0.631	0.481	0.549
BERT	0.769	0.914	0.759	0.820	0.507	0.602	0.589	0.635	0.508	0.630
+EPiDA with EDA	0.786	0.931	0.813	0.832	0.538	0.641	0.598	0.652	0.525	0.629
+EPiDA with CWE	0.780	0.922	0.821	0.834	0.546	0.642	0.597	0.655	0.517	0.630
+EPiDA with TextAttack	0.762	0.930	0.816	0.839	0.551	0.621	0.595	0.634	0.505	0.626
XLNet	0.746	0.904	0.749	0.776	0.563	0.620	0.576	0.651	0.522	0.626
+EPiDA with EDA	0.756	0.906	0.768	0.790	0.556	0.609	0.588	0.651	0.536	0.625
+EPiDA with CWE	0.750	0.894	0.779	0.795	0.554	0.608	0.592	0.659	0.532	0.627
+EPiDA with TextAttack	0.758	0.909	0.790	0.798	0.555	0.591	0.570	0.654	0.528	0.618

Table 4: Performance comparison with different DA algorithms and classification models on five classification tasks.

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

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

Table 5: Ablation study on TREC 1% and Irony 1%. Here, DA, REM, CEM, OA and PT indicate whether applying DA, REM, CEM, online DA (performing multiple DA operations) and pre-training, respectively.

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 CEM 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 ($s_{tot} = \alpha s_{div} + (1 - \alpha)s_{qua}$, α 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 re-

Metric	EDA	REM only	CEM only	EPiDA
Error Rate↓	3.05%	6.75%	0.64%	1.53%
Distance↑($\times 10^{-2}$)	0.54	1.21	0.25	0.78

Table 6: Error rate and distance on **Sentiment** dataset.

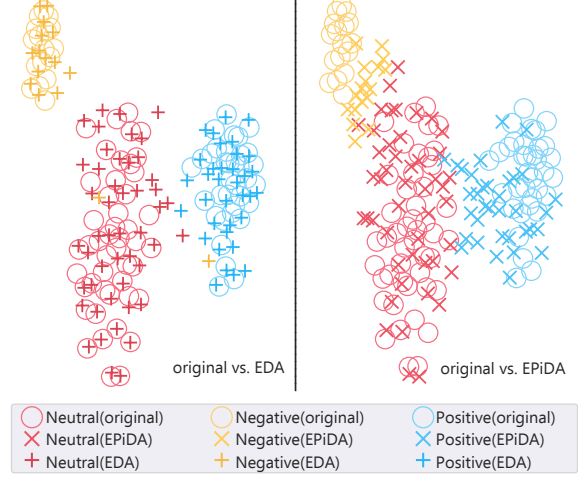


Figure 2: Hidden state visualization of the sentiment analysis task by t-SNE. Left: original and EDA augmented data; Right: original and EPiDA augmented data. Different colors mean different classes (Neutral, Negative and Positive), and different shapes mean different samples (original, generated by EPiDA and EDA).

sults (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 have 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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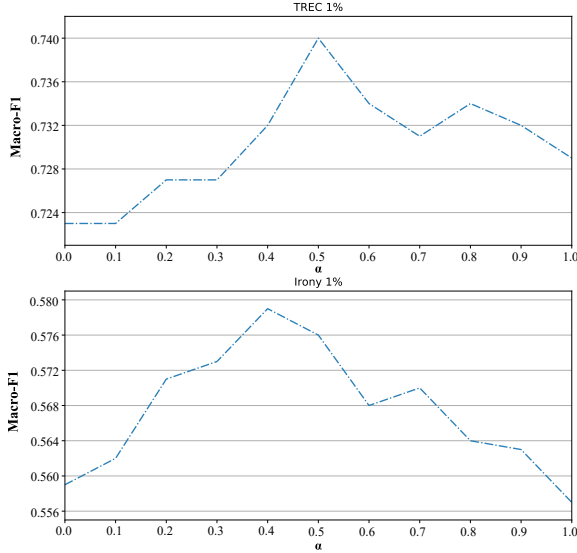


Figure 3: The Macro-F1 classification performances under different α . Top: **TREC 1%**, Bottom: **Irony 1%**.

A Weighted Addition of REM and CEM

Here we discuss the usage of weighted addition to combine REM and CEM. That is to say we introduce an additional hyperparameter α , $\alpha \in [0, 1]$ to control the trade-off of REM and CEM:

$$s_{tot} = \alpha s_{div} + (1 - \alpha) s_{qua} \quad (11)$$

A larger α highlights diversity and suppresses quality, and vice versa.

We discuss the influence of α on two datasets: **TREC** and **Irony**. We also use CNN (Kim, 2014) as the classifier and Macro-F1 as the metric and report the average results over five times repeated experiments. The classification performance under different α is presented in Fig. 3.

As shown in Fig. 3, in **TREC** and **Irony** tasks, the best values of α are 0.5 and 0.4, respectively. Although $\alpha = 0.4$ (0.579 vs. 0.576) performs better on the **Irony** task, 0.5 is sufficient to achieve satisfactory results on both tasks. Ergo, we set α to 0.5 in this paper.

B Ablation Study on Loss Function

Here we take an ablation study to support the combined loss function used in our paper. Actually, they are three loss functions in this paper.

The first one is the original loss function without performing DA

$$L_o(\omega) = \frac{1}{n} \sum_{i=1}^n l(\omega^\top \phi(x_i); y_i), \quad (12)$$

Loss Function	TREC 1%	Irony 1%
Eq. (12)	0.722	0.534
Eq. (13)	0.736	0.474
Eq. (14)	0.740	0.576

Table 7: Ablation study of different loss functions at TREC 1% and Irony 1%. The results are reported by Macro-F1 under five times repeated experiments.

EDA	+EPiDA	CWE	+EiPDA	DataBoost
188.4	43.8	30.7	10.1	1.0

Table 8: Generation speed comparison with existing DA methods. The speed is measured by the samples generated per Second. Except for DataBoost whose data are cited from (Liu et al., 2020), all the other methods' results are obtained on a NVIDIA RTX 3090.

which means we do not take DA to enrich the training data.

The second is the new loss function after using DA:

$$L_g(\omega) = \frac{1}{n} \sum_{i=1}^n \frac{1}{m} \sum_{j=1}^m l(\omega^\top \phi(t_i^j); y_i). \quad (13)$$

The third is the combined loss function:

$$L(\omega) = L_o(\omega) + L_g(\omega). \quad (14)$$

The experimental results of different loss functions at **TREC 1%** and **Irony 1%** is presented in Tab. 7. The combined loss function Eq. (14) outperforms Eq. (12) and Eq. (13) in **TREC 1%** and **Irony 1%**. As mentioned earlier (*c.f.* Visualization study in main paper), the samples augmented by EPiDA are more diverse than the original samples, which also causes a deviation. Such deviation limits the classification performance. However, the combined loss function Eq. (14) solved this problem by mixing the augmented samples and the original samples.

C Generation Speed

Tab. 8 presents the results of generation speed of EPiDA. We evaluate the speed by the number of samples generated by a DA algorithm per second. As shown in Tab. 8, after using EPiDA, EDA and CWE are still faster than DataBoost.

D Effect of the amplification factor K .

By grid search, we present the performance results of different K values in Tab. 9, from which we set K to 3 in our experiments.

K	2	3	5	7	10
Macro-F1	0.573	0.577	0.576	0.574	0.575

Table 9: Comparison of the classification performance on Irony 1% under different amplification factor K values.

Method	Accuracy
SST-10% ($ \mathcal{D}_{train} = 0.8K, \mathcal{D}_{devtest} = 0.1K$)	
NOAUG	25.4
EDA (Wei and Zou, 2019)	40.6
CWE (Kobayashi, 2018)	44.9
SUB ² (Shi et al., 2021)	45.8
EPiDA+EDA	43.5
EPiDA+CWE	45.9

Table 10: Accuracy ($\times 100$) on the SST standard test set. The best numbers in each section are bolded.

E More Verification of EPiDA

In order to fully demonstrate the performance of EPiDA, we additionally follow the experimental settings of (Shi et al., 2021) and compare our method with SUB². The dataset and classifier in this experiment is SST (Socher et al., 2013) and XLM-R (Conneau et al., 2019), respectively. Following (Shi et al., 2021), to avoid over-fitting to the small development set and tuning on test set issues, we introduce small "development test" (devtest) sets for SST, and only evaluate on the test sets using classifiers with the best devtest performance. The experimental results are placed in Tab. 10. As shown in Tab. 10, after introducing EPiDA, the performance of EDA and CWE are improved. Besides, our method can also achieve comparable performance with SUB² in SST task, which demonstrates the superiority of our framework.

Method	Corpus	
	AGNews	MR
BERT	0.944	0.868
VDA	0.945	0.878
EPiDA with EDA	0.949	0.879

Table 11: Accuracy ($\times 100$) on the test sets of AGNews and MR. The best numbers in each section are bolded.

We also provide the experimental results following the setting of VDA (Zhou et al., 2021) in AGNews (Zhang et al., 2015) and MR (Pang and Lee, 2005) corpus. We take BERT as classifier, the experimental results are placed in Tab. 11. As shown in Tab. 11, EPiDA outperforms VDA in classifica-

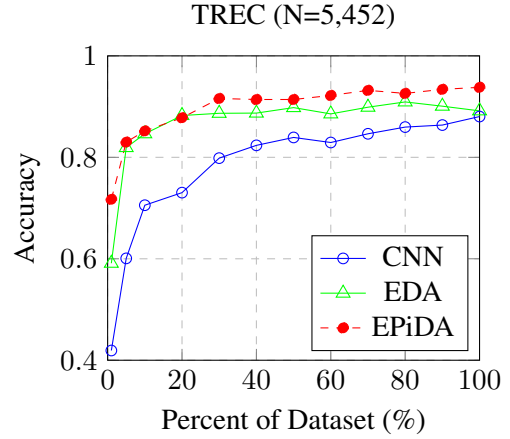


Figure 4: Classification accuracy w/o EPiDA for various original data sizes (before DA) used for training.

tion accuracy.

F Apply EPiDA performs in high-resource settings

In Fig. 4 we provide classification performance vs. original training data size. EPiDA performs well in low-resource settings. However, even when all the data are used, EPiDA still boosts accuracy (CNN: 0.88, EDA: 0.89, ours: 0.93).

G Visualization Case of REM and CEM

Here we provide the visualization results of using REM and CEM separately to illustrate the benefits of REM and CEM more clearly. As shown in Fig. 5, REM encourages to enhance diversity while low-quality samples with wrong labels will be generated. In contrast, CEM encourages to generate high-quality while less-diversity samples.

H Visualization Case of CWE

Fig. 6 show the visualization result of CWE (Kobayashi, 2018) and EPiDA+CWE. Similar conclusions can also be drawn from Fig. 6. CWE itself has the ability of enhancing diversity, and with the help of EPiDA, the quality of the generation has been dramatically improved (See Positive Class).

I Core Implementation Code

The implementation of REM and CEM is available at Fig. 7. Here, the calculation of mutual information refers to (Ji et al., 2019).

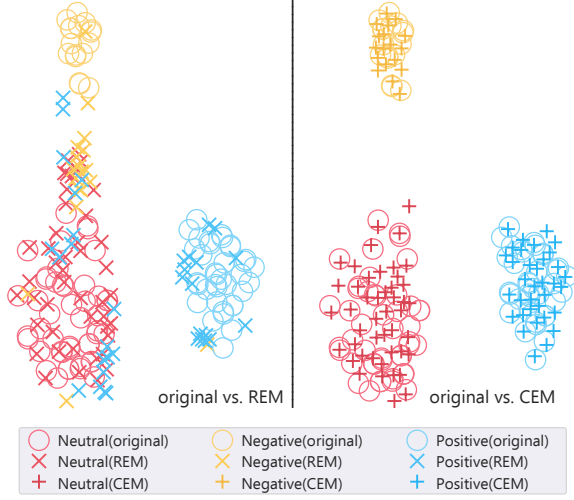


Figure 5: t-SNE hidden state visualization results of Sentiment Analysis task. Left: original vs. REM only; Right: original vs. CEM only. Different colors represent different classes (Neutral, Negative, and Positive), while different shapes represent different augmentation algorithms (original, REM only and CEM only).

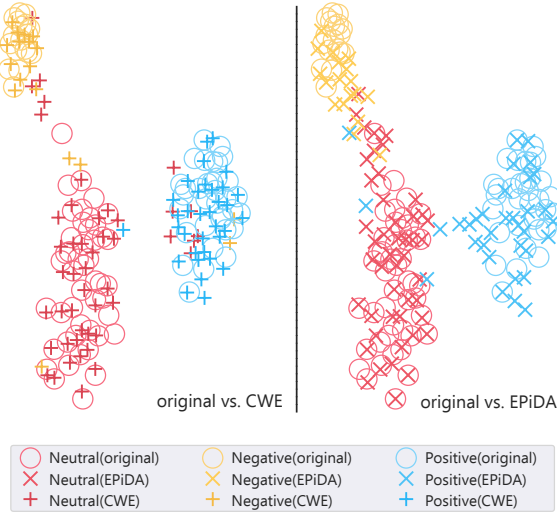


Figure 6: t-SNE hidden state visualization results of Sentiment Analysis task. Left: original vs. CWE; Right: original vs. EPiDA+CWE. Different colors represent different classes (Neutral, Negative, and Positive), while different shapes represent different augmentation algorithms (original, CWE only and EPiDA+CWE).

```

EPS = 1e-10
def REM(z, zt):
    z[(z < EPS).data] = EPS
    return -torch.sum(zt*torch.log(z))
def MI(z, zt):
    C = zt.size()[1]
    P = (z.unsqueeze(2) * zt.unsqueeze(1)).sum(dim=0)
    P = ((P + P.t()) / 2) / P.sum()
    P[(P < EPS).data] = EPS
    Pi = P.sum(dim=1).view(C, 1).expand(C, C)
    Pj = P.sum(dim=0).view(1, C).expand(C, C)
    return 1.0 - (P * (log(Pi) + log(Pj) -
        log(P))).sum()
def H(z):
    z[(z < EPS).data] = EPS
    return -(z*torch.log(z)).sum()
def CEM(z, zt):
    return MI(z, zt) - H(z)

```

Figure 7: Python implementation of REM and CEM. z is the probability distribution predicted by the classifier, and z_t is the probability distribution of original sample.

J Replacement of REM and CEM

Here we discuss the replacement of REM and CEM. In other words, we separately use PPL or cosine similarity mentioned in (Zuo et al., 2021) to replace REM or CEM to control diversity or quality. The experimental results are presented in Tab. 12. As shown in Tab. 12, REM+CEM outperforms other variants, which demonstrates the superiority of our method.

K More Implementation Details

Here we supply additional details of our implementation.

Dataset Preprocessing: We clean all punctuation, stop words, hashtags, numbers and URL links in the tweets corpora.

Data Augmentation Algorithms: There are three DA algorithms used in this paper: EDA (Wei and Zou, 2019)¹, CWE (Kobayashi, 2018)², and TextAttack (Morris et al., 2020)³.

Classifiers: Here we provide the implementation of the classifiers. There are four classifiers used in our paper: CNN (Kim, 2014)⁴, BERT (Devlin et al., 2019)⁵, XLNet (Yang et al., 2019)⁶ and XLM-R (Conneau et al., 2019)⁷.

Random Seeds: The random seeds used in this paper are 0,1,2,3 and 4, respectively.

¹https://github.com/jasonwei20/eda_nlp

²<https://github.com/makcedward/nlpaug>

³<https://github.com/QData/TextAttack>

⁴<https://github.com/galsang/CNN-sentence-classification-pytorch>

⁵https://huggingface.co/transformers/model_doc/bert.html

⁶https://huggingface.co/transformers/model_doc/xlnet.html

⁷https://huggingface.co/transformers/model_doc/xlmroberta.html

REM	PPL	CEM	CosSim	TREC 1%	Irony 1%
✓	-	✓	-	0.740	0.576
-	✓	✓	-	0.731	0.567
✓	-	-	✓	0.736	0.566
-	✓	-	✓	0.730	0.562

Table 12: Ablation study of the replacement of REM and CEM at TREC 1% and Irony 1%. The results are reported by Macro-F1 under five times repeated experiments.

Others: We take AdamW (Loshchilov and Hutter, 2018) as the optimizer. All the experiments are conducted at 4 NVIDIA RTX 3090 GPUs with Pytorch1.8.

L Limitation

The major limitation of EPiDA is the training time. Although EPDA can bring performance improvements, it will reduce the training speed by at least K (the amplification factor) times. This means that when the DA method and the classifier itself are cumbersome, the overall training time will be long. Besides, how to measure or define samples' value is still an open problem.

M Supplementary Example

In Tab. 13, we provide several detailed augmentation results of EPiDA. m and K are set to 3. Therefore, 9 candidate samples will be generated.

Task/Selected	Sentence	<i>s_{div}</i>	<i>s_{qua}</i>	<i>s_{tot}</i>
Sentiment	I'm about to eat four hot dogs and watch Miss USA. <u>Happy</u> Sunday.	0.00	1.00	1.00
✓	I am about to eat four hot dogs and watch Miss usa. <u>Happy</u> Sunday.	0.10	0.83	0.93
	I'm about to eat four track hot dogs and watch Miss USA. <u>Happy</u> Sunday.	0.17	0.70	0.87
	I'm about to eat four hot dogs and watch Miss USA. <u>Happy</u> Sunday.	0.00	1.00	1.00
	I'm about to eat four hot live dogs and watch Miss USA. <u>Happy</u> Sunday.	0.06	0.98	1.04
	I'm about to eat four hot dogs and watch Miss USA. <u>Gold</u> Sunday.	0.24	0.58	0.82
	I'm about to eat four hot dogs and watch Sun Miss USA. <u>Happy</u> Sunday.	0.00	0.98	0.98
	I'm about to eat hot dogs and watch Miss USA. <u>Happy</u> Sunday.	0.03	0.99	1.02
	I'm about to eat quadruplet hot dogs and watch Miss USA. <u>Sunday</u> .	1.00	0.00	1.00
	I'm about to eat four hot dogs and watch Miss USA. <u>Happy</u> Sunday.	0.00	1.00	1.00
Irony	A wonderful day of starting <u>work</u> at 6am	0.00	1.00	1.00
✓	A day wonderful of starting <u>work</u> at 6am	0.43	0.48	0.91
	A 6am day of starting <u>work</u> at wonderful	0.21	0.73	0.94
	A wonderful of starting <u>work</u> at 6am	0.75	0.18	0.93
	A grand day of starting <u>work</u> at 6am	0.39	0.53	0.92
	Day wonderful a of starting <u>work</u> at 6am	0.92	0.07	0.99
	A wonderful day starting of <u>work</u> at 6am	0.56	0.35	0.91
	A wonderful day of starting at 6am	1.00	0.00	1.00
	A day of starting <u>work</u> at 6am	0.87	0.12	0.99
✓	A wonderful day at starting <u>work</u> of 6am	0.75	0.18	0.93

Table 13: Some examples selected by SEAS. Underlined words are salient words. The first column will be checked if this augmented sample is selected by SEAS.