Selective Text Augmentation with Word Roles for Low-Resource Text Classification

Biyang Guo *, Songqiao Han *, Hailiang Huang*†
AI Lab, School of Information Management and Engineering, Shanghai University of Finance and Economics, Shanghai, China, 200433
guobiyang2020@gmail.com, {han.songqiao, hlhuang}@shufe.edu.cn

Abstract

Data augmentation techniques are widely used in text classification tasks to improve the performance of classifiers, especially in low-resource scenarios. Most previous methods conduct text augmentation without considering the different functionalities of the words in the text, which may generate unsatisfactory samples. Different words may play different roles in text classification, which inspires us to strategically select the proper roles for text augmentation. In this work, we first identify the relationships between the words in the text and the text category from the perspectives of statistical correlation and semantic similarity, and then utilize them to divide the words into four roles — Gold, Venture, Bonus, and Trivial words, which have different functionalities for text classification. Based on these word roles, we present a new augmentation technique called STA (Selective Text Augmentation) where different text-editing operations are selectively applied to words with specific roles. STA can generate diverse and relatively clean samples, while preserving the original core semantics, and is also quite simple to implement. Extensive experiments on 5 benchmark low-resource text classification datasets illustrate that augmented samples produced by STA successfully boost the performance of classification models which significantly outperforms previous non-selective methods. Cross-dataset experiments further indicate that STA can help the classifiers generalize better to other datasets than previous methods.

Introduction

Text classification is one of the fundamental tasks in Natural Language Processing (NLP), which has wide applications in news filtering, paper categorization, sentiment analysis, and so on. Plenty of algorithms, especially deep learning models have achieved great success in text classification, such as recurrent neural networks (RNN) (Liu, Qi, and Huang[2016], Wang et al.[2018]), convolutional networks (CNN) (Kim[2014]) and BERT models (Devlin et al.[2019] Sanh et al.[2019]). The success of deep learning is usually built on the large training data with good quality, which may not be easily available in real applications. Therefore, data augmentation techniques have attracted more and more attention both in academic and industrial communities to improve the generalization ability of text classification models when training data is limited (Bayer, Kaufhold, and Reuter[2021]). In this paper, we focus on the low-resource text classification tasks where only small labeled data is available.

A lot of text augmentation techniques have been designed to generate more training data. For examples, text-editing methods (Wei and Zou[2019], Feng et al.[2020]) expand the training data based on simple text-editing rules, such as word replacement and insertion. Back-translation techniques (Sennrich, Haddow, and Birch[2016], Yu et al.[2018]) generate new samples by first translating the samples into another language and then back to the original language. Language model based methods (Kobayashi[2018], Anaby-Tavor et al.[2020], Kumar, Choudhary, and Cho[2020]) utilize pretrained language models to synthesize new text for training. However, previous methods mainly augment the text in a non-selective manner, without considering the different roles of different words, which may result in undesirable augmented samples: 1) Important class-indicating words may be altered, resulting in some damage to the original meaning or even changing the label of the original text; 2) Unimportant words, noisy words or misleading words may be enhanced after augmentation, which may hurt the generalization ability.

To tackle these issues, we propose to first recognize the word roles in the text, and then selectively apply augmenta-
We conclude our contributions as follows: STA significantly outperforms other baselines with an average accuracy improvement at nearly 5% and 2.6% with less than 4% on average in 3 cross-dataset generalization tasks. Our proposed method to assign one label from the randomly chosen words from the text, which brings more diversity but has risk of damaging the core semantics or even changing the label of the original text. Contextual Augmentation utilizes language model to predict the masked words for substitution based on contextual embeddings, which can generate fluent sentences, but lacks diversity. Back-translation methods (Yu et al. 2018; Silfverberg et al. 2017) are able to generate diverse and label-preserving samples but usually require large encoder-decoder translation models to guarantee the performance. Generative methods like (Anaby-Tavor et al. 2020; Kumar, Choudhary, and Cho 2020) can synthesize diverse sentences but require continue pre-training/fine-tuning on down-stream tasks before they can be used. Additionally, none of the above methods try to filter out the potential noise in the text, therefore some misleading words may be enhanced after augmentation, which may hurt the generalization ability.

In this work, we attempt to design a lightweight text augmentation method, which can generate diverse and clean samples while preserving the core semantics. Therefore, we mainly focus on text-editing-based approach and study how to generate better training samples with simple text-editing operations without the need of pretrained language models.

Methodology

Word Roles Recognition

Word Roles Assume that we have a text classification task to train a model to assign one label from \(C = \{c_1, c_2, ..., c_k\}\) to a sentence or document. The training set is \(D\) and its vocabulary is \(V\). For a word \(w_i \in V\) and a category \(c_j \in C\), we can examine their relationship from two perspectives:

- **Statistical Correlation.** This measures how frequent the word \(w_i\) co-occurs with class \(c_j\) while not with other classes in the training set.

Word Roles Assume that we have a text classification task to train a model to assign one label from \(C = \{c_1, c_2, ..., c_k\}\) to a sentence or document. The training set is \(D\) and its vocabulary is \(V\). For a word \(w_i \in V\) and a category \(c_j \in C\), we can examine their relationship from two perspectives:

- **Statistical Correlation.** This measures how frequent the word \(w_i\) co-occurs with class \(c_j\) while not with other classes in the training set.
• **Semantic Similarity.** This measures how much semantics the word $w_i$ share with the label of class $c_j$.

  With the two perspectives, all the words in a training document can be divided into four different roles (Figure 1):

  1. **Gold** words: these are useful class-indicating words, with high statistical correlation and high semantic similarity with the corresponding category;

  2. **Venture** words: these words usually co-occur frequently with their corresponding categories but have low semantic similarities. Thanks to their high statistical correlation with the class, these Venture words can usually bring extra information about the class. However, their low semantic similarity puts them at greater risk to be the noise or misleading words, which are harmful for model training;

  3. **Bonus** words: these words have low statistical correlation but high semantic similarity. Bonus words usually don’t occur frequently in the training data, but are quite useful for model’s generalization ability;

  4. **Trivial** words: these are those with low statistical correlation and low semantic similarity, which are perhaps less important in model prediction.

**Word Roles Recognition**

To recognize the words of different roles in a dataset, we should decide proper metrics to measure the above two perspectives.

For the measurement of statistical correlation with the class, we employ weighted log-likelihood ratio (WLLR) to select the class-correlated words from the text sample. This is inspired by (Yu and Jiang 2016) where WLLR is used to find out the “pivot words” for sentiment analysis. The WLLR score is computed by:

$$\text{wllr}(w, y) = p(w|y)\log\left(\frac{p(w|y)}{p(w|\bar{y})}\right)$$

where $w$ is a word, $y$ is a certain class and $\bar{y}$ represents all the other classes in the classification dataset. $p(w|y)$ and $p(w|\bar{y})$ are the probabilities of observing $w$ in samples labeled with $y$ and with other labels respectively. We use the frequency of a word occurring in the certain class to estimate the probability.

To measure the semantic similarity between a word and the meaning of the class label, a straightforward way is to use word vectors pre-trained with skip-gram (Mikolov et al. 2013) or Glove (Pennington, Socher, and Manning 2014).

We are not using transformer-based models like BERT for similarity measuring due to their high inference cost. Some also reveal that static word-embeddings can achieve comparable and even better performance than BERT-like models in similarity measurement tasks, especially in word-level (Reimers and Gurevych 2019). We compute the cosine similarity between a word and a class label to see their semantic distance:

$$\text{similarity}(w, l) = \frac{v_w \cdot v_l}{\|v_w\|\|v_l\|}$$

where $l$ represents the label and $v_w, v_l$ are word vectors for the word $w$ and the label $l$. We can also use a description of the label to obtain $v_l$ by averaging the word vectors of each word in the description for better label representation. In our experiments, we find that simply using the word or phrase of the label itself is enough to measure the similarity between a word and the category.

We compute the WLLR and similarity scores of each word, and set a threshold to divide the high and low scores (or set different thresholds respectively). We call the words with high (low) WLLR scores as $C_h (C_l)$ and words with high (low) similarity scores as $S_h (S_l)$. Then we can extract these words with the following rules:

$$W_G = \{w|w \in C_h \cap S_h\}$$
$$W_V = \{w|w \in C_h \cap S_l\}$$
$$W_B = \{w|w \in C_l \cap S_h\}$$
$$W_T = \{w|w \in C_l \cap S_l\}$$

where $W_G, W_V, W_B$ and $W_T$ are Gold, Venture, Bonus, and Trivial words respectively.

Given a training sample, there are two strategies to assign the roles to the words from the text: *global* or *local*. The global strategy determine the thresholds for roles division based on all the words in the vocabulary, while for local strategy the division is based on the words from the current sample. In other words, the local strategy use a relative view to distinguish high and low scores, therefore the a word’s role may change when it occurs in another sample.

In our experiments, we use the *median number* as the threshold for the local strategy, and choose the *upper (lower)*
quartile as the high (low) score threshold for the global strategy. We find these choices of thresholds to work well in our first try and did not tune these thresholds. Tuning these hyper-parameters might result in further gains for our proposed method.

A Real Case for Illustration Here we provide an actual example to show the differences of these roles more vividly. We randomly sample 100 documents from the 20 Newsgroup\textsuperscript{[2]} text classification dataset, which consists of 20 categories. We do the word roles recognition using the global strategy and some examples are show in Table\textsuperscript{[1]}

As shown in Table\textsuperscript{[1]} Gold words are highly related to their corresponding category, like "transistor", "circuit" and "batteries" for the electronics class. Venture words are not semantically related to their classes, but these words co-occur frequently with the corresponding categories in the given dataset. Intuitively, we expect the models to learn class-indicating features from these Gold words, while less from the Venture words, since some of these Venture words might be misleading. For instance, words like "sufficient" and "signature" appear lots of times in electronics documents of the dataset, but we shouldn’t rely on these words to tell if a document is about electronics or not. However, according to our preliminary experiments, these Venture words are usually learned by the classifiers as evidence for certain categories, and are likely to result in wrong predictions. Bonus words are semantically similar to the categories, but are less commonly found in these categories. Trivial words seem to be uninformative and are less important for prediction. The examples illustrate that our proposed four kinds of word roles are reasonable and can provide insights for text classification and data augmentation. Note that we only use a subset with 100 documents to identify the roles in these examples, more precise roles recognition can be achieved when more data are provided.

Selective Text Augmentation

Based on the recognized word roles, we propose a new text augmentation technique called STA (Selective Text Augmentation), which consists of four operations. Given a piece of text from the training set, one of the following text-editing operations will be applied:

- **Selective Replacement**: Select \( n \) words, except for the Gold words, from the text and then replace these chosen words with their synonyms or similar words. Can be formulated as candidates \( = \{ w | w \in W_T \} \).
- **Selective Insertion**: Select \( n \) words, except for the Venture words, from the text and then insert their synonyms into the original text at random place. Can be formulated as candidates \( = \{ w | w \in W_G \} \).
- **Selective Deletion**: Choose \( n \) words, except for the Gold words, from the text and then delete them. Can be formulated as candidates \( = \{ w | w \in W_B \} \).
- **Positive Selection**: Only select the Gold words and concatenate them into a new sentence. By doing so, only the most important parts are remained. To make the new sentence more natural, we also randomly insert some Trivial words and punctuation. Can be formulated as candidates \( = \{ w | w \in W_G \} \).

During augmentation, each operation of STA will be used to generate different kinds of augmented text, as illustrated in Figure\textsuperscript{[2]}. The number \( n \) is determined by a hyper-parameter \( p \), which represents the augmentation strength. We can also set different strengths to these operations according to the specific tasks.

Selective Replacement makes the sample a bit more different while protecting the core semantics; Selective Insertion introduces new words into the sentence, while preventing inserting the potential misleading words, by excluding the Venture words from this operation; Selective Deletion focuses on the words which have low statistical or semantic relations with the corresponding categories, thus makes the sample cleaner and more category-related; Positive selection can be viewed as another type of deletion operation where all the Venture and Bonus words are deleted from the text. By doing so, the potential noise or misleading words are removed, which may help the text classification model to learn the most class-indicating features of the task.

In fact, more sophisticated methods can be designed based on the proposed word roles, such as combining some of the above operations, or utilizing language models to make the generated text more fluent. However, our main purpose in this work is to provide a set of basic, simple and effective augmentation operations, taking into account the different word roles. More creative methods can be further built upon STA to make the augmentation even stronger, which we leave for future work.

Experiments

**Setup**

**Datasets.** We conduct experiments on five widely used benchmark datasets, including two sentiment classification datasets SST2\textsuperscript{[3]} (Socher et al. 2013), IMDB\textsuperscript{[4]} (Maas et al. 2011) and three topic classification datasets Yahoo Answers\textsuperscript{[5]} (Zhang, Zhao, and LeCun 2015), 20NG\textsuperscript{[6]} and BBC news.

\begin{table}[h]
\centering
\begin{tabular}{l|l}
\hline
\textbf{category: electronics} & \textbf{words} \\
\hline
\textbf{Gold:} & \{"transistor", "Electronics", "circuit", "pulses", "sensor", "batteries", "engineering", ...\} \\
\textbf{Venture:} & \{"Caruth", "sufficient", "immediate", "occur", "signature", "firing", "Oliver", "Mr", ...\} \\
\textbf{Bonus:} & \{"Computer", "systems", "ca", "Engineering", "@", "etc", "world", "system", ...\} \\
\textbf{Trivial:} & \{"had", "were", "On", "was", "article", "Organization", "did", "From", ...\} \\
\hline
\end{tabular}
\caption{Real examples of word roles. These words are extracted from the documents of the electronics category of the 20 Newsgroups dataset with only 100 samples.}
\end{table}

\textsuperscript{[1]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups}

\textsuperscript{[2]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups}

\textsuperscript{[3]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[4]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[5]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[6]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[7]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[8]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[9]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[10]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[11]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}

\textsuperscript{[12]} \url{https://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups/Twenty+Newsgroups}
Since we focus on text classification in low-resource scenarios in this work, we randomly sample $n = \{50, 100\}$ examples from the training sets of these datasets for the main experiments. We also evaluate our proposed methods with increasing training size ($n = \{50, 100, 500, 1000\}$) for NG and BBC datasets to further illustrate the effectiveness when more labeled data is available. We use the original full test sets of these datasets for evaluation.

**Baselines.** In our main experiments, we compare the following methods: **Non-aug**: train the classifier without using any data augmentation techniques; EDA (Wei and Zou [2019]): first randomly select some tokens from the original text, and then apply one of the following text-editing operations: synonyms replacement, synonyms insertion, deletion and word position swap; EDA-w2v: original EDA utilizes Word2Vec (Mikolov et al. [2013]) to find similar words; MLM-Aug (Kumar, Choudhary, and Cho [2020]): utilizing the masked language modeling (MLM) ability of DistilBERT-base (Sanh et al. [2019]) to replace certain words according to the contextual embedding. We have also tried BERT-base (Devlin et al. [2019]) and RoBERTa-base (Liu et al. [2019]) for MLM-Aug but found they are inferior to DistilBERT-base in our experiments; **Back-Trans**: translate a sequence into another language and then back into the original language, using pre-trained encoder-decoder translation models. We use the translation models trained on the Tatoeba corpus of four languages (es, zh, ru, de) as the intermediate language (Tiedemann [2020]).

For our proposed STA, we experiment two strategies of roles assignment: **STA-global**: using the global strategy for roles assignment; **STA-local**: using the local strategy for roles assignment.

**Settings.** In our main experiments, we use DistilBERT-base (Sanh et al. [2019]) as the backbone for text classifiers, which is a lightweight transformer model distilled from BERT (Devlin et al. [2019]). To verify the effectiveness of our proposed augmentation method on larger models, we also evaluate on BERT-base, discussed in later sections.

We randomly choose 20% of the training set as the validation set, use the AdamW (Loshchilov and Hutter [2017]) optimizer with learning rate $\ell r = 5e - 5$ for training and use early-stopping with patience=10 to choose the best model.

We augment the text 4 times for all augmentation methods for fair comparison. We run all experiments with 5 random seeds and report the average performance. We use publicly available Word2Vec model[^3] to find the most similar words for synonyms searching in EDA-w2v and STA. For the proportion of words to be changed during augmentation, we experiment three levels of augmentation strength $p = \{5\%, 10\%, 20\%\}$ and choose the strength with the highest validation accuracy. If the number of role words are less than $p$ (not enough for selection), we then select random words from the text as supplements. For other baselines, $p$ is set as recommended in original papers.

**Main Results**

The main results is reported in Table 2. From the results, we can see that all text augmentation methods are beneficial for text classifiers to improve the performance in this low-resource setting. Among all the baselines, EDA-w2v and Back-Trans are competitive methods, which are significantly better than MLM-Aug. The two strategies of our proposed STA both significantly outperform other baselines, with an average accuracy improvement at nearly 5% over the best baseline (Back-Trans) when $n = 50$ with STA-global, and 2.6% over the best baseline (EDA-w2v) when $n = 100$ with STA-local. In particular, for NG dataset, which is a quite complicated text classification dataset with 20 classes and many sub-classes, STA-global improves the performance by nearly 7% over EDA-w2v with only 50 initial training examples. For IMDB, a long text sentiment classification task, STA-global achieved a nearly 10% performance gain over EDA-w2v when $n = 50$. These results reveal that with the knowledge of word roles and augmenting the text in a selective manner, STA can help the model to achieve better generalization ability than traditional non-selective data augmentation methods.

Comparing the performances of STA-global and STA-local, we can see that the global strategy performs better when fewer samples are given while the opposite is true for the local strategy. When the data size is too small, assigning the word roles with global strategy can be more accurate, that might be the reason why STA-global achieves relatively better results when train size is only 50.

STA is slightly inferior to EDA for BBC when $n = 50$, which may result from over-fitting problem, since BBC is

| methods               | NG     | Yahoo | BBC   | IMDB  | SST2  | avg.  | NG     | Yahoo | BBC   | IMDB  | SST2  | avg.  |
|-----------------------|--------|-------|-------|-------|-------|-------|--------|-------|-------|-------|-------|-------|
| **$n = 50$**          |        |       |       |       |       |       |        |       |       |       |       |       |
| non-aug               | 35.14  | 18.64 | 92.92 | 53.99 | 59.14 | 51.97 | 51.36  | 22.27 | 92.63 | 74.94 | 77.16 | 63.67 |
| EDA                   | 40.06  | 30.94 | **93.26** | 58.43 | 70.32 | 58.42 | 55.49  | 33.71 | 95.42 | 79.88 | 75.12 | 67.92 |
| EDA-w2v               | 42.56  | 29.44 | 93.15 | 60.97 | 72.66 | 59.76 | 56.48  | 33.51 | 95.15 | 79.10 | 76.20 | 68.09 |
| MLM-Aug               | 39.18  | 28.59 | 92.49 | 59.92 | 66.00 | 57.24 | 53.96  | 33.39 | 94.22 | 80.44 | 79.37 | 67.27 |
| Back-Trans            | 41.96  | 31.31 | 92.74 | 60.30 | 73.56 | 59.98 | 54.85  | **37.73** | 95.17 | 76.04 | 75.68 | 67.89 |
| **STA-global (Ours)** | **49.41** | **33.77** | 92.79 | **71.34** | 76.90 | **64.84** | **58.69** | **35.61** | **95.57** | **81.91** | **77.96** | **69.95** |
| **STA-local (Ours)**  | 46.40  | 32.34 | 93.21 | 68.56 | **77.86** | 63.68 | 58.57  | 35.75 | 95.48 | **83.75** | **79.64** | **70.64** |

| methods               | NG     | Yahoo | BBC   | IMDB  | SST2  | avg.  | NG     | Yahoo | BBC   | IMDB  | SST2  | avg.  |
|-----------------------|--------|-------|-------|-------|-------|-------|--------|-------|-------|-------|-------|-------|
| **$n = 100$**         |        |       |       |       |       |       |        |       |       |       |       |       |
| non-aug               | 40.92  | 18.95 | 93.26 | 53.99 | 59.14 | 51.97 | 51.36  | 22.27 | 92.63 | 74.94 | 77.16 | 63.67 |
| EDA                   | 40.92  | 18.95 | 93.26 | 53.99 | 59.14 | 51.97 | 51.36  | 22.27 | 92.63 | 74.94 | 77.16 | 63.67 |
| EDA-w2v               | 42.56  | 29.44 | 93.15 | 60.97 | 72.66 | 59.76 | 56.48  | 33.51 | 95.15 | 79.10 | 76.20 | 68.09 |
| MLM-Aug               | 39.18  | 28.59 | 92.49 | 59.92 | 66.00 | 57.24 | 53.96  | 33.39 | 94.22 | 80.44 | 79.37 | 67.27 |
| Back-Trans            | 41.96  | 31.31 | 92.74 | 60.30 | 73.56 | 59.98 | 54.85  | **37.73** | 95.17 | 76.04 | 75.68 | 67.89 |
| **STA-global (Ours)** | **49.41** | **33.77** | 92.79 | **71.34** | 76.90 | **64.84** | **58.69** | **35.61** | **95.57** | **81.91** | **77.96** | **69.95** |
| **STA-local (Ours)**  | 46.40  | 32.34 | 93.21 | 68.56 | **77.86** | 63.68 | 58.57  | 35.75 | 95.48 | **83.75** | **79.64** | **70.64** |
a relatively easy task where only 50 training samples can lead to over 90% test accuracy without any data augmentation. However, with the increase of train size to 100, STA surpasses all other baselines again. Back-Trans performs the best for Yahoo dataset when n = 100 while STA is the second best for this task, but STA beats Back-Trans in all other tasks.

Note that STA is a light-weight text-editing based augmentation method without using any big models. Although word2vec embeddings are needed to compute the semantic similarity during word roles recognition, it is a much faster procedure compared to MLM-Aug and Back-Trans, which use large pre-trained transformer-based models for augmentation.

Table 3: Experiments with increasing training sizes

|        | n = 50 | n = 100 | n = 500 | n = 1000 |
|--------|--------|---------|---------|----------|
| non-aug| 92.92  | 92.63   | 95.07   | 96.18    |
| EDA-w2v| 93.15  | 95.15   | 95.96   | 97.87    |
| STA-global| 94.41  | 58.69   | 73.37   | 75.35    |

|        | n = 50 | n = 100 | n = 500 | n = 1000 |
|--------|--------|---------|---------|----------|
| non-aug| 92.63  | 95.07   | 96.18   | 98.31    |
| EDA-w2v| 95.15  | 95.96   | 97.87   |          |
| STA-global| 95.57  | 96.86   | 98.31   |          |

Experiments with Larger Training Sizes We also conduct experiments with increasing training size (n = \{50, 100, 500, 1000\}) on the NG and BBC datasets as shown in Table 3. STA consistently outperforms the competitive EDA-w2v baseline when more labeled data is available.

Figure 3: Evaluation with different classifiers

**Ablation Study**

**Effectiveness of Each STA Operation** STA is composed of four operations: selective replacement, selective insertion, selective deletion and positive selection. We now evaluate each of these operations, and also compare them with non-selective operations where the words are randomly selected for text-editing. We conduct experiments on NG, IMDB and Yahoo datasets, and use the **global** strategy for STA. The results are shown in Table.

From these experiments, we have two important findings:

1. The **positive selection** of STA is particularly powerful as an augmentation operation for low-resource text classification, which is significantly better than all the other operations. The generated new text by positive selection is mainly composed of the Gold words from the text with high statistical and semantic relationships with the label. We speculate that adding these samples into the training set can help the model to learn the most class-indicating features about the class, even if only small number of examples are available.

2. **Selective insertion** is more effective than random insertion with very few examples (n = 50) but are less useful when more examples are provided (n = 100). In the contrary, selective deletion and selective replacement are more effective with larger training set. This is probably due to the fact that the word roles recognition is more accurate when providing more labeled data.

These findings can further guide us to design a more powerful selective augmentation method, which we leave for future work.

**Necessity of Both Statistical & Semantic Perspectives for Word Roles Recognition** Recall that STA is based on word roles recognition, which relies on two different relationship measurements between a word and a class: statistical correlation and semantic similarity. It is natural to ask: _do we really need both statistical correlation and semantic similarity with the class for defining word roles?_ To verify this, we conduct ablation experiments by designing two variants of STA:

1. **STA w/o Cor.** During role words recognition, we only use semantic similarity to separate the words in the text into two types: high-similarity and low-similarity words. By doing so, Gold and Bonus words, or Venture and Trivial words can no longer be distinguished from each other.

2. **STA w/o Sim.** During role words recognition, we only use statistical correlation to separate the words in the text into two types: high-correlation and low-correlation words. This way, the previous Gold and Venture words are combined together, Trivial and Bonus words are combined together.

We then follow the same word selection rules with the original STA, and experiment on NG and IMDB datasets with 100 training examples. For NG, STA uses global strategy while for IMDB STA uses local strategy. The results are reported in Table. The results illustrate that removing the statistical or semantic factor both lead to performance degradation compared to original STA for NG and IMDB tasks. **STA w/o Sim.** is worse than **STA w/o Cor.** which shows that semantic similarity plays a more important part than statisti-
Table 4: Effectiveness of each STA operation

| methods       | NG avg. | IMDB avg. | Yahoo avg. | avg.   |
|---------------|---------|-----------|-------------|--------|
| non-aug       | 35.14   | 53.99     | 18.64       | 35.92  |
| random insertion | 36.99   | 57.91     | 26.81       | 40.57  |
| random replacement | 38.62   | 59.51     | 27.30       | 41.81  |
| random deletion  | 37.49   | 62.71     | 25.97       | 42.06  |
| selective insertion | 39.13   | 59.95     | 26.83       | 41.97  |
| selective replacement | 37.37   | 58.74     | 27.00       | 41.04  |
| selective deletion  | 37.12   | 60.65     | 26.56       | 41.44  |
| positive selection | 40.84   | 75.09     | 29.63       | 48.52  |

Table 5: Necessity of both statistical & semantic views for word roles recognition

| methods       | NG avg. | IMDB avg. | Yahoo avg. | avg.   |
|---------------|---------|-----------|-------------|--------|
| non-aug       | 51.36   | 74.94     | 63.15       |        |
| EDA           | 55.49   | 79.88     | 67.68       |        |
| EDA-w2v       | 56.48   | 79.10     | 67.79       |        |
| MLM-Aug       | 53.86   | 80.44     | 67.15       |        |
| Back-Trans    | 54.85   | 76.04     | 65.44       |        |
| STA           | 58.69   | 83.75     | 71.22       |        |
| STA w/o Cor.  | 56.53   | 82.66     | 69.59       |        |
| STA w/o Sim.  | 55.92   | 80.41     | 68.17       |        |

Table 6: Cross-dataset generalization tasks

| Methods         | non-aug | EDA-w2v | STA avg. |
|-----------------|---------|---------|----------|
| FD => TH        | 75.62   | 76.54   | 75.31    |
| TH => FD        | 38.50   | 39.93   | 46.68    |
| FD => BBC       | 74.25   | 77.24   | 82.66    |
| BBC => FD       | 34.12   | 38.38   | 41.44    |
| TH => BBC       | 45.53   | 46.34   | 52.03    |
| BBC => TH       | 70.86   | 69.81   | 74.57    |
| avg.            | 56.48   | 58.04   | 62.12    |

Cross-Dataset Generalization Tasks

To further evaluate the model’s generalization ability, we also design 3 groups of cross-dataset generalization tasks, following the experimental design in [Karpukhin et al. 2020] and [Hendrycks et al. 2020], where the model is first trained in one dataset and then directly applied to a different dataset without additional fine-tuning. We choose three news classification datasets, BBC, FD and TH which share two common categories: politics and sports. Specifically, A => B means the model is trained on A dataset and evaluated on the shared classes of B dataset without additional fine-tuning. If B is of a different language, we will first translate B into the same language of A using the open-sourced translation models [Tiedemann 2020]. We randomly sample 500 examples as the training set from each source dataset and use the test set of the target dataset for evaluation. The results are reported in Table 6 which show that STA not only performs well on in-dataset prediction, but also on cross-dataset generalization tasks. We can see that the improvement of STA over EDA-w2v is more than 4% on average, which shows that the classifiers trained on augmented datasets by STA have learned more common and general features of the shared categories politics and sports than baselines. These general features are essential for cross-dataset generalization, where the data distribution of the train and test sets may be different. The selective operations of STA like positive selection and selective deletion are especially useful for denoising the dataset while enhancing the core semantics of the categories, thus are helpful for learning the general features of the categories.

Conclusion

In this work, we first present four types of word roles based on two important perspectives to measure the relationships between words and categories. We then propose a new data augmentation technique STA for text classification, which selectively edits the text according to the word roles to preserve the original semantics while introducing more diversity into the training set. Extensive experiments on 5 benchmark classification datasets and 3 groups of cross-dataset generalization tasks illustrate that STA helps the classifier acquire stronger generalization ability over other non-selective augmentation baselines.

Our proposed STA is mainly based on basic text-editing operations, more advanced methods can be designed on top of STA, such as utilizing pre-trained language models to make the generated text more fluent. In addition, the idea of word roles can also be applied to other tasks like information retrieval, document representation, and even image classification (where we can study the roles of super-pixels), which we will explore in future work.

4http://www.nlpir.org/
5http://thuctc.thunlp.org/
References

Anaby-Tavor, A.; Carmeli, B.; Goldbraich, E.; Kantor, A.; Kour, G.; Shlomov, S.; Tepper, N.; and Zwerdling, N. 2020. Do not have enough data? Deep learning to the rescue! In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, 7383–7390.

Andreas, J. 2019. Good-enough compositional data augmentation. arXiv preprint arXiv:1904.09545.

Bayer, M.; Kaufhold, M.-A.; and Reuter, C. 2021. A survey on data augmentation for text classification. arXiv preprint arXiv:2107.03158.

Chen, J.; Tam, D.; Raffel, C.; Bansal, M.; and Yang, D. 2021. An Empirical Survey of Data Augmentation for Limited Data Learning in NLP. arXiv preprint arXiv:2106.07499.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In NAACL-HLT (1).

DeVries, T.; and Taylor, G. W. 2017. Dataset augmentation in feature space. arXiv preprint arXiv:1702.05538.

Feng, S. Y.; Gangal, V.; Kang, D.; Mitamura, T.; and Hovy, E. 2020. GenAug: Data Augmentation for Finetuning Text Generators. In Proceedings of Deep Learning Inside Out (DeeLIO): The First Workshop on Knowledge Extraction and Integration for Deep Learning Architectures, 29–42. Online: Association for Computational Linguistics.

Feng, S. Y.; Gangal, V.; Wei, J.; Chandar, S.; Vosoughi, S.; Mitamura, T.; and Hovy, E. 2021. A Survey of Data Augmentation Approaches for NLP. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, 968–988.

Greene, D.; and Cunningham, P. 2006. Practical Solutions to the Problem of Diagonal Dominance in Kernel Document Clustering. In Proc. 23rd International Conference on Machine learning (ICML’06), 377–384. ACM Press.

Guo, H.; Mao, Y.; and Zhang, R. 2019. Augmenting data with mixup for sentence classification: An empirical study. arXiv preprint arXiv:1905.08941.

Hendrycks, D.; Liu, X.; Wallace, E.; Dziedzic, A.; Krishnan, R.; and Song, D. 2020. Pretrained Transformers Improve Out-of-Distribution Robustness. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, 2744–2751.

Jia, R.; and Liang, P. 2016. Data recombination for neural semantic parsing. arXiv preprint arXiv:1606.03622.

Karpukhin, V.; Oguz, B.; Min, S.; Lewis, P.; Wu, L.; Edunov, S.; Chen, D.; and Yih, W.-t. 2020. Dense Passage Retrieval for Open-Domain Question Answering. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), 6769–6781.

Kim, Y. 2014. Convolutional Neural Networks for Sentence Classification. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), 1746–1751. Doha, Qatar: Association for Computational Linguistics.

Kobayashi, S. 2018. Contextual augmentation: Data augmentation by words with paradigmatic relations. arXiv preprint arXiv:1805.06201.

Kolomiets, O.; Bethard, S.; and Moens, M.-F. 2011. Model-portability experiments for textual temporal analysis. In Proceedings of the 49th Annual meeting of the association for computational linguistics: human language technologies, volume 2, 271–276. ACL; East Stroudsburg, PA.

Kumar, V.; Choudhary, A.; and Cho, E. 2020. Data Augmentation using Pre-trained Transformer Models. In Proceedings of the 2nd Workshop on Life-long Learning for Spoken Language Systems, 18–26.

Liu, P.; Qiu, X.; and Huang, X. 2016. Recurrent neural network for text classification with multi-task learning. arXiv preprint arXiv:1605.05101.

Liu, Y.; Ott, M.; Goyal, N.; Du, J.; Joshi, M.; Chen, D.; Levy, O.; Lewis, M.; Zettlemoyer, L.; and Stoyanov, V. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Loshchilov, I.; and Hutter, F. 2017. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101.

Maas, A. L.; Daly, R. E.; Pham, P. T.; Huang, D.; Ng, A. Y.; and Potts, C. 2011. Learning Word Vectors for Sentiment Analysis. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, 142–150. Portland, Oregon, USA: Association for Computational Linguistics.

Mikolov, T.; Chen, K.; Corrado, G.; and Dean, J. 2013. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.

Miller, G. A. 1995. WordNet: a lexical database for English. Communications of the ACM, 38(11): 39–41.

Morris, J. X.; Lifland, E.; Yoo, J. Y.; Grigsby, J.; Jin, D.; and Qi, Y. 2020. Textattack: A framework for adversarial attacks, data augmentation, and adversarial training in nlp. arXiv preprint arXiv:2005.05909.

Pennington, J.; Socher, R.; and Manning, C. D. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), 1532–1543.

Reimers, N.; and Gurevych, I. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. arXiv preprint arXiv:1908.10084.

Sanh, V.; Debut, L.; Chaumond, J.; and Wolf, T. 2019. DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.

Sennrich, R.; Haddow, B.; and Birch, A. 2016. Improving Neural Machine Translation Models with Monolingual Data. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 86–96.

Silfverberg, M.; Wiemerslage, A.; Liu, L.; and Mao, L. J. 2017. Data augmentation for morphological reinflection. In Proceedings of the CoNLL SIGMORPHON 2017 Shared Task: Universal Morphological Reinflection, 90–99.
Socher, R.; Perelygin, A.; Wu, J.; Chuang, J.; Manning, C. D.; Ng, A. Y.; and Potts, C. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 conference on empirical methods in natural language processing, 1631–1642.

Sun, L.; Xia, C.; Yin, W.; Liang, T.; Yu, P. S.; and He, L. 2020. Mixup-Transformer: Dynamic Data Augmentation for NLP Tasks. arXiv preprint arXiv:2010.02394.

Tian, Y.; Sun, C.; Poole, B.; Krishnan, D.; Schmid, C.; and Isola, P. 2020. What makes for good views for contrastive learning? Advances in Neural Information Processing Systems, 33: 6827–6839.

Tiedemann, J. 2020. The Tatoeba Translation Challenge – Realistic Data Sets for Low Resource and Multilingual MT. In Proceedings of the Fifth Conference on Machine Translation, 1174–1182. Online: Association for Computational Linguistics.

Wang, W.; Gan, Z.; Wang, W.; Shen, D.; Huang, J.; Ping, W.; Satheesh, S.; and Carin, L. 2018. Topic compositional neural language model. In International Conference on Artificial Intelligence and Statistics, 356–365.

Wang, W. Y.; and Yang, D. 2015. That’s so annoying!!!: A lexical and frame-semantic embedding based data augmentation approach to automatic categorization of annoying behaviors using# petpeeve tweets. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, 2557–2563.

Wei, J.; and Zou, K. 2019. EDA: Easy Data Augmentation Techniques for Boosting Performance on Text Classification Tasks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 6382–6388. Hong Kong, China: Association for Computational Linguistics.

Xie, Q.; Dai, Z.; Hovy, E.; Luong, M.-T.; and Le, Q. V. 2019. Unsupervised data augmentation for consistency training. arXiv preprint arXiv:1904.12848.

Xie, Z.; Wang, S. I.; Li, J.; Lévy, D.; Nie, A.; Jurafsky, D.; and Ng, A. Y. 2017. Data noising as smoothing in neural network language models. arXiv preprint arXiv:1703.02573.

Yu, A. W.; Dohan, D.; Luong, M.-T.; Zhao, R.; Chen, K.; Norouzi, M.; and Le, Q. V. 2018. Qanet: Combining local convolution with global self-attention for reading comprehension. arXiv preprint arXiv:1804.09541.

Yu, J.; and Jiang, J. 2016. Learning sentence embeddings with auxiliary tasks for cross-domain sentiment classification. Association for Computational Linguistics.

Zhang, H.; Cisse, M.; Dauphin, Y. N.; and Lopez-Paz, D. 2018. mixup: Beyond Empirical Risk Minimization. In International Conference on Learning Representations.

Zhang, X.; Zhao, J.; and LeCun, Y. 2015. Character-level convolutional networks for text classification. Advances in neural information processing systems, 28.