Reprint: A randomized extrapolation based on principal components for data augmentation

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Abstract: Data scarcity and data imbalance have attracted a lot of attention in many fields. Data augmentation, explored as an effective approach to tackle them, can improve the robustness and efficiency of classification models by generating new samples. This paper presents Reprint, a simple and effective hidden-space data augmentation method for imbalanced data classification. Given hidden-space representations of samples in each class, Reprint extrapolates randomly augmented examples for the target class by using subspaces spanned by principal components to summarize the distribution structure of both the source and target class. Consequently, the examples generated would diversify the target while maintaining the original geometry of target distribution. Besides, this method involves a label refinement component which allows to synthesis of new soft labels for augmented examples. Compared with different NLP data augmentation approaches under a range of data imbalanced scenarios on four text classification benchmarks, Reprint shows prominent improvements. Moreover, through comprehensive ablation studies, we show that label refinement is better than label-preserving for augmented examples and that our method suggests stable and consistent improvements in terms of suitable choices of principal components. Moreover, Reprint is appealing for its easy-to-use since it contains only one hyperparameter determining the dimension of subspace and requires low computational resources.

Keywords: NLP Data augmentation, Hidden-space representation, Principal components, Randomized extrapolation

1 Introduction

Deep learning models have achieved state-of-the-art performance on a wide range of supervised learning tasks such as text classification [1–4]. However, since these models rely heavily on the use of abundant well-labeled datasets, their applicability may be constrained in some applied settings where labeled data is not only limited but also imbalanced [5]. For example, with the emergence of new intents or topics in the real world,
the virtual conversational assistant is asked to be able to classify these new classes, but the collection of related data for training lags behind [6,7] and their volume is quite small in comparison with that of the old mature classes.

Data augmentation is a popular method to alleviate data scarcity or imbalance. It refers to generating additional samples to the existing datasets by either duplicating examples of datasets or using transformations or model-based methods to create new synthetic examples [8–10]. Data augmentation is first widely explored in the computer vision community, where label invariant transformations such as rotation, flipping and cropping have been applied to the original images to increase their amount in classification [11–13]. Other methods include noise injection [14], mixupb[15], feature space transfer [16], random erasing [17] and adversary training [18]. The discrete nature of text data along with its complex syntactic and semantic structures make data augmentation a more difficult and underexplored task in Natural Language Processing (NLP). There exists, however, a variety of methods for text data augmentation, and many studies [19,20] have shown that these methods are capable of effectively improving model performance especially when the amount of training data is small. In the face of data with imbalanced distribution of categories, text data augmentation aims at expanding samples in minority, thereby reducing the imbalance between categories and improving the generalization ability of models. Its effectiveness has also been proved in practice [21,22]. Methods for data augmentation in NLP can be broadly categorized as token-level, sentence-level, and hidden-space augmentation (see Figure 1). Token-level augmentation methods generate new data whose semantics slightly deviate from the original data, based on properly operating on words or phrases of texts. It involves token substitution [20,23,24], swapping [25–27], deletion [20,26], insertion [20,28] and their ensemble [29]. Instead of modifying tokens, sentence-level augmentation is allowed to change the entire sentence at once while preserving the meaning of the original sentence. It overcomes the limitation of the replacement range and increases the diversity of augmented data. One common method for sentence-level augmentation is back-translation which firstly translates original text into another language and then translates it back to obtain augmented data [30–32]. Another one is text generation in which new texts can be created via some trained models [21,33–35]. Although back-translation and text generation are able to create novel and diverse data which may not exist in the original dataset, they require either significant training effort or large balanced datasets to fine-tune the model. Being simple yet effective, hidden-space augmentations demand low-resource to produce augmented data since they can work directly on the hidden-space representations of texts by adding noises, and performing interpolations [36,37] or extrapolations [20,33,38] between text representations.
Figure 1: A simple example illustrating token-level, sentence-level and hidden-space level data augmentations in NLP where $H(\cdot)$ signifies the hidden-space representation (i.e., often learned from Neural networks) of raw text and $N(0,1)$ the standard Gaussian distribution. The following figure presents how the data augmentation method GE3 generates augmented examples.

Figure 2: Augmented examples are generated in the target (i.e., minority) class by moving examples in the source (i.e., majority) class to the target class. And one can see that the augmented examples are vertically distributed while the original target examples horizontally distributed.

Recently, Wei et al. (2021) proposed a simple text data augmentation method called *good-enough example extrapolation* (GE3) and has illustrated its performance in class-imbalanced scenarios. More precisely, it generates in hidden-space augmented examples
\( \hat{X}_i^{c_t} \) with pseudo label \( \hat{y}_i = c_t \) in target class \( c_t \) by extrapolating from each sample \( X_i^{c_s} \) in source class \( c_s \), namely

\[
\hat{X}_i^{c_t} = X_i^{c_s} - \mu_{c_s} + \mu_{c_t}
\]

where \( \mu_{c_s} \) and \( \mu_{c_t} \) are respectively the mean of original samples in class \( c_s \) and \( c_t \).

Figure 2 illustrate graphically how data are augmented. Since the hidden-space representation of samples, yielded by pre-trained language models (e.g., BERT), are shown to contain geometry that is intrinsically low-dimensional and anisotropic [39–43], it is easy to see that GE3 may ignore the geometrical distinction [44] between distributions of sample representations in different classes since it simply "copies" the source distribution to the target, which might depart target’s original distribution (Figure 2).

In this paper, we aim to take into account spatial patterns between source and target distribution when generating augmented data for imbalanced datasets. We present a simple and effective method for data augmentation, which we call randomized extrapolation based on principal components or Reprint. To incorporate more spatial information on feature embedding distribution between classes, Reprint first uses two subspaces generated by principal components [45] to summarize respectively patterns and trends of both the source and target class, then the residual of the projection of each source example to the source subspace is calculated, and finally generates augmented examples for target class are by adding residuals from the source to the projection of some random candidate target example to the target subspace. Consequently, the augmented examples will be located around the subspace representation of the target, in other words, they are consistent with the pattern of the target distribution.

In addition, we give a strategy to select candidate target examples in Reprint such that generated examples would be uniformly distributed around the target distribution. We also integrate Reprint with another component called label refinement, which allows us to further create new soft labels for augmented examples. It is motivated by the label synthesis in data augmentation methods such as MIXUP but has been extended to our extrapolation method. Ablation experiments have demonstrated that it can also boost performance, serving as an important component of our method.

We test Reprint on several commonly used text classification benchmarks in a wide range of class-imbalanced scenarios. Across all benchmarks and scenarios, our method outperforms the other eight baseline models. Additionally, by investigating our method with various hyperparameters and hidden-space representations, we demonstrate its stability and universality.

The rest of the paper is organized as follows. Section 2 discusses related work. Section 3 presents the details of our method Reprint. We illustrate its performance on several text datasets and show the ablation studies in Section 4. Finally, the conclusion and future work are given in Section 5.

2 Related work

Hidden-space representation. Being widely used in the NLP community, hidden-space representations are low-dimensional continuous representations of words or sentences that capture their semantic and syntactic [46] first proposed CBOW and Skip-gram models to construct associations between contexts and central words, which allows
central words to obtain their vector representations through contexts. On this basis, Pennington et al. (2014) further solved the problem of fixed sliding window size and achieved better performance on different tasks [47]. However, the static word representation produced by the above models cannot solve the problem that word meaning varies according to their context. To address this shortcoming, [48] and [49] pre-trained respectively Bi-LSTM and Transformer-based models on the large-scale corpus to produce contextualized word representation which effectively alleviates the problem of polysemy. Both models use an unidirectional network structure, so the relations in the language considered by the current model are incomplete. Furthermore, Devlin et al. (2019) proposed a Bi-directional Transformer encoder (BERT) to solve this problem [50]. Thanks to this bidirectional structure and two new pre-training tasks (i.e., Masked Language Model and Next Sentence Predication), BERT can learn richer semantic and syntactic information in different layers. For example, Jawahar et al. (2019) found that its intermediate layers encode a rich hierarchy of linguistic information, with surface features at the bottom, syntactic features in the middle and semantic features at the top [51]. And this enables BERT to achieve state-of-the-art performance not only on text classification such as sentiment analysis, and natural language inference but also on several other natural language processing tasks.

**Text data augmentation.** There is a large body of research on text data augmentation [20,36]. For example, word or phrase replacements that transform parts of the original texts are used for text augmentation in the classification [31,52]. More advanced approaches that are capable of generating whole new texts depend on back-translation or retraining of specific neural models. These methods, however, either require a large number of training data to generate good examples that would improve downstream tasks or demand for very high computational cost. Hidden-space augmentation, which is the most related to our work, seeks to overcome these challenges by performing deformations of data examples in hidden space rather than at the text level. Zhang et al. (2018) introduced a simple and model-agnostic data augmentation routine, termed MIXUP, to construct augmented training examples based on the convex combinations of pairs of examples and their labels [15]. Chen et al. (2020) later extended this interpolation-based routine to semi-supervised text classification and selected beta distribution as the sampling distribution for the ratio to trade off between pairs of examples [36]. In parallel, extrapolation-based and label-preserving methods have also been proposed for data augmentation. Devries and Taylor (2017) proposed to synthesize new examples for a given class by extrapolating a pair of adjacent points within the same class [38]. Following a similar idea, Kumar et al. (2020) study several hidden-space augmentation techniques to improve the few-shot intent classification [33]. Wei et al. (2021) presented GE3 which further extends extrapolation from between points in the same class to distributions of different classes, and showed its performance in an imbalanced class setting [20]. Although inspired by the former, our method is notably different: firstly, the underlying geometry of distribution between classes is ignored in prior work whereas Reprint uses subspace spanned by principal components to characterize it. Secondly, Reprint is also able to synthesize new labels, rather than just hidden-space representations, for augmented examples.

**Label smoothing.** It is first proposed by Szegedy et al. (2016) in order to provide regularization for deep neural networks[53] . Instead of using hard (i.e., one-hot) labels for training, Szegedy et al. (2016) introduced label smoothing, which improves accuracy by
computing cross entropy not with the "hard" targets from the dataset, but with a weighted mixture of these targets with the uniform distribution. Although such soft labels can be effective in giving strong regularization to the model while avoiding overfitting, they treat each category equally and do not take into account the importance of the target category. In the field of NLP, label label-smoothing approach has also proved effective in practice [54, 55]. Further, Müller et al. (2019) meticulously analyzed the principles of label smoothing and explained several behaviors (e.g., closer sample cluster) observed when training deep neural networks with label smoothing [56]. They also found that label smoothing impairs distillation, despite the positive effect on generalization and calibration. To obtain a more reasonable probability distribution between the target and non-target categories, Zhang et al. (2021) proposed a new label smoothing strategy, called Online Label Smoothing[57]. This strategy generates soft labels based on model prediction statistics of the target category. Experiments have also demonstrated the effectiveness of this approach on classification tasks. Alternatively, the mixup strategy can be seen as a method of label smoothing [36, 58]. This method achieves the effect of label smoothing by weighting the labels of two training samples by averaging them, which makes the decision boundary obtained from training smoother and effectively improves the generalization performance of the model.

3 Introducing Reprint

In this section, we introduce our method, including its data augmentation mechanism and the soft labels to be endowed with those augmented examples.

3.1 Randomized extrapolation based on principal components

Given a text classification task with K output classes \{c_k, k = 1, 2, ..., K\}, let us denote by \{X^c_i \in \mathbb{R}^d, i = 1, 2, ..., n_c\} the hidden-space representations of \(n_c\) training examples in class \(c\). For each class \(c\), the mean \(\mu_c\) of all hidden-space representations in that class, and the centralized version \(\bar{X}^c_i\) of each representation \(X^c_i, i = 1, 2, ..., n_c\) are defined respectively as

\[
\mu_c = \frac{1}{n_c} \sum_{i=1}^{n_c} X^c_i
\]

\[
\bar{X}^c_i = X^c_i - \mu_c
\]

In addition, let \{\alpha^c_i, i = 1, 2, ..., h\} denote the first \(h\) principal components of the class \(c\), built on \{\bar{X}^c_i, i = 1, 2, ..., n_c\}, and \(S^c_h\) the subspace spanned by these \(h\) principal components. The projection of centered representation \(\bar{X}^c_i\) to \(S^c_h\) is given by

\[
\text{Proj}_{S^c_h}(\bar{X}^c_i) = A^c_h ((A^c_h)^t \bar{X}^c_i)
\]

where \(A^c_h = [\alpha^c_1, \alpha^c_2, ..., \alpha^c_h]\) is the projection transformation matrix whose columns are principal components, and \((A^c_h)^t\) represents the transposition of the matrix \(A^c_h\).

Reprint attempts to generate, in a randomized fashion, augmented examples by extrapolating the data distribution from a source class \(c_s\) to the target \(c_t\) in hidden space.
More precisely, for each \(X_i^{cs}\) in the source class, a corresponding augmented example \(\hat{X}^{ct}\) in the target class is generated as follows. The visualization of equation 3 is shown in Figure 3.

\[
\hat{X}^{ct} = \frac{\bar{X}_{i}^{cs} - \text{Proj}_{n_h}(\bar{X}_{i}^{cs})}{p_1} + \frac{\text{Proj}_{S_q}(\bar{X}_{j}^{ct})}{p_2} + \frac{\mu_{ct}}{p_3}
\]  

(2)

where \(p_1\) is the residual of the projection of a source example \(\bar{X}_{i}^{cs}\); \(X_j^{ct}\) is a random candidate example to be sampled from a given distribution \(P\) (see Section 3.2 for its definition) defined on the centered training set \(\{\bar{X}^{ct}_j, j = 1, 2, \ldots, n_{ct}\}\) of the target class and \(p_2\) is the projection of \(\bar{X}^{ct}_j\) to the subspace \(S_q^{ct}\) formed by the first \(q\) principal components of the target class; \(p_3\) is the target mean. Therefore, while increasing the amount and diversity of the target class, the augmented examples remain to be around the subspace representation \(S_q^{ct}\) of the target class, hence making them consistent with the original geometry of target distribution. In addition, we can also see augmented examples from another perspective: subspace representations of both source and target class can be interpreted as conserving primary and common semantic and syntactic structure shared by the examples within each class, and the residual serves as a variant of the main structure contained in the source class. Adding this variant to the projection of a target example may therefore help to diversify the augmented example while preserving a similar meaning to the origin. Dong et al. (2023) also utilized principal component analysis to preserve the aggregated real signals from neighboring features on Graph Neural Networks [59].

**Figure 3:** This figure presents how the augmented example \(\hat{X}^{ct}\) (pink point) is generated in \(\mathbb{R}^2\), where the red and purple dashed lines are respectively the first principal component of the centered source class (red triangles) and target class (purple points). The short purple
arrow (near the origin) is the projection of a centered random target example \( \bar{X}_{i}^{c_t} = X_{i}^{c_t} - \mu_{c_t} \) on its first component in the target class, and the two short red dashed arrows are both the residual (i.e., \( p_{t} \) in equation 2) of the projection of a centered source example \( \bar{X}_{j}^{c_s} \). We use a green line to represent the target mean \( \mu_{c_t} \).

For each class in the training set, we could generate a set of extrapolated samples from every other class, multiplying approximately the size of the training set by a factor \( K \). In the training process, the classification model will be trained on the union of original data and extrapolated ones. It is worth noticing that Reprint is model-free and simple to use, requiring little computation cost since the only hyperparameters involved are the number \( h, q \) of principal components for both source and target classes.

### 3.2 Choice of principal components and sampling distribution

We propose the first two heuristic strategies to determine the number \( h \) and \( q \) (i.e., the dimensionality of subspaces) of principal components used to explain the source and target class. The first one is to consider two subspaces of the same dimension (i.e., \( h = q \)) to represent both source and target distribution, and choose an optimal value in terms of its performance on the test set. The second one relies on the explained variance ratio which is defined as the percentage of variance explained by each of the selected components, and \( h \) (or \( q \)) is selected such that a certain amount, for example 90\%, of variance can be explained by the first \( h \) (or \( q \)) principal components in source (or target) class.

In addition, for the choice of sampling distribution \( P \) for random candidate \( \bar{X}_{j}^{c_t} \) in equation 2, we set it as a uniform distribution over centered target training set \( \{\bar{X}_{c_t}^{j}, j = 1,2, \ldots n_{c_t}\} \) of target class \( c_t \), i.e.,

\[
P(\bar{X}_{j}^{c_t} = \bar{X}_{j}^{c_t}) = \frac{1}{n_{c_t}}, j = 1,2, \ldots ,n_{c_t}
\]

Following this choice, augmented examples generated by equation 2 will be uniformly distributed along the underlying pattern of the target distribution.

### 3.3 Label refinement for augmented examples

We also propose another component named label refinement which attempts to integrate label synthesis used in interpolation-based augmentation into our method to generate new labels, rather than just hidden-space representations, for augmented examples. By combining equations 1 and 2, the augmented example \( \tilde{X}_{i}^{c_t} \) for target class \( c_t \) can be rewritten as

\[
\tilde{X}_{i}^{c_t} = \left( I_{d} - A_{h}^{cs}(A_{h}^{cs})^{t} \right) \hat{X}_{i}^{c_t} + A_{q}^{cs}(A_{q}^{cs})^{t} \hat{X}_{j}^{c_t} + \mu_{c_t}
\]

where \( I_{d} \) represents the identity matrix. We synthesize new label \( \hat{y}_{i}^{c_t} \) for \( \tilde{X}_{i}^{c_t} \) as

\[
\hat{y}_{i}^{c_t} = \begin{cases} 
\lambda y_{i}^{c_s} + (1 - \lambda) y_{i}^{c_t}, & \text{if } |W_{c_s}^{t}| > 0 \text{ and } |W_{c_t}^{t}| > 0, \\
y_{i}^{c_t}, & \text{else.}
\end{cases}
\]

(3)
where $y^{c_s}$ and $y^{c_t}$ denotes respectively one-hot label (i.e., hard label) representation for class $c_s$ and $c_t$, and $\lambda = |W^{c_s}|/(|W^{c_s}| + |W^{c_t}|)$ represents the ratio between two determinants $|W^{c_s}|$ and $|W^{c_t}|$. In other words, if the augmented example is extrapolated as the sum of two linear transformations for which inner products between $W^{c_s} \tilde{X}^{c_s}_i$ (respectively $W^{c_t} \tilde{X}^{c_t}_j$) and its domain $\tilde{X}^{c_s}_i$ (respectively $\tilde{X}^{c_t}_j$) are both strictly positive, then the new label for augmented example is created as a linear combination of both source and target label where the weight is computed as the determinant of two transformation matrices. Otherwise, it is preserved as the hard label of the target class. One can regard this way of generating pseudo-labels for augmented samples as a derivative of mix-up in the sense that the weights of two mixing labels, originally in accordance with the weight of two combining samples, are now computed by the determinants (i.e., volumes) of transformation matrices associated with two samples.

4 Experiments

In this section, we test Reprint on various text classification benchmark datasets. We first give a brief introduction about the datasets, the class-imbalanced scenario and experiment settings on which our experiments are performed. Next, we describe some baseline models with which we are about to compare, including some data augmentation baselines relying on extrapolation and other baselines built on either interpolation or token-level augmentation. Finally, we present the performance of both our method and baselines on various datasets, the results of which demonstrate the effectiveness of our approach. Additional ablation studies are also given, showing how different components involved in our method contribute to the result.

4.1 Datasets

We run our experiments on the following benchmarks in text classification.

1. **SNIPS** [60]: Snips Voice Platform is a dataset of over 16,000 crowdsourced queries distributed among 7 user intents of various complexity. Each intent has around 1,800 training samples, and the test set has 700 samples altogether.

2. **Yahoo Answers** [61]: The Yahoo Answers topic classification dataset consists of 10 largest main categories from the Yahoo! Answers Comprehensive Questions and Answers. Each class contains 6,000 testing samples. As original training set is too large, we constrained its size to at most 3000 for each class.

3. **AG News** [58]: It consists of the 4 largest classes of original news corpus. Each topic class has 30,000 training samples and 1,900 testing samples. Due to its large training set, the maximum number of training samples used for each class in training is set to 2,000.

4. **DBpedia** [62]: It includes structured content collected from Wikipedia. For each of the 14 classes, we only use a subset containing 2,500 out of 40,000 training samples, but evaluate our approach on the whole test set.

4.2 Experiment settings

For the above datasets, we artificially create a class-imbalanced scenario through random sampling. Specifically, half of the classes of each dataset would be randomly selected to equip with only a small number $n_{small}$ of samples while each of the remaining...
classes would set to have \( n_{\text{large}} \) samples (i.e., \( n_{\text{large}} = \{1800,3000,2000,2500\} \)) respectively for the four datasets mentioned above. Moreover, we consider a range of values (i.e., 32, 64, 128) for \( n_{\text{small}} \) to simulate different class-imbalanced scenarios. Besides, throughout the experiments, we use a BERT-based-uncased [50] pre-trained language model to encode the text, and represent it in hidden space using average pooling over the output of encoder’s last layer. The weights in BERT encoder are frozen, and an additional MLP classifier with softmax is added on top for classification. After applying data augmentation methods to these imbalanced datasets, an MLP classifier would leverage both original and augmented data for training. Since the test set of different benchmarks is in fact class-balanced, we evaluate the performance of our method only on accuracy, obtained on the test set. To eliminate the seed effect in training set, we run all experiments for five random seeds and the encoder only reads the first 512 tokens of text without any additional preprocessing.

4.3 Baselines

To test the effectiveness of our method, we compare it with the following baseline models:

1. **UPSPL** (Upsampling) is a simple tool handling class-imbalanced scenarios by sampling directly from dataset.
2. **NOISE** (Gaussian Noise) generates samples from \( \mathcal{N}(0,0.1) \) and adds them to the existing samples to form an augmented example.
3. **SMOTE** [37] is a simple and commonly used method to solve data imbalance. By selecting examples that are close in the feature space using K-Nearest Neighbor, new samples are created by their interpolations.
4. **EDA** [52] is an easy way to perform data augmentation while having high interpretability. It makes good use of text editing techniques and could generate novel samples with a certain degree of diversity.
5. **TMIX** [36] creates augmented samples in hidden space. Given a pair of examples in two different classes, augmented features and labels are interpolated by their convex combination.
6. **WE** (Within-Extrapolation [38]) extrapolates between hidden-space representations of two examples \( X_i^c \) and \( X_j^c \) of the same class \( c \) to create augmented examples as

\[
\hat{X}^c = \lambda (X_i^c - X_j^c) + X_i^c,
\]

where \( \lambda \) is set to be 0.5 in the experiment.
7. **LD** (Linear Delta [44]) adds the bias between two examples \( X_i^c \) and \( X_j^c \) of the same class \( c \) to another sample \( X_k^c \) to form an augmented example as

\[
\hat{X}^c = (X_i^c - X_j^c) + X_k^c
\]
8. **GE3** [20] generates an augmented sample \( \hat{X}_{ct} \) for target class \( c_t \) by extrapolating from a sample \( X_i^{cs} \) in source class \( c_s \) as

\[
\hat{X}_{ct} = X_i^{cs} - \mu_{cs} + \mu_{ct}
\]
where $\mu_{c_s}$ and $\mu_{c_t}$ are respectively the mean of original samples in class $c_s$ and $c_t$.

To cope with data-imbalanced scenarios, our method would follow the same data augmentation strategy as GE3. As for other approaches mentioned above, they would generate samples for minority classes until the training samples of each class are of approximately the same size.

### 4.4 Results

#### 4.4.1 Test accuracy of models

Table 1 compares the performance of Reprint and baseline models on four text classification datasets with the size $n_{small}$ of minority class varying from 32 to 128. The mean accuracy and standard deviation are calculated based on five random seeds. It is noted that Reprint consistently outperforms baselines on all benchmarks, with an average improvement of 5.20% of accuracy over UPSPL under different $n_{small}$ values.

| Dataset | Snips        | Yahoo Answer |
|---------|--------------|---------------|
|         | $n_{small}$  | 32 | 64 | 128 | 32 | 64 | 128 |
| UPSPL   | 88.97±0.83   | 92.11±1.06   | 93.60±0.51 | 46.88±0.39 | 50.36±0.39 | 53.84±0.53 |
| SMOTE   | 89.00±0.83   | 91.97±0.91   | 93.54±0.51 | 46.62±0.43 | 50.52±0.43 | 54.12±0.58 |
| TMIX    | 89.00±1.61   | 92.46±1.07   | 94.34±0.28 | 53.92±3.33 | 59.51±3.22 | 60.08±0.78 |
| EDA     | 88.31±1.22   | 92.01±1.34   | 92.65±0.57 | 46.24±0.34 | 50.52±0.35 | 53.78±0.41 |
| LD      | 85.74±1.09   | 89.69±0.57   | 92.11±0.78 | 46.70±0.45 | 52.25±0.23 | 58.88±0.39 |
| WE      | 85.69±0.97   | 90.06±0.77   | 92.43±0.39 | 44.44±0.53 | 49.36±0.42 | 55.87±0.43 |
| NOISE   | 89.17±0.99   | 92.60±0.93   | 94.00±0.78 | 53.47±0.24 | 59.48±0.41 | 63.42±0.52 |
| GE3     | 92.03±1.19   | 94.23±0.77   | 95.03±0.58 | 53.32±0.24 | 59.06±0.18 | 63.04±0.41 |
| Reprint | 92.05±1.15   | 94.23±0.90   | 95.03±0.36 | 59.01±0.47 | 63.08±0.26 | 65.14±0.64 |
| AG news | UPSPL        | 74.08±1.73   | 79.14±1.03 | 82.56±0.30 | 93.38±0.18 | 95.50±0.41 | 96.85±0.13 |
|         | SMOTE        | 74.23±1.74   | 79.31±1.00 | 82.63±0.27 | 93.24±0.20 | 95.36±0.41 | 96.73±0.16 |
|         | TMIX         | 75.64±1.85   | 80.20±1.23 | 83.76±0.31 | 94.12±0.31 | 96.47±0.55 | 97.50±0.40 |
|         | EDA          | 71.64±1.87   | 77.41±1.47 | 81.62±0.58 | 92.61±0.35 | 94.86±0.37 | 96.45±0.15 |
|         | LD           | 68.53±1.71   | 73.11±1.01 | 75.83±0.99 | 90.31±0.14 | 93.45±0.34 | 95.33±0.31 |
|         | WE           | 67.74±1.67   | 72.97±0.80 | 76.44±0.90 | 90.44±0.21 | 93.66±0.49 | 95.75±0.21 |
|         | NOISE        | 75.64±1.30   | 80.79±0.81 | 84.07±0.34 | 93.67±0.17 | 95.73±0.40 | 97.04±0.11 |
|         | GE3          | 78.10±1.46   | 82.07±0.61 | 85.19±0.31 | 94.20±0.30 | 95.90±0.29 | 96.94±0.21 |
| Reprint | 80.16±1.04   | 84.04±0.86   | 86.88±0.32 | 95.63±0.16 | 96.86±0.28 | 97.54±0.12 |

In addition, although WE and LD also use extrapolation skill as ours, their
comparatively poor performance indicates that their way of in-class extrapolation is not enough to restore the original distribution of target class as our method does. SMOTE outweighs mostly the formal two but still falls behind Reprint, implying that integrating the geometry of class distribution into extrapolation could further increase the quality of augmented examples. At the same time, EDA does not achieve the same accuracy as some of the hidden-space augmentation methods such as GE3 or Reprint. We argue that this may due to that modifications of tokens on the input-level of text cannot result in augmented examples as diverse as produced by other augmentation methods, hence limiting the performance of it. Moreover, if one compares Reprint with NOISE, the improvement of accuracy shows that the prior information about the distribution structure of classes used in our method do contribute to the performance.

Moreover, it is worth noticing that both TMIX and Reprint use soft labels in training. From results in Table 1, the performance of TMIX is not as good as ours on three datasets (i.e., Snips, Yahoo Answer and AGnews) and it generally has larger standard deviation in all cases. It may be because the decision boundaries between classes are not strong enough yet, or a single-layer MLP classifier cannot provide stable training like the one [36] did on BERT. At the same time, it suggests that augmented examples generated by our method have smaller perturbation, enabling faster convergence of the classifier.

Especially, Reprint achieves comprehensive improvements in respect to datasets and sizes of minority class over one of the best competitor GE3 which can be in fact regarded as a simplified version of our approach. This performance gain demonstrates the advantage of using principal components in our method to not only account for the pattern of distribution of different classes when generating augmented examples but also to guide the synthesis of new labels for them. Figure 4 leverages the t-SNE technique [63] to visualize both original and augmented examples produced respectively by GE3 (left panel) and Reprint (right panel) in a two-dimensional plane. It illustrates the effectiveness of our method since the augmented examples generated by GE3 deviate from the target class (BookRestaurant) while those generated by ours still have fidelity to the original target distribution.

![Figure 4: The t-SNE visualisation of both original and augmented examples produced respectively by GE3 (left panel) and Reprint (right panel). The source class (RateBook) is](image-url)
in grey, and the target class (BookRestaurant) in light blue. The augmented samples (orange cross) produced by GE3 have a different distribution with respect to the target while that (dark green triangle_down) created by our method do not.

Further, we also consider two more choices for \(n_{\text{small}}\) (i.e., \(n_{\text{small}} \in \{16,256\}\)) to investigate the performance of our method in more severe imbalanced scenarios and less severe ones. Figure 5 shows the mean accuracy of both our method and the other three competitive baseline models on Yahoo Answer and DBpedia datasets under the consideration of five \(n_{\text{small}}\) values. It can be seen clearly that the improvement of our method over baselines is much more obvious when the training data is more imbalanced even though the estimation of principal components may be of large bias when the number of samples is small. In addition, as shown in Table 1, an average of 3.94% (or 1.91%) improvement is attained over GE3 in each scenario on Yahoo Answer (or AG news), which indicates the generality and stability of our method in different class-imbalanced settings.

![Figure 5](image)

**Figure 5:** The performance of Reprint with the three most competitive baselines (i.e., GE3, NOISE and TMIX) on Yahoo Answer (left panel) and DBpedia (right panel) in broader class-imbalanced scenarios with \(n_{\text{small}} \in \{16,32,64,128,256\}\).

### 4.4.2 Measurement of the discrepancy between original and augmented samples

In addition to Figure 4, we would quantitatively demonstrate in this section that the augmented samples generated by our method have smaller sample discrepancy than GE3, the most competitive baseline as shown in Table 1. More specifically, we now denote by \(X_{ct}\) the original sample of target class \(c_t\), \(\tilde{X}_{c_{br}}\) augmented sample from Reprint and \(\tilde{X}_{c_{br}}\) augmented sample from GE3, and suppose that \(X_{ct} \sim p\), \(\tilde{X}_{c_{br}} \sim q_r\) and \(\tilde{X}_{c_{br}} \sim q_g\), where \(p, q_r, q_g\) are unknown multivariate distributions in high dimension. Although many statistical approaches [64–68] have been proposed to calculate the discrepancy between two distributions, we adopt the Maximum Mean Discrepancy (MMD) proposed by [69] as a metric to measure the distance between distributions \(p\) and \(q\) since it is tailored for our setting in which samples are scarce and in high dimension. Its definition is given as follows

\[
\text{MMD}^2[F, p, q_r] = \sup_{||f||_{p} \leq 1} \left( E_{x \sim p}[f(x)] - E_{y \sim q}[f(y)] \right)^2
\]
where $\mathcal{H}$ is a reproducing kernel Hilbert space associated with the Gaussian kernel

$$K(x, y) = e^{-\alpha ||x-y||^2}$$

($\alpha > 0$) and $\mathcal{F}$ is the unit ball in $\mathcal{H}$.

An unbiased empirical estimate of $\text{MMD}^2[\mathcal{F}, p, q_r]$ is the sum of two U-statistics and a sample average [69], defined as

$$\text{MMD}^2[\mathcal{F}, X^{c_t}, \tilde{X}^{c_t}] = \frac{1}{m(m-1)} \sum_{i=1}^{m} \sum_{j=i+1}^{m} K(X^{c_t}_i, X^{c_t}_j) + \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=i+1}^{n} K(X^{c_t}_i, \tilde{X}^{c_t}_j) - \frac{2}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} K(X^{c_t}_i, \tilde{X}^{c_t}_j)$$

It is noted that $\text{MMD}^2[\mathcal{F}, X^{c_t}, \tilde{X}^{c_t}]$ measures the estimated distance between the distribution $p$ of raw samples within class $c_t$ and the distribution $q_r$ of augmented samples obtained from Reprint. The smaller this value is, the closer these two distributions are. Further, we define the mean value $\overline{\text{MMD}}_r$ (analogue for $\overline{\text{MMD}}_g$) of MMD estimates as a measurement of the global discrepancy between raw samples and augmented samples over all possible target classes, namely,

$$\overline{\text{MMD}}_r = \frac{1}{K} \sum_{c_t=1}^{K} \text{MMD}^2[\mathcal{F}, X^{c_t}, \tilde{X}^{c_t}]$$

Table 2 presents both $\overline{\text{MMD}}_r$ and $\overline{\text{MMD}}_g$, computed on SNIPS dataset with $m = n = 128$ and with the selection of 10 principal components in Reprint. It is noted that the latter is 10.46% larger than the former, indicating that the augmented sample generated by our method is closer to the original sample than that of augmented sample from GE3.

| Methods | Mean of MMD estimates |
|---------|------------------------|
| Reprint | $\overline{\text{MMD}}_r = 1.796 \times 10^{-5}$ |
| GE3     | $\overline{\text{MMD}}_g = 1.984 \times 10^{-5}$ |

### 4.5 Ablation studies

We now present ablation studies to show the effectiveness of subspace representation and label refinement in Reprint.

#### 4.5.1 Different strategies for choosing principal components

We compare two strategies mentioned in Section 3.2 to determine the subspace representation for source and target class:

1. We consider $h = q = k$ and $k \in \{1,5,10,15\}$.
2. We set the ratio of variance explained in $\{50\%, 70\%, 95\%\}$.

The left panel of Figure 6 shows the test accuracy of Reprint on DBpedia, using different strategies to choose principal components. We observe that the performance degrades when the ratio of explained variance increases from 50% to 95%, suggesting that only noises, rather than informative residual that relates to semantic and syntactic structure of source class, are incorporated in the generate augmented examples when the ratio comes to 95%. Additionally, as 1, 5, 10 and 15 principal components approximate respectively to ratio of 20%, 40%, 45% and 50%, the comparatively poor performance of our method with
one principal component (dark green line) also indicates that the performance would deteriorate if the number of principal components is too small. In other words, the subspace formed by principal components is too simple to provide sufficient representation for the underlying pattern of class distribution. On the contrary, as long as the ratio takes intermediate values, one can see that their performances always rank among the best even with various $n_{small}$ values and that their differences are small, suggesting that using subspace representation of class distribution when generating augmented examples helps to bring useful distributional information from one class to another, and this benefits the versatility of the target class. For this reason, we heuristically set $h = q = 5$ for the following experiments.

Figure 6: Ablation study of Reprint on DBpedia. The left plot gives the performances with several choices of principal components while the right plot shows the performances of our method with two different choices of labels.

4.5.2 Different choices for labels

The mixup-based approaches [15,36] have shed light on our label refinement discussed in Section 3.3. In this part, we would like to study how this refinement boosts the final result by carrying out ablation studies with the following two choices of labels for augmented examples.

1. **Label refinement** creates new soft labels for augmented examples based on the principal components, as discussed in equation 3.

2. **Hard label** preserves labels for those augmented examples and represents them by one-hot vector.

The lower panel of Figure 6 reports the accuracy achieved using the aforementioned choices of labels. The proposed label refinement can achieve better performance than a hard label with various $n_{small}$ values, and this gap becomes more significant in a more imbalanced scenario. We conjecture that the label refinement component can serve as a regularization effect to the classification model and hence improve the model generalization ability.

To illustrate the contribution provided by the two components involved in our method, Table 3 reports the decline of the accuracy of Reprint on the DBpedia dataset after striping label refinement and principal components-based subspace representation consecutively.
Table 3: Mean test accuracy of Reprint when removing label refinement and subspace representation one by one. The results are obtained on DBpedia with $n_{small} = 16$.

| Strategy                                      | Accuracy (%) |
|-----------------------------------------------|--------------|
| Reprint                                       | 93.4         |
| without label refinement                      | 92.8         |
| without label refinement & subspace representation | 91.6         |

It is noted that the drop is significantly larger when we remove the subspace representation than when only removing label refinement, indicating that the subspace representation that is used when extrapolating augmented examples has a larger impact than the label refinement on the final performance of Reprint, which highlights the crucial role of using principal components in our method.

4.6 Different hidden-space representation

In addition, to demonstrate that Reprint is not tailored for only one kind of hidden-space representations yielded by some certain language model but also has its generality and effectiveness with other model, we present the results in Table 4 with hidden-space representations now given by another pretrained language model ALBERT [70]. It is noted that our method achieves an average improvement of 4.69% of accuracy over UPSPL, and also outweighs other baseline models.

Table 4: Results using ALBERT pretrained language model

| Dataset     | n\(_{small}\) | Snips  | Yahoo Answer |
|-------------|---------------|--------|--------------|
|             | 32            | 64     | 128          | 32       | 64       | 128       |
| UPSPL       | 87.74±0.88    | 91.03±0.88 | 93.23±0.44 | 46.56±1.01 | 50.23±0.61 | 53.68±0.92 |
| SMOTE       | 87.77±0.69    | 91.03±0.71 | 93.03±0.51 | 46.01±0.60 | 49.93±0.77 | 53.51±0.94 |
| TMIX        | 88.80±1.80    | 92.06±1.28 | 93.31±0.93 | 57.45±2.15 | 58.05±1.23 | 60.88±1.57 |
| EDA         | 87.36±1.35    | 91.03±1.54 | 92.14±0.65 | 46.23±0.99 | 49.76±0.89 | 53.60±0.86 |
| LD          | 82.66±1.21    | 87.74±1.36 | 90.31±1.14 | 46.48±0.37 | 51.88±0.61 | 57.20±0.78 |
| WE          | 83.89±1.28    | 88.31±1.88 | 90.91±1.24 | 44.46±0.37 | 50.14±0.71 | 55.28±0.67 |
| NOISE       | 88.17±0.72    | 91.37±1.30 | 93.26±0.78 | 50.77±0.41 | 55.88±0.52 | 59.71±0.59 |
| GE3         | 90.00±0.69    | 92.51±0.99 | 94.09±0.59 | 52.68±0.41 | 57.50±0.64 | 61.06±0.63 |
| Reprint     | 90.83±0.69    | 92.74±0.94 | 94.29±0.80 | 57.98±0.5 | 61.29±0.36 | 62.99±0.52 |

| Dataset     | n\(_{small}\) | AG news | DBpedia |
|-------------|---------------|---------|---------|
| UPSPL       | 72.44±2.27    | 76.79±0.89 | 80.39±0.60 | 90.01±0.36 | 92.97±0.37 | 94.97±0.27 |
| SMOTE       | 72.55±2.20    | 76.91±0.83 | 80.49±0.66 | 89.85±0.39 | 92.78±0.40 | 94.82±0.29 |
| TMIX        | 74.26±1.64    | 78.97±1.27 | 82.36±1.01 | 90.86±1.37 | 94.59±1.25 | 95.20±1.13 |
| EDA         | 71.26±1.29    | 77.20±1.25 | 80.39±0.67 | 90.32±1.76 | 91.70±1.13 | 94.13±1.04 |
| LD          | 65.69±1.08    | 69.28±0.69 | 73.37±0.79 | 82.97±0.64 | 87.21±0.35 | 91.20±0.36 |
| WE          | 64.80±1.69    | 68.98±0.83 | 72.62±0.75 | 83.28±0.65 | 87.91±0.49 | 91.47±0.17 |
| NOISE       | 73.50±2.16    | 77.98±0.80 | 81.68±0.53 | 90.37±0.27 | 93.25±0.34 | 95.13±0.26 |
| GE3         | 76.08±0.94    | 79.68±0.83 | 82.93±0.34 | 92.24±0.45 | 94.32±0.20 | 95.61±0.09 |
| Reprint     | 76.71±1.30    | 81.13±1.04 | 84.50±0.54 | 92.97±0.30 | 94.92±0.24 | 95.94±0.14 |
5 Conclusion and future work

To alleviate data scarcity or class imbalance, Reprint provides a new perspective for hidden-space data augmentation. To generate augmented samples with both fidelity and variety to the target class distribution, we make use of principal components to form subspace representations for both source and target class distribution, thus the augmented samples for the target class would not only have a smaller discrepancy with original target sample distribution, but also preserve its primary semantic and syntactic structure within target class. Moreover, we provide alongside a label refinement component enabling the synthesis of new pseudo soft labels for augmented examples which can further boost the performance of our method. Through experiments on four text classification benchmark datasets, we illustrate the effectiveness of Reprint which has better test accuracy and competitive standard deviation when compared with other eight data augmentation baselines in NLP. Moreover, Reprint is appealing since it demands low computational resources and the only hyperparameter contained is the one determining the dimension of subspace.

Additionally, we provide ablation studies to show the effect of both subspace representation and label refinement components on the final results. It is found that when the explained variance ratio of principal components is of medium values, the subspace representation formed by those principal components improves the most to the test accuracy and this improvement is consistent across several class-imbalanced scenarios. Furthermore, it is also found that label refinement involved in our method achieves better results in comparison with hard labels which preserves labels for augmented examples.

In the future, we would like to extend the characterization of the geometry of class distribution from linear representation to a non-linear setting, either by using principal curves or other manifold learning methods, to provide a more elaborate description of class distribution. In addition, we plan to explore whether our method can be adapted to other settings such as semi-supervised learning. Finally, we also seek to ameliorate the sampling distribution by considering the importance of each target example in terms of their gradients or other metrics.

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Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions
Le Li: Methodology, Software, Formal Analysis, Writing-Original Draft, Supervision, Project administration. Jiale Wei: Software, Formal analysis, Investigation, Writing-Original Draft; Pai Peng: Writing-Original Draft, Visualization; Qiyuan Chen:
Ethical and informed consent for data used
Ethics Committee approval was obtained from the Institutional Ethics Committee of Central China Normal University to the commencement of the study.

Data availability
The data that support the findings of this study are openly available in:
https://github.com/sonos/nlu-benchmarkSNIP
http://wikidata.dbpedia.org/develop/datasetsDBpedia
http://groups.di.unipi.it/gulli/AG_corpus_of_news_articles.htmlAGnews
https://huggingface.co/datasets/yahoo_answers_topicsYahoo Answer

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