Early Stopping Based on Unlabeled Samples in Text Classification

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Abstract
Early stopping, which is widely used to prevent overfitting, is generally based on a separate validation set. However, in low resource settings, validation-based stopping can be risky because a small validation set may not be sufficiently representative, and the reduction in the number of samples by validation split may result in insufficient samples for training. In this study, we propose an early stopping method that uses unlabeled samples. The proposed method is based on confidence and class distribution similarities. To further improve the performance, we present a calibration method to better estimate the class distribution of the unlabeled samples. The proposed method is advantageous because it does not require a separate validation set and provides a better stopping point by using a large unlabeled set. Extensive experiments are conducted on five text classification datasets and several stop-methods are compared. Our results show that the proposed model even performs better than using an additional validation set as well as the existing stop-methods, in both balanced and imbalanced data settings. Our code is available at https://github.com/DMCB-GIST/BUS-stop.

1 Introduction
Early stopping, a form of regularization, is a widely used technique to prevent a model from over-fitting (Yao et al., 2007; Zhang et al., 2017). It is generally based on a separate validation set (Goodfellow et al., 2016). While monitoring the validation performance during training, the training process stops when the validation error starts to increase. Validation-based early stopping is advantageous because it is easy to implement and can be interpreted directly (Prechelt, 1998).

In a scenario where sufficient labeled data are available, the use of a validation set is generally preferred (Goodfellow et al., 2016). However, when only a few labeled data exist, a tradeoff problem is encountered (Kann et al., 2019; Choi and Lee, 2021). For example, although the usage of a relatively large validation set enables more reliable estimation, the number of samples for training becomes insufficient. Conversely, if small fractions of the samples are assigned to the validation set, the stopping point becomes ambiguous because the small validation set is not representative enough.

Early stopping is more important in a low resource setting because the prediction accuracy fluctuates highly during training. Such high fluctuations render it challenging when to stop the model. One way to mitigate these fluctuations is to use sufficient training data. In this context, training all the available samples would be more effective, and for this purpose, an appropriate stopping point should be determined without validation split. However, this has not been extensively studied. Duvenaud et al. (2016) and Mahsereci et al. (2017) proposed gradient-based stop-methods and applied statistical inference on the training samples. Lee and Chung (2021) suggested the usage of local intrinsic dimensionality (LID) for early stopping. In addition, some studies treat the stopping epoch as a hyperparameter: the stopping epoch is obtained by grid-search or averaging in cross validation (Choi and Lee, 2021). These methods allow the training of all the labeled samples. However, they do not consider the task-related performance metrics (e.g., accuracy) during training, and the LID and gradient-based stop criteria have not been commonly used in natural language processing (NLP). Furthermore, gradient-based stop-criteria depend on the training samples, the size of which may still be small to be representative.

In this study, we propose an early stopping method based on unlabeled samples (BUS-stop). We are motivated by the following two considerations: (i) The probabilities of the predicted class label (i.e., the prediction confidences) can serve as

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an indicator for over-fitting or under-fitting. (ii) In a better model, the output class distribution is more likely to be closer to the class distribution of the true labels. To incorporate these two assumptions, two stop criteria are proposed, and combined in the BUS-stop method. Our method monitors the prediction results of unlabeled samples during training and utilizes them for determining the stop-criteria. The first proposed stop-criterion is based on confidence similarity (conf-sim). The model stops when the prediction confidences for the unlabeled samples are most similar to the reference confidences, which are precalculated on the labeled set with cross-validation. Conf-sim is observed to reflect the long-term trend of the loss curve, and thereby assist in preventing over-training. The second stop criterion is based on the class distribution similarity (class-sim). This criterion stops the model when the predicted class distribution on the unlabeled set is most similar to the pre-estimated distribution. To this end, we present a novel estimation method for the true class distribution, which calibrates the predicted distribution by extrapolation such that it is closer to the true distribution. Class-sim is observed to reflect the short-term trend of the accuracy. Our method requires several retraining steps to obtain the reference confidences for conf-sim and the estimated class distribution for class-sim. The BUS-stop method that combines class-sim and conf-sim includes the advantages of both, and thereby performs with better accuracy and loss compared to each (class-sim and conf-sim).

The following characteristics of our method contribute to performance improvement. Our method does not require a separate validation set; hence, all the labeled samples can be trained. Training can stop at a more generalized model, using a large unlabeled set. The proposed stop-criteria, conf-sim and class-sim, consider two performance metrics, namely, the loss and accuracy.

Our contributions are summarized as follows:

- We propose BUS-stop, an early stopping method, based on unlabeled samples. BUS-stop can stop the training at a more generalized model, and the performance is better even than using an additional validation set.

- Furthermore, we present a calibration method to better estimate the class distribution. This method calibrates the output class distribution to render it closer to the true distribution, improving the class-sim performance.

- Extensive experiments are conducted on five popular text classification datasets in English. Comparison with several stop-methods demonstrates that the proposed method outperforms these existing stop-methods in both balanced and imbalanced data settings.

2 Related Work

Prechelt (1998) experimented on 14 different validation-based stop criteria. Prechelt (1998) focused on an issue that the validation error during training may represent many local minima prior to a global optimum.

Existing non-validation stop-criteria are generally based on statistical inference. Duvenaud et al. (2016) interpreted stochastic gradient descent in terms of the variational inference and proposed an estimation method for the marginal likelihood of the posterior, which was applied as an early stopping criterion. However, this method requires considerable computation for the Hessian, which is not practical in large models. Mahsereci et al. (2017) also proposed a gradient-related stopping method referred to as evidence-based stopping (EB). The EB-criterion is based on the fast-to-compute local statistics of the computed gradients. The criterion represents whether the gradients of the training samples lie within the expected range. Intrinsric dimensionality (ID), which refers to the minimum number of parameters required to represent a dataset, has been used for analyzing the training or redundancy of neural networks (Amsaleg et al., 2015). LID is a version of ID that estimates the subspace dimensions of the local regions. Lee and Chung (2021) found that LID works well as a stopping-criterion in several few-shot image classification datasets. Moreover, LID can be applied to unlabeled samples. Another method involves the pre-estimation of the the number of training epochs by training the model multiple times, such as cross validation (Choi and Lee, 2021); the model can stop at the pre-estimated (PE) stop-epoch when training all the labeled samples.

However, these methods have not been commonly studied for NLP tasks and do not consider the performance metrics during training. Furthermore, comparisons among the non-validation stop-methods have not been reported. In this study, we compare our method with the EB, LID, PE, and validation-based stopping methods on five text classification datasets. The method proposed by
Algorithm 1 Preliminary stage for BUS-stop

Input: Labeled set $D_t$, Unlabeled set $D_u$

Output: Sorted output probabilities $\vec{P}_l$, Calibrated class distribution $\vec{C}_u$

Let $Count[1\cdots n_l] = 0$
Let $P_l[1\cdots n_l] = 0$

for $t \in \{1, \cdots, T\}$ do

Initialize a model, $M$

Split $D_t$ into $D_{train}$ and $D_{val}$ at a ratio of $r$
Train the $M$ with $(D_{train}, D_{val})$

$M \leftarrow$ load the $M$ that was the best on $D_{val}$

for $x_i \in D_{val}$ do

$p_i \leftarrow M(x_i)$
$P_l[i] = P_l[i] + p_i$

$Count[i] = Count[i] + 1$
end for

$\vec{C}_u \leftarrow M(D_u)$
$\vec{C}_{val}, Acc_{val} \leftarrow M(D_{val})$
$\vec{C}_u^l = Calibration(\vec{C}_u, \vec{C}_{val}, Acc_{val})$
end for

for $x_i \in D_t$ do

$P_l[i] = P_l[i]/Count[i]$
end for

$\vec{P}_l \leftarrow$ sort $P_l$ in ascending (or descending) order

$\vec{C}_u = \sum_{t=1}^{T} \vec{C}_u^l / T$

return $\vec{P}_l, \vec{C}_u$

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Duvenaud et al. (2016) was not compared because it involves considerable computational cost.

3 Method

In this section, we describe the proposed method in detail. The main notations used are as follows: $D_t = \{(x_i, y_i)\}_{i=1}^{n_t}$ and $D_u = \{(x_i)\}_{i=1}^{n_u}$ denote the labeled and unlabeled sets, respectively. $x_i$ and $y_i$ are the $i$-th sample and its true label, respectively, and $n_l$ and $n_u$ are the numbers of labeled and unlabeled samples, respectively. $p_{ij}$ denotes the prediction probability of the $j$-th class on the $i$-th sample. Let $C$ be the true class distribution of the samples. The output probability (i.e., confidence) $p_i$ associated with the predicted label on sample $x_i$ and the predicted (i.e., output) class distribution $\vec{C}$ of the samples are defined as follows:

$$ p_i = \max_j (p_{ij}) $$

$$ \vec{C}[j] = \frac{\sum_{i=1}^{n_{data}} p_{ij}}{n_{data}} $$

where $\forall j \in \{1, \cdots, n_c\}; n_c$ is the number of classes.

3.1 Preliminary Stage

The pseudocode for the preliminary stage is summarized in Alg. 1. In the preliminary stage, the prediction confidences $\vec{P}_l$ for the labeled samples in $D_t$ and the estimated class distribution $\vec{C}_u$ of the unlabeled set $D_u$ are calculated. Using $D_t$, the model is reinitialized-and-retrained $T$-times using a resampling method such as cross-validation. In low-resource settings, such retraining enables more reliable predictions by averaging the results. Each sample in $\vec{P}_l$ is evaluated when the validation loss is the lowest. Each sample should be validated at least once; the prediction confidences are averaged for each sample. $\vec{P}_l$ (and $P_u$ in Alg. 2 as well) is sorted in order of size for confidence comparison between two different sample sets, $D_t$ and $D_u$, in the main stage; we denoted it as $\vec{P}_l$ ($\vec{P}_u$ for $P_u$).

When retraining $T$-times, the output class distributions of the unlabeled set $D_u$ are obtained and calibrated (this calibration is defined in Section 3.3). Then, the $T$ calibrated class distributions are averaged, resulting in $\vec{C}_u$. After this stage, $\vec{P}_l$ and $\vec{C}_u$ are used to calculate the similarities for the two stop criteria, conf-sim and class-sim, respectively.

3.2 Main Stage Applying BUS-stop

After the preliminary stage, we train all the labeled samples and refer to this stage as the main stage. The combined BUS-stop method applied in the main stage is summarized in Alg. 2. The unlabeled set is predicted at every epoch during training.

Conf-sim The first proposed stop criterion conf-sim $S_{conf}$ represents the similarity of the prediction confidences $\vec{P}_u$ for the unlabeled samples with the reference confidences $\vec{P}_l$. To calculate the similarity between $\vec{P}_u$ and $\vec{P}_l$, their dimensions must be the same. We sample $\vec{P}_u$ at regular intervals $\frac{n_u}{n_t}$ such that it is the same size as $\vec{P}_l$ and denoted it as $\vec{P}_u$. We use the Euclidean distance to calculate the similarity, resulting in $S_{conf}$. Then, the first stop criterion is when $S_{conf}$ has the lowest value, i.e., $\vec{P}_u$ is most similar to $\vec{P}_l$. There is a natural concern that $\vec{P}_u$ is likely to produce higher (thus dissimilar) confidences than $\vec{P}_l$ because $\vec{P}_u$ is obtained by training all the labeled samples, unlike $\vec{P}_l$. However, the fact that the confidence for each sample in $\vec{P}_l$ is obtained when the validation error is the lowest can alleviate this concern. Thereby, $S_{conf}$ can be a rough criterion for avoiding under- and over-fitting, and can reflect the trend of the loss, based on comparison with the reference confidences.

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Algorithm 2 BUS-stop in main stage

**Input:** $D_l$, $D_u$, $\bar{P}_l$, $\bar{C}_u$  
**Output:** Expected best model $M_{\text{best}}$  
Let $Queue[1 \ldots n_{\text{que}}] = 0$  
Let $B_{\text{conf}} = \infty$, and $n_{\text{pat}} = 0$  
Initialize a model, $M$  
for epoch $\in \{1, 2, 3, \ldots \}$ do  
Train the $M$ one epoch on $D_l$  
$P_u, \bar{C}_u \leftarrow M(D_u)$  
$\bar{P}_u \leftarrow$ sort $P_u$ in ascending (or descending) order  
$S_{\text{conf}} = \text{Euclidian-distance}(\bar{P}_u, \bar{P}_l)$  
$S_{\text{class}} = \text{Cosine-similarity}(\bar{C}_u, \bar{C}_u)$  
if $S_{\text{conf}} < B_{\text{conf}}$ then  
$n_{\text{pat}} = 0$ and $Queue[1 \ldots n_{\text{que}}] = 0$  
$B_{\text{conf}} = S_{\text{conf}}$  
else  
$n_{\text{pat}} = n_{\text{pat}} + 1$  
end if  
if $n_{\text{pat}} < n_{\text{que}}$ then  
if $S_{\text{class}} > \max(Queue)$ then  
$M_{\text{best}} \leftarrow$ save the current $M$  
end if  
$Queue \leftarrow \text{dequeue} \& \text{enqueue} \ S_{\text{class}}$  
else  
End training  
end if  
end for  
return $M_{\text{best}}$

**Class-sim** The second proposed stop criterion is class-sim, $S_{\text{class}}$. The predicted class distribution $\hat{C}_u$ on the unlabeled set is compared with the estimated class distribution $\bar{C}_u$ from the preliminary stage. The assumption is that a well-trained model can also predict the class distribution more accurately. Therefore, estimation of the true class distribution is crucial. A calibration method that facilitates better estimation of the class distribution is presented in Section 3.3. We use the cosine similarity to calculate the similarity between $\bar{C}_u$ and $\hat{C}_u$, and obtain $S_{\text{class}}$. The second stop criterion is when $S_{\text{class}}$ has the highest value, i.e., $\hat{C}_u$ is most similar to $\bar{C}_u$. Thereby, $S_{\text{class}}$ can reflect the short-term trend of the accuracy because it is more likely that the outputs of a higher accuracy model are closer to the true class distribution.

**BUS-stop** Finally, we combine the two stop-criteria, conf-sim and class-sim, to form the BUS-stop method, as depicted in Alg. 2. A simple product of the two stop criteria can be an ineffective stop criterion because the sizes of $S_{\text{conf}}$ and $S_{\text{class}}$ are relative. Our combined stop-criterion is to save the model with the highest $S_{\text{class}}$ among of the epochs from the lowest $S_{\text{conf}}$ to the subsequent $(n_{\text{que}}-1)$-th epoch. This technique enables fine-stopping by considering both $S_{\text{conf}}$ and $S_{\text{class}}$, which reflect the long-term and short-term performances, respectively. It is to be noted that early stopping methods should be operated as an ongoing process, and not as a type of post-hoc method. To this end, we use a fixed-size queue $Queue$, and its size $n_{\text{que}}$ as a hyperparameter, as shown in Alg. 2.

3.3 Calibration of Class Distribution

In this section, we describe the calibration of the predicted class distribution. The calibration method aims to better estimate the true class distribution of the unlabeled set, thereby improving the performance of class-sim, particularly for imbalanced classification.

Trained neural networks often involve sampling biases. For example, in binary classification, the prediction results of a model trained with a class ratio $a:b$ tend to follow the distribution of $a:b$. Thus, when the class distributions are different in the test and training sets, the model performance can deteriorate. Let us suppose the following somewhat ideal and naive situations. Let $C_u$ be the true class distribution of the unlabeled set. If the model is perfectly trained with an accuracy of 1.0, the output class distribution will be equal to $C_u$. On the other hand, if the model fails to learn any inference knowledge from training, the model will output the predictions only by its sampling bias; i.e., when the accuracy is the same as the random expectation (denoted as $\text{Acc}_{\text{min}}$, e.g., 0.5 in binary classification), the output class distribution will be equal to the sampling bias $B$. Thus, the model accuracy can reflect whether the output class distribution is closer to the sampling bias or the true distribution. In the preliminary stage, we obtained the models’ proxy accuracy and output class distribution as $\text{Acc}_{\text{val}}$.

Figure 1: Calibration example in binary classification.
and \( \hat{C}_u \), respectively. Assuming that there is an approximate linear relationship, we can define a proportional expression as follows:

\[
(1 - Acc_{\text{min}}) : (Acc_{\text{val}} - Acc_{\text{min}}) \approx (C_u - B) : (\hat{C}_u - B) \tag{1}
\]

We rearrange the above expression in terms of \( C_u \):

\[
C_u \approx B + \frac{(1 - Acc_{\text{min}})}{(Acc_{\text{val}} - Acc_{\text{min}})} (\hat{C}_u - B) \tag{2}
\]

Then, we denote the approximation of \( C_u \) as \( \bar{C}_u \).

Considering the class distribution as a vector, Eq. (2) is a type of extrapolation. \( B \) can be defined as the class distribution of \( D_{\text{train}} \) or the predicted distribution in the validation set, \( \hat{C}_{\text{val}} \), of the preliminary stage. In addition, the \( Acc \) can be replaced with F1-score. Fig. 1 illustrates an example of our calibration method.

## 4 Experimental

### 4.1 Datasets

We conducted extensive experiments using five text classification datasets. The statistics are summarized in Table 1. These datasets have been extensively used in NLP research, and are publicly available. The SST-2 (Socher et al., 2013), IMDB (Maas et al., 2011), and Elec (McAuley and Leskovec, 2013) datasets are used for sentiment analysis. SST-2 and IMDB include movie reviews, and Elec includes reviews on Amazon electronics. AG-news (Zhang et al., 2015) and DBpedia (Zhang et al., 2015) are topic classification tasks for Wikipedia and news articles, respectively. For each dataset, we sampled \( K \) labeled samples per class from the training set. \( K \) was set to 50 for low-resource settings; we also experimented by varying \( K \in \{50, 100, 200, 400, 800, 1600\} \). We used the test samples as the unlabeled set for each dataset, which is referred to as transductive setting in few-shot classification (Liu et al., 2019).

### 4.2 Methods for Comparison

In this section, we describe the various stop-criteria for comparison with our method.

**EB** The EB (Mahsereci et al., 2017) is a criterion based on gradients of training samples. The EB-criterion stops when the following condition is met:

\[
1 - \frac{|S|}{D} \sum_{k=1}^{D} \left( \frac{\nabla L_{S,k}}{\Sigma_k} \right)^2 > 0 \tag{3}
\]

where \( S \) represents a sample set, \( D \) is the number of parameters, \( \nabla L \) is the gradients of loss, and subscript \( k \) indicates the \( k \)-th weight of the total parameters. \( \Sigma \) is the variance estimator, which is calculated as follows:

\[
\Sigma_k = \frac{1}{(|S| - 1)} \sum_{x \in S} (\nabla l_k(x) - \nabla L_{S,k})^2 \tag{4}
\]

where \( \nabla l(x) \) is the loss gradient on sample \( x \). Note that \( L_{S} = \frac{1}{|S|} \sum_{x \in S} l(x) \). For further details, refer Mahsereci et al. (2017).

**LID** Lee and Chung (2021) approximated LID as follows:

\[
LID = - \sum_{x \in D_{\text{val}}} \left[ \frac{1}{m} \sum_{i=1}^{m} \ln \frac{d_i(\bar{z}(x))}{d_m(\bar{z}(x))} \right]^{-1} \tag{5}
\]

where \( \bar{z}(x) \) is the representation vector of sample \( x \), and \( d_i \) is the Euclidean distance of \( \bar{z}(x) \) and its \( i \)-th nearest neighbor. \( m \) is a hyperparameter, which denotes the number of nearest neighbors. The lowest LID is the stop criterion.

**Val-stop\_split(x)** and **Val-stop\_add(x)** Val-stop denotes validation-based stopping. Val-stop\_split(x) indicates that \( x \) validation samples per class are taken from the labeled set. Therefore, \( K-x \) samples are trained and \( x \) samples are validated for each class. Val-stop\_add(x) indicates that \( x \) additional samples per class are used for validation; i.e., Val-stop\_add(x) uses a total of \( K+x \) labeled samples per class. Val-stop\_add(x) has an unfair advantage because it uses additional labeled samples.

**PE-stop\_epoch** The stopping epoch is considered a hyperparameter, which is pre-estimated with cross-validation, as described in Section 2. We use four-fold cross-validation.

**Conf-sim** and **class-sim** can also be used as a single stop-criterion, as mentioned before. We compare the single criteria with the combined BUS-stop criterion. Conf-sim stops when \( S_{\text{conf}} \) is the lowest, and class-sim stops when \( S_{\text{class}} \) is the highest.

| Data   | Class | Train | Test  | Len |
|--------|-------|-------|-------|-----|
| SST-2  | 2     | 6.9K  | 1.8K  | 19  |
| IMDB   | 2     | 25K   | 25K   | 231 |
| Elec   | 2     | 25K   | 25K   | 107 |
| AG-news| 4     | 120K  | 7.6K  | 38  |
| DBpedia| 14    | 560K  | 70K   | 49  |

Table 1: Statistics for datasets. \( Len \) denotes the average number of words per sample.
Table 2: Performance comparison of different stop-criteria in balanced classification. We used 50 labeled samples per class for all stop-criteria except for Val-stop$_{add(25)}$. *Note that the Val-stop$_{add(25)}$ has an unfair advantage: for each class, it used 25 additional labeled samples for validation while using 50 labeled samples for training. The best performances, except for the Val-stop$_{add(25)}$, are denoted in bold. ‘≃’ denotes that the performance is statistically similar to the BUS-stop (i.e., p-value over 0.05).

| Dataset         | SST-2 | IMDb | Elec | AG-news | DBpedia | Average |
|-----------------|-------|------|------|---------|---------|---------|
| Method          | Acc   | Loss | Acc  | Loss    | Acc     | Loss    | Acc     | Loss    |
| Val-stop$_{split(25)}$ | 0.775 | 0.516 | 0.746 | 0.572 | 0.781 | 0.507 | 0.846 | 0.477 | 0.982 | 0.085 | 0.826 | 0.431 |
| EB              | 0.826  | 0.565 | 0.833  | 0.551 | 0.843  | 0.534 | 0.861  | 0.491 | 0.986  | 0.103 | 0.869 | 0.449 |
| LID             | 0.794  | 0.602 | 0.761  | 0.571 | 0.815  | 0.494 | 0.859  | 0.515 | 0.971  | 0.765 | 0.840 | 0.589 |
| PE-stop-epoch   | 0.816  | 0.628 | 0.826  | 0.585 | 0.837  | 0.524 | 0.859  | 0.487 | 0.985  | 0.079 | 0.865 | 0.460 |
| Conf-sim (ours) | 0.807  | 0.442 | 0.793  | 0.484   | 0.823  | 0.433 | 0.865  | 0.421 | 0.985  | 0.077 | 0.854 | 0.371 |
| Class-sim (ours) | 0.795  | 0.570 | 0.789  | 0.560 | 0.793  | 0.531 | 0.857  | 0.561 | 0.986  | 0.078 | 0.844 | 0.460 |
| BUS-stop (ours) | 0.831  | 0.455 | 0.828  | 0.456   | 0.848  | 0.417 | 0.865  | 0.432 | 0.986  | 0.074 | 0.872 | 0.367 |

Table 3: Over-confidence error (OE) of different stop-criteria. In DBpedia, all the OEs were close to zero.

| Method          | SST-2 | IMDb | Elec | AG-news | Avg. |
|-----------------|-------|------|------|---------|------|
| Val-stop$_{split(25)}$ | 0.052 | 0.070 | 0.049 | 0.020 | 0.048 |
| EB              | 0.119 | 0.123 | 0.117 | 0.074 | 0.109 |
| LID             | 0.088 | 0.076 | 0.058 | 0.052 | 0.069 |
| PE-stop-epoch   | 0.131 | 0.122 | 0.107 | 0.069 | 0.107 |
| Conf-sim (ours) | 0.036 | 0.064 | 0.040 | 0.011 | 0.038 |
| Class-sim (ours) | 0.079 | 0.069 | 0.064 | 0.059 | 0.068 |
| BUS-stop (ours) | 0.072 | 0.071 | 0.061 | 0.039 | 0.061 |
| Val-stop$_{add(25)}$ | 0.035 | 0.056 | 0.045 | 0.021 | 0.039 |

5 Results

5.1 Balanced Classification

Table 2 shows the results when K=50 for training. It is noted that the original test sets have a balanced class distribution. We also report the loss measure as well as accuracy because loss can imply over-training. As shown in Table 2, our BUS-stop method exhibits the best performance on an average, and the accuracy is better even than Val-stop$_{add(25)}$, which uses a larger number of labeled samples. Note that Val-stop$_{add(25)}$ uses a total of 75 labeled samples per class. The performance of Val-stop$_{split(25)}$ indicates that splitting data for validation can result in poor performance in low-resource settings. LID underperforms compared to the PE-stop-epoch that does not require unlabeled samples. Conf-sim shows the second-best loss on an average. Class-sim underperforms as a stop criterion by itself. However, the BUS-stop method, which combines these two methods, shows better performance than each one on an average. Figure 2 displays the results of conf-sim and class-sim over the epochs. More examples are presented in Appendix A. In Fig. 2, the conf-sim curve is similar to the long-term trend of the loss; however, it does...
not accurately reflect the short-term fluctuation of the performance from epochs 7–16. On the other hand, class-sim is observed to be well responsive to the short-term fluctuation of the accuracy, but does not reflect the long-term trend. BUS-stop, which is a combination of these two methods, takes advantage of the short- as well as long-term methods, and thereby facilitates fine stopping. The EB-criterion shows the statistically similar accuracy to the BUS-stop method in most datasets. In the EB-criterion and PE-stop-epoch, the average loss is not good enough compared to the high accuracy. The accuracy and loss show somewhat conflicting results. That was due to over-confidence on the misclassified samples, caused by over-training. Note that $Loss = - \sum y_i \log p_i$. Overconfidence on the wrong label makes $p_i$ close to zero on its true label $y_i$. Thus, excessively low $p_i$ can increase the loss drastically. Table 3 lists the over-confidence error (OE); the equation for OE is presented in Thulasidasan et al. (2019). This confidence error can be detrimental in various applications, as described by Guo et al. (2017).

### 5.2 Imbalanced Classification

We experimented with an imbalanced setting in binary classification tasks. For testing, we sampled 1,000 instances in the SST-2 test set, and 10,000 instances each in the IMDB and Elec test sets, with a class distribution of 2:8 (negative:positive). ‘≃’ denotes that the performance is statistically similar to the BUS-stop (i.e., $p$-value over 0.05).

| Method               | Dataset | Acc  | F1   | Loss | Acc  | F1   | Loss | Acc  | F1   | Loss | Average |
|----------------------|---------|------|------|------|------|------|------|------|------|------|---------|
| Val-stop$_{add}(25)$ | SST-2   | 0.788| 0.719| 0.499| 0.732| 0.674| 0.589| 0.783| 0.724| 0.507| 0.768   |
| EB                   | SST-2   | 0.846| 0.786| 0.504| 0.810| 0.749| 0.568| 0.839| 0.789| 0.541| 0.832   |
| LID                  | SST-2   | 0.750| 0.698| 0.632| 0.712| 0.668| 0.678| 0.780| 0.728| 0.574| 0.747   |
| PE-stop-epoch        | SST-2   | 0.843| 0.779| 0.527| 0.821| 0.763| 0.589| 0.843| 0.789| 0.521| 0.836   |
| Cont-sim (ours)      | IMDB    | 0.816| 0.754| 0.427| 0.813| 0.750| 0.432| 0.835| 0.775| 0.398| 0.821   |
| Class-sim (ours)     | IMDB    | 0.862| 0.797| 0.489| 0.844| 0.779| 0.510| 0.873| 0.807| 0.409| 0.860   |
| BUS-stop (ours)      | IMDB    | 0.860| 0.792| 0.379| 0.849| 0.787| 0.406| 0.876| 0.815| 0.343| 0.861   |
| Val-stop$_{add}(25)$ | Elec    | 0.823| 0.767| 0.412| 0.820| 0.767| 0.457| 0.837| 0.784| 0.407| 0.827   |

Table 4: Performance comparison in an imbalanced setting of binary classification tasks. We used 50 labeled samples per class for training (i.e., $K=50$), and the class distributions of the test sets were adjusted to 2:8 (negative:positive). ‘≃’ denotes that the performance is statistically similar to the BUS-stop (i.e., $p$-value over 0.05).

| Train | Test | 2:8 | 4:6 | 6:4 | 8:2 |
|-------|------|-----|-----|-----|-----|
| 2:8   | EB   | 0.845| 0.732| 0.643| 0.511|
|       | BUS-stop (ours) | 0.859| 0.719| 0.660| 0.521|
|       | Val-stop$_{add}(25)$ | 0.679| 0.660| 0.621| 0.634|
| 4:6   | EB   | 0.860| 0.820| 0.790| 0.728|
|       | BUS-stop (ours) | 0.864| 0.825| 0.815| 0.808|
|       | Val-stop$_{add}(25)$ | 0.820| 0.808| 0.801| 0.794|
| 6:4   | EB   | 0.790| 0.816| 0.825| 0.845|
|       | BUS-stop (ours) | 0.845| 0.826| 0.833| 0.864|
|       | Val-stop$_{add}(25)$ | 0.826| 0.824| 0.823| 0.824|
| 8:2   | EB   | 0.611| 0.696| 0.774| 0.870|
|       | BUS-stop (ours) | 0.682| 0.714| 0.793| 0.865|
|       | Val-stop$_{add}(25)$ | 0.667| 0.707| 0.733| 0.782|

Table 5: Accuracy comparison in various imbalanced settings (negative:positive) of the SST-2. The bold denotes the best performance of the three stop-criteria.

Impact of the training size Figure 3 indicates the accuracy curve with respect to the training size, using the IMDB dataset. The $x$ values of Val-stop$_{add}(x)$ and Val-stop$_{split}(x)$ were set to 25, 25, 50, 100, 200, and 400, according to the increase

6 Discussion
Figure 3: Accuracy by different training sizes in IMDb.

| Train | Test | 2:8 | 4:6 | 6:4 | 8:2 |
|-------|------|-----|-----|-----|-----|
| Pred, $C_u$ | 0.999 | 0.946 | 0.781 | 0.583 |
| Cali$_{Acc}$ | 0.999 | 0.954 | 0.816 | 0.653 |
| Cali$_{F1}$ | 0.997 | 0.965 | 0.915 | 0.734 |

| 4:6 | Pred, $C_u$ | 0.986 | 0.999 | 0.966 | 0.892 |
|-----| Cali$_{Acc}$ | 0.997 | 0.998 | 0.987 | 0.966 |
|     | Cali$_{F1}$ | 0.998 | 0.998 | 0.989 | 0.973 |

| 6:4 | Pred, $C_u$ | 0.939 | 0.976 | 0.998 | 0.983 |
|-----| Cali$_{Acc}$ | 0.989 | 0.992 | 0.997 | 0.994 |
|     | Cali$_{F1}$ | 0.991 | 0.984 | 0.997 | 0.994 |

| 8:2 | Pred, $C_u$ | 0.691 | 0.827 | 0.957 | 0.999 |
|-----| Cali$_{Acc}$ | 0.770 | 0.863 | 0.964 | 0.999 |
|     | Cali$_{F1}$ | 0.912 | 0.908 | 0.975 | 0.996 |

Avg.: $C_u=0.908$, Cali$_{Acc}=0.934$, Cali$_{F1}=0.958$

Table 6: Cosine similarity between the class distribution of the test set and the estimated distribution in various imbalanced settings of the SST-2 dataset.

in $K$. It can be observed that the performance of BUS-stop is good in the sufficient-data regime as well. However, the performances of the three stop-criteria converge almost similarly with the increase in the training size. The impact of splitting the samples for validation does not deteriorate the performance when $K$ is greater than 400. Rather, Val-stop$_{split(x)}$ performs slightly better when $K$ is 1600. This result suggests that when sufficient labeled data are available, validation-based stopping can be a better choice.

**Calibration performance** In the BUS-stop method, accurate estimation of the class distribution plays a crucial role. The cosine similarity between the class distribution of the test set and the estimated distributions by various estimators are shown in Table 6, where the uncalibrated output distributions ($\hat{C}_u$) and the estimated distributions by the calibration methods, based on the Acc-score (Cali$_{Acc}$) and macro F1-score (Cali$_{F1}$), were compared. When the class distributions are similar between the test and training sets, the performance of $\hat{C}_u$ is slightly better than those of the other estimators. However, the estimation by calibration based on the F1-score (Cali$_{F1}$) is better on an average, and particularly when the class distributions of the test and training sets are different. Figure 4 indicates the BUS-stop accuracies when each model stops based on the estimated class distribution in Table 6 (the same color corresponds to one cell in Table 6). For example, the yellow colors correspond to the settings in which the class distribution is 2:8 and 8:2 in the training and test sets, respectively. As shown in Fig. 4, the better the class distribution is estimated, the higher the accuracy of BUS-stop. Such high correlation indicates the importance of the class distribution estimator. This result is consistent with our assumption that the output class distribution of better models will be closer to the true distribution.

**Running time** The running times are not directly comparable owing to the different hyperparameter settings for each method. For example, the BUS-stop and PE-stop-epoch require a separate preliminary stage that consumes additional time. We add up both the times taken in the preliminary stage and main stage. We denote the average running time per epoch as $g(n_l)$ for training the labeled samples and $p(n_u)$ for predicting the unlabeled samples. The time complexity and the measured time are shown in Table 7. Note that $T$ is

| Method | Time complexity | Measured time |
|--------|-----------------|---------------|
|        | $\text{SST-2}$ ($n_u=1.8k$) | $\text{DBpedia}$ ($n_u=70k$) |
| EB     | $g(n_l) + \alpha$ | 0.32 m | 0.49 m |
| LID    | $g(n_l) + p(n_u)$ | 0.12 m | 5.02 m |
| PE-stop-epoch | $(T+1) \times g(n_l)$ | 0.43 m | 1.14 m |
| BUS-stop | $(T+1) \times g(n_l) + p(n_u)$ | 0.47 m | 5.97 m |
| Val-stop$(_{add(x)}$) | $g(n_l)$ | 0.07 m | 0.19 m |

Table 7: Running time comparison for different stop-criteria. The two longest times are denoted in bold.
Table 8: Accuracy by global selection in Val-stop.

| Method  | Val-stop<sub>add(25)</sub> | Val-stop<sub>add(25)</sub> | BUS-stop |
|---------|---------------------------|---------------------------|----------|
| Selection | local | global | local | global | local |
| SST-2   | 0.775 | 0.785 | 0.819 | 0.840 | 0.831 |
| IMDB    | 0.746 | 0.786 | 0.824 | 0.838 | 0.828 |
| Elect   | 0.781 | 0.805 | 0.842 | 0.852 | 0.848 |
| AG-news | 0.846 | 0.857 | 0.867 | 0.871 | 0.865 |

### 7 Conclusion and Future Work

Validation-based early stopping can be detrimental in low-resource settings because the reduction in the number of samples by validation split may result in insufficient samples for training. In this study, we proposed an early stopping method called BUS-stop, based on unlabeled samples. Moreover, we proposed a calibration method to better estimate the true class distribution, which was used in the BUS-stop method to improve the performance. We conducted experiments on five popular text classification datasets. The results indicated that BUS-stop outperformed the existing stop-criteria in both balanced and unbalanced settings. In particular, BUS-stop showed robustness to imbalanced classification. The proposed BUS-stop method enables the training of all the available samples and presents a better stopping point using large unlabeled samples. In future, we plan to better exploit the unlabeled samples in self-training schemes. We can also combine BUS-stop and self-training methods. BUS-stop can be used to improve the performance of the initial model, which plays an important role in the final self-training performance. Additionally, we consider applying the BUS-stop to domain adaptation tasks in the future.

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Fig. 5 provides several examples of the learning curves and the stop-criteria measurements over the epochs. The red vertical line denotes the best model selected by the BUS-stop method. The balanced and imbalanced settings are the same as the settings in Section 5.1 and 5.2, respectively. The loss and conf-sim were scaled between 0.25-0.75 for easy comparison. The BUS-stop enables fine-stopping. As shown in these figures, our method skillfully avoids the points where the performance is decreased by fluctuations.