Exploiting all samples in low-resource sentence classification: early stopping and initialization parameters

HongSeok Choi\textsuperscript{a}, Hyunju Lee\textsuperscript{a,b,*}

\textsuperscript{a}School of Electrical Engineering, Computer Science, and Artificial Intelligence Graduate School, Gwangju Institute of Science and Technology, Gwangju, South Korea, Data Mining and Computational Biology Laboratory

Abstract

In low resource settings, deep neural models have often shown lower performance due to overfitting. The primary method to solve the overfitting problem is to generalize model parameters. To this end, many researchers have depended on large external resources with various manipulation techniques. In this study, we discuss how to exploit all available samples in low resource settings, without external datasets and model manipulation. This study focuses on natural language processing task. We propose a simple algorithm to find out good initialization parameters that improve robustness to a small sample set. We apply early stopping techniques that enable the use of all samples for training. Finally, the proposed learning strategy is to train all samples with the good initialization parameters and stop the model with the early stopping techniques. Extensive experiments are conducted on seven public sentence classification datasets, and the results demonstrate that the proposed learning strategy achieves better performance than several state-of-the-art works across the seven datasets.

Keywords: Deep learning, Low resource, Sentence classification, Natural language processing, Early stopping, Good initialization parameters

\textsuperscript{*}Corresponding author

Email addresses: hongking9@gist.ac.kr (HongSeok Choi), hyunjulee@gist.ac.kr (Hyunju Lee)
1. Introduction

Deep learning has demonstrated a high capacity for encoding large and complex datasets [1]. However, in low data regime such as low resource languages [2] [3] [4], the limited data restrict the full use of deep learning. By focusing more on local optima, the high capacity sometimes leads to overfitting because small data may not be representative enough for the test set [5]. Many researchers have introduced various approaches to address this problem. For example, transfer-learning [6] [7] and multi-task learning (MTL) [8] [9] using external datasets have shown promising results on both large and small datasets. Meta-learning [10] aims to provide good initialization parameters by learning a set of sub-tasks. The common goal of these approaches is to generalize the parameters.

Another way to prevent overfitting is to use validation sets. In many studies, the fact that the lack of data makes the model prone to overfitting has forced a large fraction of samples to be split into validation sets, thereafter, the training process is subjected to early stopping based on the validation set [11]. For example, in natural language processing (NLP) tasks, Makarov and Clematide [12] used 100 samples for training but 1,000 samples for validation. Upadhyay et al. [13] used 500 and 1,000 samples for training and validation, respectively. The validation set mainly covers two kinds of problems: hyper-parameter tuning and early stopping. In low resource settings, however, the use of a validation set that consequentially reduces the training samples needs careful consideration. Even if we allocate many samples to the validation set, it is hard to obtain optimal hyper-parameters and early stopping point because the model that learns a few training samples, which are further reduced by the validation set, has weak representational power. In low resource settings, even a few samples will have a significant impact on the performance.

Training all available samples would be more effective if an appropriate early stopping technique is applied. The good (or generalized) initialization parameters will further boost the prediction performance in the low resource data.
The randomness of the initialization has a significant effect on the small sample set because the same sample set can present different results depending on the initial parameters.

To train all available samples, Mahsereci et al. [14] proposed an early stopping method without a validation set, named evidence-based (EB) stop-criterion. However, the EB-criterion was not commonly used in NLP tasks. Only a few studies applied the EB-criterion to the NLP tasks, for example, non-English report classification [15]. The aforementioned low resource approaches, such as meta-learning [10] and transfer learning [6], can provide the good initialization parameters. However, these approaches require a set of various sub-tasks or large datasets of external domain, with incrementally designed techniques, that is, model manipulation.

In this study, we propose two methods useful when the model exploits all available samples: early stopping and good initialization parameters. The proposed early stopping method pre-estimates (PE) the expected stopping point, that is named PE-stop-epoch. We compare three stop-criteria: PE-stop-epoch, EB-criterion, and validation set based stopping (Val-based). Thus, we discuss the pros and cons of the three stop-criteria. The other proposed method is a simple algorithm to find out good initialization parameters (FOGIP). The FOGIP algorithm does not require external resource or various sub-tasks and any model manipulation. Thus, one advantage is that the FOGIP algorithm can be applied with only a few labeled samples in a single task. Another advantage is the easy modularity because any additional manipulation for the model is not required. Finally, we propose a learning strategy that combines these two approaches, that is, to train all samples with the good initialization parameters and stop the training with the early stopping technique such as EB-criterion or PE-stop-epoch. We experimented on seven sentence classification datasets that are publicly available. The good initial parameters by FOGIP improved the robustness to the small sample set. Compared to several low resource approaches, the proposed learning strategy achieved better performance. We closely analyze the performance with various evaluation metrics: accuracy, loss, and calibration.
error [16]. The proposed learning strategy can be a basic step for low resource tasks.

The key contributions of this study are as follows:

- We compare the three stop-criteria: PE-stop-epoch, EB-criterion, and Val-based stopping. The PE-stop-epoch and EB-criterion can use all samples for training, while the Val-based stopping is applicable when some samples are assigned to a validation set. We provide a detailed discussion using various metrics.

- To further improve the performance, we introduce a simple algorithm, FOGIP. The FOGIP algorithm finds better initialization from multiple parameters sets, based on the error information. This algorithm has two advantages: 1) It can provide better initial parameters with a few labeled samples and without external resources. 2) Neural models can be easily integrated into this algorithm without manipulating the model.

- We conduct extensive experiments on various sentence classification datasets. The good initialization parameters, obtained by the FOGIP, consistently outperform the normally initialized ones in terms of various evaluation metrics, and enhance the robustness to the small sample set. The proposed learning strategy exceeds several state-of-the-art works for low resource settings.

2. Related work

One of the key objectives of deep learning is generalization. A generalized deep learning model can provide high prediction accuracy with relatively small amounts of data. Pre-training on large datasets can greatly generalize the parameters [17]. For example, a pre-trained model called BERT (which stands for bidirectional encoder representations from transformers) has been widely used across various NLP tasks [17]. Transfer-learning is to exploit pre-trained parameters for the target task [6, 7] and MTL is to train multiple tasks at the same
time [8, 9]. In general, when the source datasets are large enough compared to the target tasks and these source and target tasks are similar, transfer-learning and MTL become more effective [6, 7, 8, 9]. Meta-learning learns a set of tasks, to obtain the generalized initialization parameters [10]. Meta-learning aims to predict unseen classes with a few samples after training a set of tasks, while MTL covers all kinds of classes in the training process. The generalized parameters can be utilized as good initialization for the target task. One of the semi-supervised learning methods, self-training iteratively learns the unlabeled samples, the labels of which are determined based on the predicted one in the previous learning stage [18]. Data augmentation is another way to alleviate the low-data problem. For example, back-translation [19] and random token perturbation [20] were used with external resources, such as Google translate API and WordNet, respectively [21]. Further, diverse regularization techniques, such as dropout [22] and noise input, were designed to address the overfitting problem. These aforementioned methods can enhance the generalization performance; however, they also require large external resources, a set of various tasks, in-domain unlabeled samples, or model manipulation. On the other hand, our proposed learning strategy can provide good initialization parameters with a few labeled samples and without model redesign.

Kann et al. [23] investigated the applicability of the validation set in low-resource settings. They introduced other languages, instead of the original validation set, for the early stopping and hyper-parameter tuning. They concluded that assigning a large portion to the validation set is not practical. However, such small validation set may be unable to represent the test set adequately. Moreover, it is worth noting that the “other language” may not be practical in real-world low resource settings because both languages should have the same task and the different nature of other language may produce inappropriate hyper-parameters or stopping point. In this study, the proposed learning strategy does not use the validation set for the final model. The validation set is temporarily used to obtain PE-stop-epoch or the good initialization parameters, before training all samples in the final stage. The details are presented
in Section 3. For the hyper-parameters, we simply follow the default setting of the model, as presented in [17]. The experimental results in Section 6 demonstrate that the validation set in low resource settings can provide worse tuned hyper-parameters.

Mahsereci et al. [14] proposed an early stopping technique, EB-criterion. The EB-criterion enables the training of all available samples without a validation set. The optimization process stops based on the gradient distribution of the training samples. We introduce the details in Section 3. However, they experimented mainly on somewhat weak models, such as logistic regression and multilayer perceptron. Further, the EB-criterion was not commonly used in NLP tasks and low-resource settings. In this study, we apply the EB-criterion to a popular and sophisticated deep neural model, BERT [17], in various sentence classification tasks and in low resource settings. We compare the EB-criterion with the PE-stop-epoch, which is proposed in this study.

3. Methodology

In this section, we present the proposed learning strategy with its two components: the early stopping techniques and FOGIP algorithm. First, we introduce two early stopping methods, which enable the training of all available samples. The motivation is that training even a few samples more will help to improve the performance in low resource settings. Second, we describe the FOGIP algorithm, which aims to find out good initialization parameters. The motivation is that the initial parameters play a crucial role in low resource settings.

3.1. Early stopping criteria to exploit all available samples

**EB-criterion.** Mahsereci et al. [14] proposed an early stopping technique without a validation set, which is named EB-criterion. Here, we review this EB-criterion briefly. Mahsereci et al. [14] exploited the central limit theorem to calculate the EB-criterion. This EB-criterion is based on the local statistics of the gradients of the training samples. The optimizer halts when the gradient
distribution is close to its expectation. Statistically, the stopping point is when
the gradients become hard to carry new information any more as the training
continues and reaches to certain convergence level. The equation is as follows
\[\frac{2}{D} [\log p(\nabla L_S) - \mathbb{E}_{\nabla L_S \sim p}[\log p(\nabla L_S)]] = 1 - \frac{|S|}{D} \sum_{k=1}^{D} \left[ \frac{(\nabla L_{S,k})^2}{\hat{\Sigma}_k} \right] > 0 \] (1)
where \( S \) represents the sample set, \( D \) is the dimension size of parameters, \( \nabla L \)
is the gradient of loss, and the subscript \( k \) indicates a \( k \)-th weight in the total
parameters. The \( \hat{\Sigma} \) is the variance estimator, which is calculated as follows:
\[ \hat{\Sigma}_k = \frac{1}{(|S|-1)} \sum_{x \in S} (\nabla l_k(x) - \nabla L_{S,k})^2 \] (2)
where \( \odot^2 \) represents the elementwise square and \( \nabla l(x) \) is the gradient of loss on a
sample, \( x \). Note that \( L_S = \frac{1}{|S|} \sum_{x \in S} l(x) \). As shown in left side of Equation (1),
if the computed gradient is larger than its expectation, then the training stops.
We can use the right side one of Equation (1) for practical implementation. For
more details, readers can refer to [14].

**PE-stop-epoch.** To compare the EB-criterion, we propose another stopping
criterion as a baseline, which is named PE-stop-epoch. The PE-stop-epoch pre-
estimates the expected stop-epoch before training all samples. First, we split
the samples similarly to stratified \( k \)-fold cross validation, which preserves the
ratio of samples for each class. A single fold set is used as validation set and the remaining \( k-1 \) fold sets are used as training set. Next, a model is repeated \( k \) times, using each fold set as validation set exactly once. Each run stops the training when its validation loss is the lowest. Finally, the PE-stop-epoch is calculated by averaging the stop-epochs over the \( k \) runs. Figure 1 illustrates an example of the process to obtain the PE-stop-epoch when \( k \) set to 4. In this way, when training all samples without the validation set, we can simply stop the model at the PE-stop-epoch.

3.2. Algorithm to find out good initialization parameters (FOGIP)

It remains an open question to fully discover the relatedness of the initialized parameters and the sample domain. In this context, it is difficult to figure out which parameters will be more conducive to the learning in advance. Instead, a possible way is to exploit the observed results. If initial parameters are highly related to samples, then the validation loss will be low during the training process. Based on this fact, we can find parameters that have better interaction with the sample set. The FOGIP procedure is summarized in Algorithm 1. First, we divide the sample set into \( S_A \) and \( S_B \) with the same ratio. In the first phase, \( S_A \) and \( S_B \) are used for the training and validation sets, respectively. Next, we train the model using randomly initialized parameters \( P_i \) and measure the instability as the minimum validation loss. In the second phase, we swap the \( S_A \) and \( S_B \), thus, \( S_B \) is used for training and \( S_A \) is used for validation. If the instability is low for both cases (i.e. the first and second phases), then the parameters can be expected to work well on the whole sample set \( S \). In this manner, we can find out the good initialization parameters through multiple runs. The number of runs, \( n \), was set to 10.
Algorithm 1 FOGIP

Input: Sample set $S$

Output: Good parameters $P_g$

- Divide $S$ into $S_A$ and $S_B$ with same ratio.
- Initialized parameters set $P = \{P_1, \ldots, P_n\}$.
- $I_A \leftarrow \text{Instabilities}(S_A, S_B, P)$
- $I_B \leftarrow \text{Instabilities}(S_B, S_A, P)$
- $I_{sum} = I_A + I_B$
- $g \leftarrow \text{argmin}_{i \in \{1, \ldots, n\}} I_{sum}[i]$
- return $P_g$

Function Instabilities($T, V, P$)

Input: Training set $T$, Validation set $V$, Parameters set $P$

Output: Instability list $I$

- $n \leftarrow \text{length}(P)$
- Let $I[1 \ldots n]$ be a new array.
- for $i \in \{1, \ldots, n\}$ do
  - Initialize the model with $P_i$.
  - Record the $val_{losses}$ while training.
    $val_{losses} \leftarrow \text{training}(T, V)$
  - $I[i] \leftarrow \text{min}(val_{losses})$
- end for
- return $I$

4. Experiments

4.1. Dataset and experimental setting

In this section, we introduce the experimental datasets. Conneau et al. [24] introduced an evaluation toolkit for English sentence representations, which contains seven classification datasets. These datasets are popular criterion for evaluating sentence embedding [25]. Customer Reviews (CR) [26], Movie Reviews (MR) [27], and Stanford Sentiment Tree (SST) [28] are sentiment analy-
Table 1: Statistics for datasets. |C| represents the number of classes, |S| is the average length over the sentences, |Data| is the number of samples. “-“ indicates no standard split sets, and “Full” indicates the original setting, “Low” indicates our low resource settings.

sis tasks. SST includes SST-2 and SST-5 datasets according to the number of classes. SST-5 is a fine-grained version of SST-2 labels, from very negative to very positive. The original SST is annotated at both phrase and sentence levels. However, we only used sentence-level samples. SUBJ [29] is the task of determining the subjectivity of movie reviews. MPQA [30] is the opinion polarity classification and TREC [31] is the question type classification. The statistics are presented in Table 1. In the last two columns, “Full” indicates the original dataset, which is the same setting as that paper [24], and “Low” indicates our setting to implement a low resource environment. The |train+val| shows the number of available samples, that is, labeled samples in our low resource settings. Thus, we can adjust the ratio of validation set and training set within that number. We randomly split the samples by 2% and conducted a 50-fold cross validation. For CR, MR, MPQA, and SUBJ, 2% of the samples were used as the train+val set, and the remaining 98% of the samples were used as test set. For TREC, 2% of the standard training set was used as train+val set, and a standard test set was used for testing. For SST, we combined the training set with the validation set, and 2% of them were used as train+val set, and a standard test set was used for testing. All the train/val/test sets had the same class distribution in each dataset. Unless otherwise noted, we follow this setting. We used 75, 213, 212, 200, 109, 155, and 192 samples for CR, MR, MPQA, SUBJ, TREC, SST-2, and SST-5, respectively, as the train+val set, as shown in Table 1. In our settings, the experiments can guarantee more reliable
results because the test set is much larger than the training set.

4.2. Evaluation metrics

In this section, we introduce four metrics to evaluate the proposed learning strategy in various aspects. These evaluations enable the detailed analysis of the deep neural model.

Accuracy. Accuracy is a metric to measure a classification performance, which is defined as the rate of the correctly predicted samples in total samples. Accuracy is easy to interpret, however, it does not take into account the prediction probability (i.e. confidence). For example, in binary classification, two samples of 51% and 99% prediction confidence have the same contribution to the accuracy score. The equation is as follows:

\[
\text{Acc} = \frac{1}{|S|} \sum_{i \in S} \mathbb{1}(y_i = \hat{y}_i)
\]

where \(S\) is the set of sample indices, \(y\) is true label, \(\hat{y}\) is predicted label, and \(\mathbb{1}\) is indicator function.

Loss. The training of a learning model aims to minimize the loss function. Unlike accuracy, loss can reflect the probability of the predicted label. Thus, the more confident model on the correctly predicted samples results in lower (i.e. better) loss. We use categorical cross entropy as follows:

\[
\text{Loss} = -\frac{1}{|S|} \sum_{i \in S} \sum_{c \in C} \mathbb{1}(y_i = c) \log(\hat{p}_{i,c})
\]

where \(C\) is the set of classes and \(\hat{p}_{i,c}\) is the predicted probability on class \(c\).

Expected calibration error. Calibration error implies that the prediction probability of each class does not always reflect the correct likelihood of the true label [16]. In real-world application, it is a crucial problem that a machine learning system reflects correct likelihood of the predictions. For example, self-driving car need to consider the likelihood of whether the object is a pedestrian.
or not \[32\]. To estimate the calibration error, the predictions need to be grouped into \( M \) interval bins according to their confidence.

\[
Acc(B_m) = \frac{1}{|B_m|} \sum_{i \in B_m} 1(y_i = \hat{y}_i)
\]

(5)

\[
Conf(B_m) = \frac{1}{|B_m|} \sum_{i \in B_m} \max_{c \in C} \hat{p}_{i,c}
\]

(6)

where \( B_m \) represents the set of sample indices whose confidence value is within the range, \((\frac{m-1}{M}, \frac{m}{M}]\). The more the model is calibrated, the smaller the difference of \( Conf(B_m) \) and \( Acc(B_m) \) is, for all \( m \in \{1, \cdots, M\} \). Thus, expected calibration error (ECE) is defined as follows \[10\]:

\[
ECE = \sum_{m=1}^{M} \frac{|B_m|}{|S|} \left| Acc(B_m) - Conf(B_m) \right|
\]

(7)

ECE measures how calibrated a model is by considering both the over- and under-confident samples.

**Over-confidence error.** Recent studies observed that deep neural networks tend to be over-confident when trained with hard labels \[33, 34\]. Therefore, we also consider a metric to estimate over-confidence error (OE). Thulasidasan et al. defined OE as follows \[33\]:

\[
OE = \sum_{m=1}^{M} \frac{|B_m|}{|S|} \left[ Conf(B_m) \times \max(Conf(B_m) - Acc(B_m), 0) \right]
\]

(8)

Unlike ECE, OE considers only over-confident samples. In this study, we use these two metrics, ECE and OE, to estimate the calibration performance.

4.3. Implementation details

To evaluate the proposed learning strategy, BERT-base \[17\] was applied. We integrated the BERT-base into the FOGIP algorithm. For the hyperparameters, we followed the default setting presented in \[17\], instead of newly tuning on the validation set. That is because the small size of validation set is unlikely to represent the test set adequately. The experiment in Section 6
Table 2: BERT-base performance on the three stop-criteria. Each model used only 2% of the total samples (75~213 samples for each dataset). Trn/Val indicates the split ratio of training and validation sets within the 2% samples. The best performances are shown in bold.

| Trn/Val | Stop-criterion | CR  | MR  | MPQA | SUBJ | SST-2 | SST-5 | TREC |
|---------|----------------|-----|-----|------|------|-------|-------|------|
| 25:75   | Val-based      | 68.9±2.8 | 67.9±2.6 | 74.4±4.1 | 91.1±1.0 | 68.6±2.5 | 29.1±2.8 | 56.4±6.6 |
| 50:50   | Val-based      | 72.7±5.6 | 74.1±4.2 | 78.9±4.3 | 92.3±0.9 | 77.8±5.0 | 33.7±5.1 | 70.5±8.8 |
| 75:25   | Val-based      | 77.4±4.3 | 76.8±3.5 | 82.3±4.2 | 92.8±0.8 | 82.0±2.4 | 36.9±4.7 | 79.2±4.6 |
| 100:0   | PE-stop-epoch  | 81.1±3.8 | 79.3±2.1 | 84.9±2.9 | 92.9±1.2 | 83.7±3.0 | 37.6±4.3 | 81.7±4.2 |
| 100:0   | EB-criterion   | 81.0±3.5 | 79.8±1.8 | 85.4±1.5 | 93.2±0.7 | 84.7±1.8 | 40.2±2.8 | 84.0±4.0 |

5. Results

5.1. Comparison of stop-criteria

We experimented BERT-base model using 2% of the total samples as train+val set. Table 2 lists the results of different stop-criteria for each dataset and Table...
Table 3: Average performance of the stop-criteria over the seven datasets.

| Trn/Val | Stop-criterion | Accuracy ($\times 100$) | Loss | ECE  | OE   |
|---------|----------------|-------------------------|------|------|------|
| 25:75   | Val-based      | 65.1±4.5                | 763±0.60 | .061±.027 | .031±.025 |
| 50:50   | Val-based      | 71.4±4.4                | 669±0.68 | .061±.026 | .034±.026 |
| 75:25   | Val-based      | 75.3±3.5                | 615±0.78 | .071±.037 | .045±.037 |
| 100:0   | PE-stop-epoch  | 77.6±3.1                | 608±.089 | .089±.034 | .072±.032 |
| 100:0   | EB-criterion   | 78.5±2.3                | 799±0.93 | .155±.020 | .141±.019 |

3 displays the average result over the datasets. PE-stop-epoch and EB-criterion were also compared with Val-based stopping, which assigns some samples for validation set and stops the training at the lowest validation loss. For the Val-based stopping, we experimented with adjusting the ratio of training and validation sets. The Trn/Val was set to 25:75, 50:50, and 75:25, respectively. For the PE-stop-epoch and EB-criterion, all available samples were used for training, that is, Trn/Val was 100:0. As shown in Table 2 and 3, the EB-criterion resulted in best accuracy across all the datasets while it showed relatively lower performance in terms of loss and calibration error. In general, the Val-based stop-criteria resulted in lower accuracy, yet better calibration performance than the PE-stop-epoch and EB-criterion. We observed that the accuracy was lower and the calibration performance was better as the ratio of the validation set increased. The larger validation set could represent the test set more adequately, thereby reducing the calibration error. However, the prediction performance, such as accuracy and loss, was low since the large validation set reduces the training samples by that amount. This result supports the fact that training even a few samples more are non-trivial for the prediction performance in low resource settings. It is noted that the primary evaluation metric should be prediction performance, such as accuracy and loss, while the calibration error should be used as secondary metric. This is because, for example, if all the samples were predicted as 51% confidence and the accuracy was equally 51%, the calibration error would be zero. In this context, using validation set in low resource settings may not be proper for the prediction performance. Meanwhile, the PE-stop-epoch showed the lowest loss and second-best accuracy, in overall
Table 4: BERT-base performance when the model was initialized with the good parameters obtained by the FOGIP algorithm. Each model was trained only using 2% of the total samples (75-213 samples for each dataset). The results were compared with normally initialized model. The improvements are shown in bold.

datasets. Further, the calibration error of the PE-stop-epoch was as low as about 50-60% of the EB-criterion. An observation is that the model with the higher accuracy resulted in the worse calibration performance. Section 6 analyses the learning curve for this observation and discusses why these different results were produced between the PE-stop-epoch and EB-criterion.

5.2. Good initialization parameters

After finding the good initialization parameters using the FOGIP algorithm, the next step is to train all available samples (Trn/Val=100:0) with those pa-
Average result over the datasets

| Initialization | Stop-criterion | Accuracy (x100) | Loss | ECE  | OE  |
|---------------|----------------|----------------|------|------|-----|
| Good-init     | PE-stop-epoch  | 79.0±2.2       | 0.580±.072 | 0.086±.027 | 0.071±.027 |
|               | EB-criterion   | 79.4±2.0       | 0.777±.083 | 0.140±.017 | 0.137±.017 |
| Improvement   | PE-stop-epoch  | +1.4           | -0.028  | -0.003 | -0.001 |
|               | EB-criterion   | +0.9           | -0.022  | -0.006 | -0.004 |

Table 5: Average performance of the initialization parameters over the seven datasets.

parameters. We experimented using two stop-criteria: PE-stop-epoch and EB-criterion. For the BERT-base in the FOGIP, we covered the parameters only in the final classification layer as it provides only one set of pre-trained parameters. Although the parameters of the final layer account for even less than \(0.01\%\) (<11K) of the total in the BERT-base (≈110M), Table 4 and 5 show that this approach can further improve the performance. The results were compared with the normally initialized parameters. The accuracy consistently increased in all datasets, up to 3.4% in the SST-5 dataset (Table 4), and it was more boosted at the PE-stop-epoch (Table 5). As a result, the PE-stop-epoch resulted in similar accuracy with the EB-criterion yet better loss and calibration performances. As shown in Table 5, the good initialization parameters also improved the loss and calibration performances as well as the accuracy. This result demonstrates that the FOGIP algorithm can provide more robust initial parameters to small sample sets. In Section 6, we discuss the effect of the good initial parameters according to the training size. The advantage is that this FOGIP algorithm does not require any external resource and model redesign, as mentioned in Section 1. Unlike other low resource approaches such as meta-learning and MTL, the FOGIP can be applied with a few labeled samples in a single task. Further, other neural models can be easily inserted into this FOGIP algorithm without manipulation. One drawback of this approach is the training time; it requires training \(2n\) times more. However, the training time will not be impractical due to the small size of the data. This experiment indicates that the validation loss conveys information about the relatedness between the samples and parameters.
| Method          | Trn/Val | CR    | MR    | MPQA  | SUBJ  | SST-2 | SST-5 | TREC  |
|-----------------|---------|-------|-------|-------|-------|-------|-------|-------|
| BERT-base       | 75:25   | 77.2±4.7 | 76.5±3.5 | 92.5±6.2 | 92.8±0.8 | 92.0±2.4 | 36.9±4.7 | 79.2±4.0 |
| Back-translation| 75:25   | 76.3±6.4 | 74.9±6.4 | 83.8±3.0 | 92.5±0.9 | 86.7±3.8 | 37.6±3.4 | 78.7±4.2 |
| EDA [20]       | 75:25   | 70.1±3.8 | 75.8±3.2 | 84.8±1.9 | 91.3±1.6 | 81.7±2.1 | 38.9±4.0 | 77.5±6.0 |
| Hu et al. [37] | 75:25   | 81.3±3.1 | 78.6±4.1 | 83.5±4.6 | 91.8±1.2 | 82.8±2.9 | 39.0±2.6 | 77.9±3.9 |
| Norm-PE (Ours) | 100:0   | 81.1±3.8 | 79.3±2.1 | 84.9±2.9 | 92.9±1.2 | 83.7±3.0 | 37.6±4.3 | 83.7±4.2 |
| Good-PE (Ours) | 100:0   | 82.7±4.0 | 79.8±1.4 | 85.9±2.2 | 93.4±0.6 | 85.4±1.6 | 41.2±2.2 | 84.6±3.5 |

Table 6: Accuracy (×100) comparison with data augmentation and sample weighting techniques. Each model used 2% of the total samples (75∼213 samples for each dataset). “↓” indicates that the performance was lower than the baseline. “Good-PE” represents the model used the good initialization parameters and PE-stop-epoch.

Therefore, the observed good parameters can result in further improvement.

5.3. Comparison with other approaches

In this section, we compare the proposed learning strategy with two kinds of low resource approach: data augmentation and sample weighting techniques. There are many other approaches such as self-training that exploit a large number of unlabeled samples; however, this study assumes that no unlabeled samples are available. For the proposed learning strategy, we report the result of the PE-stop-epoch since it showed significant performance across the four evaluation metrics. Note that we did not apply any additional augmentation and weighting techniques to our approach. EDA [20] stands for easy data augmentation, which randomly deletes, inserts, or swaps some tokens, or substitutes with their synonyms, when given a sentence. For the synonym substitution, WordNet [21] was used. Hu et al. [37] proposed a state-of-the-art data manipulation technique. They applied reinforcement learning to a language model to generate new tokens in the sentence. The reinforcement algorithm dynamically learns which tokens can obtain performance gain. Ren et al. [36] proposed a sample weighting method that dynamically determines the sample importance when training. We augmented four samples per one sample for the augmentation techniques. Thus, the model learns a total of five times the training samples: four augmented samples and one original sample. For back-translation, we used Google translate API[2] with four languages: German, Spanish, Chinese, and Hindi. These
comparative models used Val-based stopping where Trn/Val was set to 75:25. Table 6 shows that simply training more natural samples outperforms adding artificial samples augmented by the manipulation techniques. The proposed learning strategy, Good-PE, achieved better performance compared to the data manipulating methods. Further, the results show that the augmentation can be harmful in several datasets (e.g. EDA in MR). In contrast, the Good-PE and back-translation resulted in balanced performance gains across the datasets. However, the back-translation depends on an additional pre-trained translation model while the Good-PE strategy can build on a single model. The results suggest that the proposed learning strategy can be helpful when limited to a few labeled samples.

6. Discussion

6.1. Validation set for hyper-parameter tuning

The experiments in the previous section demonstrated that involving as many samples as possible to the training process is better than using validation sets. We have applied PE-stop-epoch and EB-criterion for early stopping. Meanwhile, the validation set also can be used for hyper-parameter tun-

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Figure 2: Hyper-parameters comparison.

2https://translate.google.com/
However, a small-sized validation set may not provide well-tuned hyper-parameters. Figure 2 compares the two results, one model was trained with default hyper-parameter setting, and other one was trained with tuned hyper-parameters. The default hyper-parameter setting is the same as that used in this paper: learning rate is $2 \times 10^{-5}$, drop-out is 0.1, and batch size is 32. For the hyper-parameter tuning, we used validation set where the Trn/Val is set to 50:50. After tuning, we set the Trn/Val to 100:0 and trained BERT-base model with the tuned hyper-parameters. The Norm-PE strategy was used for training. We greedily tuned within a range: $[1 \times 10^{-5}, 2 \times 10^{-5}, 4 \times 10^{-5}, 8 \times 10^{-5}]$ for learning rate, $[0.1, 0.3]$ for drop-out and $[16, 32]$ for batch size. As shown in Figure 2, the tuned hyper-parameters were slightly better (1.1% improvement) in only two datasets, MPQA and SST-5, while they showed worse performance in the remaining five datasets. The default setting showed at least 1.0% and at most 3.6% higher accuracy than the tuned hyper-parameters. This experiment demonstrates that the validation set may not be adequate for the hyper-parameter tuning in low resource settings.

6.2. PE-stop-epoch vs. EB-criterion

As shown in Table 2, the EB-criterion resulted in better accuracy but worse loss and calibration error than the PE-stop-epoch. Figure 3 illustrates why the
Figure 4: Stopping point comparison. Best-test-epoch indicates the point where the test loss is the lowest during training.

Stop-Epoch

![Graph showing average stopping points in each dataset.]

Figure 4: Stopping point comparison. Best-test-epoch indicates the point where the test loss is the lowest during training.

stop-criteria produced these different results. We applied both the EB-criterion and PE-stop-epoch where the Trn/Val was set to 100:0, and recorded the test performance at every epoch. As shown in the left side of Figure 3, the EB-criterion met the Equation 1 at the later epoch while the PE-stop-epoch was nearly close to the ideal stopping point. In addition, the model tended to be over-confident on the predicted samples as the training continued. This over-confidence resulted in slightly better accuracy but worse loss and calibration error. The confidence histogram (right side in Figure 3) clearly shows that the calibration was better at the PE-stop-epoch, that is, the gap of the test accuracy and average confidence was significantly smaller than the EB-criterion. Figure 4 shows the average stopping points in each dataset. In general, the PE-stop-epoch was closer to the best-test-epoch than the EB-criterion. Indeed, the EB-criterion showed significantly different stopping epoch. The PE-stop-epoch is calculated by practically taking the validation samples into account, whereas the EB-criterion only depends on the gradients of the training samples without reference to direct evaluation of the unseen samples. In this context, this experiment implies that the EB-criterion may not be suitable in low resource NLP tasks.
6.3. Performance by the data size

We investigated how effective the proposed learning strategy is for different data sizes. Figure 5 displays the results in CR and SST-2 datasets. We compared with the Val-based stopping where the drop-out was set to 0.1 and 0.3. As shown in Figure 5, the performances became similar as more data were used. The good initialization parameters and training all samples were more effective in low resource settings. When the drop-out was set to 0.3, the Val-based performance increased faster than the drop-out of 0.1. When using the 20% of SST-2 dataset, the Val-based of 0.3 drop-out even outperformed the Good-PE method. Indeed, the well-tuned drop-out would be more helpful when stopping based on the adequate size of validation set because the estimation is more likely to be reliable. This experiment suggests that using the validation set is more effective if the data size is large enough.

7. Conclusion

In this study, we presented a learning strategy that can be applied with only a few labeled samples and without model redesign. In low resource settings, even a few samples have significant impact on the performance. The proposed learning strategy exploits all available samples to enhance the model performance. This learning strategy involves an algorithm to find out good
initialization parameters (FOGIP) and early stopping method that can use all samples for training. We compared three early stopping criteria: PE-stop-epoch, EB-criterion, and Val-based stopping. We conducted extensive experiments on seven sentence classification datasets. The experimental results demonstrated that the good initial parameters, obtained by the FOGIP algorithm, enhance the robustness to the small sample set. Further, the proposed learning strategy significantly outperformed several data manipulation techniques. However, the disadvantage is that the FOGIP requires more training time. This study was limited to sentence classification tasks for English. For future work, we plan to address practical low resource languages and various NLP tasks.

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