LOPS: Learning Order Inspired Pseudo-Label Selection for Weakly Supervised Text Classification

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Abstract

Weakly supervised text classification methods typically train a deep neural classifier based on pseudo-labels. The quality of pseudo-labels is crucial to final performance but they are inevitably noisy due to their heuristic nature, so selecting the correct ones has a huge potential for performance boost. One straightforward solution is to select samples based on the softmax probability scores in the neural classifier corresponding to their pseudo-labels. However, we show through our experiments that such solutions are ineffective and unstable due to the erroneously high-confidence predictions from poorly calibrated models. Recent studies on the memorization effects of deep neural models suggest that these models first memorize training samples with clean labels and then those with noisy labels. Inspired by this observation, we propose a novel pseudo-label selection method LOPS that takes learning order of samples into consideration. We hypothesize that the learning order reflects the probability of wrong annotation in terms of ranking, and therefore, propose to select the samples that are learnt earlier. LOPS can be viewed as a strong performance-boost plug-in to most existing weakly-supervised text classification methods, as confirmed in extensive experiments on four real-world datasets.

1 Introduction

Weakly supervised text classification methods (Agichtein and Gravano, 2000; Riloff et al., 2003; Tao et al., 2015; Meng et al., 2018; Mekala and Shang, 2020; Mekala et al., 2020, 2021) typically start with generating pseudo-labels, and train a deep neural classifier to learn the mapping between documents and classes. There is no doubt that the quality of pseudo-labels plays a fundamental role in the final classification accuracy, however, they are inevitably noisy due to their heuristic

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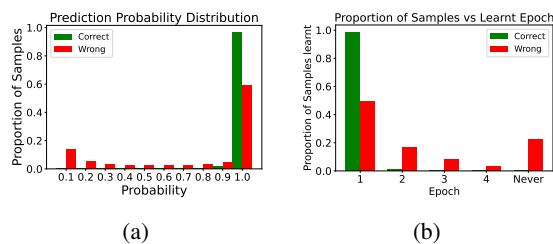* Jingbo Shang is the corresponding author.

Figure 1: Distributions of correct and wrong instances using different pseudo-label selection strategies on the NYT-Coarse dataset for its initial pseudo-labels. The base classifier is BERT. (a) is based on the softmax probability of samples' pseudo-labels and (b) is based on the earliest epochs at which samples are learnt.

nature. Pseudo-labels are typically generated by some heuristic, for example, through string matching between the documents and user-provided seed words (Mekala and Shang, 2020). Deep neural networks (DNNs) trained on such noisy labels have a high risk of making erroneous predictions. More importantly, when self-training is employed, such error can be further amplified upon boostrapping.

To address this problem, in this paper, we study the pseudo-label selection in weakly supervised text classification, aiming to select a high quality subset of the pseudo-labeled documents (in every iteration when using self-training) that can potentially achieve a higher classification accuracy.

A straightforward solution is to first train a deep neural classifier based on the pseudo-labeled documents and then threshold the documents by the predicted probability scores corresponding to their pseudo-labels. However, DNNs usually have a poor calibration and generate overconfident predicted probability scores (Guo et al., 2017). For example, on New York Times (NYT) coarse-grained dataset, as shown in Figure 1(a), 60% of wrong instances in the pseudo-labeled documents have a predicted probability by BERT greater than 0.9 for their wrong pseudo-labels.

Recent studies on the memorization effects of DNNs show that they memorize easy and clean in-
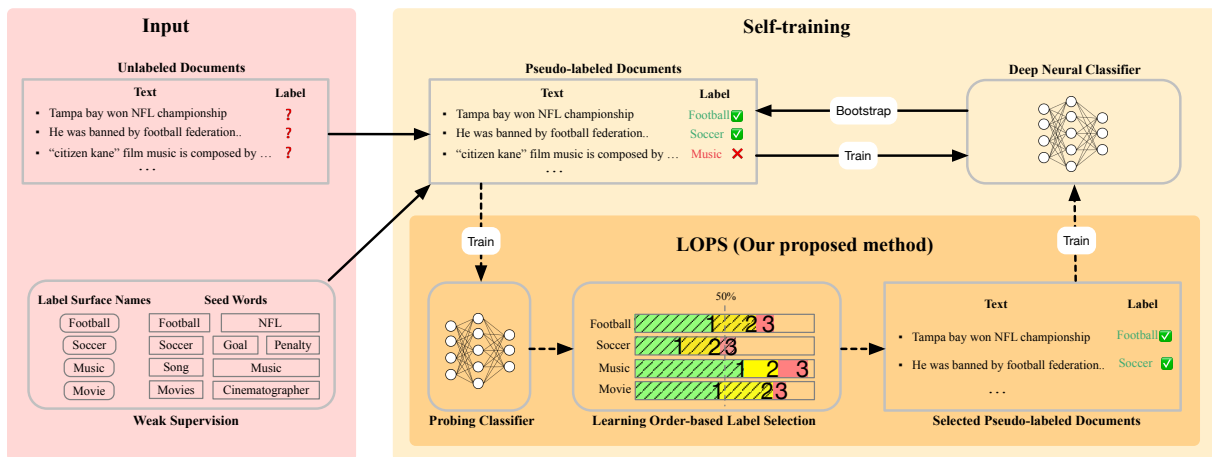
Figure 2: An overview of our proposed LOPS and how it plugs into self-training frameworks to replace the conventional training step. Given pseudo-labeled samples, LOPS trains a probing classifier to obtain their learning order and we stop the training when at least $\tau\%$ of samples corresponding to each class are learnt and select the learnt samples. The numbers shown are learnt epochs and the samples in the shaded part are selected. A text classifier is trained on selected pseudo-labeled documents that is further used for inference and bootstrapping.

stances first, and gradually learn hard instances and eventually memorize the wrong annotations (Arpit et al., 2017; Geifman et al., 2019; Zhang et al., 2021). We have confirmed this in our experiments for different classifiers. For example, as shown in Figure 1(b), BERT classifier learns most of the clean instances in the first epoch and learns wrong instances across all epochs. Although it also learns good number of wrong instances in the first epoch, it is significantly less than the probability-based selection in Figure 1(a). Therefore, we define the learning order of a pseudo-labeled document as the epoch when it is learnt during training i.e. when the training model's prediction is the same as its given pseudo-label. Since correct samples are learnt first, we hypothesize that learning order-based selection will be able to filter out wrongly labeled samples.

Inspired by our observation, we propose a novel learning order inspired pseudo-label selection method LOPS, as shown in Figure 2. Specifically, LOPS involves training a probing classifier on pseudo-labeled data and tracking the learning order of samples. We define a sample is learnt if and only if the classifier trained on pseudo-labels gives the same argmax prediction as its pseudo-label at the end of an epoch. We stop the training when at least $\tau\%$ of samples corresponding to each class are learnt and select all the learnt samples. Then, we train a text classifier on these selected pseudo-labeled documents that is further used for inference. We empirically show that LOPS can boost the accuracy of various weakly supervised

text classification methods and it is much more effective and stable than probability score-based selections.

Our contributions are summarized as follows:
- We propose a novel pseudo-label selection method LOPS that takes learning order of samples into consideration.
- We show that selection based on learning order is much stable and effective than selection based on probability scores.
- Extensive experiments and case studies on real-world datasets with different classifiers and weakly supervised text classification methods demonstrate significant performance gains upon using LOPS. It can be viewed as a solid performance-boost plug-in for weak supervision.

Reproducibility. We will release the code and datasets on Github[1].

2 Related Work

Pseudo-Labels in Weakly Supervised Text Classification. Since the weakly supervised text classification methods lack gold annotations, pseudo-labeling has been a common phenomenon to generate initial supervision. Pseudo-labeling depends on the type of weak supervision. Mekala and Shang (2020) and Mekala et al. (2020) have a few label-indicative seed words as supervision and they generate pseudo-labels using string-matching where a document is assigned a label whose aggregated term frequency of seed words is maximum. (Meng

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[1] https://github.com/dheeraj7596/LOPS

et al., 2018) generates pseudo-documents using the seed information corresponding to a label. (Wang et al., 2021) takes only label names as supervision and generates class-oriented document representations, and cluster them to create a pseudo-training set. Under the same scenario, (Mekala et al., 2021) consider samples that exclusively contain the label surface name as its respective weak supervision. In (Karamanolakis et al., 2021b), pseudo-labels are created from the predictions of a trained neural network. (Arachie and Huang, 2021) combines different weak signals to produce soft labels.

Label Selection. There are different lines of work aiming to select true-labeled examples from a noisy training set. One line of work involves training multiple networks to guide the learning process. Along this direction, (Malach and Shalev-Shwartz, 2017) maintains two DNNs and update them based on their disagreement. (Jiang et al., 2018b) learns another neural network that provides data-driven curriculum. (Han et al., 2018; Yu et al., 2019) use co-training where they select instances based on small loss criteria and cross-train two networks simultaneously. (Huang et al., 2019) considers the training loss as the metric to filter out noise. (Swayamdipta et al., 2020) uses model's confidence and its variability across epochs to identify wrongly labeled samples. Another line of work learns weights for the training data. Along this line, (Ren et al., 2018) propose a meta-learning algorithm that learns weights corresponding to training examples based on their gradient directions. (Fang et al., 2020) learns dynamic importance weighting that iterates between weight estimation and weighted classification. Recently, (Rizve et al., 2021) propose utilizing uncertainty to perform label selection.

Training dynamics. In deep learning regime, models with large capacity are typically more robust to outliers. Nevertheless, data examples can still exhibit diverse levels of difficulties. Arpit et al. (2017) finds that data examples are not learned equally when injecting noisy data into training. Easy examples are often learned first. Hacohen et al. (2020) further shows such order of learning examples is shared by different random initializations and neural architectures. Toneva et al. (2019) shows that certain examples are forgotten frequently during training, which means that they can be first classified correctly, then incorrectly. Model performance can be largely maintained when removing those

Table 1: Noise ratios of different pseudo-label heuristics on NYT-Fine dataset.

Pseudo-label Heuristic	Noise Ratio
vMF distribution modeling (Meng et al., 2018)	46.17%
String-Match (Mekala et al., 2020)	31.80%
Contextualized String-Match (Mekala and Shang, 2020)	31.24%
Exclusive String-Match (Mekala et al., 2021)	52.13%
Clustering (Wang et al., 2021)	15.64%

least forgettable examples from training.

3 Problem and Motivation

Weakly supervised classification refers to the problem with inputs (1) a set of unlabeled text documents $\mathcal{S} = \{x\}$, where $x \in \mathcal{X}$. (2) and M target labels $\mathcal{C} = \{1, \ldots, M\}$. Our goal is to find a labeling function $f : \mathcal{X} \rightarrow \mathcal{C}$ that maps every document x to its true label. Here we denote y^* as the *unknown* true label of a document x. To cold start the classification of unlabeled documents, a source of weak supervision has to be introduced, which can come from various sources such as label surface names (Wang et al., 2021), label-indicative seed words (Mekala and Shang, 2020), or rules (Karamanolakis et al., 2021a). Given a "weak" labeling function $w : \mathcal{X} \rightarrow \mathcal{C}$, pseudo-labels are then generated on a subset of the unlabeled documents, which yields a labeled subset $\mathcal{D} = \{(x, w(x))\}$. For convenience, we denote $\mathcal{D}[j]$ to be the set of all documents that are pseudo-labeled as class j in $\mathcal{D}$, namely $\mathcal{D}[j] = \{(x, w(x)) \in \mathcal{D} | w(x) = j\}$.
Pseudo-labels are noisy due to their heuristic nature. For example, on the NYT fine-grained dataset, we generate pseudo-labels using five different strategies (Meng et al., 2018; Mekala and Shang, 2020; Mekala et al., 2020, 2021; Wang et al., 2021) and compute their noise ratios. As expected, no strategy is perfect and all of them generate noisy labels, ranging from 15% to 50% (see Table 1).

When a classifier is trained on such noisy training data, it can make some high confident erroneous predictions. And, upon bootstrapping the classifier on unlabeled data, it has a snowball effect where such high confident erroneous predictions are added to the training data, and thus corrupting it more. As this process repeats for a few iterations, it adds more noise and significantly affects the final performance. Therefore, identifying and selecting the correctly labeled samples is necessary and has a huge potential for a boost in performance. Note that, if the labels are not selected carefully, it could instead hurt the performance.
Our pseudo-label selection problem. The weak

supervision is likely to generate a noisy labeled set, which means $w(x) \neq y^*$ for some documents x. We denote $\mathcal{D}_{\checkmark}$ as the set of correctly labeled documents and $\mathcal{D}_{\times} = \mathcal{D} \setminus \mathcal{D}_{\checkmark}$ as the set of wrongly labeled documents, where $\mathcal{D}_{\checkmark} = \{(x, w(x)) | w(x) = y^*\}$. The problem of pseudo-label selection is thus to identify $\mathcal{D}_{\checkmark}$.

Note that pseudo-label selection is conceptually related to failure prediction (Hecker et al., 2018; Jiang et al., 2018a; Corbière et al., 2019) and out-of-distribution detection (Hendrycks and Gimpel, 2017; Devries and Taylor, 2018; Liang et al., 2018; Lee et al., 2018). However, the major difference here is for pseudo-label selection we have to detect wrong annotations in the training phase instead of inference phase.

4 Our LOPS Framework

In this section, we explain our framework LOPS in detail. First, we give an overview of confidence function-based pseudo-label selection and discuss probability score as confidence function. Then, we explain learning order as confidence function. Finally, we show our algorithm that performs selection based on learning order.

4.1 Overview: Confidence function-based Pseudo-label Selection

In this section, we briefly introduce confidence function and discuss commonly-used probability score as confidence function.

Confidence function $\kappa : \mathcal{X} \times \mathcal{C} \to [0, 1]$, assigns a value to each labeled document, which represents our confidence of its pseudo-label being correct. Then, we can perform the selection by choosing a threshold γ on confidence function. We denote the set of labeled documents selected based on κ and γ as $\hat{\mathcal{D}}_{\checkmark}(\kappa, \gamma)$, namely

$$\hat{\mathcal{D}}_{\checkmark}(\kappa, \gamma) = \{(x, w(x)) \in \mathcal{D} \mid \kappa(x, w(x)) > \gamma\}$$

An optimal confidence function κ^* should be able to perfectly distinguish the correctly labeled documents from wrongly labeled ones, namely there exists a threshold γ^* such that $\hat{\mathcal{D}}_{\checkmark}(\kappa^*, \gamma^*) = \mathcal{D}_{\checkmark}$.
Probability score as confidence function. One commonly-used intuitive confidence function for pseudo-label selection is the model's prediction probability scores corresponding to the pseudo-labels. Probability scores have been used as confidence functions to select samples for bootstrapping (Meng et al., 2018, 2019; Mekala and Shang,

2020). Specifically, let $\mathbf{f} : \mathcal{X} \to [0, 1]^{|\mathcal{C}|}$ be a probabilistic classifier trained on pseudo-labeled documents and $\mathbf{f}(x)[j]$ represents the predicted probability of document x belonging to class j, $\mathbf{f}(x)[w(x)]$ is used as the confidence function. However, due to the poor calibration of DNNs (Guo et al., 2017), probability scores of wrongly labeled documents are usually high. As a result, it might be difficult to distinguish correctly- and wrongly-labeled documents based on probability scores.

4.2 LOPS: Learning Order as Confidence Function

Learning order. Learning order of a pseudo-labeled document is the epoch when it is learnt during training, or more specifically when its label predicted by the model matches its given pseudo-label. Recent studies show that a DNN learns clean samples first and then gradually memorizes the noisy samples (Arpit et al., 2017). We thus hypothesize that learning order can reflect the probability of wrong pseudo-label in terms of ranking.

We now utilize learning order to define a confidence function. Specifically, let $\mathbf{f}^t(\cdot)$ be the classifier being trained at epoch t, and T as the total number of epochs, the learning order of document x can be defined as

$$\eta(x, w(x)) = 1 - \frac{1}{T} \min\{t \mid \arg\max_j \mathbf{f}^t(x)[j] = w(x)\},$$
(1)

where $t \in \{1, \ldots, T\}$. Here we have negated and scaled the learning order to be complied with the convention of confidence function i.e. higher confidence implies higher probability of a correct label. We calculate the learning order at the granularity of epoch because the model would have seen all the training data by the end of an epoch, and hence, the learning order computed would be fair for all documents. In case when the epoch number is not sufficient to distinguish the documents, one can increase the granularity of the learning order, for example, the batch number at which the document is learnt. Granularity higher than the epoch incurs extra training cost as a document will be examined more than once in each epoch.

4.3 LOPS: Putting it all together

Motivated by previous analyses, we utilize learning order to select pseudo-labels. We train a probing classifier on all pseudo-labeled documents and track their first learnt epoch during training. The confidence function can then be calculated based

Algorithm 1: LOPS Method

Input: A set of documents $\mathcal{D}$ pseudo-labeled by w, Probing Classifier $\mathbf{f}$.
Output: Selected documents $\hat{\mathcal{D}}_{\checkmark}$
for epoch $t = 1, 2, \ldots, T$ **do**
  Train $\mathbf{f}$ on $\mathcal{D}$
  for $(x, w(x)) \in \mathcal{D}$ **do**
    if $\arg\max_j \mathbf{f}(x)[j] = w(x)$ **then**
      if $|\hat{\mathcal{D}}_{\checkmark}[w(x)]|/|\mathcal{D}[w(x)]| < \tau\%$ **then**
        $\hat{\mathcal{D}}_{\checkmark} = \hat{\mathcal{D}}_{\checkmark} \cup \{(x, w(x))\}$
  if $|\hat{\mathcal{D}}_{\checkmark}[j]|/|\mathcal{D}[j]| \geq \tau\%$ **for all** j **then**
    Break
Return $\hat{\mathcal{D}}_{\checkmark}$

Algorithm 2: Self-training with LOPS

Input: Unlabeled data $\mathcal{D}$, Classifier C, Weak Supervision w.
Output: Prediction labels $predLabs$
$\hat{\mathcal{D}}$ = Generate Pseudo-labels for $\mathcal{D}$, w
for iteration $it = 1, 2, \ldots, n_{its}$ **do**
  $\mathcal{D}_{sel}$ = LOPS $(\hat{\mathcal{D}}, C)$
  Train C on $\mathcal{D}_{sel}$
  $predLabs, predProbs$ = Predict$(C, \mathcal{D})$
  $\hat{\mathcal{D}} = \hat{\mathcal{D}} \cup \{x \mid predProbs(x) > \delta\}$
Return $predLabs$

on Equation (1). Finally, we rank the documents based on their confidence and select the top-$\tau\%$ for each label independently.

To maximize the efficiency of LOPS, we utilize the fact that the top-ranked documents are learned earlier, and conduct the confidence calculation and pseudo-label selection simultaneously during training. Specifically, for each label, a document is selected once it is learnt, until the fraction of selected documents exceeds $\tau\%$ in this label. Whenever the fractions of selected documents exceeds $\tau\%$ for all labels, we stop the training. The pseudo-code is shown in Algorithm 1. Note that LOPS can be plugged to any self-training based weakly-supervised classification framework as shown in Algorithm 2.

5 Experiments

We evaluate our label selection method based on end-to-end classification performance using different state-of-the-art classifiers and weakly supervised text classification frameworks. And also, we evaluate learning order as a confidence function and provide a comparison with probability score as confidence function.

Table 2: Dataset statistics.

Dataset	# Docs	# labels	Noise Ratio(%)
NYT-Coarse	13,081	5	11.47
NYT-Fine	13,081	26	31.80
20News-Coarse	17,871	5	12.50
20News-Fine	17,871	17	25.67
AGNews	120,000	4	16.26
Books	33,594	8	37.32

5.1 Datasets

We experiment on four datasets: New York Times (**NYT**), 20 Newsgroups (**20News**), **AG-News** (Zhang et al., 2015), **Books** (Wan and McAuley, 2018; Wan et al., 2019). NYT and 20News datasets also have fine-grained labels which are also used for evaluation. Initial pseudo-labels are generated using String-Match (Mekala and Shang, 2020). The dataset statistics and corresponding noise ratios of initial pseudo-labels are provided in Table 2 and more details are provided in Appendix A.1.

5.2 Compared Methods

We compare with several label selection methods mentioned below:

- **O2U-Net:** (Huang et al., 2019) trains a classifier cyclically to make its status transfer from overfitting to underfitting and records losses of each sample. They consider the normalized loss as the metric to filter out the noise.
- **MC-Dropout:** (Mukherjee and Awadallah, 2020) performs pseudo-label selection based on uncertainty estimates computed using probability scores.
- **Entropy:** is similar to MC-Dropout, however uses entropy to compute uncertainty scores.
- **Probability:** We sort the prediction probabilities corresponding to pseudo-labels in descending order and select the same number of samples as LOPS in each iteration of bootstrapping.
- **Random:** We randomly select the same number of samples as LOPS in each iteration of bootstrapping. To avoid skewed selection, we sample in a stratified fashion based on class labels.
- **Learning Stability (stability):** (Dong et al., 2021) introduced a metric to measure the data quality based on the frequency of events that an example is predicted correctly throughout the training. We sort the samples based on learning stability in descending order i.e. most stable to least stable and select the same number of samples as LOPS in each iteration of bootstrapping.

Table 3: Evaluation results on six datasets using different combinations of classifiers and pseudo-label selection methods. Initial pseudo-labels are generated using String-Match. Micro- and Macro-F1 scores are used as evaluation metrics. Each experiment is repeated with three random seeds, mean and their respective standard deviations are presented in percentages. For a fair comparison, we consider the same number of samples for all baselines as LOPS in each iteration. Abnormally high standard deviations are highlighted in *blue* and low performances are highlighted in *red*. LOPS outperforming *Standard* is made bold and baselines performing better than our method are made bold. Statistical significance results are in Appendix A.5.

| Classifier | Method | Coarse-grained Datasets | | | | | | | | Fine-grained Datasets | | | |
| | | NYT-Coarse | | 20News-Coarse | | AGNews | | Books | | NYT-Fine | | 20News-Fine | |
		Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1
BERT	Standard	90.1(0.17)	80.3(0.91)	77.3(0.27)	76.4(0.76)	75.4(0.64)	75.4(0.47)	55.7(0.54)	57.9(0.82)	77.2(0.36)	71.6(0.43)	70.0(0.30)	69.6(0.25)
	LOPS	**94.6(0.36)**	**88.4(0.50)**	**81.7(1.00)**	**80.7(0.43)**	**79.5(0.86)**	**79.5(0.58)**	**57.7(0.87)**	**59.5(0.46)**	**84.3(0.54)**	**81.6(0.34)**	**73.8(0.61)**	**72.7(1.00)**
	MC-Dropout	89.3(0.41)	79.3(0.45)	80.7(0.17)	77.7(0.24)	75.8(0.34)	75.0(0.41)	55.1(0.15)	56.7(0.61)	72.1(0.74)	69.0(0.41)	68.0(0.21)	68.7(0.26)
	Entropy	91.2(0.41)	83.1(0.47)	80.4(0.23)	78.0(0.54)	**80.4(0.47)**	**80.0(0.42)**	55.2(0.74)	56.7(0.42)	43.4(9.84)	18.1(6.98)	64.3(0.74)	63.6(0.83)
	O2U-Net	92.9(0.41)	85.9(0.69)	80.9(0.28)	78.5(0.19)	79.8(0.47)	79.8(0.53)	55.8(0.27)	56.8(0.36)	14.7(10.24)	8.70(7.31)	71.1(0.36)	71.2(0.75)
	Random	90.3(0.47)	80.9(0.47)	79.0(1.00)	76.8(1.50)	76.3(0.35)	76.3(0.65)	56.1(0.18)	58.2(0.35)	78.4(0.94)	71.7(0.47)	71.4(0.50)	70.6(1.00)
	Probability	92.3(1.50)	85.1(2.00)	78.6(2.50)	77.5(3.00)	77.4(1.25)	77.6(1.34)	54.3(1.12)	56.5(1.43)	46.6(2.50)	22.3(0.50)	47.8(23.50)	47.9(23.50)
	Stability	93.3(0.50)	86.5(0.50)	76.7(5.00)	75.4(5.00)	79.3(0.75)	79.5(0.35)	55.0(0.43)	57.0(0.19)	48.1(29.50)	35.5(33.50)	73.5(0.50)	72.5(1.00)
	OptimalFilter	98.3(0.27)	96.4(0.37)	94.7(0.37)	94.9(0.61)	89.4(0.46)	89.3(0.76)	76.2(0.21)	76.7(0.19)	97.4(0.71)	92.2(0.62)	87.6(0.37)	86.5(0.36)
XLNet	Standard	89.2(0.74)	80.1(0.64)	77.6(0.39)	75.4(0.68)	72.7(0.97)	72.4(0.53)	57.6(0.31)	58.7(0.46)	77.4(0.34)	71.3(0.75)	60.7(0.74)	66.5(0.61)
	LOPS	**89.5(0.17)**	**81.4(0.90)**	**82.5(0.50)**	**81.2(0.20)**	**77.7(0.57)**	**77.7(0.54)**	**58.5(0.65)**	**59.4(0.67)**	**80.7(0.22)**	**77.4(0.83)**	**70.6(0.31)**	**70.4(0.27)**
	MC-Dropout	88.5(0.41)	80.4(0.38)	77.1(0.28)	73.2(0.53)	74.7(0.71)	73.2(0.36)	56.4(0.41)	58.0(0.74)	74.9(0.96)	68.9(0.84)	66.9(0.45)	68.5(0.62)
	Entropy	**92.4(0.42)**	**85.4(0.51)**	78.2(0.36)	74.4(0.45)	72.9(0.67)	72.0(0.51)	54.5(0.74)	56.6(0.65)	77.9(0.67)	70.7(0.38)	68.8(0.65)	69.5(0.74)
	O2U-Net	92.2(0.37)	84.6(0.24)	80.5(0.93)	77.4(0.57)	71.6(0.69)	68.8(0.61)	58.1(0.17)	**59.9(0.52)**	79.6(0.47)	76.8(0.59)	67.2(0.64)	69.0(0.26)
	Random	90.7(0.03)	80.5(0.51)	78.6(0.50)	75.4(1.00)	67.5(0.22)	67.4(0.63)	57.5(0.43)	58.3(0.45)	76.6(0.94)	72.7(0.70)	67.3(0.40)	67.2(0.32)
	Probability	91.3(0.29)	83.4(0.50)	77.4(1.00)	75.2(0.30)	70.1(1.09)	70.4(1.14)	54.6(1.42)	56.3(1.26)	38.2(6.50)	36.5(1.00)	69.5(0.82)	69.2(0.12)
	Stability	91.4(1.00)	82.3(1.50)	79.7(1.50)	77.6(1.50)	74.3(1.10)	74.5(0.87)	56.3(0.88)	58.1(0.97)	79.5(0.50)	76.3(1.10)	68.5(0.49)	68.4(1.00)
	OptimalFilter	98.3(0.12)	96.5(0.21)	94.5(0.23)	94.4(0.29)	89.3(0.28)	89.7(0.39)	76.4(0.44)	76.3(0.43)	97.4(0.32)	93.6(0.38)	86.6(0.43)	86.4(0.35)
GPT-2	Standard	91.1(0.24)	82.3(0.28)	78.4(0.26)	76.3(0.38)	61.3(0.28)	61.2(0.43)	51.6(0.41)	53.3(0.37)	76.2(0.41)	69.5(0.38)	70.5(0.46)	70.4(0.38)
	LOPS	**95.2(0.49)**	**89.1(0.51)**	**82.5(0.57)**	**80.3(0.63)**	**75.7(0.52)**	**75.3(0.31)**	**56.8(0.89)**	**58.6(0.63)**	**80.4(0.09)**	**76.3(0.21)**	**70.6(0.76)**	**70.5(0.48)**
	MC-Dropout	89.2(0.14)	79.8(0.51)	80.2(0.63)	77.1(0.57)	65.5(0.34)	65.1(0.94)	49.5(0.74)	51.5(0.54)	74.1(0.62)	68.2(0.21)	70.4(0.47)	70.8(0.65)
	Entropy	93.1(0.32)	85.9(0.36)	80.8(0.65)	77.9(0.84)	65.4(0.85)	65.3(0.54)	54.3(0.32)	55.5(0.47)	77.4(0.42)	75.3(0.65)	69.1(0.62)	69.6(0.21)
	O2U-Net	93.8(0.89)	87.5(0.24)	81.2(0.76)	77.9(0.37)	72.0(0.38)	70.7(0.75)	55.1(0.27)	57.2(0.67)	80.2(0.41)	**79.4(0.58)**	70.3(0.24)	**71.4(0.16)**
	Random	90.2(0.42)	80.2(0.56)	79.7(0.46)	78.4(0.32)	68.2(0.18)	68.1(0.19)	53.4(0.46)	55.3(0.42)	77.5(0.52)	70.4(1.02)	69.4(0.21)	69.3(0.29)
	Probability	93.3(1.04)	85.5(1.13)	80.4(1.49)	78.5(1.50)	66.2(0.69)	66.6(0.89)	51.7(1.11)	54.5(1.09)	76.7(0.57)	71.3(0.69)	69.4(1.21)	69.3(1.18)
	Stability	94.4(0.56)	88.6(0.59)	81.4(1.02)	78.6(1.50)	72.4(0.58)	72.3(0.53)	53.6(1.02)	55.3(1.13)	79.4(0.62)	75.3(0.65)	**70.6(0.68)**	70.4(0.63)
	OptimalFilter	98.3(0.24)	96.2(0.21)	94.2(0.23)	93.3(0.27)	88.7(0.26)	88.4(0.28)	72.3(0.19)	73.7(0.22)	97.3(0.18)	92.4(0.19)	86.1(0.35)	85.5(0.38)

To perform controlled experiments with a fair comparison, we consider the same number of samples as LOPS in each iteration for all above baselines because we cannot tune individual thresholds for each dataset since there is no human-annotated data under the weakly supervised setting and one fixed threshold for all datasets doesn't work as distribution of prediction probability varies across datasets.

We also present experimental results without any label selection in addition to the probability threshold δ while bootstrapping (denoted by *Standard*) as lower bound and with all the wrongly annotated samples removed as *OptimalFilter*.

5.3 Experimental Settings

For all our experiments, we consider seed words used in (Mekala and Shang, 2020; Wang et al., 2021) as weak supervision and generate initial pseudo-labels using String-Match (Mekala et al., 2020) unless specified. The average number of seeds are 4 per class. We experiment on three state-of-the-art text classifiers: (1) **BERT** (bert-base-uncased) (Devlin et al., 2019), (2) **XLNet** (xlnet-base-cased) (Yang et al.,

Table 4: Evaluation results of weakly supervised text classification frameworks with LOPS. This demonstrates that LOPS can be easily plugged in and improves the performance.

| Method | NYT-Coarse | | NYT-Fine | | 20News-Coarse | | 20News-Fine | | AGNews | | Books | |
	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1
					ConWea							
Standard	93.1	87.2	87.4	77.4	74.3	74.6	68.7	68.7	73.4	73.4	52.3	52.6
LOPS	94.2	90.1	87.5	78.6	79.7	78.4	70.4	70.6	79.2	79.2	57.5	58.7
					X-Class							
Standard	96.3	93.3	86.6	74.7	58.2	61.1	70.4	70.4	82.4	82.3	53.6	54.2
LOPS	96.2	93.3	86.8	73.8	60.7	62.3	71.2	71.2	83.6	82.7	54.2	56.3
					WeSTClass							
Standard	92.3	86.0	67.1	60.4	53.2	49.4	54.9	54.9	80.4	80.1	49.7	48.1
LOPS	93.4	88.1	68.4	63.8	53.3	51.5	61.1	60.5	81.4	81.3	51.2	49.8
					LOTClass							
Standard	70.1	30.3	5.3	4.1	47.0	35.0	12.3	10.6	84.9	84.7	19.9	16.1
LOPS	70.1	30.3	3.5	2.9	45.7	32.6	7.8	4.1	86.2	86.1	15.8	10.3

2019), and (3) **GPT-2** (Radford et al., 2019). We follow the same self-training method for all classifiers that starts with generating pseudo-labels, training a classifier on pseudo-labeled data, and bootstrap it on unlabelled data by adding samples whose prediction probabilities are greater than δ. Following (Mekala and Shang, 2020), we assume that weak supervision $\mathcal{W}$ is of reasonable quality i.e. majority of pseudo-labels are good. Therefore,

we set τ to 50%. While training the classifiers, we fine-tune BERT, XLNet, GPT-2 for 4 epochs. We bootstrap all the classifiers for 5 iterations with the probability threshold δ as 0.6. We also experiment on state-of-the-art weakly supervised text classification methods: **ConWea** (Mekala and Shang, 2020), **X-Class** (Wang et al., 2021), **WeSTClass** (Meng et al., 2018), and **LOTClass** (Meng et al., 2020). Three of them are self-training-based methods and more details are mentioned in Appendix A.2.

5.4 End-to-End Classification Performance

5.4.1 Results: Different Classifiers

We summarize the evaluation results with different combinations of classifiers and selection methods in Table 3. All experiments are run on three random seeds and mean, standard deviations are reported.

As shown in Table 3, upon plugging our proposed method LOPS, we observe a significant boost in performance consistently over ***Standard*** with all the classifiers. We observe that LOPS always outperforms random selection which shows that the selection in LOPS is strategic and principled. LOPS performs better than probability and stability based selection methods in most of the cases. This shows that LOPS is very effective in removing wrongly labeled and preserving correctly labeled samples. LOPS also performs better than O2U-Net (Huang et al., 2019) and MC-Dropout (Mukherjee and Awadallah, 2020) in most of the datasets demonstrating the effectiveness of learning order as confidence function.

We also observe a significant boost in performance over ***Standard*** with all the classifiers in the case of fine-grained datasets as well. In some cases like BERT on NYT-Fine, the improvement is as high as 7 points on micro-f1 and 10 points on macro-f1. We observe abnormally low performances of probability and stability based selection methods in some scenarios (highlighted in *red*). This is because the number of noisy labels are more in fine-grained datasets and gets amplified with self-training and resulting in high noise. Moreover, we also observe that probability and stability based selections are biased towards majority labels and select wrong majority labels over correct minority labels. For example, the precision of pseudo-labels belonging to minority classes like *cosmos*, *gun control*, and *abortion* in NYT-Fine before selection is 100% and it selected almost none of these whereas it selected 700 wrong documents belonging to a ma-

jority labels like, *international business*. Although stratified selection can be employed to address this problem, this ends up having a same threshold and selecting a fixed ratio of samples for every dataset, which might not be optimal for every dataset.

We have to note unusually high standard deviation for probability and stability in some cases (highlighted in *blue*). This demonstrates that these selection methods are unstable. LOPS is comparatively more stable and its effectiveness is largely due to its invariance. Although these methods outperform LOPS in a few cases, their unstable nature makes them unreliable. Therefore, we believe LOPS is superior than compared methods.

5.4.2 Results: Different Weakly-Supervised Text Classification Methods

We summarize the evaluation results with different weakly supervised methods in Table 4. The results demonstrate that LOPS improves the performance of ConWea and WeSTClass significantly on all datasets and X-Class sometimes. Note that, X-Class sets a confidence threshold and selects only top-50% instances, which provides a hidden advantage and LOPS improves the performance on top of it for some datasets. We have to note the significantly low performance of LOTClass. It is observed that LOTClass requires a wide variety of contexts of label surface names from the input corpus to generate high quality category vocabulary, which plays a key role in performance (Wang et al., 2021). The performance is comparitively worse in fine-grained classes than coarse-grained classes because LOTClass assumes that the replacements of label surface names are indicative of its respective label. However, this might not be a valid assumption for fine-grained classes (Mekala et al., 2021). Among the datasets we experimented on, these requirements are satisfied only by AGNews dataset where there are many documents(120000) classified broadly into 4 categories and we observe a performance boost using LOPS on this dataset. Due to poor quality of pseudo-labels for other datasets, there is no increment in performance with LOPS.

5.5 Learning Order vs Probability Score: Evaluating Confidence Functions

In this section, we define evaluating a confidence function and compare learning order and probability score as confidence functions.

Evaluation of a confidence function. Ideally, there exists a threshold for a given confidence
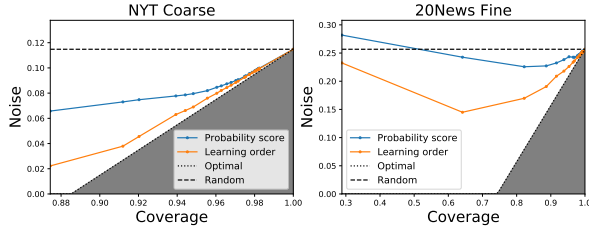
Figure 3: NC-curves of learning order and probability score with BERT as the classifier.
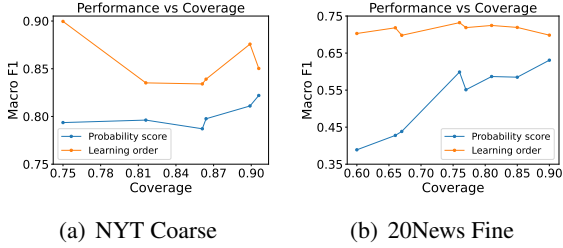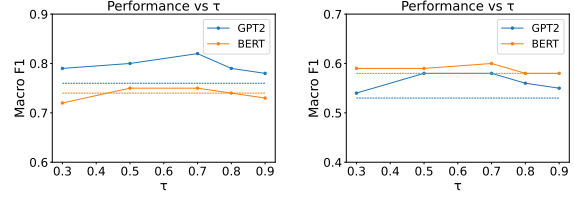

(a) NYT Coarse   (b) 20News Fine

Figure 4: Macro-F_1 vs Coverage on NYT-Coarse & 20News-Fine using BERT with LOPS and Probability score based selection.

function that perfectly distinguishes correctly and wrongly labeled samples. However, in practice, confidence functions may not suffice such ideal condition. There always exists a trade-off between *noise* $\epsilon(\kappa, \gamma)$ and *coverage* $\phi(\kappa, \gamma)$, defined as:

$$\epsilon(\kappa, \gamma) = \frac{|\hat{\mathcal{D}}_\checkmark(\kappa, \gamma) \cap \mathcal{D}_\times|}{|\hat{\mathcal{D}}_\checkmark(\kappa, \gamma)|}, \quad \phi(\kappa, \gamma) = \frac{|\hat{\mathcal{D}}_\checkmark(\kappa, \gamma)|}{|\mathcal{D}|}.$$

The coverage is the fraction of labeled documents being selected and the noise is the fraction of wrongly labeled documents within selected documents. A small threshold leads to high coverage i.e. most labeled documents will be selected, thus being more noisy. And a high threshold leads to an opposite situation. Therefore, to evaluate a confidence function, we plot noise and coverage at various thresholds, which we refer as the *noise-coverage curve* (NC-curve) and compute the *area under the noise-coverage curve* (AUNC). As shown in figure 3, an optimal confidence function selects wrongly labeled documents only after selecting all the correctly labeled documents, hence generates a NC-curve in the shape of a rectifier, namely $\epsilon = \max(0, \phi - |\mathcal{D}_\checkmark|/|\mathcal{D}|)$. A random confidence function always selects the same fraction of wrongly labeled documents, hence an NC-curve with a constant value. An ideal confidence function should minimize AUNC.
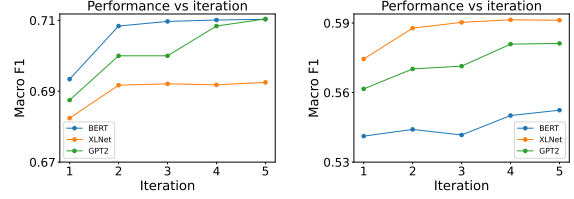
Learning Order vs Probability Score. We plot NC-curves of learning order and probability scores in Figure 3 with BERT classifier on NYT-Coarse, 20News-Fine datasets. To isolate them from the ef-

(a) 20News Coarse   (b) Books

Figure 5: Macro-F_1 vs τ on 20News-Coarse & Books using GPT2 and BERT with LOPS. The dashed lines represent performance with no label selection.

(a) 20News Fine   (b) Books

Figure 6: Macro-F_1 vs iteration on 20News-Fine & Books using BERT, XLNet, GPT2 with LOPS.

fects of bootstrapping, we don't perform any bootstrapping. We also plot the end-to-end performance vs coverage in Figure 4. From Figure 3, we observe that learning order has significantly smaller AUNC compared to the probability score. In some datasets such as NYT-Coarse, it even approaches optimal confidence function. In fine-grained datasets like 20News-Fine, the calibration is so poor that the probability score is even worse than random, which explains poor empirical results of Probability-based selection on fine-grained datasets. From Figure 4, we observe that the performance with LOPS is significantly better and more stable than Probability.

5.6 Performance vs τ

To study the effect of τ on performance, we plot macro-f1 vs τ on 20News-coarse and Books datasets using GPT2 and BERT classifiers, shown in Figure 5. We observe that the performance increases initially and gradually drops down at higher τ values. The lower τ values imply being highly selective and thus the few number of selected samples are not enough for the model to generalize. The higher τ values imply poor selection with many noisy labels, making the performance to drop. From the plot, we can observe that the performance is robust for middle τ values i.e. $50 - 70\%$.

5.7 Performance vs iteration

The plot of performance vs the number of iteration of bootstrapping is shown in Figure 6. We observe

that the macro f1 increases initially and gradually converges at the later iterations.

6 Conclusion and Future Work

In this paper, we proposed LOPS, a novel learning order inspired pseudo-label selection method. Our method is inspired from recent studies on memorization effects that showed that clean samples are learnt first and then wrong samples are memorized. Experimental results demonstrate that our method is effective, stable and can act as a performance boost plugin on many text classifiers and weakly supervised text classification methods. In the future, we are interested in automatically identifying the right granularity to measure learning order for a given dataset. Moreover, we are also interested in analyzing the learning order in classification tasks in image and speech domains.

7 Limitations

Since we select 50% of the samples based on learning order, our method requires the absolute number of pseudo-labeled samples to be high enough so that the final classifier has significant number of selected samples to learn and generalize on. For example, we experimented on a subset of 2613 samples from 20news-fine dataset with noise rate 20%. With LOPS, the macro f1 is 68.3% and without any selection the macro-f1 is 70.1%. We attribute this performance drop to the lack of generalization using the few selected samples from LOPS. Since in real-life scenario, obtaining noisy annotations is cheaper, we believe this limitation can be addressed comfortably.

8 Acknowledgements

9 Ethical Consideration

This paper proposes a label selection method for weakly supervised text classification frameworks. The aim of the paper is to detect the noise caused by the heuristic pseudo-labels and we don't intend to introduce any biased selection. Based on our experiments, we manually inspected some filtered samples and we didn't find any underlying pattern. Hence, we do not anticipate any major ethical concerns.

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A Appendix

A.1 Datasets

The details of datasets are provided below:

- **The New York Times (NYT):** The NYT dataset is a collection of news articles published by The New York Times. They are classified into 5 coarse-grained genres (e.g., science, sports) and 25 fine-grained categories (e.g., music, football, dance, basketball).

- **The 20 Newsgroups (20News):** The 20News dataset[2] is a collection of newsgroup documents partitioned widely into 6 groups (e.g., recreation, computers) and 20 fine-grained classes (e.g., graphics, windows, baseball, hockey). Following (Wang et al., 2021), coarse- and fine-grained miscellaneous labels are ignored.

- **AGNews** (Zhang et al., 2015) is a huge collection of news articles categorized into four coarse-grained topics such as business, politics, sports, and technology.

- **Books** (Wan and McAuley, 2018; Wan et al., 2019) is a dataset containing description of books, user-book interactions, and users' book reviews collected from a popular online book review website Goodreads[3]. Following (Mekala et al., 2020), we select books belonging to eight popular genres. Using the title and description as text, we aim to predict the genre of a book.

A.2 Compared Weakly Supervised Text Classification Methods

We compared with following state-of-the-art weakly supervised text classification methods described below[4]:

- **ConWea** (Mekala and Shang, 2020) is a seed-word driven iterative framework that uses pre-trained language models to contextualize the weak supervision.

- **X-Class** (Wang et al., 2021) takes only label surface names as supervision and learns class-oriented document representations. These document representations are aligned to classes, computing pseudo labels for training a classifier.

- **WeSTClass** (Meng et al., 2018) generates pseudo documents using seed information and refines the model through a self-training module

that bootstraps on unlabeled documents.

- **LOTClass** (Meng et al., 2020) queries replacements of class names using BERT (Devlin et al., 2019) and constructs a category vocabulary for each class. This is used to pseudo-label the documents via string matching. A classifier is trained on this pseudo-labeled data with further self-training.

We use the public implementations of these methods and modify them to plug-in our filter. Specifically, in WeSTClass and LOTClass, we add our filter after generating the pseudo documents; in ConWea, we add our filter before training the text classifier; and for X-Class, we plug-in our filter after learning the document-class alignment.

A.3 Experimental Settings

Train-Test sets. We remove the labels in the whole dataset and our task is to assign labels to these unlabeled samples. We measure our performance on the whole dataset by comparing it with their respective gold labels.

Computation Infrastructure. We performed our experiments on NVIDIA RTX A6000 GPU. The batch size for training BERT is 32, RoBERTa is 32, GPT2 is 4, XLNet is 1. The running time for BERT and RoBERTa took 3 hrs, GPT2 took 6 hours, and XLNet took 12 hrs.

A.4 Additional Experiments

We also compare with **RoBERTa** (`roberta-base`) (Liu et al., 2019) as text classifier. We fine-tune it for 3 epochs. The results are shown in Table 5.

A.5 Statistical Significance Tests

We perform a paired t-test between LOPS and each of the other baseline filtering techniques for all classifiers and on all datasets. The results are showed in Table 6. From these p-values, we can conclude that the performance improvement over baselines is significant.

A.6 Example samples

A few incorrectly pseudo-labeled samples from NYT-Fine dataset that are selected by probability-based selection by BERT are shown in Table 7 We observe a high probability assigned to each incorrect pseudo-label whereas these are learnt by the classifier at later epochs. These wrongly annotated samples induce error that gets propagated and amplified over the iterations. By not selecting these

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[2] http://qwone.com/~jason/20Newsgroups/
[3] https://www.goodreads.com/
[4] We also considered experimenting on ASTRA, however the instructions to run on custom datasets were not made public yet.

Table 5: Evaluation results on six datasets using RoBERTa classifier and pseudo-label selection methods. Initial pseudo-labels are generated using String-Match. Micro- and Macro-F1 scores and their respective standard deviations are presented in percentages. For a fair comparison, we consider the same number of samples for all baselines as LOPS in each iteration. Abnormally high standard deviations are highlighted in *blue* and low performances are highlighted in *red*. Baselines performing better than our method are made bold.

| Classifier | Method | Coarse-grained Datasets | | | | | | | | Fine-grained Datasets | | | |
| | | NYT-Coarse | | 20News-Coarse | | AGNews | | Books | | NYT-Fine | | 20News-Fine | |
		Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1	Mi-F1	Ma-F1
RoBERTa	Standard	90.2(0.41)	82.1(0.24)	76.5(0.41)	75.7(0.58)	74.4(0.44)	74.2(0.71)	57.6(0.29)	58.6(0.53)	79.4(0.65)	76.6(0.54)	67.4(0.67)	67.3(0.87)
	LOPS	**92.4(2.99)**	**85.6(3.00)**	**77.5(2.00)**	**75.8(2.00)**	**75.6(0.22)**	**75.5(0.27)**	**59.7(0.41)**	**60.5(0.45)**	**81.8(0.90)**	**80.7(0.50)**	**70.7(0.68)**	**70.8(0.34)**
	O2U-Net	93.1(0.14)	86.3(0.26)	76.5(0.19)	73.4(1.47)	**77.6(0.36)**	**77.1(0.54)**	58.5(0.64)	59.9(0.32)	79.2(0.28)	77.5(1.17)	68.4(0.47)	68.3(0.15)
	Random	92.3(0.21)	84.4(0.82)	76.5(1.00)	74.5(1.00)	74.6(0.32)	74.2(0.27)	56.4(0.57)	58.7(0.32)	76.6(1.25)	74.8(0.34)	68.4(0.23)	68.5(0.23)
	Probability	**93.4(0.48)**	**87.5(1.00)**	76.7(0.50)	75.4(1.00)	76.2(0.89)	76.3(1.12)	56.2(1.28)	57.4(1.85)	26.6(23.00)	14.4(11.50)	46.2(23.00)	45.3(23.50)
	Stability	90.5(1.09)	83.3(0.50)	**78.5(1.00)**	**76.0(1.50)**	76.5(0.48)	76.5(0.64)	58.5(1.18)	59.5(1.06)	21.5(12.50)	9.2(5.00)	70.3(1.00)	70.6(1.00)
	OptimalFilter	98.2(0.17)	96.1(0.16)	94.3(0.74)	94.5(0.35)	89.7(0.17)	89.3(0.28)	76.5(0.29)	77.7(0.22)	97.4(0.34)	92.8(0.26)	85.3(0.32)	85.5(0.65)

Table 6: Statistical significance results.

Classifier	Method	NYT-Coarse	NYT-Fine	20News-Coarse	20News-Fine	AGNews	Books
BERT	Standard	1.93×10^{-112}	1.92×10^{-105}	7.08×10^{-80}	9.37×10^{-79}	1.05×10^{-74}	7.15×10^{-96}
	Random	1.58×10^{-115}	2.01×10^{-105}	5.98×10^{-94}	7.32×10^{-39}	4.26×10^{-81}	3.25×10^{-100}
	Probability	1.69×10^{-112}	6.25×10^{-189}	4.19×10^{-120}	6.71×10^{-136}	5.13×10^{-71}	8.72×10^{-123}
	Stability	2.63×10^{-33}	2.41×10^{-194}	2.78×10^{-58}	4.07×10^{-9}	1.36×10^{-45}	1.24×10^{-97}
RoBERTa	Standard	6.06×10^{-100}	1.82×10^{-63}	5.4×10^{-3}	3.09×10^{-109}	2.13×10^{-57}	1.15×10^{-22}
	Random	8.38×10^{-94}	3.55×10^{-71}	3.26×10^{-39}	5.20×10^{-101}	5.12×10^{-72}	1.75×10^{-61}
	Probability	5.27×10^{-62}	9.18×10^{-193}	1.39×10^{-71}	1.13×10^{-85}	4.03×10^{-24}	2.16×10^{-72}
	Stability	1.46×10^{-86}	3.39×10^{-188}	6.28×10^{-5}	8.71×10^{-107}	1.17×10^{-76}	1.81×10^{-65}
XLNet	Standard	3.14×10^{-79}	4.68×10^{-139}	5.42×10^{-112}	4.17×10^{-103}	1.69×10^{-114}	5.63×10^{-107}
	Random	3.26×10^{-71}	2.97×10^{-48}	2.56×10^{-77}	5.32×10^{-75}	6.38×10^{-32}	4.38×10^{-48}
	Probability	4.12×10^{-29}	1.36×10^{-63}	7.25×10^{-19}	6.27×10^{-47}	1.57×10^{-31}	6.23×10^{-32}
	Stability	6.17×10^{-29}	4.27×10^{-44}	1.47×10^{-73}	3.57×10^{-41}	1.79×10^{-28}	3.48×10^{-56}
GPT-2	Standard	6.09×10^{-50}	1.10×10^{-98}	2.05×10^{-57}	1.22×10^{-5}	4.68×10^{-91}	1.56×10^{-65}
	Random	2.54×10^{-22}	6.97×10^{-81}	4.25×10^{-91}	9.89×10^{-38}	6.39×10^{-77}	8.70×10^{-63}
	Probability	5.52×10^{-49}	2.37×10^{-89}	7.02×10^{-85}	1.05×10^{-83}	1.99×10^{-63}	3.44×10^{-49}
	Stability	6.15×10^{-110}	3.88×10^{-31}	3.40×10^{-66}	6.27×10^{-78}	2.21×10^{-47}	2.36×10^{-41}

wrong instances, LOPS curbs this and boosts the performance.

A.7 Learning Order vs Probability Score: Threshold Analysis

Ideally, there exists a threshold for a given confidence function that perfectly distinguishes the correctly and wrongly labeled samples. However, in practice, confidence functions may not be possible to suffice such ideal condition. For a given confidence function, one wishes to select pseudo-labels based on a threshold such that the noise is low and the coverage is high. We define ratio between noise and coverage as *NC-ratio*, namely $r(\kappa, \gamma) = \frac{\epsilon(\kappa,\gamma)}{\phi(\kappa,\gamma)}$. An optimal threshold has the lowest NC-ratio. Therefore, we evaluate confidence function by plotting NC-ratio at different thresholds.

We plot NC-ratios of learning order and probability scores with BERT classifier in Figure 8 on NYT-Coarse, 20News-Fine datasets. To isolate them from the effects of bootstrapping, we don't perform any bootstrapping. As shown in Figure 8, when selecting the optimal threshold, learning order has significantly lower NC-ratios for all datasets compared to probability score. Furthermore, the optimal thresholds of learning order for all datasets are almost the same. In contrast, the optimal thresholds of probability score vary greatly across different datasets due to the poor calibration of DNNs. Finally, we also observe that the NC-ratio for probability score often changes greatly around the optimal threshold, which poses difficulty in locating the optimal threshold. In contrast, since there are only few possible thresholds for learning order, it is easier to find the optimal threshold. From the performance vs threshold plot in Figure 9, we can observe that learning order performs better than Probability score across multiple thresholds. Therefore, in terms of both performance and robustness, learning order is a more effective confidence function than probability score.

Table 7: Incorrectly pseudo-labeled samples selected by probability-based selection are shown below. These samples are learnt at later epochs, thus LOPS avoids selecting them.

| Document	Pseudo-label
Corinthians have received offer from tottenham hotspur for brazil's paulinho although the midfielder said on saturday he would not decide his future until after the confederations cup ."there is an official offer from tottenham to corinthians but, as i did when there was an inter milan offer, i'll sit and decide with my family before i make any decision," paulinho told reporters.	Football Softmax Prob: 0.96 Learnt Epoch: 2
Brittney griner and elena delle donne were poised to make history as the first pair of rookies from same class to start wnba all-star game. Now, neither will be playing as both are sidelined with injuries. It's a tough blow for the league, which has been marketing the two budding stars.	Baseball Softmax Prob: 0.96 Learnt Epoch: 2
Denmark central defender simon kjaer has joined french side lille from vfl wolfsburg on a four-year deal. Lille paid two million euros. 72 million pounds for the 24-year-old kjaer, who has won 35 caps for his country. He joined wolfsburg from palermo for 12 million euros.	Intl. Business Softmax Prob: 0.94 Learnt Epoch: 2
Fiorentina striker giuseppe rossi is quickly making up for lost time after suffering successive knee ligament injuries which kept him out of action for the best part of two years.	Football Softmax Prob: 0.95 Learnt Epoch: 2
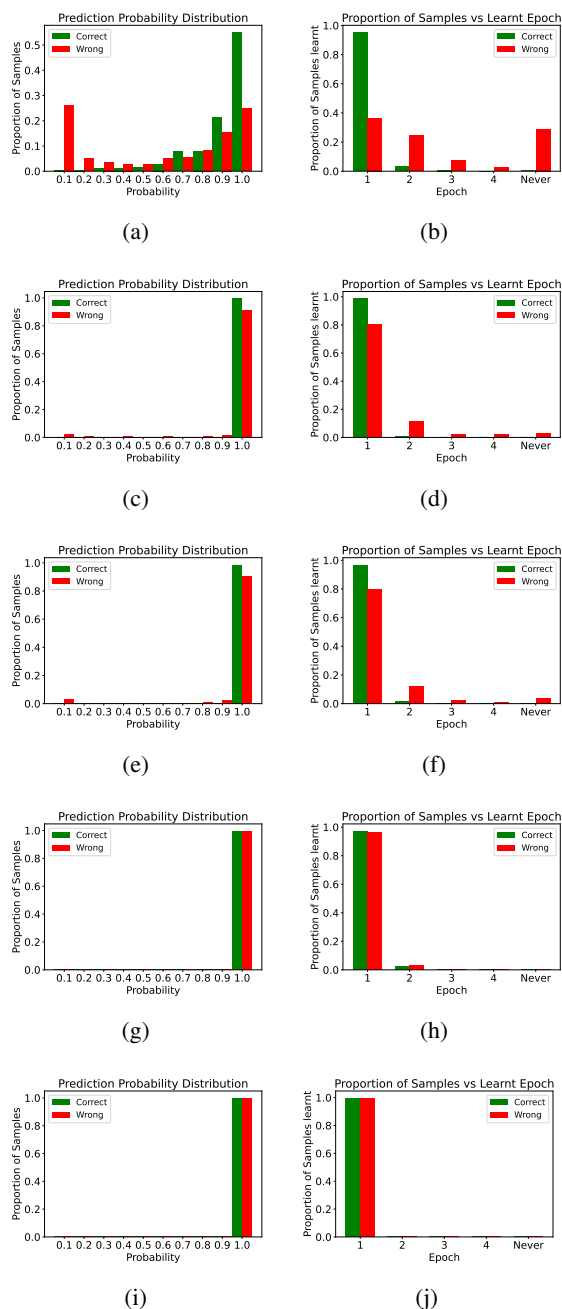
Figure 7: Distributions of correctly and wrongly labeled pseudo-labels using different selection strategies on all datasets for its initial pseudo-labels. The base classifier is BERT. Each row represents a dataset. Figure (a), (b) represents NYT-Fine, (c), (d) represents 20News-Coarse, (e), (f) represents 20News-Fine, (g), (h) represents Books, and (i), (j) represents AGNews datasets respectively. Left column is based on the softmax probability of samples' pseudo-labels and right column is based on the earliest epochs at which samples are learnt.
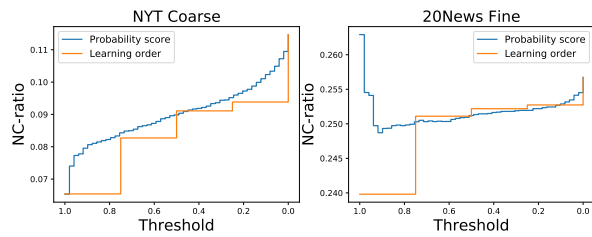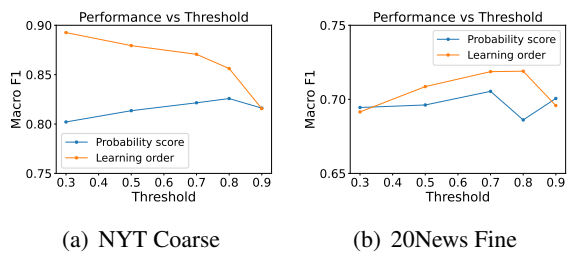
Figure 8: NC-ratios of learning order and probability score with BERT as the classifier.

(a) NYT Coarse　　　(b) 20News Fine

Figure 9: Macro-F_1 scores vs Threshold on NYT-Coarse & 20News-Fine datasets using BERT classifier with LOPS and Probability score based selection.