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Calibrated Self-Training for Cross-Domain Bearing Fault Diagnosis

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Fault diagnosis of rolling bearings is a crucial task in Prognostics and Health Management, as rolling elements are ubiquitous in industrial assets. Data-driven approaches based on deep neural networks have made significant progress in this area. However, they require collecting large representative labeled data sets. However, in industrial settings, assets are often operated in conditions different from the ones in which labeled data were collected, requiring a transfer between working conditions. In this work, we tackle the classification of bearing fault types and severity levels in the setting of unsupervised domain adaptation (UDA), where labeled data are available in a source domain and only unlabeled data are available in a different but related target domain. We focus on UDA with self-training methods, based on pseudo-labeling of target samples. One major challenge in these methods is to avoid error accumulation due to low-quality pseudo-labels. To address this challenge, we propose incorporating post-hoc calibration, such as the well-known temperature scaling, into the self-training process to increase the quality of selected pseudo-labels. We implement our proposed calibration approach in two self-training algorithms, *Calibrated Pseudo-Labeling* and *Calibrated Adaptive Teacher*, and demonstrate their competitive results on the Paderborn University (PU) benchmark for fault diagnosis of rolling bearings under varying operating conditions.

Keywords: Bearing fault diagnosis, Domain adaptation, Self-training, Pseudo-labels, Confidence, Calibration

1. Introduction

Applications of unsupervised domain adaptation (UDA) methods to bearing fault diagnosis, such as domain-adversarial neural networks (DANN), have been studied on several data sets by Zhao et al. (2021). Self-training methods based on pseudo-labeling of target samples have also been explored in the literature Wu et al. (2020); Zhu et al. (2022); Wang et al. (2022). In particular, *curriculum pseudo-labeling* (CPL), first introduced for semi-supervised learning, is a strategy where pseudo-labels (PLs) are gradually introduced during the learning process in a "easy-to-hard" manner, starting with the most confident target predictions and using prediction confidence (i.e., maximum softmax probability) as a proxy for correctness. Once the model is adapted to the target domain, more samples can be explored. CPL can also dynamically adjust the confidence threshold for each class during training based on its current accuracy using an *adaptive threshold*. This accounts for the varying difficulties of classes and enables target samples from low-confidence classes to participate early in the training. Another very effective approach is the *Mean Teacher* framework, where a student network receives target PLs from a teacher network, which is updated by exponential moving average (EMA) of the student weights. In the *Adaptive Teacher* (AT) Li et al. (2022), a domain discriminator is added to jointly align features (see Figure 1). However, none of these works has studied model calibration.

2. Calibrated self-training

A model is *well-calibrated* if its confidence scores actually correspond to the accuracy of the predictions. As our aim is to increase the accuracy of the selected PLs and confidence is used as a proxy for accuracy, we seek well-calibrated target outputs. Hence, we propose to calibrate the model outputs before selecting the confident PLs to train on. We evaluate post-hoc calibration via temperature scaling (using only source labels) and calibrated predictions with covariate shift (CPCS) Park et al. (2020) to account for domain shift.

Domain Adaptation with Calibrated Pseudo-Labeling (DA-CPL) combines DANN and CPL with an adaptive threshold. Between each training epoch, re-calibration is performed and the PLs are produced based on the calibrated target predictions. Similarly, we propose **Calibrated Adaptive Teacher (CAT)** to improve the Adaptive Teacher by calibrating the teacher network's predictions on target samples, as depicted on Figure 1. In both methods, the loss function has 3 terms: a supervised source loss $\mathcal{L}_{\mathrm{C}}$, a target pseudo-labeling loss $\mathcal{L}_{\mathrm{PL}}$ and the domain classifier term $\mathcal{L}_{\mathrm{DC}}$.

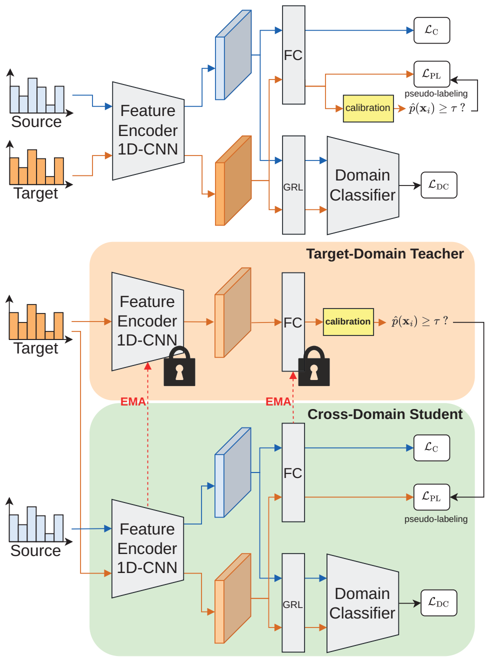

Fig. 1. DA-CPL (top) and CAT (bottom).

3. Experimental results

Experiments are carried out on the Paderborn University (PU) data set Lessmeier et al. (2016), which comprises challenging transfer learning tasks between 4 operating conditions. For brevity, results are reported only for the transfer task 0→1 and time-domain inputs. In Table 1, we report the accuracy and expected calibration error (ECE) on the target test set. We use the same experimental setting as Zhao et al. (2021) and introduce calibration at epoch 150. All experiments are repeated 5 times with different random train/test splits and initializations because we noticed a large variability between runs. We measure the performance at the last training iteration. Our results demonstrate that introducing calibration significantly improves the accuracy and reduces ECE on the target data. Even though temperature scaling does not account for domain shift, it is still effective in our experiments thanks to the well-aligned features. Moreover, CAT outperforms existing methods and achieves state-of-the-art performance on this task.

Table 1. Results on the PU data set (task 0→1).

Method	Accuracy (%) ↑	ECE (%) ↓
Source-only	15.15 ± 1.03	78.90 ± 0.96
DANN	36.96 ± 2.45	55.70 ± 2.27
DA-PL	36.44 ± 3.20	58.27 ± 2.78
+ adaptive thresh.	37.52 ± 3.32	57.57 ± 2.88
DA-CPL (Ours)		
+ temp. scaling	36.75 ± 3.89	44.13 ± 2.72
+ CPCS	38.77 ± 3.01	21.08 ± 10.2
AT	38.47 ± 2.83	52.79 ± 2.78
+ adaptive thresh.	42.24 ± 3.07	44.93 ± 4.07
CAT (Ours)		
+ temp. scaling	46.01 ± 3.01	22.44 ± 5.37
+ CPCS	$\mathbf{46.81} \pm 2.75$	$\mathbf{8.61} \pm 3.56$

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