ABSTRACT
The recently proposed Mean Teacher has achieved state-of-the-art results in several semi-supervised learning benchmarks. The Mean Teacher method can exploit large-scale unlabeled data in a self-ensembling manner. In this paper, an effective Couple Learning method based on a well-trained model and a Mean Teacher model is proposed. The proposed pseudo-labels generated model (PLG) can increase strongly-labeled data and weakly-labeled data to improve performance of the Mean Teacher method. The Mean Teacher method can suppress noise in pseudo-labels data. The Couple Learning method can extract more information in the compound training data. These experimental results on Task 4 of the DCASE2020 challenge demonstrate the superiority of the proposed method, achieving about 39.18% F1-score on public eval set, outperforming the baseline system’s 37.12% by a significant margin.

Index Terms— semi-supervised, pseudo-label, Mean Teacher, sound event detection

1. INTRODUCTION
Sounds carry a large amount of information about our everyday life environment and physical events. Developing signal processing methods to automatically extract this information has huge potential in several applications, for example, searching for multimedia based on its audio content, making context-aware mobile devices, robots, cars. However, a significant amount of research is still needed to reliably recognize sound scenes and individual sound sources in realistic soundscapes. Promoted by the annual DCASE challenges [1][2][3], the SOTA in weakly labeled semi-supervised sound event detection (SED) has progressed rapidly recent years. Several approaches have been proposed for weakly labeled SED [4][5][6][7]. (Stacked convolutional and recurrent neural network [4], Adaptive pooling operators [5], attentional supervision [6].) Most recent SOTA approaches, e.g., [6][8][9][10], rely on neural attention. To perform audios tagging a neural network learns to attend to the time range where the sound event is active. Afterwards the network can be employed to locate sound events in time although no strong labels have been used during training. Semi-supervised SED is dominated by teacher student approaches [11][12], where the teacher and student networks are jointly trained employing an additional loss for consistency between their predictions on unlabeled data.

Before this paper, many scholars separate the use of pseudo-labels data from the Mean Teacher method. Some scholars focus on the improvement of pseudo-labels data on semi-supervised tasks [13][14][15], and some scholars focus on the improvement of semi-supervised tasks by Mean Teacher method [16]. In this paper, the authors present the Couple Learning method which employs pseudo-labels data jointly with Mean Teacher in semi-supervised SED tasks. Description of the method is given in Fig. 1. The Couple Learning method has two main stages. The first stage is designed to employ a well-trained model to make pseudo weak and strong labels for the original unlabeled data and also make pseudo strong labels for the original weakly labeled data. The pseudo-labels generated here contain a lot of noise. The second stage is designed to employ the Mean Teacher model which is based on a convolutional recurrent neural network (CRNN) model to train the final model using at inference time. The Mean Teacher model employs the combination of baseline dataset and generated pseudo dataset. The baseline dataset contains few numbers of strongly labeled data and weakly labeled data and large number of unlabeled data. The generated pseudo dataset contains pseudo-strong labels generated from unlabeled data (UPS), pseudo-weak labels generated from unlabeled data (UPW) and pseudo-strong labels generated from weakly-labeled data (WPS) data. Experiments show that using pseudo-labels in Mean Teacher model can improve its performance. This method can actually be employed in other tasks.
2. METHODOLOGY

2.1. Couple Learning

To overcome the limitations of the Mean Teacher based CRNN model, the authors propose the Couple Learning method to provide more effective information for model training. The PLG model can extract information from the raw data by way of generating pseudo-labels, but it also introduces noise which will have a negative impact on the training process. The Mean Teacher method just has the noise suppression mechanism. It employs unlabeled data to penalize noise. It maintains an exponential moving average of label predictions on each training example, and penalizes predictions that are inconsistent with this target. Therefore, the contribution of the Couple Learning method is that it uses the information in the compound data more effectively. From this perspective, the Mean Teacher method and the PLG model are the best partners.

More formally, the authors define the classification cost $J_1$ as the expected distance between the prediction (with weights $\theta$, real-input $x$, and pseudo-input $\chi$) and the label (with real-label $y$ and pseudo-label $y'$). The classification cost of Couple Learning method can be described as:

$$J_1(\theta) = -\frac{1}{N} \left\{ \sum y \log[f(x, \theta)] + \sum y' \log[f(\chi, \theta)] \right\}$$  \hspace{1cm} (1)

The authors employ cross entropy as the classification cost in most of our experiments.

The authors define the consistency cost $J_2$ as the expected distance between the prediction of the student model (with weights $\theta'$ and noise $\eta'$) and the prediction of the teacher model (with weights $\theta$ and noise $\eta$). The consistency cost of Couple Learning method can be described as:

$$J_2(\theta) = E_{x, \eta', \eta} \left[ \|f(x, \theta', \eta') - f(x, \theta, \eta)\|^2 \right]$$  \hspace{1cm} (2)

The authors can approximate the consistency cost function $J_2$ by sampling noise $\eta$, $\eta'$ at each training step with stochastic gradient descent. The authors employ mean squared error (MSE) as the consistency cost in most of our experiments \cite{14}.

2.2. PLG model

The greatest challenge to semi-supervised tasks is that there are too few labeled data to distill knowledge. The target of this task is to extract knowledge as much as possible from unlabeled or weakly labeled data. The PLG model reached this target. The next task is to find a suitable PLG model. In this paper, the authors employed the Mean Teacher CRNN model itself to implement the PLG model. The Mean Teacher CRNN model is the baseline of DCASE2020 challenge task4. The PLG model can have many choices, it can be other network structures, it can be an ensemble of multiple neural networks \cite{17} or it can be a rough manual labeling system. The labeled data generated by the PLG model contains a lot of noise, even close to 50%.

2.3. Mean Teacher CRNN model

Our baseline system is inspired by the baseline of DCASE2020 task4 \cite{16}. It employs a Mean Teacher method and a CRNN model. Each batch contains a combination of unlabeled, weakly and strongly labeled clips during training stage. The system achieves a goal which not only makes effective use of
labeled data and unlabeled data, but also integrates strongly-labeled data and weakly labeled data. The Mean Teacher method contains a student model and a teacher model, both models employ a CNN block and two RNN blocks, both RNN is bidirectional gated recurrent unit (GRU).

2.3.1. Combination of labeled and unlabeled clips

The system employs a Mean Teacher method which is a combination of two models, a student model and a teacher model. The two model both have the same architecture. The student model is employed at inference time in final, while the teacher model is designed to guide the student model during trainings. An exponential moving average of the student model’s weights is computed as the teacher model’s weight. This method allows for exploiting both labeled and unlabeled data through the consistency costs. The student model is trained with the classification costs only on labeled clips. The teacher model is not trained, its weights are a moving average of the student model at each epoch. During trainings, the teacher model receives the same input as the student model but with additive Gaussian noise which is brought by unlabeled clips. It helps to train the student model via a consistency loss for predictions for all the clips in the batch.

2.3.2. Combination of strongly-labeled and weakly-labeled clips

The model is a combination of convolutional neural network (CNN) and recurrent neural network (RNN) called CRNN. The uniqueness of this model is the calculation of the cost. The model organically combines strongly-labeled clips and weakly labeled clips through two sets of parallel loss functions. The authors calculate the classification cost which employs binary cross-entropy between the student model and the labels. The binary cross-entropy loss is computed at the frame level for the strongly-labeled clips and at the clip level for the weakly labeled clips. At the same time, the authors calculate the consistency cost which employs mean-squared error between the student model and the teacher model. The mean-squared error is computed at the frame level for the strongly-labeled synthetic clips and at the clip level for the weakly labeled clips.

3. EXPERIMENTS

The proposed method was applied to the DCASE 2020 Challenge Task 4. The experiments are designed to demonstrate the performance of our proposed Couple Learning system. The authors have done three sets of experiments to verify the contribution of the Couple Learning method. Details of baseline system are in section 2.3.
validation set. The experiments proved the contributions of Mean Teacher method and PLG models.

| Model                  | Validation | public eval |
|------------------------|------------|-------------|
| CRNN                   | 28.14      | 33.56       |
| + Mean Teacher(Baseline)| 32.39      | 37.12       |
| + PLG                  | 30.04      | 35.26       |
| + Mean Teacher + PLG   | 33.93      | 39.18       |

Table 1. EB-F1(%) results with different methods

| PLG Model      | FBCRNN | Baseline |
|----------------|--------|----------|
| Baseline       | 32.39  | 32.39    |
| + UPW          | 33.95  | 30.06    |
| + WPS          | 35.80  | 32.15    |
| + UPS          | 37.24  | 32.42    |
| + UPS + WPS    | 37.97  | 33.52    |
| + UPS + WPS + UPW | 41.33  | 33.93    |

Table 2. EB-F1(%) results with different pseudo-labels on validation set

4.2. Contributions of the three kinds of pseudo-labels

In order to further prove the performance of the PLG model on semi-supervised SED task, the authors did the following experiments. Our results are given in Table 2. The table presents the performance of semi-supervised SED depending on the pseudo-labels data or not. The original baseline was not using pseudo-labels data. Adding additional pseudo-labels data to the train set improves the performance because the information included in the data is effectively mined. The performance is improved obviously when adding UPW, WPS, UPS individually. We obtained the best performance when adding all of UPW, WPS and UPS. Based on these results, this paper concludes that pseudo-labeled data is necessary for sound event detection.

As shown in Table 2. The authors employed forward-backward convolutional recurrent neural network (FBCRNN) model [17] as the PLG model in the first column. The EB-F1 of the baseline system is 32.39%, while the EB-f1 can reach to 30.06% when the authors added the UPW data. It can reach to 32.15% when added the WPS data. It also can reach to 32.42% when added the UPS data. These three results are all close to the baseline. The EB-F1 up to 33.52% when added both the UPS and WPS data to train a model. Finally, the authors added all the three data to train a model, the EB-F1 up to 33.93%, increased by 4.67% relative to baseline.

4.3. Contribution of the Couple Learning method

As shown in Fig. 2, from overall, the baseline system employed Hybrid, which is an ensemble model [17] as PLG is the best, employed FBCRNN model as PLG is the second, employed itself (Mean Teacher CRNN model) as PLG is the third. Their performances are higher than baseline.

This set of experiments also verified the impact of different input-order of real-labels and pseudo-labels in an epoch. Real first (RF) means that all real-labels data are arranged before pseudo-labels data in an epoch. Pseudo first (PF) means that all pseudo-labels data are arranged before real-labels data in an epoch. Random means that all pseudo-labels and real-labels data randomly arrange in an epoch. In other words, PF and RF only employ the Couple Learning method in a part of each epoch, and random employs the Couple Learning method in the whole of each epoch.

The random fully mixes the unlabeled data and the pseudo-labeled data on each batch, and it has the best performance on the three PLG models. PF is better than RF when Hybrid is employed as a PLG model, RF is better than PF when FBCRNN is employed as a PLG model, and RF is better than PF when the baseline itself is employed as a PLG model. These experimental results further proved that the unlabeled data has a noise suppression performance on the pseudo-labeled data in the Couple Learning method.

5. CONCLUSION

In this paper the authors provide the details of the Couple Learning method for a semi-supervised task. The method is based on the baseline of the DCASE2020 task4, which em-
ploys Mean Teacher method with CRNN model, the PLG
model is then incorporated into the system to further improve
the performance. Our experiments claimed that both the PLG
model and the Mean Teacher method bring improvements in
system performance, and the combination of them brought
greater improvement. Therefore, the authors conclude that
Mean Teacher and pseudo-labels are good partners. This pa-
ter proved that the Couple Learning method is a simple and
powerful solution. Furthermore, more suitable loss functions,
more perfect network structures or more fitting PLG models
have great potential to improve the system performance. The
authors hope to verify the contribution of the Couple Learning
method on more semi-supervised tasks in future work.

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