Selective Pseudo-labeling and Class-wise Discriminative Fusion for Sound Event Detection

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Abstract

In recent years, exploring effective sound separation (SSep) techniques to improve overlapping sound event detection (SED) attracts more and more attention. Creating accurate separation signals to avoid the catastrophic error accumulation during SED model training is very important and challenging. In this study, we first propose a novel selective pseudo-labeling approach, termed SPL, to produce high confidence separated target events from blind sound separation outputs. These target events are then used to fine-tune the original SED model that pre-trained on the sound mixtures in a multi-objective learning style. Then, to further leverage the SSep outputs, a class-wise discriminative fusion is proposed to improve the final SED performances, by combining multiple frame-level event predictions of both sound mixtures and their separated signals. All experiments are performed on the public DCASE 2021 Task 4 dataset, and results show that our approaches significantly outperform the official baselines, the collar-based F1, PSDS1 and PSDS2 performances are improved from 44.3%, 37.3% and 54.9% to 46.5%, 44.5% and 75.4%, respectively.

Index Terms: Sound event detection, Sound Separation, pseudo-labeling, class-wise discriminative fusion

1. Introduction

Sound conveys a wide range of important information in our daily lives. These sounds make us better to understand changes in our physical environment and to perceive events occurring around us. Sound event detection (SED) is a task of detecting both the onset and offset of a sound event. It has widespread applications for real-world intelligent human-interaction systems, including smart home devices, mobile devices, smart headphones, etc. However, there are many challenges in real SED applications, including audio signal degradation from acoustic reverberation, or the real recordings may contain not only overlapping predefined target events, but also nontarget events and a large number of environmental noise. These overlapping recordings are normally called sound mixtures in the sound separation (SSep) field, their complicated acoustic nature brings more interference to the distinction of target event categories and the detection of event time-stamps.

In the past few years, as one of the most important challenges in SED tasks, the overlapping sound events problem has been tackled in many perspectives. In [6], authors trained the SED model as a multi-label system where the most energetic sound events are usually detected more accurately than the rest.

While in [6], a set of binary classifiers were built to alleviate the SED overlapping problem. Other approaches based on signal processing techniques were also investigated, such as using factorization techniques on the inputs of the classifier [5, 7], or exploiting spatial information when available [5, etc.

In recent years, with the Task 4 Challenge of Detection and Classification of Acoustic Scenes and Events (DCASE) that launched in 2020 and 2021 [9, 10], more and more works tend to explore methods for the multiple events overlapping problem in SED. Start from these two challenges, participants are encouraged to propose systems that use sound separation jointly with the sound event detection. Organizers provided a baseline SSep model [11, 12] that can be used for pre-processing to separate overlapping events and extract foreground from the background sounds [13]. Motivated by DCASE Task 4, [14] combined the SSep and SED by fusing the general SED systems results with SSep-SED systems that were trained using separated sources from an SSep system; [9] proposed an SED-aware separation method to remove the background noise rather than full foregrounds separation from the mixtures. Intuitively, sound separation seems like a natural candidate to deal with the overlapping SED [15, 16]. However, there are still many problems when combining the SSep and SED, for example, the separation system has its own error, which will lead to wrong guidance of the SED system training, and if we joint train the SSep and SED models, it is very difficult to balance multiple loss function between these two tasks. Therefore, how to effectively leverage the sound separation to improve SED with overlapping acoustic events is very fundamental and challenging.

In this paper, we propose a new framework to utilize the sound separation for reducing the impact of overlapping problem in SED. Two main contributions are provided: 1) A novel selective pseudo-labeling (SPL) approach is proposed. It produces high confidence single-event clips from the blind sound separation outputs, by comparing their weakly labels with the corresponding pseudo-labels that predicted by a well pretrained audio tagging model. These single-event clips are then used to improve the SED by fine-tuning the original pre-trained model with a multi-objective learning strategy; 2) We provide a class-wise discriminative fusion to exploit the complementary information between different SED models with mixture and the SSep separated single-event recording inputs. This fusion is performed at the frame-level predictions, using discriminative class-wise weights that optimized on the SED development set. All experiments are performed on DCASE 2021 Task 4 challenge, the “Sound Event Detection and Separation in Domestic Environments”. Results show that our proposed methods can achieve competitive performances with the top ranked systems that reported in the DCASE challenge.
2. Blind Sound Separation

In DCASE 2021 Task 4 challenge, the official sound separation and sound event detection baseline (we call it as SSep-J-MT) used a well pre-trained sound separation model to further improve the pre-trained SED model [17]. This separation model follows a similar universal sound separation system architecture as in [11], it can separate an input sound mixture into a fixed number of sources. The model is a TDCN++ masking network using STFT analysis/synthesis, and it was trained in an unsupervised way with MixIT criterion [13] on the YFCC100m (1600 hours) dataset [18]. Using this well pre-trained SSep model, all the Task 4 data was separated in an offline pre-processing way. Then, the pre-trained SSep model was fine-tuned on all of the separated sound events. In SSep-J-MT [13], predictions of target events were obtained by ensembling the fine-tuned SED model with the original SED model using a learnt weight during system training. The same pre-trained SSep model in the SSep-J-MT system is also used in our work.

3. Proposed methods

Unlike using all of the separated sounds to fine-tune the original SED model in the DCASE 2021 Task 4 SSep-J-MT baseline, in this work, we propose a new joint framework to combine the SSep and SED models to enhance the overall sound event detection performance. The whole framework is illustrated in Fig. 1. It contains four main modules, including the (a) offline SSep pre-processing, (b) selective pseudo-labeling, (c) multi-objective model fine-tuning and (d) class-wise discriminative score fusion. Details of these modules are presented in the following sections.

3.1. Selective Pseudo-labeling

Detecting multiple overlapping sound events are typically more difficult than isolated events. SSep can be used for SED by first separating the single-event sounds in a mixed signal, and then applying SED on each of them to improve the detection performance [15] [16]. Generally, the results obtained on well separated signals should be more accurate than the ones on original mixtures. However, using SSep to improve SED is not a simple problem. The separated sounds may contain errors or still a mixed signal, they can also be background noise or non-target events. The confidence of these separated signals are highly dependent on how good the SSep model is. Therefore, how to well exploit these separated signals during combing the SSep and SED becomes interesting and important.

In this study, we aim to well utilize the available weakly and strongly labeled mixtures to improve the SED system, by choosing high-quality separated sounds which contain only one single event that produced from an SSep system to update the original SED model. Details are illustrated in Fig. 1(b). Given an input mixture signal $x$, it first be separated into $N$ clips, $x_1, x_2, \ldots, x_N$ by a well pre-trained SSep system, TDCN++. The blind separated sound clips are used to fine-tune the original SED model that trained on the mixtures $x$. In this study, we propose a new joint framework to combine the SSep and SED models to enhance the overall sound event detection performance. The whole framework is illustrated in Fig. 1. It contains four main modules, including the (a) offline SSep pre-processing, (b) selective pseudo-labeling, (c) multi-objective model fine-tuning and (d) class-wise discriminative score fusion. Details of these modules are presented in the following sections.

$$S = \{(x_i, L_i) | L_i \in \{G_1, G_2, \ldots, G_k\}, i = 1, 2, \ldots, N\}$$

where $S$ is the set of selected separated single-event clips whose pseudo-labels belong to the weak labels of input mixture $x$. $G_i$ is the $i$-th weak label of $x$ and $k$ is the target event source number that labeled for mixture $x$, such as, if $x$ contains cat, dog, dishes and speech, then $k = 4$. $N$ is 1 plus the maximum source number of each audio mixture in the development set, because the input mixture may contain non-target events or background noise that are taken as ‘other’ class in our AT model.

Figure 1(c) demonstrates an example of the pseudo-label selection process (PL selection module in Fig. 1(b)). Providing each separated signal with pseudo-label, we compare each pseudo-label with the ground-truth (collected from weak/strong label) of event classes that labeled for target sources in the mixture signal, if it is single-event and can be found in the ground-truth, then we think that, this single-event clip is separated well by an SSep, and its pseudo-label can be trust. As in Fig. 1(c), only the separated single-event clip with cat and speech are selected for next multi-objective SED model fine-tuning. Actually, in our selective pseudo-labeling, only the weak labels of training mixtures are required to guarantee the quality of selected single-event pseudo-labels of the blind sound separation outputs.

3.2. Multi-objective Model Fine-tuning

In the SSep-J-MT baseline of DCASE 2021 Task 4 [19], all the blind separated sound clips are used to fine-tune the original sound event detection model that trained on the mixtures with a multi-class network targets. However, as discussed in the above section, the separation quality highly depends on the
SSep model, these separated sound clips may still contain many errors. The official SSep-J-MT baseline may bring these errors into the SED model fine-tuning and constrain the SSep potential for improving the SED performance.

In this work, as the official SSep-J-MT, we still use the same multi-objective model fine-tuning approach but different inputs to improve the final SED model. Details are shown in Fig(1c). Instead of using all the blind separated clips, we only take the high-quality single-event clips that selected according to Equation (1) to perform the SED model fine-tuning. In Fig(1c), Sum all means directly adding all the selected single-event clips together to form a new mixture sound. F-SED represents the fine-tuned SED model using selected single-event clips. pre \( \hat{N} \) means the sound detection prediction of \( \hat{N} \)-th input clip. With the pre-trained SED model as initialization, the F-SED model is fine-tuned using a multi-objective way to obtain the final prediction as follows:

\[
P_{\text{final}} = \alpha \cdot P_{\text{SED}} + (1 - \alpha) \cdot P_{F-\text{SED}}
\]

where \( P_{\text{final}} \) is the final prediction of the joint module J-SED (in Fig(1c)) given a random input sound mixture \( x \). \( P_{\text{SED}} \) and \( P_{F-\text{SED}} \) represent the SED model and F-SED model predictions respectively, and \( \alpha \) is the weight parameter to be learnt.

Given the \( P_{\text{final}} \) and freezing the pre-trained SED model, the whole F-SED model is finally fine-tuned using the standard total connectional binary cross entropy (BCE) loss for weakly supervised teacher-student structure SED model training. Details of training strategy can be found in our previous work [21].

3.3. Class-wise Discriminative Score Fusion

Combining the sound event decisions of multiple SED models often can result in better overall performance than using single model. In this study, based on the provided SSep-SED joint framework, we propose to combine multiple models at frame-level predictions, using the weights that calculated to reflect the class-wise sound event discrimination. The idea is motivated by the weighted average of softmax form that used in [23, 24]. Given \( M \) SED models, and frame-level posterior probability \( P_{cm} \) of class \( c, c \in \{1, 2, ..., C\} \) on model \( m, m \in \{1, 2, ..., M\} \), the final ensemble system posterior probability of each frame belongs to class \( c \), \( P_{c} \) is defined as:

\[
P_{c} \left( P_{cm}, F_{1m} \right) = \frac{1}{M} \sum_{m=1}^{M} P_{cm} \left[ \frac{\exp \left( \beta \cdot F_{1m} \right)}{\sum_{c'} \exp \left( \beta \cdot F_{1m} \right)} \right]
\]

where \( F_{1m} \) is the development set class-wise F1-score [24] of class \( c \) on model \( m \). \( \beta \) is a tunable scalar parameter.

From Equation (3), it’s clear that, the prediction combination weight for each \( P_{cm} \) can reflect the class-wise importance of model \( m \) for event class \( c \), it means that if model \( m \) can achieve better F1-score on the development set, then, this model has a better discrimination to class \( c \), a larger weight will be assigned to \( P_{cm} \) during the multiple prediction combination.

The specific prediction combination is shown in Fig(1d). During SED inference, for any input sound mixture \( x \), we obtain three frame-level predictions \( P_{cm} \) and class-wise F1-scores using the joint module (J-SED), the pre-trained SED and the F-SED model, respectively. The former module using all the blind separated clips as input, the later two models directly take the raw mixture signal as input. The final prediction is achieved by combining the three outputs using Equation (3). As three SED models trained from different ways, the joint module pays more attention to the well separated single-event segments, while the original pre-trained model and F-SED model may effectively avoid the errors introduced by SSep. Therefore, we think that using class-wise discrimination weights can well exploit the complementary information between different models, by leveraging the individual advantage of each model to produce better overall sound event detection performance.

4. Experiments and Results

4.1. Datasets and Features

All our experiments are performed on the dataset of DCASE 2021 Task4 Challenge [25]. It is a sound event detection task in domestic environments. The target of the systems is to provide not only the event class but also the event time localization given that multiple events can be present in an audio recording. The training set includes 1,578 clips (2,244 class occurrences) of weakly labeled, 14,412 clips of unlabeled and 10,000 strongly labeled audio clips. 1,168 strongly labeled clips are taken as the development clips. We extract 128 log mel-band magnitudes as features, and each 10-second audio clip is transformed into 512 frames.

4.2. Experimental setups

We use the two DCASE 2021 Task 4 baseline systems [25] as our baselines, one is the standard Mean-Teacher (MT) model [26, 27], and the other is the MT with sound separation (SSep-J-MT) [13]. Both MT and SSep-J-MT models have the same teacher-student asymmetric neural network structure, and Fig(2) shows the details of their student branch (the teacher branch is exactly the same). With the same model structure as MT, the AT, SED and F-SED models in the joint framework of Fig(1) are improved by using our previous proposed adaptive focal loss training strategy and event-specific post-processing technique during model training [21, 23].

The event-based F1-score (Collar-based F1) is used to measure the SED system performance. It is computed with a 200ms collar on onsets and a 200ms/20% of the events length collar on offsets [24]. In order to understand better what the behavior for different real scenarios that emphasize different systems properties, DCASE 2021 Task 4 provided two types of poly-phonic sound event detection scores (PSDS), PSDS1 and PSDS2 [29] as contrastive measures to evaluate systems. F1-scores are computed using a single operating point (decision thresholds=0.5) while PSDS values are computed using 50 operating points (linearly distributed from 0.01 to 0.99).

4.3. Results and Discussions

4.3.1. Overall Results

All our techniques are evaluated on the DCASE 2021 Task 4 validation set, the ground-truth of test set is not released. Results are shown in Table(1) MT and SSep-J-MT are the official baselines. SED, F-SED and J-SED represent three
different sound event detection models that shown in Fig 1. The detection inference procedures of system 2, 6 and 7 are shown in Fig 1(b). The prefix SSep of system 1, 3 and 4-5 means the input mixture sounds are first separated using the offline SSep pre-processing (Fig 1(a)) before they are fed into SED, F-SED and J-SED models during inference, while systems 0, 2 and 7 without SSep prefix means directly using the original mixture sound as model inputs during SED inference. System 3 is exactly the same as system 1 except for replacing the MT model by our SED, and it is also the same with system 6 without our proposed selective pseudo-labeling block. System 8, 9 and 10 are the three system fusion results using simple equal weight average, logistic regression [30] and our proposed class-wise discriminative fusion that performed on frame-level posterior probability of system 2, 6 and 7, respectively.

Table 1: F1-scores (%) and PSDS (%) measures of the proposed methods.

| ID | System                  | Collar-based F1 | PSDS1 (%) | PSDS2 (%) |
|----|-------------------------|-----------------|-----------|-----------|
| 0  | MT                      | 40.1            | 34.2      | 52.7      |
| 1  | S Sep−J−MT [13]         | 44.3            | 37.3      | 54.9      |
| 2  | SED                     | 42.0            | 41.8      | 71.7      |
| 3  | S Sep−J−SED (w/o SPL)   | 43.0            | 42.0      | 72.1      |
| 4  | S Sep−SED               | 42.8            | 41.8      | 71.9      |
| 5  | S Sep−F−SED             | 43.6            | 42.1      | 72.2      |
| 6  | S Sep−J−SED             | 44.4            | 42.8      | 73.6      |
| 7  | F−SED                   | 42.6            | 42.1      | 74.1      |
| 8  | Avg(2,6,7)              | 45.6            | 43.2      | 74.5      |
| 9  | LR(2,6,7)               | 45.7            | 42.9      | 74.6      |
| 10 | Class-wise(2,6,7)       | 46.5            | 44.5      | 75.4      |

From Table 1, first, we see system 2, the SED achieves significant performance gains over system 0, MT, the collar-based F1 is improved from 40.1% to 42.0%, and PSDS1, PSDS2 are improved from 34.2%, 52.7% to 41.8% and 71.7%. These big gains indicate that, our previously proposed adaptive focal loss and ESP are very effective to improve the baseline MT. Second, comparing system 0 and 1, it’s obvious to see the effectiveness of sound separation to SED, and from system 2 to 3, we also see performance gains are brought by S Sep with our SED system, even these gains are relatively small because of the improved SED. This means that the S Sep can reduce the impact of sound overlapping in SED to some extent.

Third, system 4, 5, 6 shows using blind separated clips to test three different models in Fig 1(c). It’s clear to see that, the fine-tuned model, F−SED is better than original SED model. And the joint module, J−SED is better than both SED and F−SED. It indicates that the multi-objective model fine-tuning can effectively improve the detection ability of SED system. Because the final prediction of J−SED is the combination of SED and F−SED with a learnt weight. Therefore, for SED inference with S Sep pre-processing, we only use system 6, S Sep−J−SED for further system combination.

Fourth, by comparing system 6 and 3, it’s clear that our proposed selective pseudo-labeling brings absolute 1.4%, 0.8% and 1.5% collar-based F1, PSDS1 and PSDS2 improvement, respectively. And system 6 also outperforms the official baseline system 1 significantly in both PSDS1 and PSDS2.

Finally, to well exploit the complementary information in all the three available SED models, the pre-trained SED, the fine-tuned F−SED and their joint model J−SED, we choose to perform system fusion of 2, 6 and 7 to further improve the final SED predictions, because they use the original input mixture and S Sep separated sounds in different ways with their best attempts. Comparing results of system 8, 9, 10, we see the proposed class-wise discriminative fusion not only performs better than other two traditional system fusion methods, but also achieves much better performances than three single systems, either in collar-based F1, or in the PSDS values.

4.3.2. Class-wise Results

Table 2: Class-wise performance (in collar-based F1-score (%)) with different sound event detection systems.

| Event class/System | SED | F−SED | S Sep−J−SED | Class-wise(2,6,7) |
|--------------------|-----|-------|-------------|-------------------|
| Alarm/bell/ringing | 38.2| 38.3  | 41.1        | 42.3              |
| Blender             | 43.3| 43.2  | 44.6        | 44.8              |
| Cat                | 69.2| 69.4  | 68.7        | 71.0              |
| Dishes             | 25.2| 26.1  | 32.3        | 33.6              |
| Dog                | 40.8| 45.1  | 38.9        | 46.5              |
| Electric slaver/toothbrush | 17.3 | 17.4 | 19.9 | 20.3 |
| Frying             | 45.8| 45.0  | 48.9        | 49.2              |
| Running water      | 36.1| 33.9  | 43.6        | 43.5              |
| Speech             | 52.4| 53.7  | 56.7        | 59.2              |
| Vacuum cleaner     | 51.7| 53.9  | 49.3        | 54.1              |
| Collar-based F1 (Average) | 42.0 | 42.6 | 44.4 | 46.5 |

Table 2 presents the class-wise collar-based F1-scores for system 2(SED), 6(F−SED), 7(SSep−J−SED) and their fusion results. It’s clear that different system has its own advantage to detect different types of target events. Such as, SED and F−SED are better to detect ‘Cat’, ‘Dog’ and ‘Vacuum cleaner’, while SSep−J−SED has more advantage to detect other 7 types of events. Almost all the events detection performances are improved by class-wise discriminative fusion, especially the most obvious gains as shown in bold for ‘Alarm/bell/ringing’, ‘Cat’, ‘Dishes’, ‘Dog’ and ‘Speech’, and the average F1 is also much better than single systems. It means that the proposed fusion method can well exploit the detection ability of different models for different event classes.

5. Conclusion

In this work, we propose a new training strategy of using sound separation to enhance SED system. Different from previous works that directly using the blind separated sound clips to fine-tune the SED model, we propose a selective pseudo-labeling (SPL) method to select the high quality separated recordings for updating a joint SED model, using the multi-objective model fine-tuning strategy. In addition, a class-wise discriminative score fusion is further proposed, it is performed at the frame-level posterior probabilities to improve the final SED system performance. This score fusion uses the class-wise weights to exploit each system’s advantage on different sound event detection. The proposed techniques are validated on the dataset of DCASE 2021 Task 4 Challenge, experimental results show that both the proposed SPL and class-wise based score fusion achieve significant performance improvements over the official baselines, and our final SED system performances are competitive with the ones from top ranked systems in DCASE 2021 Task 4 Challenge. Our future work will focus on designing a better separation system to improve the SED system.
6. References

[1] A. Southern, F. Stevens, and D. Murphy, “Sounding out smart cities: Auralization and soundscape monitoring for environmental sound design,” *The Journal of the Acoustical Society of America*, vol. 141, no. 5, pp. 3880–3880, 2017.

[2] R. Radhakrishnan, A. Divakaran, and A. Smaragdis, “Audio analysis for surveillance applications,” in *IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, 2005, pp. 158–161.

[3] E. Benetos, G. Lafay, M. Lagrange, and M. D. Plumbley, “Detection of overlapping acoustic events using a temporally-constrained probabilistic model,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2016, pp. 6450–6454.

[4] J. Salamon and J. P. Bello, “Feature learning with deep scattering for urban sound analysis,” in *IEEE European Signal Processing Conference (EUSIPCO)*, 2015, pp. 724–728.

[5] R. Serizel, N. Turpault, A. Shah, and J. Salamon, “Sound event detection in synthetic dynamic environments,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 86–90.

[6] A. Mesaros, T. Heittola, and T. Virtanen, “Tut database for acoustic scene classification and sound event detection,” in *24th European Signal Processing Conference (EUSIPCO)*, 2016, pp. 1128–1132.

[7] V. Bisot, S. Essid, and G. Richard, “Overlapping sound event detection with supervised nonnegative matrix factorization,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2017, pp. 31–35.

[8] S. Adamavane, A. Politis, and T. Virtanen, “Multichannel sound event detection using 3D convolutional neural networks for learning inter-channel features,” in *IEEE International joint conference on neural networks (IJCNN)*, 2018, pp. 1–7.

[9] S. Cornell, G. Pepe, E. Principi, M. Pariente, M. Olivera, L. Gabrielli, and S. Squartini, “The univmp-inria systems for the dcase 2020 task 4,” in *IEEE DCASE2020 Challenge*, Tech. Rep., 2020.

[10] N. Turpault, R. Serizel, S. Wisdom, H. Erdogan, J. R. Hershey, E. Fonseca, P. Seetharaman, and J. Salamon, “Sound event detection and separation: a benchmark on dased synthetic soundscapes,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2021, pp. 840–844.

[11] I. Kavaleros, S. Wisdom, H. Erdogan, B. Patton, K. Wilson, J. Le Roux, and J. R. Hershey, “Universal sound separation,” in *IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA)*, 2019, pp. 175–179.

[12] S. Wisdom, E. Tzinis, H. Erdogan, R. J. Weiss, K. Wilson, and J. R. Hershey, “Unsupervised sound separation using mixtures of mixtures,” arXiv, e-prints, pp. arXiv–2006, 2020.

[13] N. Turpault, S. Wisdom, H. Erdogan, J. Hershey, R. Serizel, E. Fonseca, P. Seetharaman, and J. Salamon, “Improving sound event detection in domestic environments using sound separation,” arXiv, preprint arXiv:2007.03932, 2020.

[14] Y. Huang, L. Lin, S. Ma, X. Wang, H. Liu, Y. Qian, M. Liu, and K. Ouch, “Guided multi-branch learning systems for dcase 2020 task 4,” arXiv, preprint arXiv:2007.10638, 2020.

[15] T. Heittola, A. Mesaros, T. Virtanen, and M. Gabbouj, “Supervised model training for overlapping sound events based on unsupervised source separation,” in *IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP)*, 2013, pp. 8677–8681.

[16] Q. Kong, Y. Wang, X. Song, Y. Cao, W. Wang, and M. D. Plumbley, “Source separation with weakly labelled data: An approach to computational auditory scene analysis,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 101–105.

[17] N. Turpault, R. Serizel, A. Parag Shah, and J. Salamon, “Sound event detection in domestic environments with weakly labeled data and soundscape synthesis,” in *Workshop on Detection and Classification of Acoustic Scenes and Events (DCASE)*, United States, October 2019.

[18] B. Thomée, D. A. Shamma, G. Friedland, B. Elizalde, K. Ni, D. Poland, D. Borth, and L.-J. Li, “Yfcc100m: The new data in multimedia research,” *Communications of the ACM*, vol. 59, no. 2, pp. 64–73, 2016.

[19] E. Tzinis, S. Wisdom, J. R. Hershey, A. Jansen, and D. P. Ellis, “Improving universal sound separation using sound classification,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 96–100.

[20] [http://dcase.community/challenge2021](http://dcase.community/challenge2021)

[21] Y. Liang, Y. Long, Y. Li, J. Liang, and Y. Wang, “Joint framework with deep feature distillation and adaptive focal loss for weakly supervised audio tagging and acoustic event detection,” *Digital Signal Processing*, p. 103446, 2022.

[22] J. Salamon, B. McFee, P. Li, and J. Bello, “Multiple instance learning for sound event detection,” in *IEEE DCASE Challenge*, Munich, Tech. Rep., 2017.

[23] T. Hayashi, T. Yoshimura, and Y. Adachi, “Conformer-based id-aware autoencoder for unsupervised anomalous sound detection,” in *IEEE DCAE2020 Challenge*, Tech. Rep., 2020.

[24] A. Mesaros, T. Heittola, and T. Virtanen, “Metrics for polyphonic sound event detection,” *Applied Sciences*, vol. 6, no. 6, p. 162, 2016.

[25] N. Turpault and R. Serizel, “Training sound event detection on a heterogeneous dataset,” arXiv, preprint arXiv:2007.03931, 2020.

[26] L. Delphín-Poulat and C. Plapous, “Mean teacher with data augmentation for dcase 2019 task 4,” *Orange Labs Lannion, France*, Tech. Rep., 2019.

[27] A. Tarvainen and H. Valpola, “Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results,” in *Advances in neural information processing systems (NIPS)*, 2017, pp. 1195–1204.

[28] Y. Liang, T. Tang, and Y. Long, “Adaptive focal loss with data augmentation for semi-supervised sound event detection,” in *IEEE DCASE2021 Challenge*, Tech. Rep., June 2021.

[29] C. Bilen, G. Ferroni, F. Tuveri, J. Azcarreta, and S. Krstulović, “A framework for the robust evaluation of sound event detection,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 61–65.

[30] N. Brümmner, “Focal multi-class: Toolkit for evaluation, fusion and calibration of multi-class recognition scorers,” Software available at [http://sites.google.com/site/nikobrummer/focalmulticlass](http://sites.google.com/site/nikobrummer/focalmulticlass), vol. 33, p. 39, 2007.