ADDRESSING MISSING LABELS IN LARGE-SCALE SOUND EVENT RECOGNITION USING A TEACHER- STUDENT FRAMEWORK WITH LOSS MASKING

Eduardo Fonseca\textsuperscript{1}\textsuperscript{*}, Shawn Hershey\textsuperscript{2}, Manoj Plakal\textsuperscript{2}, Daniel P. W. Ellis\textsuperscript{2}, Aren Jansen\textsuperscript{2}, R. Channing Moore\textsuperscript{2}, Xavier Serra\textsuperscript{1}

\textsuperscript{1}Music Technology Group, Universitat Pompeu Fabra, Barcelona \{name.surname\}@upf.edu
\textsuperscript{2}Google Research, New York, NY, USA \{shershey,plakal,dpwe,arenjansen,channingmoore\}@google.com

ABSTRACT

The study of label noise in sound event recognition has recently gained attention with the advent of larger and noisier datasets. This work addresses the problem of missing labels, one of the big weaknesses of large audio datasets, and one of the most conspicuous issues for AudioSet. We propose a simple and model-agnostic method based on a teacher-student framework with loss masking to first identify the most critical missing label candidates, and then ignore their contribution during the learning process. We find that a simple optimisation of the training label set improves recognition performance without additional compute. We discover that most of the improvement comes from ignoring a critical tiny portion of the missing labels. We also show that the damage done by missing labels is larger as the training set gets smaller, yet it can still be observed even when training with massive amounts of audio. We believe these insights can generalize to other large-scale datasets.

Index Terms— Sound event recognition, label noise, missing labels, teacher-student, loss masking

1. INTRODUCTION

As Sound Event Recognition (SER) has gained increasing attention in recent years \cite{1}, research in this field has moved from small datasets encompassing few hours of audio \cite{2,3,4,5}, to larger datasets with much greater coverage and duration \cite{6,7}. A milestone was the release of AudioSet—a dataset of 527 everyday sound classes organized with a hierarchical ontology, that includes around 2 million audio segments of $\approx$10s in its released version \cite{6}. However, large-scale audio datasets inevitably bring in label noise issues, since it is intractable to exhaustively annotate such massive amounts of audio. The resulting issues of less-precise labels can cause various problems including performance decreases and unnecessarily long training times \cite{6}, and can become a critical impediment to the success of SER. Consequently, label noise in SER has lately become a focus of interest. Previous work analyses the impact of label noise in these tasks \cite{9,10}, as well as proposes ways to mitigate its negative effect \cite{11,12,13,14}. A DCASE 2019 Challenge Task was launched to foster research in this topic \cite{2}.

AudioSet presents a number of label noise problems. Some are due to shortcomings in the annotation process, e.g., missing or incorrect labels. Others are related to the hierarchical structure of the AudioSet Ontology, e.g., a segment may be annotated with a leaf class label but not with its parent one, or annotated with a label that is not the most specific within its hierarchical path. Still other problems arise from the temporally-weak labels (i.e., clip-level labels), where the class label may be active only during a small (and unknown) portion of the audio segment. Finally, some semantic inconsistencies may exist as the ontology allows for several sound attributes to be associated to one type of sound event (while not all of them may have been annotated). Despite these label noise problems, they have been directly addressed in only a few of the previous works using AudioSet (e.g., \cite{13,14}), while the majority of efforts focus on deriving more sophisticated network architectures that ignore or downplay the idiosyncrasies of the labeled audio data (e.g., \cite{15,16}).

In this work, we focus on one of the most frequent label noise problems in AudioSet: its missing labels. The study of missing labels in SER has received very little attention. To our knowledge, this specific topic has been covered only by Meire et al. \cite{9}, where robustness to missing labels is studied by gradually simulating them in a synthetic dataset of 20 classes. Our contribution is two-fold. First, we propose a simple and model-architecture-agnostic method based on a teacher-student framework to first identify the most critical potentially missing labels in AudioSet, and then ignore their contribution in the learning process through a loss masking approach. We then analyse the effect of the proposed method via a set of experiments using two model architectures of different capacity and two train sets of different size. We find that a simple optimisation of the training label set can lead to a non-negligible improvement in recognition performance without additional computational cost. We discover that most of the improvement comes from ignoring a critical tiny portion of the missing labels. We also show that the damage done by missing labels (and the performance boost obtained by discarding them) is higher in smaller train sets, but that the impact of these labelling errors can still be observed when training with massive amounts of audio. The ultimate goal is to demonstrate how prior knowledge of a dataset can be leveraged to build simple, efficient, and model-agnostic solutions to improve recognition performance, which can complement other approaches focused on improving network architectures.

This paper is organized as follows. Sections 2 and 3 present the problem of missing labels in AudioSet, and the proposed method. Sections 4 and 5 describe the experimental setup and the experiments conducted. Final remarks are given in Section 6.

2. MISSING LABELS IN AUDIOSET

We refer to missing labels as those labels that would be included in an ideal, exhaustive annotation but which are are missing from the current set. The existence of missing labels in AudioSet is due to the dataset curation process. This process consisted of two steps: the compilation of a list of candidate labels per clip, and the hu-
Fig. 1. Proposed method. First: Identification of potential missing labels per class using teacher’s predictions and creation of enhanced label set. Second: Training a student model while ignoring missing labels through loss masking.

man validation of the labels nominated in that list. This process is also adopted in other large-scale datasets, e.g., [17]. In the case of AudioSet, the list of candidate labels was compiled by means of a series of automatic methods, including the processing of the available metadata (e.g., video title and/or description) as well as a query-by-example method. These methods can be sub-optimal due to the high inter- and intra-class variation of sound events in the AudioSet Ontology [6]. In addition, the list of candidate labels was limited to a maximum of ten labels per clip. There are therefore several ways by which some existing sound events fail to be nominated by the system, or are nominated but ranked below the top ten, thus leading to missing labels. We call the nominated labels that have received human validation explicit labels (that can in turn be positive or negative, depending on the human rating being “Present” or “Not Present”). The remaining labels which are not proposed by the nomination system (the vast majority) are referred to as implicit negative labels, and have received no human validation. In light of the above, it is likely that some of the implicit negative labels are indeed missing (positive) labels.

AudioSet poses a multi-label audio tagging problem, which is usually addressed by a deep neural network with an output layer composed by C independent binary classifiers, with C being the number of classes in the vocabulary. In this setting, binary classification loss functions are typically adopted, composed by two terms, one accounting for the positive examples, and the other for the negative ones. The default option is binary cross-entropy, expressed by:

\[
\mathcal{L} = -\sum_{c=1}^{C} y_c \log(p_c) + (1 - y_c) \log(1 - p_c),
\]  

(1)

where \(p_c\) represents the network output prediction and \(y_c\) the ground truth label for class \(c\). The implicit negative labels are considered negative examples (despite not having been rated), and are, therefore, covered by the second term of (1). If a sound event is actually present, we want the model to emit a high score even if the “Present” label is missing. However, this virtuous behaviour will be penalized, with the penalty increasing for higher output predictions, due to the backpropagation of an artificially high loss contribution, which causes a misleading gradient update. We hypothesize this hinders the learning process to some extent.

3. METHOD

We propose a simple two-step strategy based on a teacher-student framework [1] depicted in Fig. 1. First, a teacher model is trained using the original AudioSet labels, \(y\). We use the trained teacher model to predict scores for the train set, leading to a set of \(\mathbb{R}^{C \times 1}\) scores per audio clip. The teacher’s predicted scores are used to take decisions on labels’ veracity. We focus on the predictions associated with the implicit negative labels as explained in Section 2. Our hypothesis is that the top-scored implicit negative labels (henceforth, top-scored negatives) are likely to correspond mostly to missing “Present” labels, i.e., false negatives. Under this hypothesis, we rank implicit negative labels based on the teacher’s predictions and we create a new label set, \(\tilde{y}\), by flagging a given percentage of the top-scored negatives per class, with the intention of ignoring them later in the students learning. Note that, unlike other teacher-student pipelines where teachers predictions are used as ground truth to train a student (e.g., via soft labels [18][19]), our case features a skeptical teacher whose supervision is used to highlight flaws in the current ground truth, estimating potentially missing labels and flagging them in a new label set. The outcome of this first step is an enhanced training label set, \(\tilde{y}\), where the label information is encoded as multi-hot target vectors with three states (positive, negative, and to-be-ignored labels).

The second step consists of training a student model using the label set optimised through the teachers predictions. The goal here is to ignore the loss contributions of the previously flagged labels in the loss function computation. This is done through a simple loss masking approach, where we minimally modify the student’s learning pipeline so as to create a binary mask of size \(C \times 1\) per input example, using the information encoded in the new target label vector. Each element of the binary mask, \(M_c\), is defined as

\[
M_c = \begin{cases} 
0, & \text{if label is implicit negative and score } > t_c \\
1, & \text{otherwise,} 
\end{cases}
\]

(2)

where \(t_c\) is a per-class threshold computed as a given percentile of the per-class scores distribution. In practice, we compute the loss function \(\mathcal{L}\) following (1) as usual, and then \(M_c\) is applied to the negative term of \(\mathcal{L}\) in order to discard the loss contributions of potentially missing labels.

Another way to introduce this method is from the perspective of knowledge distillation [20]. A typical formulation of distillation is \(\mathcal{L}(\hat{p}_{\text{teacher} \rightarrow \text{student}})\), whereas our method could be formulated as \(\mathcal{L}(f(\hat{p}_{\text{teacher}}, p_{\text{student}}))\) for \(f\) identity, standard distillation is recovered. We define one instantiation of \(f\) as a nonlinear transform applied to the teacher scores for the implicit negatives—our skeptical teacher. Similarly, other classes of \(f\) might also be relevant to accommodate label noise.
Table 1. Train sets and architectures used in our experiments.

| Train set | clips   | hours |
|-----------|---------|-------|
| tramall   | 506,721 | 1407  |
| tr_large  | 2,467,357 | 6853 |

| Architecture | parameters | Mult-Adds |
|--------------|------------|-----------|
| ResNet-50    | 30M        | 1860M     |
| MobileNetV1  | 3.7M       | 69.2M     |

4. EXPERIMENTAL SETUP

We evaluate the proposed method using an internal version of AudioSet [6], consisting of over 2 million audio clips of \( \approx 10 \)s length each, and labeled using an ontology of \( C = 527 \) audio classes. In order to study the impact of missing labels as a function of training data size, we use two train sets as specified in Table 1. The train sets are designed to share a similar class distribution, but one is approximately five times larger than the other. For evaluation, we use an internal eval set of 47,132 audio clips. Incoming audio clips are transformed to log-mel spectrograms using a 25ms Hann window with 10ms hop, and \( F = 64 \) mel log-energy bands. The network is presented with time-frequency patches of \( d = 64 \) at \( l = 96 \) frames (corresponding to a duration of 0.96s) with 50\% overlap.

In order to assess the impact of missing labels on models of different capacity, we employ two Convolutional Neural Network (CNN) architectures: ResNet-50 [21] and MobileNetV1 [22]. Both are taken from the computer vision literature and have also proven successful in audio recognition research (see [24] and the recently released YAMNet [23]). ResNet-50 is based on residual units, with shortcut connections that perform identity mappings added to the outputs of a small group of stacked layers. This allows information to pass through while leaving additional residual mappings to be learned, and was found to support the training of substantially deeper networks, thus yielding accuracy gains [21]. MobileNetV1 is based on the so-called depthwise-separable convolutions, in which a standard convolution (that filters and combines inputs into outputs in the same step) is factorized into \( i \) a depthwise convolution that does the filtering and \( ii \) a 1x1 convolution to combine the results into a set of outputs. This decomposition reduces computation and model size significantly [22]. Table 1 shows model size and Mult-Adds for both architectures. For training we use Adam optimizer [24] and a fixed learning rate of 1e-5. We use random weight initialization with a standard deviation of 0.001.

4.1. Evaluation

For evaluation, we pass each 0.96s evaluation patch through the model to compute classifier output scores, which are then averaged per-class across all patches in a clip to obtain clip-level predictions, as done in [6]. As evaluation metrics we use primarily \( d' \) and \( lrap \). \( d' \) (d-prime) is a within-class metric, that is, it ranks all test samples according to the classifier score for a given class. \( d' \) can be computed as a monotonic transform of ROC AUC, and describes the separation between unit-variance normal distributions that would achieve the same AUC. In order to avoid the impact of missing positive labels in the evaluation set, only samples with explicit labels for a given class (both positive and negative) are used in the calculation of \( d' \) for that class. (Because this excludes many “easy” samples, the resulting \( d' \) values are substantially lower than including all non-positive samples as negatives.) More details about this metric can be found in [23, 25]. Label-weighted label-ranking average precision (\( lrap \)) is a between-class metric, that is, it evaluates the overall ranking across all classifier outputs for every test sample. Specifically, \( lrap \) measures, for every ground truth test label \( c \), what fraction of the predicted top-ranked labels down to \( c \) are among the ground truth. More details about this metric can be found in [7]. Both metrics are computed individually on a per-class basis, then averaged with equal weight (i.e., balanced averaging) across all classes to yield the overall performance shown in Table 3 and Fig. 2. Non-pathological \( d' \in [0, \infty] \) while \( lrap \in [0, 1] \).

5. EXPERIMENTS

As explained in Section 4, we first train a teacher model with the unmodified labels and use it to predict scores in the train set. We used an internal ResNet-50 model for the teacher which had been trained using several tweaks to improve performance, similar to those used in the publicly-released YAMNet model [23]. Based on the teachers predicted scores, we generate a total of 18 new label sets, each of them using a different threshold \( t_c \), i.e., discarding a different proportion of top-scored negatives in the train set. Finally, for every enhanced label set, we train a student model on the train set, and predict on the evaluation set, reporting the best performance obtained.

5.1. Overall performance vs. discarded negatives

The results in Fig. 2 illustrate the impact of missing labels by plotting performance (\( d' \) and \( lrap \)) as a function of the amount of top-scored negatives discarded, similar to the treatment of noisy ImageNet labels in [20]. We experiment with progressively discarding \( t_c \in \{0, 0.1, 0.2, 0.4, 0.6, 0.8, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20\} \% \) of top-scored negatives for the two train sets and architectures of Section 4. Each point in the lines is the result of one experiment trial using one label set with a given amount of discarded negatives. The initial point at the left (at \( x = 0.0\% \), marked with a square) corresponds to the standard training, i.e., no labels ignored and all false negative labels included. We use it as our baseline. As a particular example, Table 2 illustrates the details of the operating point of 0.1\% discard in \( tramall \) for the Ambulance (siren) and Speech classes. The total number of labels is the number of clips in the train set (506,721). The number of explicit labels (i.e., human rated, which are both positive and negative) is usually a tiny portion, in the range of a few hundreds or thousands (as in Ambulance (siren)), except for a few high prior classes such as Speech. Implicit labels (all negative) form the remainder of the clips. Note that Ambulance (siren) represents the typical case that holds for the vast majority of classes, while Speech represents an extreme case relevant to only a handful of classes. In this operating point, we ignore the top-scored 0.1\% of the implicit negatives, which is usually around 500 labels per class, except for the few high prior classes, in which it is less.

Common to all the curves of Fig. 2, we observe three regions from left to right: a steep increase at the beginning of the curve, followed by a sweet-spot, and a final decay that is more severe in

\[\text{https://github.com/tensorflow/models/tree/master/research/audioset/yamnet} \]
Table 2. Label counts for two example classes at one operating point of Fig 2 (tr_small and discarding 0.1% of top-scored negatives).

| Class            | Total   | Explicit | Implicit | To Ignore |
|------------------|---------|----------|----------|-----------|
| Ambulance (siren)| 506,721 | 1657     | 505,064  | 504       |
| Speech           | 506,721 | 464,262  | 42,459   | 42        |

\( \omega \text{lap} \) than in \( d' \). A possible interpretation of this behaviour is as follows. We conjecture that the top-scored negatives correspond either to missing “Present” labels (i.e., false negatives (FNs)), or they are “decoys”, difficult (and thus informative) true negatives (TNs), perhaps from similar classes, and especially useful in learning. First, we remove some critical FNs that damage the learning process, hence the sudden performance increase at the left of the curves. As we continue discarding more top-scored negatives, we keep removing FNs, but we also start to remove some TNs. Therefore, performance increases more slowly, until a sweet-spot is reached where both effects cancel out. Finally, if we keep ignoring more top-scored negatives, performance is degraded. As to why the decay in \( d' \) is much less pronounced than in \( \omega \text{lap} \), a possible explanation lies in the way \( d' \) works. \( d' \) characterizes the separation of the positive and negative score distributions as the distance between their means. It may be that removing the high scoring tails changes the mean of the negative distribution (hence \( d' \) increases suddenly), but as we remove more labels with much more frequent scores the mean of the negative distribution barely changes (and consequently so \( d' \)). By contrast, \( \omega \text{lap} \) does not suffer from this issue, its curves showing a decay as expected. Based on this intuition, we consider the right end of the \( d' \) curves less reliable.

Table 3 lists the performances for baselines and best operating points for architectures and train sets considered.

| Model       | Train set | \( d' \) | \( \omega \text{lap} \) |
|-------------|-----------|----------|-------------------------|
|             | baseline  | best     | baseline                | best        |
| ResNet-50   | tr_small  | 1.186    | 1.244                   | 0.363       | 0.425   |
|             | tr_large  | 1.334    | 1.367                   | 0.451       | 0.484   |
| MobileNetV1 | tr_small  | 1.132    | 1.192                   | 0.357       | 0.409   |
|             | tr_large  | 1.290    | 1.322                   | 0.425       | 0.468   |

Effect of ignoring the highest ranked top-scored negatives. The proposed method yields performance improvements in all cases considered. The best operating points are usually between 3 and 6% discarded for \( d' \), and between 1 and 4\% for \( \omega \text{lap} \). We believe this result is relevant as AudioSet training examples are often treated as if they had complete labels. However, the most important pattern we observe in all cases is the consistent steep increase at the beginning of the curves. In all cases, most of the improvement comes from removing just \( \approx 1\% \) of the top-scored negatives. Further, in most cases, just by removing a tiny percentage \((<=0.2\%)\) of (potentially) missing labels, approximately half of the total boost is already attained. Two observations can be made from these findings. First, this indicates that a tiny portion of labels is troublesome and it is moderately affecting classifier performance, a concept which is basis for disciplines like instance selection, where it is assumed that not all training examples are equally informative, some of them being redundant and some being harmful. Second, these findings become interesting as they contrast with the common trend of acquiring more and more training data to improve recognition performance, even if noise-labeled (something we also find useful in our experiments in general).

Effect of train set size. Table 3 shows improvements with respect to the baseline of \( \approx 0.060 \) for \( d' \) when training with \( \text{tr_small} \) for both architectures, whereas when using \( \text{tr_large} \), improvements are almost half of that \((\approx 0.033)\). This relationship also holds for \( \omega \text{lap} \) when using ResNet-50, whereas when using MobileNetV1, the performance difference between training with \( \text{tr_small} \) and \( \text{tr_large} \) is smaller. These results seem to indicate that the damage done by missing labels, and consequently the performance boost obtained by discarding them, can be higher when the dataset is smaller. A possible explanation is that larger amounts of data help to mitigate the effect of these errors in the label space, which accords with [23]. However, even when training with massive amounts of audio (almost 7000h, see Table 1), the impact of these labelling errors can still be observed. The \( d' \) sweet spot occurs roughly in the same region for both train sets. The \( \omega \text{lap} \) sweet spot seems to move slightly to minimal discards when training with larger amounts of data.

Effect of model architectures. The proposed method is effective for both model architectures considered despite having different underlying principles and significantly different numbers of parameters, in a proportion of around 8:1 (see Section 4). The overall trend of the curves in Fig. 2 is similar for both architectures. As can be seen in Table 3, in terms of \( d' \), both architectures show very similar improvements with respect to their corresponding baselines. In terms of \( \omega \text{lap} \), however, results are inconsistent, with ResNet-50 providing a greater improvement than MobileNetV1 when training on \( \text{tr_small} \), and vice versa when training on \( \text{tr_large} \). We do by chance, absolute improvements for both metrics are numerically similar in this case, despite the metrics are conceptually different and their numeric range is also different.
not observe consistently larger improvements using ResNet-50, even though its much larger number of parameters might lead one to expect it to overt fit labeling errors more readily. As an aside, regardless of missing labels, when comparing baselines, ResNet-50 outperforms MobileNetV1 as expected, but not by a particularly large margin considering the huge difference in number of parameters between the architectures.

Effect on evaluation metrics. By looking at Table 3, it can be seen that d' improvements reach up to relative 5.3% (MobileNetV1) and lrap improvements reach up to relative 17.1% (ResNet-50), both cases occurring when using tr_small (≈ half a million clips), where improvements are more evident.

Finally, we carried out a small informal listening test in which we inspected some of the clips associated with the discarded top-scored negatives for a few classes. As expected, most clips were missing “Present” labels, some of them being flagrant labeling errors, but difficult to detect considering the huge train set size. These findings indicate that the proposed method, while simple, is effective in identifying missing labels in a human annotated dataset like AudioSet, and it is able to improve training over unnoticed missing labels. While the presented results are specific to AudioSet, we believe this insight will apply equally to large-scale audio datasets, especially those annotated via human validation of labels. Additionally, it can be useful for dataset cleaning or labeling refinement.

In line with findings in Section 5.1 about the effect of train set size. Classes that benefit the most out of this process are: Waterfall, Fusilade, Sizzle and Bubbling, featuring improvements greater than 0.3. The procedure carried out can be useful to detect classes with labeling errors, applicable in dataset cleaning or labeling refinement. Re-labelling a small amount of flagged top-scored negatives may lead to even better results than the proposed method.

Table 4 lists the number of classes in which performance improves, along with the average improvement, for every group of classes. In light of Fig. 3 and Table 4, we see the following. Classes with high prior tend to get slightly worse. While the performance changes observed are relatively small, this is somewhat surprising as the number of labels ignored is even smaller in these cases—a possible explanation is that most of the labels being discarded correspond to informative TNs. On the contrary, groups of classes with medium and small priors present a similar percentage of classes showing improvement, being slightly larger in the group of small classes. In addition, the average improvement is also higher in the group of small classes, with an absolute difference of 0.02. While a more in-depth study is needed before making stronger claims, results seem to indicate that the impact of missing labels (and of the proposed method) is greater on classes with low prior, which goes in line with findings in Section 5.1 about the effect of train set size. Classes that benefit the most out of this process are: Waterfall, Fusilade, Sizzle and Bubbling, featuring improvements greater than 0.3. The procedure carried out can be useful to detect classes with labeling errors, applicable in dataset cleaning or labeling refinement. Re-labelling a small amount of flagged top-scored negatives may lead to even better results than the proposed method.

6. CONCLUSION

We have identified missing labels as a pathology in the labelling of AudioSet. We have proposed a simple method based on a teacher-student framework with loss masking to first identify the most critical potentially missing labels, and then ignore them during the learning process. Our main findings are: i) most of the improvement comes from filtering out a tiny portion (<1%) of the most critical estimated missing labels, showing a moderate impact on performance; ii) the damage done by missing labels (and the performance boost obtained by discarding them) becomes higher as the train set gets smaller—however, even when training with massive amounts of audio, the impact of these labelling errors can still be observed; iii) when applied to two CNN architectures of different nature and size the proposed method behaves similarly in both cases. These findings indicate that the proposed method, while simple, is effective in identifying missing labels in a human annotated dataset like AudioSet, and it is able to improve training over unnoticed missing labels. Additionally, it can be useful for dataset cleaning or labeling refinement. We believe this insight will apply equally to large-scale audio datasets beyond AudioSet, since the problem of missing labels is endemic.
7. REFERENCES

[1] Tuomas Virtanen, Mark D Plumbley, and Dan Ellis, *Computational Analysis of Sound Scenes and Events*, Springer, 2018.

[2] Peter Foster, Siddharth Sigta, Sacha Krstulovic, Jon Barker, and Mark D Plumbley, “CHiME-home: A dataset for sound source recognition in a domestic environment,” in *Workshop on Applications of Signal Processing to Audio and Acoustics*. IEEE, 2015.

[3] Karol J Piczak, “Esc: Dataset for environmental sound classification,” in *Proceedings of the ACM International Conference on Multimedia*. ACM, 2015, pp. 1015–1018.

[4] Justin Salamon, Christopher Jacoby, and Juan Pablo Bello, “A dataset and taxonomy for urban sound research,” in *Proceedings of the ACM International Conference on Multimedia*. ACM, 2014, pp. 1041–1044.

[5] Eduardo Fonseca, Manoj Plakal, Frederic Font, Daniel P.W. Ellis, Xavier Favory, Jordi Pons, and Xavier Serra, “General-purpose tagging of Freesound audio with AudioSet labels: task description, dataset, and baseline,” in *Proceedings of the Detection and Classification of Acoustic Scenes and Events 2018 Workshop* (DCASE2018), 2018.

[6] Jort F. Gemmeke, Daniel P. W. Ellis, Dylan Freedman, Arien Jansen, Wade Lawrence, R. Channing Moore, Manoj Plakal, and Marvin Ritter, “Audio set: An ontology and human-labeled dataset for audio events,” in *Proc. IEEE ICASSP 2017*, New Orleans, LA, 2017.

[7] Eduardo Fonseca, Manoj Plakal, Frederic Font, Daniel P. W. Ellis, and Xavier Serra, “Audio tagging with noisy labels and minimal supervision,” in *Proceedings of the Detection and Classification of Acoustic Scenes and Events 2019 Workshop* (DCASE2019), NY, USA, 2019.

[8] Benoît Frémay and Michel Verleysen, “Classification in the presence of label noise: a survey,” *IEEE transactions on neural networks and learning systems*, vol. 25, no. 5, 2014.

[9] Maarten Meire, Peter Karsmakers, and Lode Vuegen, “The impact of missing labels and overlapping sound events on multi-label multi-instance learning for sound event classification,” in *Proceedings of the Detection and Classification of Acoustic Scenes and Events 2019 Workshop* (DCASE2019), NY, USA, 2019.

[10] Ankit Shah, Anurag Kumar, Alexander G Hauptmann, and Bhiksha Raj, “A closer look at weak label learning for audio events,” *arXiv preprint arXiv:1804.09288*, 2018.

[11] Eduardo Fonseca, Manoj Plakal, Daniel P. W. Ellis, Frederic Font, Xavier Favory, and Xavier Serra, “Learning sound event classifiers from web audio with noisy labels,” in *Proc. IEEE ICASSP 2019*, Brighton, UK, 2019.

[12] Eduardo Fonseca, Frederic Font, and Xavier Serra, “Model-agnostic approaches to handling noisy labels when training sound event classifiers,” in *Proceedings of IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, New York, US, 2019.

[13] Anurag Kumar, Ankit Shah, Alex Hauptmann, and Bhiksha Raj, “Learning sound events from webly labeled data,” *arXiv preprint arXiv:1811.09967*, 2018.

[14] Anurag Kumar and Vamsi Krishna Ithapu, “Secost: Sequential co-supervision for weakly labeled audio event detection,” *arXiv preprint arXiv:1910.11789*, 2019.

[15] Qiuqiang Kong, Yin Cao, Turab Iqbal, Xuyuan Wang, Wenwu Wang, and Mark D Plumbley, “Panns: Large-scale pretrained audio neural networks for audio pattern recognition,” *arXiv preprint arXiv:1912.10211*, 2019.

[16] Logan Ford, Hao Tang, François Grondin, and James Glass, “A deep residual network for large-scale acoustic scene analysis,” *Proc. Interspeech 2019*, pp. 2568–2572, 2019.

[17] Eduardo Fonseca, Jordi Pons, Xavier Favory, Frederic Font, Dmitry Bogdanov, André Ferraro, Sergio Oramas, Alastair Porter, and Xavier Serra, “Freesound Datasets: a platform for the creation of open audio datasets,” in *Proceedings of the 18th International Society for Music Information Retrieval Conference (ISMIR 2017)*, Suzhou, China, 2017, pp. 486–493.

[18] Jimmy Ba and Rich Caruana, “Do deep nets really need to be deep?,” in *Advances in neural information processing systems*, 2014, pp. 2654–2662.

[19] Jinyu Li, Rui Zhao, Jui-Ting Huang, and Yifan Gong, “Learning small-size dnn with output-distribution-based criteria,” in *Fifteenth annual conference of the international speech communication association*, 2014.

[20] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean, “Distilling the knowledge in a neural network,” *NIPS Deep Learning and Representation Learning Workshop*, 2015.

[21] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[22] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam, “Mobilenets: Efficient convolutional neural networks for mobile vision applications,” *arXiv preprint arXiv:1704.04861*, 2017.

[23] Shawn Hershey, Sourish Chaudhuri, Daniel PW Ellis, Jort F Gemmeke, Arien Jansen, R Channing Moore, Manoj Plakal, Devin Platt, Rif A Saurous, Bryan Seybold, et al., “Cnn architectures for large-scale audio classification,” in *2017 ieee international conference on acoustics, speech and signal processing (icassp)*. IEEE, 2017, pp. 131–135.

[24] Diederik P Kingma and Jimmy Ba, “Adam: A method for stochastic optimization,” in *ICLR*, 2015.

[25] David Marvin Green, John A Swets, et al., *Signal detection theory and psychophysics*, vol. 1, Wiley New York, 1966.

[26] Curtis G Northcutt, Lu Jiang, and Isaac L Chuang, “Confident learning: Estimating uncertainty in dataset labels,” *arXiv preprint arXiv:1911.00068*, 2019.

[27] Huan Liu and Hiroshi Motoda, “On issues of instance selection,” *Data Mining and Knowledge Discovery*, vol. 6, no. 2, pp. 115, 2002.

[28] Chen Sun, Abhinav Shrivastava, Saurabh Singh, and Abhinav Gupta, “Revisiting unreasonable effectiveness of data in deep learning era,” in *Proceedings of the IEEE international conference on computer vision*, 2017, pp. 843–852.