DCASE 2018 TASK 2: ITERATIVE TRAINING, LABEL SMOOTHING, AND BACKGROUND NOISE NORMALIZATION FOR AUDIO EVENT TAGGING

Technical Report

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ABSTRACT

This paper describes an approach from our submissions for DCASE 2018 Task 2: general-purpose audio tagging of Freesound content with AudioSet labels. To tackle the problem of diverse recording environments, we propose to use background noise normalization. To tackle the problem of noisy labels, we propose to use pseudo-label for automatic label verification and label smoothing to reduce the over-fitting. We train several convolutional neural networks with data augmentation and different input sizes for the automatic label verification process. The procedure is promising to improve the quality of datasets for audio classification. On the public leader board for the competition, our single model and an ensemble of 8 models score 0.941 and 0.963 respectively.

Index Terms— Audio event tagging, Background noise normalization, Convolutional neural networks, DCASE 2018, Label smoothing, Pseudo-label

1. INTRODUCTION

The FreesoundDataset (FSD) [1] is an open general-purpose and large-scale audio dataset with the aim to promote the advancement in audio research. The data are crowd-sourced and dynamically added into the dataset via the Freesound platform, where everyone can contribute his or her own records. Such method to collect data has several advantages such that the dataset can be developed into a large dataset with a great variety in audio contents, and researchers have full access to the raw audio wave files. However the crowd-sourcing mechanism also introduces several challenges such that unverified labels, a wide range of recording devices, recording environments, and audio quality.

Task 2 (audio tagging) of Dcase 2018 challenge [2] explores some of the aforementioned challenges of the FSD. In Task 2, participants are asked to classify audio clips extracted from FSD using a subset of labels from AudioSet Ontology [3]. There are a total of 41 labels, that cover a wide ranges of sound activities, for examples musical instruments, human sounds, domestic sounds, and animals. The training set consists of 9473 audio clips with different lengths, out of which 3710 samples have manually-verified label and 5763 samples have non-verified labels. This is an imbalanced dataset. The number of samples for each classes varied between 94 to 300 samples per class. The test set consists of 9400 audio clips, out of which around 1600 samples are used to evaluate the system performance.

The main challenges of Task 2 are the noisy labels, large number of classes compared to the number of training samples, and the diverse nature of crowd-sourced data. A popular approach for supervised learning using cross-entropy error with noisy labels is label smoothing [4, 5]. A network is over-confident when it places all probability on a single class in the training set [5]. Label smoothing instead assigns a value less than 1 to the target class and some value to other classes in the one hot encoded label. This technique is equivalent to regularization the network by penalizing lowe entropy output distribution [5]. The audio tagging dataset has more than 60% non-verified labels that are automatically annotated, thus it is expected that there are many samples with incorrect labels. As the number of non-verified samples is large compared to the size of the dataset, it is not the best strategy to just use label smoothing to deal with noisy label problem. Another approach is to use pseudo-label [6, 7], which is a widely used technique in semi-supervised learning. Pseudo-labelling technique iteratively assigns pseudo-labels to some unlabelled data and use those data together with labelled data in the next training iteration. To reduce the effect of the noisy label problem in Task 2 challenge, we propose to use pseudo-labelling technique to iteratively and automatically verify the non-verified portion of the dataset. For those samples that the classified labels from the pseudo-labelling process are different from the non-verified labels or the classification probability are below a certain threshold, we employ label smoothing because we are unsure if these samples are labelled incorrectly or they are from a different subset of the target class.

Crowd-sourced data comes from different recording environments, for example a telephone sound can be recorded in a quite home or in a noisy street. These background noise introduces more variability to the signal and potentially reduce the performance of the learning algorithm as it overfits to the background noise. A common approach to mitigate the problem of background noise is multi-condition training [8, 9] where different background noises are artificially added into the signals to simulate different environments. Multi-condition training can be interpreted as a data augmentation technique, thus the performance of the algorithm depends on how many conditions that it is trained on. To reduce the effect

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of background noise in crowd-source data, we propose to normalize the audio signal by the background noise. The background noise normalization is inspired by the psychoacoustic and physiological observations that humans and other mammals dynamically adapt to the time-varying background noise level and selectively pay attention to sound signals that are above the noise level.

A common approach for audio event classification for small audio datasets such as ESC50 [10], Urbansoudn8K [11], and TUT Acoustic Scenes [12] are feature extraction using log-mel energy, data augmentation using pitch-shift, time-stretch, block mixing [13], random erasing/cutout [14, 15], and classification using deep neural network [16, 17]. The data set for Task 2 is slightly larger than Urbansound8K but has more classes. In this paper, we will follow this general approach, and add in the background noise normalization to build a concrete ensemble to automatically verify the training data via pseudo-labelling. Task 2 is hosted on Kaggle website. Our best single model and best ensemble score 0.941 and 0.963 respectively on the public leader board (PLB).

We organize the paper as follows. Section II show the building blocks of a sound event tagging model. Section III presents the automatic label verification. We report the experimental results and DCASE 2018 submission in Section IV. Finally, we conclude the paper in Section V.

2. BUILDING A SOUND EVENT TAGGING MODEL

We use the following parameters to convert the provided mono audio files from time domain to frequency domain via short time Fourier transform (STFT): sampling rate of 44.1 kHz, length-1024 FFTs, hanning window with 50% overlap.

2.1. Preprocessing

Our preprocessing step consists of silent removal and repeating short audio clip. For each audio sample, we use librosa [18] to trim the silent part of the audio. After that, we remove frames whose energies fall below the 10^{th} percentile of all the frame energies of that sample. Experimental results show that silent removal improve accuracy of the model because there are many segments within an audio clips that does not contain the sound of interest. For audio samples that are shorter than the required length for deep neural network, we repeat the signal instead of zero padding.

2.2. Background noise normalization

Let $\mathbf{X}$ be the audio signal in STFT domain. $\mathbf{X}$ is a matrix of size $n\_ffts/2$ x n_frames, where n_ffts is the number of FFT points and n_frames is the number of time frame. For each audio clip, the local background noise $\mathbf{x_{noise}}$ of size $n\_ffts/2$ x 1 can be estimated such that $\mathbf{x_{noise}}(\mathbf{i})$ is some percentile, (let say 10^{th}) of signal magnitude in frequency band i. For application with streaming or continuous input, background noise can be adaptively estimated and update for different segments of audio files [19]. The signal can be normalized by the background noise as

$$\mathbf{X_{bgnorm}} = \mathbf{X}/\mathbf{x_{noise}} \quad (1)$$

Fig. 1 show an example of background noise normalization. After normalization, the background noise becomes Gaussian white noise, and the signals above the background noise are highlighted. Thus the proposed normalization is promising to reduce the effect of different background noises to the classification.

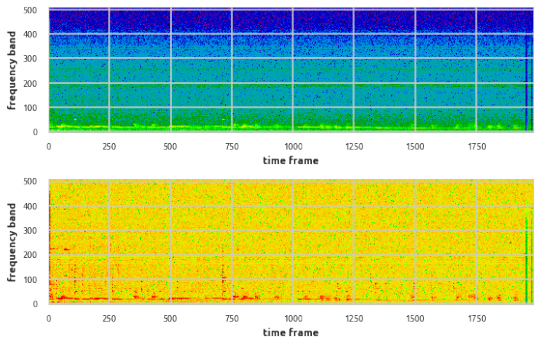

Figure 1: Example of background noise normalization for an audio clip with label "Chime": Top is the unmodified STFT; Bottom is the normalized STFT

2.3. Feature extraction

We use librosa [18] to extract log-scale mel-spectrogram energy with the following parameters: maximum frequency of 18000 kHz and mel frequency filter bank of size 96.

2.4. Data augmentation

We use librosa [18] to generate the pitch-shift and time-stretch signal before training as the processing time is large. The chosen pitch shift values in semitones are $[-2, -1, 1, 2]$. The chosen time-stretch ratios are [0.9, 0.95,1.05, 1.1]. We also augment data on-the-fly during training using mix-up [13], random erasing and cut-out [14, 15]. The data augmentation improves the performance of the algorithm, which is consistent with other researches [17].

2.5. Training model

We divide the provided training data into train (80%) and development set (20%). We use the competition evaluation metrics, mean average precision @ 3 (MAP3) as the criteria to select network parameters. A convolutional neural network (CNN) that is a variant of VGG architecture [20] is used in our experiment. The CNN takes inputs as patches of log-mel spectrogram. The network architecture for input of size 128 frames and 96 mel bands is shown in Table 1. There are total of 11 layers, which is similar to Vggish [21]. For training, we randomly extract patches from the log-mel spectrogram. The patches are normalized with the mean and standard deviation of all frames of all audio samples in the training set. For testing, we extract patches using a sliding window with hop size of 8 frames. The final prediction probability is the average prediction probabilities of all the patches. To further improve the classification results, we extend the CNNs to take a second set of input which are the local mean and local standard deviation across all mel-frequency bands of each input patch. The mean and standard deviation is fed into two fully connected layers with 64 and 10 hidden neurons before being concatenated to the first fully connected layer of the CNN in Table 1.

3. AUTOMATIC LABEL VERIFICATION

The dataset contains diverse audio events with different lengths, such as short-duration gun shot and long-duration chime. To im-

Table 1: Model architecture for input of shape $(128, 96)$.

Stage	Output	Layers
Conv1	64x48	3x3, 24, BN, ReLU
		3x3, 24, BN, ReLU, maxpool, stride 2
Conv2	32x24	3x3, 48, BN, ReLU
		3x3, 48, BN, ReLU, maxpool, stride 2
Conv3	16x12	3x3, 48, BN, ReLU
		3x3, 48, BN, ReLU, maxpool, stride 2
Conv4	8x6	3x3, 64, BN, ReLU
		3x3, 64, BN, ReLU, maxpool, stride 2
Conv5	8x6	1x1, 64, BN, ReLU
fully connected	1x1	drop out, 128 fc, ReLU
		drop out, 41 fc, softmax
Number of parameters		5.48 x 10^5

prove the reliability of the label verification process, we build a ensemble of 3 CNN models. The three CNN models take patches of size $(128, 96)$, $(171, 96)$, and $(257, 96)$, which corresponds to audio segments of length 1.5 s, 2 s, and 3 s respectively. The second model use background noise normalized STFT to extract log-mel features. We combine the three models using their geometric mean as it has higher score on PLB than arithmetic mean. We start the iterative training process with the verified labels. We only include the samples, of which the pseudo-labels are similar to the non-verified labels, and classification probability greater than 0.5 to the training dataset for the next iteration. Our assumptions is that the model that automatically annotated the non-verified labels is reliable, and there are more samples with correct non-verified labels than those with incorrect labels. This assumption is justified as a model train on all the verified and non-verified samples score reasonably on PLB.

Table 2 show the progress of the automatic label verification process using pseudo-label. The non-verified labels are considered ground truth. We used MAP3 as evaluation metrics to compare the classified label with the provided non-verified labels. The algorithm returns the best 3 predictions for each audio sample. MAP3 returns score of 1, $1/2$, and $1/3$, if the ground truth is matched with the best, the second best, and the third best prediction respectively and returns a score of 0 otherwise. After the first iteration, our ensemble returns 3910 first best classifications, 537 second best classifications, 256 third best classifications, and 1060 incorrect classification. Out of 3910 first best classification, 2680 samples have classification probability greater than 0.5, thus they are added into the training set for the next iteration. We stop the process at iteration 4 when the number of incorrect classifications reach plateau. At iteration 4, we add 569 out of 576 first best classification with probabilities above 0.1. We relabel 152 samples out of 827 incorrect classification which has probability greater than 0.5. The final training sets consists of 8039 verified samples and 1424 non-verified samples. Fig. 2 shows the histogram of classification probability of first best classification for iteration 1 and 4. At iteration 1, there are more "correct" non-verified samples, the ensemble returns high degree of confidence for many non-verified samples. At iteration 4, the distribution classification probabilities of first best guesses shifts toward 0. The left-over non-verified samples are either incorrectly annotated or contains variances of the audio class that the ensemble have not seen before. For those 1424 left-over non-verified data, we use label smoothing [22], which is defined as

$$y(i) = \begin{cases} \epsilon/k & \text{if i is none target} \\ 1 - (k-1)/k * \epsilon & \text{if i is target,} \end{cases} \quad (2)$$

Table 2: Iterative training for label verification.

# of iteration	Iter 0	Iter 1	Iter 2	Iter 3	Iter 4
# of verified samples	3710	3710	6390	7077	7470
# of new added samples	-	2680	687	393	569
# of correct pred at 1^{st} position	-	3910	1420	900	576
# of correct pred at 2^{nd} position	-	537	473	456	379
# of correct pred at 3^{rd} position	-	256	276	195	221
# of incorrect labels	-	1060	914	845	827
total # of non-verified labels	5763	5763	3083	2396	2003
map3	-	0.740	0.567	0.498	0.419

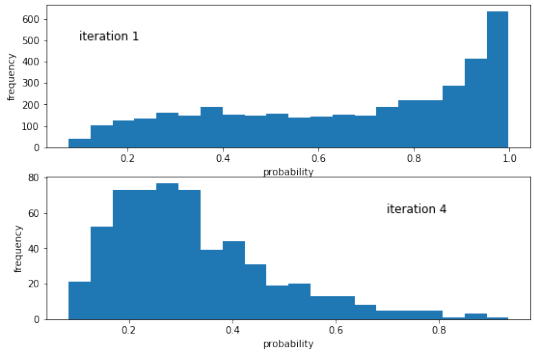

Figure 2: Histogram of classification probability of samples that the output of pseudo-labelling ensemble are the same as provided non-verified labels: Top is histogram for iteration 1; Bottom is histogram for iteration 4

where $y(i)$ is one hot encoded ground truth, k is the number of classes and ϵ is some small value. We sample ϵ from a uniform distribution between 0.1 and 0.3.

4. SUBMISSIONS FOR DCASE 2018 TASK 2

In this section, we listed the progress of our submissions to Kaggle platform to evaluate the effectively of our proposed method.

Model 1 is trained on all verified and non-verified data, segment length of 1.5 seconds, without silent removal, background normalization data augmentation, label smoothing and pseudo-label. Its score on PLB is 0.912. It appears that the non-verified data have many correct labels.

Model 2 is trained on all verified and non-verified data, segment length of 2 seconds, with background noise normalization. Ensemble of Model 1 and 2 scores 0.928 on PLB. This shows that background normalization and combining different segments lengths are helpful. It is interesting that the MAP3 score of Model 2 on our development set is slightly lower than those of Model 1, however combining two models pushes the score on PLB significantly. From the observation that ensembles of diverse models normally perform well, we hypothesize that the background noise normalization provides some important emphasis of the signal that are not obvious in the non-normalized version.

Model 3 is trained on all verified and non-verified data, segment length of 1.5 seconds, with silent removal, data augmentation. Ensemble of Model 1, 2 and 3 scores 0.950 on PLB. This big jump on PLB shows the importance of data augmentation and silent removal, which is consistent with other researches that use small-medium size audio datasets [17, 23].

Our 3-model ensemble for pseudo-labelling scores 0.899, 0.932, and 0.937 respectively on iteration 1, 2, and 3. This shows that the more data we used for training, the better the validation score. The score at iteration 3 with 7077 sample in the training set score lower than the previous ensemble of Model 1, 2, 3. This implies that the network can tolerate noisy labels and do better with more data.

We name the three models for pseudo-labelling process at iteration 4 Model 4, 5 and 6. Ensemble of Model 1, 2, 3, 4, 5 and 6 scores 0.956 on the PLB. Pseudo-labelling also improves the score.

Model 7 is trained on re-labelled data after iteration 4 with label smoothing, segment length of 1.5 seconds. It scores 0.941 on PLB, which is higher than any other single model. The pseudo-label process improves the learning of the models, and label smoothing reduces the label uncertainty. Ensemble of Model 1, 2, 3, 4, 5, 6, and 7 score 0.961 on PLB

Model 8 is trained on re-labelled data after iteration 4 with label smoothing, segment length of 2 seconds, background noise normalization and multiple inputs. The ensemble of Model 1, 2, 3, 4, 5, 6, 7, and 8 score 0.963 on PLB which is the highest validation score we obtained on PLB.

5. CONCLUSION

Dataset with high quality labels are crucial to supervised learning, however manual annotations are expensive and time-consuming. The experimental results presented in this paper show that for small audio datasets, it is possible to increase the dataset size by training different models to automatically label new data. Manually annotation will be helpful for those "difficult" samples that the models couldn't resolve. However, thanks to pseudo-labelling, the amount of samples that needs manually annotation can be reduced significantly. The number of training samples that are incorrectly annotated is unknown at the time of the competition ends, however, we can observe that the learning models are quite robust to some degree of incorrect annotation. The proposed background noise normalization introduces a new view of the signal to the CNNs. In addition, it is useful to use different input lengths for different models to improve the ensemble accuracy on dataset with diverse audio events. In conclusion, the proposed approach shows meaningful improvement compared to the baseline system.

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