Deep CNN Framework for Audio Event Recognition using Weakly Labeled Web Data

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Abstract—The development of audio event recognition models requires labeled training data, which are generally hard to obtain. One promising source of recordings of audio events is the large amount of multimedia data on the web. In particular, if the audio content analysis must itself be performed on web audio, it is important to train the recognizers themselves from such data. Training from these web data, however, poses several challenges, the most important being the availability of labels: labels, if any, that may be obtained for the data are generally weak, and not of the kind conventionally required for training detectors or classifiers. We propose that learning algorithms that can exploit weak labels offer an effective method to learn from web data. We then propose a robust and efficient deep convolutional neural network (CNN) based framework to learn audio event recognizers from weakly labeled data. The proposed method can train from and analyze recordings of variable length in an efficient manner and outperforms a network trained with strongly labeled web data by a considerable margin.

Index Terms—Audio Events, CNN, Web Data, Weak Labels

I. INTRODUCTION

In last few years audio event recognition and detection (AER) has become an important research problem in the broad area of Machine Learning and Signal Processing. Besides surveillance [1], where AER had its earliest applications, it has several other applications such as content-based indexing and retrieval of multimedia data [2], [3], [4], human computer interaction [5], and wildlife monitoring [6], [7], to name a few. Multimedia content analysis for indexing and retrieval is perhaps the most important one, given that the amount of multimedia data on the web is growing at an exponential rate. Audio is an important component of multimedia data and can provide important cues to the semantic content of the data. However, unlike its visual counterpart, AER has not yet moved up to very large scale model training in terms of both training data size and number of events. For vision, most large-scale image datasets have been collected from the web [8], [9]. Multimedia data on the web are an important source of audio events as well. However, the recordings are usually unlabeled; to use them to train models for audio events one must label them with the time stamps that mark the temporal boundaries of the occurrences of different audio events.

This form of labels, often referred to as “strong” labels, is a major bottleneck in large scale training of models for AER. Creating such labeled audio data is very difficult. The first problem is that marking temporal boundaries of audio events is a time-consuming and expensive process. Often one must go back and forth several times in a recording to mark the beginnings and ends of audio events. Moreover, for many sound events there is also a problem of interpretation. Consider for example, an audio recording of Footsteps sounds shown in Figure 1. A recording of Footsteps. Different annotators might mark different numbers of beginning and ends

Figure 1. How many beginnings and ends should be marked for this recording: one, two, four, or eight? Different annotators will interpret the event differently and assign different beginning and ends to the footsteps. Besides making the annotation task harder, this also creates unnecessary variability in the event examples, which is likely to confuse any algorithm that attempts to learn the underlying structure and composition of the audio event.

To address the problems of working with strongly labeled data, [10] proposed that audio-event detects may be trained using weakly labeled data. In weakly labeled data only the presence or absence of the events is indicated; their actual location within the recordings is not marked. Since time stamps need not be marked it is much easier to label a recording for audio events. Moreover, the event when present in the recording is available to the learner in its entire natural form, without any assumption or bias about the beginning and ends which might get introduced by the annotator. Hence, the learning algorithm interprets the data in a more natural way.

In this work we argue that weak-label based learning approaches for AER gives us ways to exploit the vast and growing amount of multimedia data on the web; which as we stated before are a rich source of audio events. One can use the metadata associated with the multimedia recordings to automatically generate weak labels for them. Video-sharing websites such as Youtube allows one to easily collect large amount of weakly labeled data for any given audio event. Hence, using web data the AER framework can be developed without requiring explicit labeling effort. This forms the primary motivation of this work where we aim to use web data for training audio event recognition models. A second motivation is that in order to be able to successfully deploy AER models for content-based indexing and retrieval of multimedia, and other real world applications, it is perhaps essential to train models on these data.

Very little has been done in this direction as learning from weakly labeled web data presents several challenges. Web multimedia data are primarily consumer generated and are generally noisy. Recordings have inconsistent quality. The weak labels may encompass long audio segments, whereas the audio event of interest may itself be very short. Often, several sounds events overlap, unlike the exemplars found in several of the...
audio events datasets such as [11], [12].

Multiple Instance Learning (MIL) approaches have previously been proposed in [10] for training models from weakly labeled data; however they are difficult to scale up to utilize large amounts of audio data. Deep learning approaches are well suited for training audio-event recognition models from large scale web data. Hershey et al. [13] used audio from Youtube videos to train and compare different well known Convolutional Neural Network (CNN) architectures for AER. Although they acknowledge the web data as being weakly labeled, the CNN models are trained in a fully supervised manner under the assumption that the labels are, in fact, strong. More specifically, audio recordings are chunked into small fixed-length segments to train the CNN model. The labels of these segments are taken to be the same as the recording-level labels – in essence, the event is assumed to be present throughout the recording. This, however, is not an efficient approach as it can result in significant amount of label noise. An audio event, say door bell ringing, may be present for only a few seconds in a recording which may be several minutes long, a fact that is ignored in assuming that the label is strong. Moreover, segment wise training of CNN is cumbersome and computationally inefficient. Segmenting recordings is a preprocessing step in itself, and often one must experiment with different segment sizes, which would require repeated preprocessing of the data. Also, a significant portion of computational operations done by the network are common over different segments and in segment-wise training these operations are repeated.

In this paper we propose a CNN-based framework which treats weak labels as weak and factors in this information during training. Our experimental results show that this is much superior to training done under the strong-label assumptions. Moreover, our proposed framework can process input recordings of variable length, which makes the training and test process more efficient and convenient. The network design does not require a fixed size input and hence segmentation as a preprocessing step is not needed. The segmentation of audio recordings is automatically done by the network and the network design controls the segment and hop size. It is also computationally efficient as common operations are not repeated.

The rest of the paper is organized as follows. In Section 2 we describe our proposed framework. In Section 3 we give details of our experiments and results and finally conclude in Section 4.

II. CNN FOR AUDIO EVENTS

Before going into the details of CNN models for AER, we describe the audio features used to train them.

A. Features: Multi Scale

Log-scaled mel spectrograms (which we will refer to simply as mel spectra) have previously been successfully used with CNNs for AER [14], [15], [13]. We use mel spectra in this work also. However, we employ 4 different FFT sizes to extract multi-scale mel-spectral features, in order to expose the network to features at different FFT scales, which can be helpful for recognizing sound events. Moreover, it can also be thought of as a data augmentation method. The sampling rate for all recordings is 44100 Hz. Window (FFT) sizes used are 23ms (1024), 11.5ms (512), 46ms (2048), and 92ms (4096). The hop size is fixed to 11.5ms (512) for all four window sizes and 128 mel-bands are used to extract mel spectra.

B. CNN for Strong Labels

CNN-based neural network architectures have been adopted for audio event and scene recognition when strongly-labeled data are available [13], [15], [13], [16]. As stated before, popular CNN architectures such as Vgg, ResNet were used in [13] to train models using web data under the strong label assumption. Here also, we use a Vgg-like [17] architecture which serves as the base for our proposed framework.

The input \(X \in \mathbb{R}^{128 \times 128}\) to the network are 128 frames of mel spectra. These 128 frames represent a segment (~1.5 s) of full audio recording. The network \(\mathcal{N}(\cdot)\) design is as follows:

- C1P1 (Convolution followed by Pooling) – 96 Filters of receptive field \((3 \times 3)\), Stride - 1, Padding - 1 and ReLU activation. Max pooling over \((2 \times 2)\)
- C2P2 (Convolution followed by Pooling) – 128 Filters of receptive field \((3 \times 3)\), Stride - 1, Padding - 1 and ReLU activation. Max pooling over \((2 \times 2)\)
- C3P3 (Convolution followed by Pooling) – 128 Filters of receptive field \((3 \times 3)\), Stride - 1, Padding - 1 and ReLU activation. Max pooling over \((2 \times 2)\)
- C4P4 (Convolution followed by Pooling) – 256 Filters of receptive field \((3 \times 3)\), Stride - 1, Padding - 1 and ReLU activation. Max pooling over \((2 \times 2)\)
- C5P5 (Convolution followed by Pooling) – 256 Filters of receptive field \((3 \times 3)\), Stride - 1, Padding - 1 and ReLU activation. Max pooling over \((2 \times 2)\)
- FC1 (Fully connected) - 256 hidden units, ReLU activation
- FC2 (Fully Connected, Output Layer) - Hidden units = \(C\) (number of classes), Sigmoid activation.

A dropout rate [18] at 0.5 is applied to input to layer FC1 and FC2. This network trains on fixed input size \((X' \in \mathbb{R}^{128 \times 128})\) and the network can be used to train on weakly labeled data by considering each segment \(X'\) to have same label as full recording. This training mechanism used in [13] will be referred as Strong Label Assumption Training (SLAT) here.

Multi-label Problem: Often several audio events are simultaneously present in an audio recording. Hence, we design our network for multi-label training and prediction. The sigmoid output in the last layer can be considered as class specific posterior for any given input. Binary cross entropy function as shown in Eq [1] is then used to compute loss with respect to each class.

\[
l(y_c, p_c) = -y_c \log(p_c) - (1 - y_c) \log(1 - p_c)
\]

In Eq [1] \(y_c\) and \(p_c = \mathcal{N}(X')\) are target and network output for \(c^{th}\) class respectively. The overall loss function is the mean of losses over all classes, Eq [2]

\[
L(X, y) = \frac{1}{C} \sum_{c=1}^{C} l(y_c, p_c)
\]
C. CNN for Weakly Labeled

Recording Level Loss: For weakly labeled data labels are available only at recording level. Hence, we do not know the labels for each segments and we need to compute loss at the recording level. To compute the loss for a given recording, we argue that the loss should be computed with respect to the segment which gives the maximum output (for that event class). If the weak label marks presence of an event then the segment with maximal output for that event class is the best candidate to contain that event. Hence, loss should be computed with respect to this segment. If the event is marked to be absent then this loss pushes the recording towards negative (0) label. This is idea is adopted from multiple instance learning methods where “max” instance often characterizes bags [10], [19], [20].

Variable Length Recording and Segments: Length of audio recordings in general vary a lot, this is especially true for web data. So, one simple way to adopt $N_S$ (which takes fixed size input) for weakly labeled training is to pass the segments one by one through the network, then compute the recording level loss w.r.t the segment which gives the maximal output. Implementation wise this would be a cumbersome process. Moreover, similar to SLAT this is also a computationally inefficient mechanism as their are common computations across segments which should should not be redone.

To address this problem, we propose to convert the fully connected layers (FC1, FC2) into fully convolutional layers [21] as follows.

- FCv1 (Convolution Layer) - 256 Filter of receptive fields (4 x 4), Stride - 1, No padding and ReLU activation.
- FCv2 (Convolution Layer) - nclasses Filters of size (1 X 1), Stride - 1, and Sigmoid Activation.

The above changes provides an elegant way to process a variable length recording through the network. Let $N_T$ be the network $N_S$ with FC1 and FC2 replaced by FCv1 and FCv2.

Consider a training recording with 1280 frames i.e $X \in R^{1280 \times 128}$. If we pass this input through $N_T$, the output layer will have size $(C \times 37 \times 1)$ where $C$ is number of classes, 37 is number of segments. This output is exactly same as considering a window (segment) of 128 frames, forwarding it through $N_S$, moving the window by 32 frames to get next window (segment) and repeating the process. We will have 37 segments and we will obtain outputs for each segment one by one. However, FCv1 and FCv2 allows to process the whole recording in an efficient manner in one forward pass. Hence, we get output for each segment over all classes in a single forward pass.

The exact window (segment) and hop size can be controlled by designing the convolution and pooling layers accordingly. In our case, to keep things simple, we kept a window and hop size of 128 and 32 mel-frames. This was achieved by convolution layers which does not affect the output size along time and frequency (1 X 128 X 128 to 96 X 128 X 128 and so on) and pooling layers which reduces the size by half (96 X 128 X 128 to 96 X 64 X 64 and so on). After C5P5, the size has reduced by a factor of 32. Note, computations which are common over different segments will not be repeated in this case where only a single forward pass is needed.

The final CNN network, $N_W$, for weakly labeled AER is shown in Figure 2 along with an example of output shape after each layer for a recording with 1280 frames in mel spectra. Note that the method of adopting $N_S$ for weakly labeled case is completely generic and in principle can be appropriately applied to any network design. Our proposed framework considers weakly labeled recordings as weak and provides an efficient way to train CNN models on weakly labeled audio. We will refer this method as Weakly Labeled Event Recognition (WLER).

Prediction: During prediction mel spectra for the test recording at each FFT size is forwarded through the network and then the average output score for each class across all FFT sizes is considered as the final output.

III. EXPERIMENTS AND RESULTS

A. Baseline

We compare our proposed framework against SLAT. Network $N_S$ is trained on recording segments where each segment is given the recording level label. During prediction the recording level score for each class is obtained by taking max over segment scores. Finally, averaging across all 4 mel spectra features similar to weak label case is done.

B. Datasets

We consider two different web data sources for training. Urbansounds (US): Urbansounds [11] dataset gives us human annotated weakly labeled data. The source of audio recordings in this dataset is Freesound website [22]. 10 events namely Air Conditioner, Car Horn, Children Playing, Dog Barking, Drilling, Engine Idling, Gunshot, Jackhammer, Siren and Street Music were manually marked in the recordings. This dataset contains time stamps information as well. We do not use that information and all experiments rely only on weak labels. A total of 1302 recordings, amounting to about 27 hours is present in the dataset, with recording length varying from a few seconds to around 10 minutes. The dataset comes pre-divided into 10 folds. We use first 4 for training (533 recordings), next 2 (262 recordings) for validation and last 4 (502 recordings) as testing set.


**Youtube Training Set**: The importance of weakly labeled learning lies in being able to obtain labeled data directly from web without any human labeling effort and be able to train robust AER models from these data. To show this, we collect training data for the 10 sound events directly from Youtube.

Collecting videos from Youtube and automatically getting their weak labels is a challenge in itself. In this work we propose a simple yet effective strategy to collect weakly labeled data from Youtube. We form the text query for searching on Youtube by adding the keyword “sound” to the event name, e.g. children playing sound. We then select the top 125 videos under 10 minutes duration retrieved by Youtube and mark them to contain that event. The duration of recording varies from 0.6 seconds to ~10 min., with average duration of 2.1 minutes. The total audio data collected is around 48 hours.

**Audioset Test Set**: US dataset is a relatively clean dataset. Often it is required to recognize events in low quality consumer generated data, which are more like the noisy web data we use for training here. To test our approach on data of such form and nature, we used the “Eval” set from Audioset dataset [23]. The source of Audioset is also Youtube. 9 events out of the 10 events considered are present in Audioset (except street music) and we will present results only for 9 events. A total of 761 test recordings exist with durations of 10 seconds for most cases. We ensured that these test recordings are not part of our Youtube training set.

Note that, due to mel spectra feature extraction at 4 different FFT scales, the total experimental data is four times in all cases.

**C. Results**

Librosa [24] was used for feature extraction. The CNN frameworks were implemented using Theano [25] and Lasagne [26]. Adagrad [27] optimization with a learning rate of 0.001 is used to update network parameters. The networks are trained for 150 Epochs and the best model among all epochs is selected using US validation set. We use Average Precision (AP) for each class as performance metric and Mean Average Precision (MAP) over all classes as overall metric.

Table [II-C] shows performance of different methods on US test set. For US dataset training, we observed that weakly labeled framework always outperforms corresponding training done with simplistic strong label assumption. In terms of MAP, we see an absolute improvement of 12.3%. For several events WLER improves performance by over 10 − 15% in absolute terms, showing that weakly labeled data needs to be considered as weakly labeled and strong label assumptions hurts learning. For training with Youtube collected dataset also, we see WLER outperforms SLAT by 7.3% in terms of MAP, justifying WLER over SLAT. The quality, nature and form of Youtube training data is very different from Urbansounds dataset. For example, it is much more noisy, overlapping sounds are dominant. Hence, US training set outperforms Youtube training on US test set.

Table [II-C] shows performance on the Audioset test set. First of all WLER is once again superior to SLAT for both training datasets. WLER outperforms SLAT by absolute 11.3% for Youtube training. On this dataset clearly Youtube training data does better. This shows that for content based retrieval of wild multimedia data on web and for applications where the need is to recognize events in consumer generated data, it is important to train on such data. Recognizing classes such as Air Conditioner and Jackhammer in Audioset is hard. These events can be easily confused with other types of events and noises which are often present in Youtube quality data.

### IV. Conclusions

In this paper we proposed a deep CNN framework to learn audio event recognition using web data. We showed it is possible to collect weakly labeled data directly from web and then train AER models using that. Our proposed CNN based learning framework nicely incorporates weakly labeled nature of the audio data. It outperforms train mechanism which makes strong label assumption by a considerable margin. Moreover, the proposed framework can efficiently handle recordings of variable length during training as well as testing. No pre-processing to segment the recording into fixed length is required. Besides a better and smoother implementation process this is also computationally more efficient.

Our proposed framework can perform temporal localization as well, the output of $\lambda_W$ before GPL layer is the output for different segments. Hence, in principle the network can roughly locate where an event occurred. We plan to investigate this aspect of the framework in future.

| Event Name       | US Training SLAT | Youtube Training SLAT | Youtube Training WLTER |
|------------------|------------------|-----------------------|------------------------|
| Air Conditioner  | 0.209            | 0.214                 | 0.073                  | 0.099                  |
| Car Horn         | 0.432            | 0.650                 | 0.403                  | 0.696                  |
| Children Playing | 0.731            | 0.876                 | 0.532                  | 0.760                  |
| Dog Bark         | 0.855            | 0.912                 | 0.807                  | 0.816                  |
| Drilling         | 0.687            | 0.779                 | 0.299                  | 0.295                  |
| Engine Idling    | 0.273            | 0.416                 | 0.220                  | 0.228                  |
| Gunshot          | 0.831            | 0.954                 | 0.826                  | 0.851                  |
| Jackhammer       | 0.667            | 0.721                 | 0.088                  | 0.350                  |
| Siren            | 0.599            | 0.776                 | 0.557                  | 0.505                  |
| Street Music     | 0.858            | 0.864                 | 0.663                  | 0.599                  |
| MAP              | 0.614            | 0.737                 | 0.447                  | 0.520                  |

**Table I**

**Performance (AP) on US Test Set. WLER outperforms SLAT for both training datasets.**

| Event Name       | US Training SLAT | Youtube Training SLAT | Youtube Training WLTER |
|------------------|------------------|-----------------------|------------------------|
| Air Conditioner  | 0.059            | 0.074                 | 0.137                  | 0.199                  |
| Car Horn         | 0.114            | 0.369                 | 0.345                  | 0.564                  |
| Children Playing | 0.558            | 0.496                 | 0.279                  | 0.487                  |
| Dog Bark         | 0.501            | 0.588                 | 0.709                  | 0.714                  |
| Drilling         | 0.395            | 0.340                 | 0.271                  | 0.401                  |
| Engine Idling    | 0.165            | 0.173                 | 0.344                  | 0.423                  |
| Gunshot          | 0.509            | 0.627                 | 0.653                  | 0.864                  |
| Jackhammer       | 0.098            | 0.150                 | 0.120                  | 0.199                  |
| Siren            | 0.579            | 0.593                 | 0.768                  | 0.774                  |
| MAP              | 0.331            | 0.379                 | 0.403                  | 0.514                  |

**Table II**

**APs on Audioset Test Set. WLER again outperforms SLAT**
