ABSTRACT

Recent studies have put into question the commonly assumed shift invariance property of convolutional networks, showing that small shifts in the input can affect the output predictions substantially. In this paper, we ask whether lack of shift invariance is a problem in sound event classification, and whether there are benefits in addressing it. Specifically, we evaluate two pooling methods to improve shift invariance in CNNs, based on low-pass filtering and adaptive sampling of incoming feature maps. These methods are implemented via small architectural modifications inserted into the pooling layers of CNNs. We evaluate the effect of these architectural changes on the FSD50K dataset using models of different capacity and in presence of strong regularization. We show that these modifications consistently improve sound event classification in all cases considered, without adding any (or adding very few) trainable parameters, which makes them an appealing alternative to conventional pooling layers. The outcome is a new state-of-the-art mAP of 0.541 on the FSD50K classification benchmark.

Index Terms—Shift invariance, sound event classification, low-pass filtering, adaptive polyphase sampling, convolutional neural networks

1. INTRODUCTION

Convolutional Neural Networks (CNNs) have been one of the cornerstones of Sound Event Classification or Tagging (SET) in recent years [1, 2, 3, 4]. One of their commonly assumed properties is shift or translation invariance, by which output predictions are not affected by small shifts (or even small deformations) in the input signal. In theory, this is ensured by the convolution and pooling operations forming the CNNs. However, recent works in computer vision uncover that this is not always the case. Azulay and Weiss find that small shifts and transformations in the input can change the network’s predictions substantially [5]. In particular, they quantify that by shifting or resizing a random input image by one single pixel, the top class predicted can change with a probability of up to 15% and 30%, respectively. This and other recent related works [6, 7] empirically show the brittleness of CNNs against minor input perturbations, and their only partial invariance to shifts.

These works argue that one of the causes of the lack of shift invariance is a wrongly executed subsampling operation that ignores the classic sampling theorem. This theorem establishes that, for the subsampling operation to be done correctly, the sampling rate must be at least twice the highest frequency in the incoming signal [8]. Otherwise, aliasing problems can occur, generating lack of shift invariance in the system, and potentially causing a certain distortion in the downsampled output, where some of the highest frequency components can overlay other low frequency ones. To address this issue, the classical signal processing measure is to introduce an anti-aliasing low-pass filter before downsampling in order to limit the signal’s band according to the Nyquist frequency [8]. In CNNs, subsampling operations are prevalent through strided layers, e.g., convolution or pooling layers with a stride larger than one. As anti-aliasing actions are not usually taken, feature maps containing high frequency components may lead to shift invariance and/or distortion problems.

The findings above have led to the rise of a recent and growing area of research aimed at increasing shift invariance in CNNs, either through architectural improvements [7, 9, 10] or via data augmentation [6]. In this work, we are interested in the former, which usually revolves around the idea of improving the subsampling operations. The predominant trend consists of adding anti-aliasing measures to the CNN architectures. Similarly to the signal processing fix, some works adopt different low-pass filter based solutions, mainly for image recognition [7, 10] and more recently also for speech recognition [11]. Zhang demonstrates that adding blurring to deep convolutional networks before the strided operations (convolution and pooling) provides increased accuracy on ImageNet [12] and improved robustness to image perturbations [7]. Vasconcelos et al. conduct a study to isolate the impact of aliasing within the different modules of a ResNet-50 architecture [10]. Bruguier et al. insert 1D low-pass filters to operate along the temporal dimension of feature maps before stacking layers in a RNN-based model for speech recognition [11].

In contrast to the anti-aliasing line of work, another alternative is to design architectural changes to explicitly enforce invariance in the network. For example, several previous works focus on increasing the invariance of CNNs to rotations in input images, by applying constraints to the convolutional filters [13] or proposing ad hoc operations to enforce this property [14]. Recently, to address the lack of shift invariance caused by subsampling operations, Chaman and Dokmanic propose a downsampling mechanism called adaptive polyphase sampling [9]. The key idea is to avoid using the same fixed sampling grid for subsampling a feature map (as typically done in CNNs), but instead select it adaptively based on some criterion (e.g., choosing the grid that produces a downsampled output with highest energy). To our knowledge, this kind of techniques aimed at fostering shift invariance in CNNs have not been evaluated for sound event classification.

In this paper, we ask whether lack of shift invariance is a problem in sound event recognition, and whether there are benefits in addressing it. To this end, we apply several mechanisms aimed at increasing shift invariance in the subsampling operations of CNNs, and evaluate them on a large-vocabulary sound event classification task. Specifically, we adopt mechanisms from the two trends mentioned above, namely, low-pass filters (non-trainable as proposed in [7], as well as a trainable version proposed by us), and adaptive...
We focus on the effect of low-pass filtering feature maps before MaxPool within CNNs. First, in the event that the feature maps present a series of transients. In its corresponding feature map, the energy variations given by such a sequence of transients can generate high frequencies, even at the lowest end of the spectrum.

Adaptive polyphase sampling [9]. We insert these architectural changes into the max-pooling layers of VGG variants [15], and we evaluate their effect on the FSD50K dataset [16] using models of small and large capacity, and in presence of a strong regularizer (mixup augmentation [17]). We show that these simple changes consistently improve sound event classification in all cases considered. Further, this is achieved without adding any (or adding very few) trainable parameters, which makes the proposed pooling mechanisms an appealing alternative to conventional pooling layers. The outcome is a new state-of-the-art mAP of 0.541 on the FSD50K classification benchmark when not using external training data. Code will be made available in the final version of the paper.

2. METHOD

Our focus is on evaluating mechanisms to improve shift invariance applied to the subsampling operations within max-pooling layers in CNNs. A max-pooling layer with squared size \( k \times k \) and stride \( s \) can be understood as the cascade of two operations: i) a densely-evaluated (i.e., with unit stride) max-pooling operation with size \( k \), followed by ii) a subsampling operation with stride \( s \) greater than unity.

2.1. Low-Pass Filtering Before Subsampling

We focus on the effect of low-pass filtering feature maps before subsampling in the context of a max-pooling layer, inspired by Zhang [7]. The subsampling operation may incur in aliasing problems as the incoming signal (the feature map) is not band-limited. The classic signal-processing fix is to add a low-pass filter before subsampling [8]. One manner to realize this filter is through a 2D kernel, \( LPF_{m,n} \), of size \( m \times n \), such that the max-pooling layer for an incoming feature map \( x \) becomes

\[
y_{lpf} = \text{Subsample}_s(LPF_{m,n}(\text{MaxPool}_{k,1}(x))),
\]

where \( \text{MaxPool}_{k,1} \) is a max-pooling operation across areas of size \( k \times k \) and unit stride, \( LPF_{m,n} \) applies a low-pass filter of size \( m \times n \), and \( \text{Subsample}_s \) denotes naive subsampling with a stride \( s \).

This simple measure can have different benefits when applied within CNNs. First, in the event that the feature maps present energy variations of too high frequency for the subsampling operation to be carried out without errors, \( LPF_{m,n} \) will help mitigate aliasing, thus reducing the amount of corrupted information flowing through the network. Second, the signal processing literature demonstrates how preventing aliasing can favour shift invariance in a given process [8]. One way to see it is that \( LPF_{m,n} \) spreads possible sharp patterns across neighbouring feature map bins. Intuitively, when subsampling differently shifted versions of a spectrogram, the subsampled feature maps are likely to be more structurally similar if they have been previously low-pass filtered. This could provide the network with improved generalization to this kind of small shifts, potentially increasing classification performance. Third, \( LPF_{m,n} \) is effectively blurring or smoothing out the incoming feature map, which could be understood as a form of regularization. For example, L2 regularization is a common way to penalize outlier weights with large absolute values, driving them close towards zero [18]. It could be argued that the proposed \( LPF_{m,n} \) inflicts a similar effect on the feature map bins, smoothing out the most drastic energy variations or, in other words, attenuating the high frequency components in the 2D signal formed by the feature map. In Sec. 4 we discuss through experiments which of these hypotheses seem more plausible.

In terms of implementation, some of the most basic characteristics of common 2D image-oriented low-pass filter kernels are having non-negative weights that add up to unity [19]. This can be realized in several ways.

**Non-trainable low-pass filters.** These are commonly defined as binomial filters, which are in turn discrete approximations of Gaussian filters. To generate 1D binomial filters, a simple manner is to repeatedly convolve the base averaging mask \([1,1]\) with itself, in order to get filter masks such as \([1,2,1]\), \([1,3,3,1]\), or \([1,4,6,4,1]\), for one, two and three convolutions, respectively. Then, a 2D squared binomial mask can be obtained simply by convolving a 1D binomial filter with its transpose [19]. In Sec. 4 we denote this type of filters as BlurrPool for consistency with [7] as the non-trainable low-pass filters that we use in our experiments are largely inspired by this work.

**Trainable low-pass filters.** These can be defined by randomly initializing a kernel with dimensions \( m \times n \), and learning their weights through back propagation. In order to imprint the low-pass nature to the filter, its weights can be passed through a softmax function to ensure non-negativity and normalization. An alternative is to create auxiliary loss functions to encourage the filter weights to adopt a low-pass behaviour through loss penalization. In Sec. 4 we denote this type of filters as Trainable Low-Pass Filter (TLPF).

In this work, we compare non-trainable low-pass filters (BlurrPool) and trainable low-pass filters constrained via softmax (TLPF), for simplicity. A given low-pass filter can be applied over the incoming feature map via a convolution operation that also incorporates the required subsampling stride \( s \). More specifically, \( \text{Subsample}_s(LPF_{m,n}(\cdot)) \) in (1) is implemented using a depth-wise separable convolution using \( LPF_{m,n} \) (either trainable or non-trainable) and stride \( s \).

2.2. Adaptive Polyphase Sampling

Adaptive polyphase sampling (APS) is a downsampling mechanism that directly addresses the lack of shift invariance caused by subsampling operations [9]. The underlying principle of APS is based on a simple observation: the result of subsampling a time-frequency (T-F) patch and subsampling its shifted-by-one-bin version can be different when bins are sampled at the same fixed positions. This happens because the energies captured by the same grid over two shifted patches are likely to be different. However, when subsampling a feature map, multiple candidate grids could actually be used instead of always using the same grid (as typically done). Intuitively, a time/frequency shift applied over an input patch could be seen conceptually as translating its energy bins from one grid to another. One way to be robust to these shifts is to select the subsampling grid adaptively based on some criterion, such that the grid follows the shift at the input.

More formally, given an input feature map \( x \), and considering a subsampling operation\(^2\) with stride 2, there are four possible grids

\(^2\)This subsampling operation would follow a densely-evaluated max
that can be used for subsampling, depending on which bin from the four options in each 2x2 area is passed to the output. Subsampling with each grid will yield one of the four possible candidate subsampled feature maps, termed polyphase components [9], which can be denoted as \( \{y_{ij}\}_{i,j=0}^3 \). Analogously, if we consider a shifted-by-one-bin version of the input feature map, \( \bar{x} \), its polyphase components are given by \( \{\bar{y}_{ij}\}_{i,j=0}^3 \).

The conventional course of action consists of always choosing the same subsampling grid and consequently returning the same polyphase component (e.g., \( y_{00} \) by picking the top left bin in each 2x2 area). However, as mentioned, depending on the input patch, this will likely cause different downsampled outputs when the patch is simply shifted by one bin \( (y_{00} \neq \bar{y}_{00}) \). It can be demonstrated that the set \( \{\bar{y}_{ij}\} \) is a re-ordered version of \( \{y_{ij}\} [9] \) (which may be potentially shifted, but carrying identical energy values). Therefore, by adaptively choosing a polyphase component in a permutation invariant way, a very similar subsampled output, \( y_{iaps,japs} \), would be obtained regardless of sampling from \( x \) or \( \bar{x} \). The adaptive selection can be done by maximizing a given criterion, for example, maximizing some norm \( \| \cdot \|_p \), as given by

\[
i_{aps}, j_{aps} = \arg \max_{i,j} \| y_{ij} \|_p^1, \quad (2)
\]

where \( p \in \{1, 2\} \). In this way, robustness to incoming time/frequency shifts is increased.

The benefit from APS comes from the generalization to shifts embedded in the network’s architecture, in a fashion conceptually similar to what is done with \( \text{LTPF}_{m,n} \) (Sec. 2.1). APS, in contrast, provides no explicit measures against potential aliasing problems.

### 3. EXPERIMENTAL SETUP

#### 3.1. Evaluation and Training Details

We evaluate the proposed methods on a large-vocabulary sound event tagging task using the recently released FSD50k dataset [16]. FSD50k is open dataset of sound events containing over 51k Freesound audio clips, totalling over 100h of audio manually labeled using 200 classes drawn from the AudioSet Ontology [20]. We follow the evaluation procedure proposed in the FSD50K paper [16] (with minor deviations), which is outlined next. Incoming clips are transformed to log-mel spectrograms using a 30ms Hann window with 10ms hop, and 96 bands. To deal with the variable-length clips, we use T-F patches of 1s, equivalent to 101 frames, yielding patches of \( T \times F \approx 101 \times 96 \) that feed the networks. Clips shorter than 1s are replicated while longer clips are trimmed, in several patches with 50% overlap inheriting the clip-level label. We train, validate and evaluate using the proposed \textit{train} set, \textit{val} set and \textit{eval} set [16]. Models are trained using Adam optimizer [21] to minimize binary cross-entropy loss. Learning rate is 3e-5, halved whenever the validation metric plateaus for 10 epochs. Models are trained up to 150 epochs, early stopping the training whenever the validation metric is not improved in 20 epochs. We use a batch size of 128 and shuffle training examples between epochs. Once the training is over, the model checkpoint with the best validation metric is selected to predict scores and evaluate performance on the eval set. For inference, we compute output scores for every (eval or val) T-F patch, then average per-class scores across all patches in a clip to obtain clip-level predictions. Our evaluation metric is balanced mean Average Precision (mAP), that is, mAP computed on a per-class basis, then averaged with equal weight across all classes to yield the overall performance, following [16, 20, 1].

#### 3.2. Baseline Model

As a base network, we use a VGG-like architecture [15]. This type of architecture has been widely used for SET [2, 22, 23, 24] and is the most competitive baseline for FSD50K when compared to others of higher complexity [16]—which also accords with recent music tagging evaluations [25]. Due to its limited size compared to other baselines [16], it allows for faster experimentation. In addition, this architecture features several max-pooling layers that allow the study of the proposed pooling mechanisms. Specifically, the network that we use for the majority of our experiments is similar to a VGG type A [15]. The network, denoted as VGG41, consists of 4 convolutional blocks, with each block comprising two convolutions with a receptive field of \((3, 3)\), and each convolution followed by Batch Normalization [26] and ReLU activation. Between the blocks, max-pooling layers of size \((2, 2)\) (and same stride) are placed by default—they will be substituted by the proposed pooling mechanisms. A densely-evaluated max pooling operation (of size \(3x3\) and unit stride) will sometimes be inserted between the convolutions within each block—we will refer to it as \textit{intra-block pooling} (IBP). This provides partial translation invariance but not dimensionality reduction, allowing the same (max) element in the feature map to be transferred to the output in adjacent spatial locations. This tweak has been applied in various non-audio applications [27], and to a lesser extent also in SET tasks [24]. Finally, in order to summarize the final feature map information before the output classifier, we use a global pooling in which we aggregate information along the spectral dimension via averaging for every time step, before max pooling the outcome in the time dimension. We found out that aggregating first spectral and then temporal information in this manner is the most beneficial for our task among other combinations. VGG41 has 1.2M weights, which allows for relatively fast experimentation. The baseline and topline systems using VGG41 are then evaluated using VGG42 (of 4.9M weights), where we double the width of the network with respect to VGG41 (i.e., using twice the number of filters in every convolutional layer).

#### 3.3. mixup

We will evaluate the top performing methods proposed in Sec. 2 with or without mixup augmentation [17] in order to analyze their behavior in presence of a strong regularizer. Mixup acts as a regularizer by encouraging networks to predict less confidently on linear interpolations of training examples. In particular, it augments the training distribution by creating virtual examples under the assumption that linear interpolations in the feature space correspond to linear interpolations in the label space. Following [17], we sample \( \lambda \) from a beta distribution \( \lambda \sim \text{Beta}(\alpha, \alpha) \), for \( \alpha \in (0, \infty) \). The hyper-parameter \( \alpha \), which controls the interpolation strength, is set to 1.25 after tuning on the val set.

We choose mixup because the concept of mixing sounds is an audio-informed operation, and it has been proven useful for SET [2, 28, 3] and other sound event research tasks [29]. In our view, mixup can be interpreted from two different perspectives. First, it is a regularizer to mitigate overfitting, which can be important at our scale of data, especially for some classes that present less than 100

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While it may seem that blurring the feature maps can smooth out the feature maps (the larger the size, the stronger the smoothing effect). This technique is beneficial for CNN-based sound event classification. Our motivation to combine the proposed methods with mixup is to analyze their behavior in presence of a strong regularizer. If they act solely as a general form of regularization, we would expect them to provide limited boosts when combined with mixup. We do observe a certain improvement decrease when combined, but the boosts are still solid, both when using VGG41 and VGG42 (center and right columns). These results suggest that the proposed methods are addressing problems beyond lack of regularization, presumably reinforcing robustness to time/frequency shifts at the input.

When inserting the proposed methods into VGG42 in presence of mixup (right column), it can be seen that TLPF slightly outperforms APS, showing boosts of 0.018 and 0.014 over the baseline, respectively.

4. EXPERIMENTS

We evaluate the methods proposed in Sec. 2 on the SET task posed by FSD50K, using VGG41 (Table 1) and also using mixup and VGG42 (Table 2). Training clips. Second, mixup is a mechanism that allows to cover during training a diversity of examples that may be encountered in evaluation, hence improving generalization. In particular, upon the creation of FSD50K, audio clips with multiple sound sources were prioritized to some extent for the eval set, whereas the dev set presents a higher proportion of single-source clips. It can therefore be argued that a kind of domain shift exists between both sets, which is being partially compensated through mixup. Hence, this type of augmentation is specially well aligned with the recognition task of FSD50K.

4.1. Evaluation using a Small Model

Table 1 shows the results of the pooling mechanisms inserted into VGG41 individually (top section) as well as in some combinations (bottom section). It can be seen that all the evaluated methods outperform the baseline system, that is, inserting each of the methods alone into a standard VGG-like architecture improves recognition performance. The boosts range from 0.003 in the worst case (APS) to 0.023 in the best case (APS + TLPF 5x5 + IBP). If we focus on the low-pass filter based solutions, we observe that this classical signal processing technique is beneficial for CNN-based sound event classification. While it may seem that blurring the feature maps can smooth out relevant detailed information, thus leading to performance degradation, results indicate that it is indeed helpful. The choice of trainable or non-trainable low-pass filters does not seem critical, yet the trainable version TLPF seems to produce slightly higher mAP values. The different sizes of these filters allow to find a trade-off between high-frequency smoothing and loss of information in the incoming feature maps (the larger the size, the stronger the smoothing effect). Results seem to indicate that larger smoothing areas (5x5 vs 3x3) are beneficial. By looking at results with APS, it seems that this method is sensitive to the choice of norm criterion in our experiments, with l1 clearly outperforming l2. Interestingly, a naive tweak like IBP also shows some impact, although more modest than that of the other methods. The two top methods when applied individually are APS l1 and TLPF 5x5, showing on par performance.

We set out to combine some of the methods in order to see if they are complementary. Combining IBP (which operates between convolutions within every block) and low-pass filtering (which operates before subsampling between convolutional blocks) seems to provide a small but consistent boost, for both BlurPool and TLPF. When joining the top performing methods (specifically, low-pass filtering the incoming feature maps with TLPF 5x5, followed by subsampling them with APS), we do not observe further performance boosts—in fact, we observe a small degradation. This is somewhat unexpected as the fact that they have different underlying principles (with TLPF oriented to anti-aliasing) invites to expect gains from their combination. Further analysis is needed to better understand this result and how they interact together.

4.2. Evaluation using Regularization and a Larger Model

Next, we select the two pooling mechanisms found to perform best on VGG41 (in bold in Table 1), one based on low-pass filtering and another based on APS—the two trends considered in this work. Table 2 shows the results using the selected pooling mechanisms, now adding mixup augmentation and also doubling the width of the network, which means multiplying its number of weights approximately by four. The left column lists the best values from Table 1, showing boosts of 0.023 and 0.024 with respect to the baseline. When we add mixup to VGG41 (center column) substantial performance improvements are observed, demonstrating the good alignment of this operation with SET in general (which accords with [2, 3]) and with the FSD50K classification task in particular (as discussed in Sec. 3.3). The APS method slightly outperforms TLPF, showing boosts with respect to the baseline of 0.017 and 0.014, respectively.

Table 1: mAP obtained by inserting different pooling mechanisms into the VGG41 baseline. TLPF = Trainable Low-Pass Filter, APS = Adaptive Polyphase Sampling, IBP = Intra-block Pooling.

| Method | mAP |
|--------|-----|
| VGG41 (baseline) | 0.457 |
| + BlurPool 3x3 | 0.475 |
| + BlurPool 5x5 | 0.476 |
| + TLPF 3x3 | 0.476 |
| + TLPF 5x5 | 0.479 |
| + APS l1 | 0.480 |
| + APS l2 | 0.460 |
| + IBP | 0.472 |
| + BlurPool 5x5 + IBP | 0.479 |
| + TLPF 5x5 + IBP | 0.481 |
| + TLPF 5x5 + APS l1 | 0.476 |
| + TLPF 5x5 + APS l2 | 0.478 |

Table 2: mAP obtained by using the top performing pooling mechanisms from Table 1 in presence of mixup and with the larger capacity VGG42. TLPF = Trainable Low-Pass Filter, APS = Adaptive Polyphase Sampling, IBP = Intra-block Pooling.

| Method | VGG41 | VGG41 + mixup | VGG42 + mixup |
|--------|-------|---------------|---------------|
| Baseline | 0.457 | 0.497 | 0.523 |
| + APS l1 | 0.480 | 0.514 | 0.538 |
| (0.023) | (0.017) | (0.015) |
| + TLPF 5x5 + IBP | 0.481 | 0.511 | 0.541 |
| (0.024) | (0.014) | (0.018) |
Table 3: State-of-the-art on FSD50K.

| Method                                      | mAP  |
|---------------------------------------------|------|
| Baseline [16]                               | 0.434|
| PSLA (not using ImageNet) [3]               | 0.452|
| Audio Transformers [30]                     | 0.537|
| VGG42 + APS $l_1$ (ours)                    | 0.538|
| VGG42 + TLPF 5x5 + IBP (ours)               | 0.541|
| PSLA (using ImageNet) [3]                   | 0.567|

respectively. These results indicate that the evaluated pooling mechanisms are also beneficial when inserted into larger-capacity models (in our case, increasing the capacity from 1.2 to 4.9M weights), where performance is more competitive.

4.3. Discussion

We have seen that two methods with different underlying principles targeting the increase of shift invariance yield improvements within the same ballpark in our task. This fact seems to indicate that there is indeed some lack of this property in the CNN under test, and that reinforcing shift invariance is beneficial for sound event classification. One interesting observation is that while anti-aliasing measures are helpful to increase performance and presumably shift invariance, they do not seem strictly necessary in light of the overall similar performance attained by APS.

In terms of model size, the impact is negligible for all evaluated methods. Specifically, TLPF5x5 adds 6k (0.5%) and 12k (0.24%) trainable parameters over VGG41 and VGG42 respectively. Its non-trainable counterpart (BlurPool 5x5) adds the same number of non-trainable parameters. APS does not require any additional parameters (trainable or non-trainable). The additional compute required by the methods is also limited. For the low-pass filtering methods, one additional convolution is needed to apply the low-pass filter over the incoming feature maps for every subsampling operation. Analogously, the only additional compute required by APS is the computation of the polyphase components and their norms in every subsampling operation. The proposed architectural modifications, which apply only to the pooling layers, yield consistent recognition improvements when inserted into a well-known CNN, with minimal additional computation. This makes them an appealing alternative to conventional pooling layers.

4.4. Comparison with Previous Work

Table 3 lists the reported state-of-the-art on FSD50K. Our best system obtains state-of-the-art performance of 0.541 on FSD50K, slightly outperforming recent Transformer-based approaches (0.537) [30], as well as the PSLA approach when trained only on FSD50K (0.452) [3]. PSLA makes use of a collection of training techniques (ImageNet pretraining, data balancing and augmentation, label enhancement, weight averaging, and ensemble of several models) [3]. Among all of them, the key ingredient seems to be ImageNet pretraining, without which the performance decreases dramatically. Using transfer learning from ImageNet provides substantial performance boosts, however we consider transfer learning from external datasets a different track. Our proposed state-of-the-art approach consists of simple architectural changes inserted into a widely-used CNN at minimal computational cost along with simple augmentation.

5. CONCLUSION

We have evaluated two pooling methods to improve shift invariance in CNNs in the context of a sound event classification task. These methods are based on low-pass filtering and adaptive sampling of incoming feature maps, and are implemented via small modifications in the pooling layers of CNNs. We have evaluated the effect of these architectural changes on the FSD50K dataset, using models of different capacity and in presence of strong regularization. Results suggest that the models evaluated indeed present a problem of only-partial shift invariance, and that adopting the proposed methods to improve it yields recognition boosts. This is based mainly on two observations: i) the architectural changes improve classification in all cases considered, even in presence of strong regularization, which indicates that the methods are addressing issues beyond lack of regularization; ii) the improvements observed are within the same ballpark, despite the methods having different underlying principles. The proposed architectural changes applied to a widely-used CNN yield consistent recognition improvements with minimal additional computation, which makes them an appealing alternative to conventional pooling layers. Our best system achieves a new state-of-the-art mAP of 0.541 on FSD50K.
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