Abstract

We present an MatchboxNet - an end-to-end neural network for speech command recognition. MatchboxNet is a deep residual network composed from blocks of 1D time-channel separable convolution, batch-normalization, ReLU and dropout layers. MatchboxNet reaches state-of-the-art accuracy on the Google Speech Commands dataset while having significantly fewer parameters than similar models. The small footprint of MatchboxNet makes it an attractive candidate for devices with limited computational resources. The model is highly scalable, so model accuracy can be improved with modest additional memory and compute. Finally, we show how intensive data augmentation using an auxiliary noise dataset improves robustness in the presence of background noise.

Index Terms: key word spotting, speech commands recognition, deep neural networks, depth-wise separable convolution

1. Introduction

We present MatchboxNet, a new compact, end-to-end neural network for keyword spotting (KWS) specifically designed for devices with low computational and memory resources. MatchboxNet builds on the QuartzNet architecture [1]. It consists of a stack of blocks with residual connections [2]. Each block is composed from 1D time-channel separable convolutions (these are similar to 2D depth-wise separable convolutions [3, 4]), batch normalization, ReLU and dropout layers.

This paper makes the following contributions:
1. An end-to-end neural model for speech command recognition based on 1D time-channel separable convolutions
2. The model achieves state-of-the-art accuracy on Google Speech Command datasets [5] but requires significantly fewer parameters than models which achieve similar accuracy.
3. The model scales well with the number of parameters.
4. A methodology to improve the model’s robustness to background speech and noise.

2. Related Work

Neural network (NN)-based systems for Automatic Speech Recognition (ASR) have a long history, spearheaded by Time Delay Neural Networks (TDNN) for isolated word recognition [6, 7]. TDNN and Recurrent NNs (RNNs) were first used together with Hidden Markov Models (HMMs) in hybrid systems, where NN was used only for phonetic classification [8,9,10].

Rapid progress in deep learning for ASR [11,12,13] triggered research in end-to-end NN-based models for KWS. In 2015 Sainath and Parada proposed a convolutional NN for a small-footprint KWS [14]. Their model was composed of two convolutional layers, max-pooling in the temporal dimension, linear, and soft-max layers. Following the success of ResNets [2] in computer vision, Qian et al. [15] applied ResNets for ASR. Arik et al. [16] suggested Convolutional-RNN, which combined the strengths of convolutional layers and recurrent layers to exploit long-range context.

The introduction of the Google Speech Command dataset [5] in 2018 accelerated research in KWS and resulted in variety of new NN-based models, including deep residual networks [17,18], special RNN with weight sharing [19], an RNN-Transducer with attention [20], and CNN with dilated convolutions and gating mechanisms [21].

3. MatchboxNet Architecture

The MatchboxNet architecture is based on the QuartzNet end-to-end convolutional NN for ASR [1]. Similar to QuartzNet, MatchboxNet uses 1D time-channel separable convolutions to reduce model size versus regular 1D convolutions.

A MatchboxNet-BxRxC model has B residual blocks. Each block has R sub-blocks. All sub-blocks in a block have
of re-balancing.

...steps, and 2 continuous frequency mask of size $[0, 15]$ in the range of $0.05, a hold ratio of 45%, and a polynomial (2nd order) decay for the remaining 50% of the schedule. We use a maximum learning rate of 0.05 and a minimum learning rate of 0.001. We also incorporate weight decay of 0.001. We train all models for 200 epochs using mixed precision [26] on 2 V-100 GPUs with a batch size of 128 per GPU. All experiments were carried out using the NeMo toolkit [27] and plan to make all code necessary to reproduce these results available.

4.2. Results
Comparing with other published results, MatchboxNet-3x1x64 and MatchboxNet-3x2x64 obtain state-of-the-art (SOTA) accuracy on the Google Speech Commands dataset v1 and close to the SOTA on dataset v2, while requiring significantly fewer parameters than other models (see Table 2 and Table 3). For comparison we used the following models:

- DenseNet-BC: a variant of ResNets with dense connectivity in between layers of each block [28]. An intermediate point-wise convolution layer applied prior to the convolution block acts as a "bottleneck (B)" layer to reduce number of parameters. The number of channels in the convolutional layer can be reduced via a "compression (C)" factor.

- EdgeSpeechNet: ResNet-like deep residual ConvNet optimized for edge devices [29].

- Harmonic Tensor 2D-CNN: triangular band-pass filters of the $n$th harmonic of center frequencies, are extracted and concatenated into a Harmonic Tensor of dimensionality $H \times F \times T$ (harmonic × frequency × time) which is then passed into a simple 2D-Convolutional NN [30].

- 'Embedding + Head': the acoustic embedding model with multiple heads is pre-trained to distinguish between various keyword groups on 200 million 2-second audio clips from YouTube. These heads are discarded after pre-training, and a single head is used to fine-tune the embedding model on the downstream task [31].

### 4. Experiments
We train MatchboxNet on the Google Speech Commands Dataset [5]. The dataset has two versions which we denote by v1 and v2. Version 1 has 65,000 utterances from various speakers, each utterance is 1 second long. Each of these utterances belongs to one of 30 classes corresponding to common words like Yes, No, "Go", "Stop", "Left", "Down", numerical digits, etc. Version 2 has 105,000 utterances, each 1 second long, belonging to one of 35 classes. We re-balanced both training datasets so all classes will have the same number of samples by duplication of random samples.

4.1. Training Methodology
First, the input audio wave is converted into sequence of 64 mel-frequency cepstral coefficients (MFCC) calculated from 25ms windows with a 10ms overlap. We perform symmetric padding of the temporal dimension with zeros to fixed length of 128 feature vectors per sample.

Next, the input is augmented with time shift perturbations in the range of $T = [-5, 5]$ milliseconds and white noise with magnitude $[-90, -40]$ dB. In addition, we applied SpecAugment [22] with 2 continuous time mask of size $[0, 25]$ time steps, and 2 continuous frequency mask of size $[0, 15]$ frequency bands. We also used SpecCutout [23], with 5 rectangular masks with time and frequency dimensions similar to used in SpecAugment.

All models are trained with the NovoGrad optimizer [24], with $\beta_1 = 0.95$ and $\beta_2 = 0.5$. We utilize the Warmup-Hold-Decay learning rate schedule as in [25] with a warm-up ratio of 5%, a hold ratio of 45%, and a polynomial (2nd order) decay.

### Table 1: MatchboxNet-3x2x64 model has B=3 blocks, each block has R=2 time-channel separable convolutional sub-blocks with C=64 channels, plus 4 additional sub-blocks: prologue - Conv1, and epilogue - Conv2, Conv3, Conv4).

| Block | # Blocks | # Sub Blocks | # Output Channels | Kernel |
|-------|----------|--------------|-------------------|--------|
| Conv1 | 1        | 1            | 128               |        |
| B1    | 1        | 2            | 64                |        |
| B2    | 1        | 2            | 64                |        |
| B3    | 1        | 2            | 64                |        |
| Conv2 | 1        | 1            | 128               | 29, dilation=2 |
| Conv3 | 1        | 1            | 128               | 1      |
| Conv4 | 1        | 1            | # classes         | 1      |
| Soft-max | 1 | 1 | # classes | 1 |

Cross-entropy

### Table 2: MatchboxNet on Google Speech Commands dataset v1, the accuracy is averaged over 5 trials (95% Confidence Interval).

| Model          | # Parameters, K | Accuracy, %   | Reference |
|----------------|-----------------|---------------|-----------|
| ResNet-15      | 238             | 95.8 ± 0.351  | [17]      |
| DenseNet-BC-100| 800             | 96.77         | [29]      |
| EdgeSpeechNet-A| 107             | 96.80         | [29]      |
| MatchboxNet-3x1x64 | 77          | 97.21 ± 0.067 |           |
| MatchboxNet-3x2x64 | 93          | 97.48 ± 0.107 |           |

### Table 3: MatchboxNet on Google Speech Commands dataset v2, the accuracy is averaged over 5 trials (95% Confidence Interval).

| Model          | # Parameters, K | Accuracy, % | Reference |
|----------------|-----------------|-------------|-----------|
| Attention RNN  | 202             | 94.39       | [33]      |
| Harmonic Tensor 2D-CNN | 385         | 96.39       | [30]      |
| 'Embedding + Head' Model | 385       | 97.7        | [31]      |
| MatchboxNet-3x1x64 | 77          | 96.91 ± 0.101 |          |
| MatchboxNet-3x2x64 | 93          | 97.21 ± 0.072 |          |
| MatchboxNet-6x2x64 | 140         | 97.37 ± 0.110 |          |
4.3. Model Scaling

We study the model scalability on the Google Speech Commands dataset v2 using MatchboxNet-3x2x64 as baseline. We scale model up using two methods: increase the depth $B \times R$ or increase the number of channels $C$. We found that both methods work in a similar way – the accuracy increases with model size until we hit $\approx 97.6\%$ (Table 4).

Table 4: Scaling up MatchboxNet depth and number of channels, Speech Commands Dataset v2

| B  | R  | C    | # Parameters, K | Accuracy, % |
|----|----|------|-----------------|-------------|
| 3  | 2  | 64   | 93              | 97.21       |
| 3  | 3  | 64   | 109             | 97.36       |
| 3  | 4  | 64   | 125             | 97.17       |
| 3  | 5  | 64   | 149             | 97.37       |
| 4  | 2  | 64   | 109             | 97.20       |
| 5  | 2  | 64   | 124             | 97.31       |
| 6  | 2  | 64   | 140             | 97.55       |
| 3  | 2  | 80   | 118             | 97.44       |
| 3  | 2  | 96   | 145             | 97.41       |
| 3  | 2  | 112  | 177             | 97.63       |

5. Model Robustness to Noise

To improve the robustness of MatchboxNet in the presence of noise, we retrained the model with background noise designed to interfere with speech signal. We construct a background noise dataset using audio samples from the Freesound database [34]. We partition each of these audio samples into segments of 1 second each, with no overlap between segments. Following this methodology, we obtain close to 55,000 noise samples.

5.1. Training with Noise Augmentation

We train MatchboxNet-3x1x64 by augmenting all training samples with randomly sampled noise segments. We scale the signal to noise ratio (SNR) randomly between 0 to 50 dB. In cases where the noise segment has a shorter duration than the training sample, we randomly augment a sub-segment of the training sample. The model accuracy on clean data is similar to the baseline model trained with basic augmentation only (Table 5).

Table 5: MatchboxNet-3x1x64 trained with additional background speech and noise augmentation, Google Speech Commands dataset v2. Accuracy (%) is averaged over 5 trials (95% confidence interval).

| Model                   | Augmentation                  | Accuracy, %       |
|-------------------------|-------------------------------|-------------------|
| MatchboxNet 3x1x64      | basic                         | 96.91 ± 0.101    |
| MatchboxNet 3x1x64      | + background speech and noise | 97.05 ± 0.099    |

In order to evaluate the model robustness to environmental noise and background speech, we test the model with different noise conditions with SNR from -10 dB to +50 dB. We evaluate each test sample with 10 different randomly sampled noise segments, and compute the average accuracy over the entire test set. The model trained with additional noise augmentation is significantly more robust to external noise, even when the noise signal is much higher in amplitude than the noise used during training (Fig. 2).

Figure 2: MatchboxNet-3 $\times 1 \times 64$ trained with background noise augmentation, Speech Commands dataset v2. Accuracy vs SNR.

5.2. Speech Commands Recognition with Background Speech and Noise Detection

To use a keyword spotting model in a continuous audio stream, it should be able to differentiate speech commands from the background speech or noise. For this, we added roughly 3500 samples for environmental noise and similar number of background speech samples from Freesound database to the training set. We re-trained a MatchboxNet-3x1x64 model to classify all original commands plus two additional classes - ‘background noise’ and ‘background voice’. The model accuracy on the expanded speech commands datasets is shown in Table 6. Training with additional background speech and noise augmentation significantly improves the model robustness to noise (Fig. 3).

Table 6: MatchboxNet-3 $\times 1 \times 64$ trained with additional background speech and noise augmentation, expanded Speech Commands dataset. Accuracy (%) is averaged over 5 trials (95% confidence interval).

| Model                   | Dataset | # Parameters | Accuracy, %       |
|-------------------------|---------|--------------|-------------------|
| MatchboxNet-3x1x64      | v1      | 77K          | 96.88 ± 0.073     |
| MatchboxNet-3x1x64      | v2      | 77K          | 96.97 ± 0.071     |
5.3. Robustness To Noise With Model Scaling
We further evaluate the relative robustness of larger MatchboxNet models to environmental noise and background speech. We train two models, MatchboxNet-3×1×64 and 6×2×64 with the exact same noise augmentation scheme as described above. We then evaluate the models on the unseen test set, perturbed by 10 random noise samples per test sample and compute the average accuracy. While both models are highly robust to external noise, MatchboxNet-6×2×64 consistently outperforms the smaller MatchboxNet-3×1×64 (see Table 7 and Figure 4).

| Model          | SNR (dB) |
|---------------|----------|
|               | -10 | 0 | 10 | 20 | 30 | 40 | 50 |
| 3×1×64        | 69.62 | 87.21 | 94.53 | 96.40 | 96.89 | 97.05 | 97.09 |
| 6×2×64        | 71.02 | 88.81 | 95.04 | 96.74 | 97.16 | 97.29 | 97.33 |

Table 7: MatchboxNet-3 × 1 × 64 and MatchboxNet-6 × 2 × 64 trained with additional background speech and noise augmentation. Accuracy (%) is averaged over 10 trials with random noise.

Figure 4: MatchboxNet-3 × 1 × 64 and MatchboxNet-6 × 2 × 64 trained with additional background speech and noise augmentation. Accuracy vs SNR.

6. Conclusions
In this paper, we present MatchboxNet, a new end-to-end deep neural network architecture for efficient recognition of speech commands on devices with limited computational and memory resources. MatchboxNet is a deep residual network composed from 1D time-channel separable convolution, batch-norm layers, ReLU and dropout layers. The model has state-of-the-art accuracy on the Google Speech Commands v1 dataset with significantly fewer parameters than models with similar accuracy. MatchboxNet is scalable, allowing it to be deployed on devices with different memory and compute capabilities. By using intensive data augmentation with auxiliary background noise during training, we have shown the model can be made very robust with respect to background noise.

7. Acknowledgments
We would like to thank NVIDIA AI Applications team for the help and valuable feedback.

8. References
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