Speech Command Recognition [1]

Project done as part of course EE5600

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Overview



Problem Statement

Proposed Methodology

Dataset

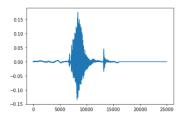
Experiments & Results

Conclusion

Problem Statement



- Design and implementation of a speech command recognition framework
- ▶ In this work we train and test a neural attention model [1] on a speech command dataset prepared from scratch



(a) Example speech command file

Proposed Methodology



Neural Attention Network:

- ▶ Neural attention network is an RNN with attention mechanism
- ► The input to the model is the mel-scale spectrogram (we will discuss its construction in Dataset section)
- ▶ The two initial layers are 2D convolutional layers which extract local temporal relations from the input. The conv layer's output is then fed to bidirectional LSTM (B-LSTM). B-LSTM captures long term (global) relationships from the input
- ▶ B-LSTM's output is a 1D vector whose weighted average is then fed to FCN. FCN output is used to classify the audio files into commands

Dataset



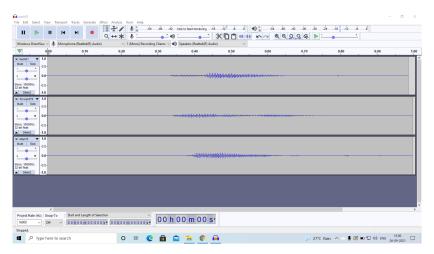


Figure 3: Snapshot of data collection

Dataset (cont.)



- ► The speech command dataset contains 400 .wav audio files for 5 speech commands viz. forward, back, right, left and stop
- ► The audio is recorded at sampling rate 16KHz and .wav file is stored in 32 bit format
- ► Neural attention network takes mel-scale spectrogram as input and hence .wav files are converted to mel-scale spectrogram using kapre library

Experiments & Results



Model Training and Validation:

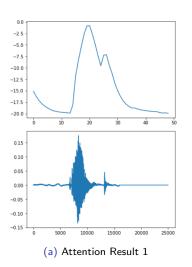
```
F→ Epoch 1/10
286/286 - 20s - loss: 1.3585e-09 - sparse categorical accuracy: 1.0000 - val loss: 0.0261 - val sparse categorical accuracy: 0.9964
Epoch 2/10
286/286 - 20s - loss: 1.1495e-09 - sparse categorical accuracy: 1.0000 - val loss: 0.0263 - val sparse categorical accuracy: 0.9964
Epoch 3/10
286/286 - 20s - loss: 8.1507e-10 - sparse categorical accuracy: 1.0000 - val loss: 0.0279 - val sparse categorical accuracy: 0.9964
Epoch 4/10
286/286 - 20s - loss: 5.6428e-10 - sparse categorical accuracy: 1.0000 - val loss: 0.0296 - val sparse categorical accuracy: 0.9964
Epoch 5/10
286/286 - 20s - loss: 3.3439e-10 - sparse categorical accuracy: 1.0000 - val loss: 0.0300 - val sparse categorical accuracy: 0.9958
Froch 6/10
286/286 - 20s - loss: 3.9709e-10 - sparse categorical accuracy: 1.0000 - val loss: 0.0322 - val sparse categorical accuracy: 0.9958
Epoch 7/10
286/286 - 20s - loss: 2.5079e-10 - sparse categorical accuracy: 1.0000 - val loss: 0.0333 - val sparse categorical accuracy: 0.9958
Epoch 8/10
286/286 - 20s - loss: 1.4629e-10 - sparse categorical accuracy: 1.0000 - val loss: 0.0354 - val sparse categorical accuracy: 0.9958
Epoch 9/10
286/286 - 23s - loss: 1.4629e-10 - sparse categorical accuracy: 1.0000 - val loss: 0.0363 - val sparse categorical accuracy: 0.9958
Epoch 10/10
286/286 - 20s - loss: 8.3597e-11 - sparse categorical accuracy: 1.0000 - val loss: 0.0372 - val sparse categorical accuracy: 0.9958
<keras.callbacks.History at 0x7efce2468bd0>
```

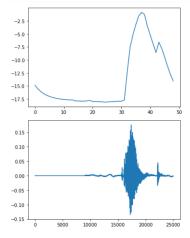
Experiments & Results (cont.)



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Attention Results:





(b) Attention Result 2

Conclusion



- According to the training and test procedure, we observe that the neural attention network overfits to the data
- ► To avoid overfitting and generalizing the model we implement batch-normalization and dropout layers. The performance seems to improve slightly.

THANK YOU!

Bibliography



[1] D. C. de Andrade, S. Leo, M. L. D. S. Viana, and C. Bernkopf, "A neural attention model for speech command recognition," arXiv preprint arXiv:1808.08929, 2018.