Deep Learning for Speaker Recognition

Sai Prabhakar Pandi Selvaraj
CMU
spndise@andrew.cmu.edu

Sandeep Konam
CMU
skonam@andrew.cmu.edu

Abstract

Automated speaker recognition has become increasingly popular to aid in crime investigations and authorization processes with the advances in computer science. Speaker recognition or broadly speech recognition has been an active area of research for the past two decades. There has been significant improvement in the recognition accuracy due to the recent resurgence of deep neural networks. In this work we built a LSTM based speaker recognition system on a dataset collected from Cousera lectures. We achieved an accuracy of 93%. Prior to applying deep-learning techniques, we tested on a base-line using feed-forward network on a different dataset and achieved an accuracy of 96.48%. Results show that the deep learning network could detect the speakers very well except in cases where there is significant overlap in the speaker's accent and tone.

1 Introduction

Finding a way to make computers understand the human languages has been a subject for research for a long period of time. Speech recognition is the ability of a machine or program to identify words and phrases in spoken language and convert them to a machine-readable format. An area related to speech recognition is speaker recognition. Speaker recognition is easiest explained as the ability to identify who is speaking, based on audio data.

In this we have explored the use of recurrent neural network for speaker recognition. As a baseline and a proof of concept we have tested the gender detection using shallow neural network, which is done using features from dataset containing phonemes. And since phonemes are the fundamental building block of the speech this should serve as a perfect baseline. The recurrent neural network used for this experiment is Fast Long short term memory unit (Fast-LSTM), which avoid many shortcoming of a naive recurrent neural network, for speaker detection on text-independent data.

2 Related Work

In the first part section we will look at previous work done in the domain of Gender Identification. Konig and Morgan (1992) extracted 12 Linear Prediction coding Coefficients (LPC) and the energy feature for every 500 ms and used a Multi-Layer Perceptron (MLP) as a classifier for gender detection [1] and obtained good results. Vergin and Farhat (1996) used the first two formants estimated from vowels to classify gender based on a 7 seconds sentences reporting 85% of classification accuracy on the Air Travel Information System (ATIS) corpus (Hemphill Charles et al., 1990), containing specifically recorded clean speech [2]. Parris and Carey (1996) combined pitch and HMM for gender identification reporting results of 97.3% [3]. Their experiments have been carried out on sentences of 5 seconds from the OGI database. [4] Reports studies on the behavior of specific speech units, such as phonemes, for each gender were carried out. This overview of the existing techniques for gender identification shows that the reported accuracies are generally based on sentences from 3 to 7 seconds obtained manually. We have implemented Azghadi, S. M. et.al.[5], where speech segments have 1 second length and obtained 96.49% accuracy.

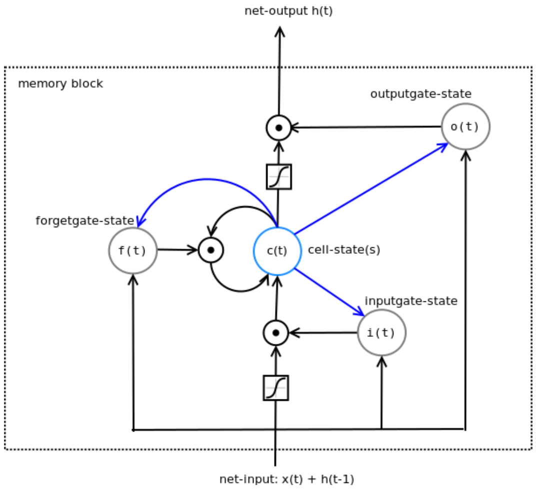


Figure 1: One memory unit of a LSTM. Shown in blue are the peephole connections which we have not used to make the network train faster.

In this part of the section we will focus on recent work using recurrent neural network for speaker recognition, in particular work on long short term memory units. To the author's knowledge there there are two main work recently in the domain of using LSTM for speaker recognition, [7] also explores the effectiveness of LSTM in this domain, specifically it compare LSTM with simple RNN and DNN. They also address the issues of scalability with LSTM, that is having deep LSTM based architectures dramatically increases the number of parameters to train. The propose architectures introduces a recurrent projection layer between the LSTM layer (which itself has no recursion) and the output layer. Which decreases their training time considerably. [8] Uses Bidirectional LSTM, with peephole connections on similar dataset as our work and obtained similar results 93% on text-independent dataset.

3 RNN and LSTM

In this section we will look at the basic intuition behind RNNs and LSTMs and compare them

RNNs in contrast to feed forward network are cyclic, and they can be interpreted as having feedback through time steps. This makes them effective in learning sequential information, as this give them a form of memory across time. Typical RNNs have direct connection form the output of the network in the previous timestep to the current timestep. Unfortunately this kind of direct connection cannot be effectively used for learning relations in the time sequence spanning large number of timesteps (say 100). The root of the problem is in the way the networks are trained which is BPTT, having lot of back propagations causes vanishing and exploding gradients problem which hamper the training over large timesteps. The solution that has proven to give the best results up till now is named Long Short-Term Memory, introduced by Hochreiter and Schmidhuber [9].

A recurrent network can be said to store information in a combination of long- and short-term memory. The short-term memory is formed by the activation of units, containing the recent history of the network. The longterm memory is instead formed by the slowly changing weights of the unit transitions that are holding experience based information about the system. Long Short-Term Memory is an attempt to extend the time that a RNN can hold important information. Since its invention [9] LSTM has gotten improved with several additions to its structure. The enhancements have, as mentioned earlier, been forget gates [10] and peephole connections [11]. The version of LSTM we use does not use peephole connections and is called as Fast-LSTM– since it has lesser number of weights it trains faster. Performance wise the author believes there is a very little variation in the types of LSTM that are used in practice.

Instead of the hidden nodes in a traditional RNN, see Figure **??**, an LSTM RNN makes use of something called memory blocks. The memory blocks are recurrently connected units that in themselves hold a network of units. Inside these memory blocks is where the solution to the vanishing gradient problem lies. The memory blocks are made up of a memory cell, an input gate, an output gate and a forget gate, these gates learn when to update the memory, output the information stored in the memory and when to forget the memory respectively. The equations governing the memory unit are shown in Equation **??**.

$$\begin{aligned} i[t] &= (W[x- > i]x[t] + W[h- > i]h[t1] + b[1- > i]) \\ f[t] &= (W[x- > f]x[t] + W[h- > f]h[t1] + b[1- > f]) \\ z[t] &= tanh(W[x- > c]x[t] + W[h- > c]h[t1] + b[1- > c]) \\ c[t] &= f[t]c[t1] + i[t]z[t] \\ o[t] &= (W[x- > o]x[t] + W[h- > o]h[t1] + b[1- > o]) \\ h[t] &= o[t]tanh(c[t]) \end{aligned} \tag{1}$$

4 Experimental Setup

4.1 Gender detection

The detection involves two parts, first is the feature extraction and next is our classifying based on neural network. In general, female speech has higher pitch (120 - 200 Hz) than male speech (60 - 120 Hz) and could therefore be used to discriminate between men and women. Another important feature is short term acoustic features which describe the spectral components of the audio signal. Fast Fourier Transform can be used to extract the spectral components of the signal. However, such features which are extracted at a short term basis (several ms) have a great variability for the male and female speech and captures phoneme like characteristics which is not required. For the problem of gender classification, we actually need features that do not capture the linguistic information such as words or phonemes. Since, fourier transform can capture the discriminating features we choose this as our only feature.

4.1.1 Dataset

In the work we have used the Harvard-Haskins database of Regularly-Timed Speech. This database contains acoustic data from speakers who were uttering sequences of alternating syllables in an evenly-timed fashion. The database contains acoustic data from 6 speakers (3 male, 3 female). All utterances in this database have 11 syllables, and consist of the syllable /ba/ alternating with another syllable.

The data processed were divided in training (70%), validation (15%) and test (15%) sets randomly. Validation curve was used to decide which iteration to stop during training thus to prevent overfitting.

4.1.2 Feature extraction

Each of the datafiles are about 49 seconds with the sampling frequency of 1000Hz. The data were divided into smaller speech samples (uniformly) of at-most 4seconds (the data were padded with zeros if the sample is smaller than 4s). Fourier transformation was performed using FFT for each of the data (4s). Since the FFT signal for symmetric we discard the second half the signal and scale the absolute value of the signal according to the length of the data, to discount the effect of padding. The training data were then normalize each of the features to the range of [0,1]. The feature vector are of length 2049.

Previous works in gender classification [5] indicate that the MLP with one hidden layer with 11 hidden neuron performs the best. We use cross entropy cost function with sigmoid activation function for the neurons.

The project's second part deals with the speaker recognition which will be done in a data set containing words or sentences the speaker will be speaking. The authors thought it would be better to work with phonemes data before going to higher level (sentences), since the phonemes are the fundamental building block of the human speech the algorithm.

4.1.3 Platform

The training was done in Matlab's Neural Network Toolbox using batch gradient descent method. Overall training took 163 seconds for 188 epochs in CPU 64-bit i3 processor with 2.2GHz using single core.

4.2 Speaker recognition

4.2.1 Dataset

In this work, we have created dataset from Coursera lectures. Our dataset consists of acoustic data from 12 male speakers. It was thought that using speakers of the same sex would be a greater challenge for the network, compared to doing the research with a research base of mixed female and male speakers. The language spoken on all of the audio books is English. However, some speakers use a British accent and some American. All the audio files used were studio recorded. Thus, they would not represent a real life situation with regards to background noise, for example

We chose two lectures of 10-12 minutes for each speaker, which amounts to 20-24 minutes of audio for each speaker. We split the available data to widely adopted 70-15-15 percentage where training data constitutes 70

4.2.2 Feature extraction

The sound waves must be processed and converted into a set of discrete features that can be used as input to the LSTM neural network. In this thesis, the features withdrawn from the sound waves were Mel Frequency Cepstral Coefficients (MFCC) together with their differentials and accelerations, i.e Delta and Delta-Delta coefficients. By their characteristics they represent features of speech signals that are important for the phonetic information. These features are withdrawn from the short time power spectrum and represent the characteristics of the signal that are emotionally independent. From every frame, 13 MFCC coefficients were extracted using a set of 26 filter-bank channels. To better model the behavior of the signal, the differentials and accelerations of the MFCC coefficients were calculated. All these features were combined into a feature vector of size 39. The feature vectors served as input to the neural network.

4.2.3 Network Architecture and Training

The speaker recognition work in [2], analyzed the classification and concluded that the network using two hidden layers with 25 LSTM units each performed best. We decided to experiment with same hyperparameters, but decided to change the type of LSTM, we used Fast-LSTM with same hyperparameter and finally a non-recurrent unit to convert the number of outputs from 25 → 12, with a softmax classifier on top of it. The final network is as shown below:

```
nn.Sequencer @ nn.Recursor @ nn.Sequential {
  [input -> (1) -> (2) -> (3) -> (4) -> output]
  (1): nn.FastLSTM(39 -> 25)
  (2): nn.FastLSTM(25 -> 25)
  (3): nn.Linear(25 -> 12)
  (4): nn.LogSoftMax
}
```

Frameworks like 'nn.Sequential', 'nn.Sequencer' and 'nn.Recursor' [12] are used to facilitate the min-batch training. Training was done using backpropagation length of 20 timesteps, with batchsize of 12 and a momentum of .9 (high momentum to avoid local minima). The learning rates were set according the the following Equation **??**, where i is the epoch number.

$$LearningRate \;=\; 0.005 \;- i * \frac{0.005 - .000001}{250} \tag{2}$$

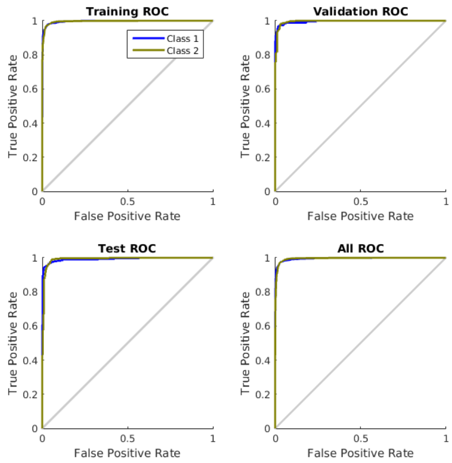


Figure 2: ROC graph of the classifier for gender detection

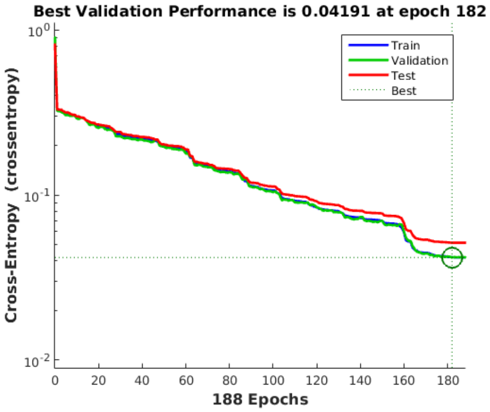


Figure 3: Training, test and validation error vs Epochs. Best model obtained at 182 epoch, for gender detection

4.2.4 Platform

We have built our project using torch7 framework. Computation was done on Intel Core i7-6700HQ CPU with 15.5 GB RAM and NVIDIA GPU of 4GB. Training took approximately 17.5 hrs.

5 Results and Discussion

5.1 Gender detection

Best Performance was obtained by training with 182 epochs– Figure **??** , and from the test produced 96.48%. From the confusion matrix– Figure **??**, it can be seen that the network performs relatively similarly for male and female. From ROC curve– Figure **??**, it can be inferred that the classifier is close to perfect. Analyzing the errors of training and validation curve it can be noticed that the classifier during the training has converged. It should be noted that experiments using higher or lower number of neurons in the hidden layer were tested and discarded as, using higher number of neurons didn't improve the accuracy by expected amount and lowering the number of neurons led to decreased accuracy.

	Predicted as Male	Predicted as Female
Actually Male	282	14
Actually Female	8	322

Figure 4: Confusion matrix for gender detection

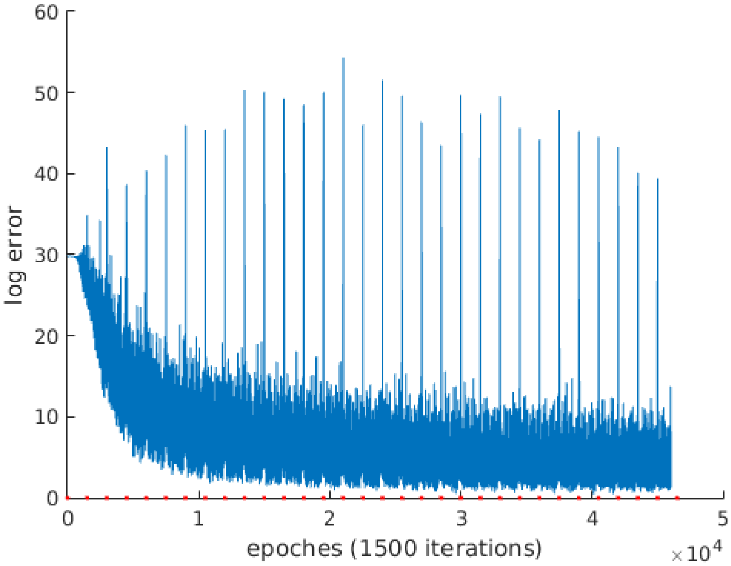
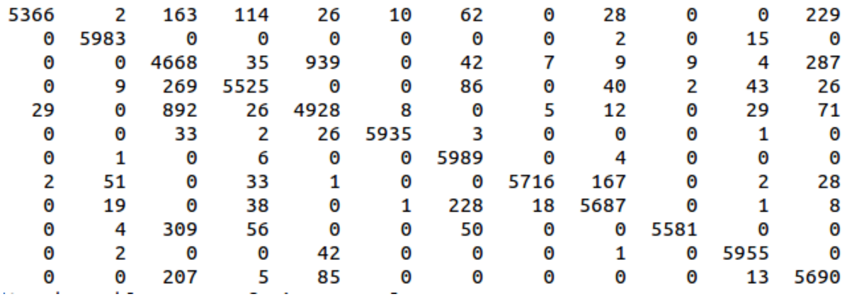


Figure 5: Training error

5.2 Speaker recognition

Figure **??** shows the training error vs the epochs. From the training it is observable that the network has converged. The big spikes in the training error graphs are exactly one per epoch, so the author think that this is some small (< 250 ms) non-verbal audio section in one of the datasets.

From the confusion matrix it can be seen that significant confusion occurred between classes 3 and 5 i.e speakers 3 and 5. Speaker 5s audio is confused 892 times with speaker 3s audio and speaker 3s audio is confused 939 times with speaker 5s audio. After listening to their respective voices manually, it is noticed that significant overlap exists in their tone and accent at certain points, hence the significant confusion caused could be justified. Speaker 3. Dr. Gerhard Wickler, The University of Edinburgh, and Speaker 5. Dr. Magnus Egerstedt, Georgia Institute of Technology.



```
5366     2   163   114    26    10    62     0    28     0     0   229
   0  5983     0     0     0     0     0     0     2     0    15     0
   0     0  4668    35   939     0    42     7     9     9     4   287
   0     9   269  5525     0     0    86     0    40     2    43    26
  29     0   892    26  4928     8     0     5    12     0    29    71
   0     0    33     2    26  5935     3     0     0     0     1     0
   0     1     0     6     0     0  5989     0     4     0     0     0
   2    51     0    33     1     0     0  5716   167     0     2    28
   0    19     0    38     0     1   228    18  5687     0     1     8
   0     4   309    56     0     0    50     0     0  5581     0     0
   0     2     0     0    42     0     0     0     1     0  5955     0
   0     0   207     5    85     0     0     0     0     0    13  5690
```

Figure 6: Confusion matrix for speaker recognition

6 Conclusion

The results– 93% accuracy, we obtained in a text-independent dataset were less ideal than the ones used in [2], even then we obtained similar accuracy using LSTMs with lesser complexity that is we have used LSTMs without peephole connections while the former used Bidirectional-LSTMs with peephole connections. With which we can conclude that LSTMs are much more capable in performing sequential analysis that what was predicted in [2]. And more explorations on LSTMs have to be done. Hence the authors believe that the state-of-the-art variations in LSTM bring changes only in terms of training time but not a significant improvement in performance.

References

[1] Konig, Y. and Morgan, N., GDNN a Gender Dependent Neural Network for Continuous Speech Recognition, International Joint Conference on Neural Networks, 1992. IJCNN, Vol. 2, 7-11, pp. 332-337.

[2] Rivarol, V., Farhat, A., and OShaughnessy D., Robust Gender-Dependent Acoustic-Phonetic Modelling in Continuous Speech Recognition Based on a New Automatic Male Female Classification, Proc. Fourth International Conference on Spoken Language, 1996. ICSLP 96, Vol. 2, 3-6, pp. 1081-1084.

[3] Parris, E.S. and Carey, M. J., Language Independent Gender Identification, Proc IEEE IASSP, pp. 685-688.

[4] Martland, P., Whiteside, S.P., Beet, S.W., and Baghai-Ravaiy, Analysis of Ten Vowel Sounds Across Gender and Regional Cultural Accent Proc Fourth International Conference on Spoken Language, 1996. ICSLP 96, Vol. 4, 3-6, pp. 2231-2234.

[5] Mostafa Rahimi Azghadi, S.and Reza Bonyadi, M.and Shahhosseini, Hamed, Gender Classification Based on FeedForward Backpropagation Neural Network, Artificial Intelligence and Innovations 2007: from Theory to Applications: Proceedings of the 4th IFIP International Conference on Artificial Intelligence Applications and Innovations (AIAI 2007), Springer US,Boston, MA,299304.

[6] Alex Graves. Rnnlib: A recurrent neural network library for sequence learning problems.http://sourceforge.net/projects/rnnl/.

[7] H. Sak, A. Senior, and F. Beaufays, Long short-term memory based recurrent neural network architectures for large vocabulary speech recognition, Tech. Rep. 14021128v1 [cs.NE], Feb. 2014, arXiv.

[8] Larsson, Joel. ”Optimizing text-independent speaker recognition using an LSTM neural network.” (2014).

[9] Sepp Hochreiter and Jurgen Schmidhuber. Long short-term memory. 1997.

[10] F.A. Gers, J. Schmidhuber, and F. Cummins. Learning to forget: continual prediction with lstm. In Artificial Neural Networks, 1999. ICANN 99. Ninth International Conference on (Conf. Publ. No. 470), volume 2, pages 850855 vol.2, 1999. doi: 10.1049/cp:19991218.

[11] Felix A. Gers, Nicol N. Schraudolph, and Jurgen Schmidhuber. Learning precise timing with lstm recurrent networks. J. Mach. Learn. Res., 3:115143, March 2003. ISSN 1532-4435. doi: 10.1162/153244303768966139. URL http://dx.doi.org/10.1162/ 153244303768966139.

[12] Lonard, Nicholas, Sagar Waghmare, Yang Wang, and Jin-Hwa Kim. rnn: Recurrent Library for Torch. arXiv preprint arXiv:1511.07889 (2015).