MULTI-TASK LEARNING FOR SPEAKER VERIFICATION AND VOICE TRIGGER DETECTION

Siddharth Sigtia, Erik Marchi, Sachin Kajarekar, Devang Naik, John Bridle

Apple

ABSTRACT

Automatic speech transcription and speaker recognition are usually treated as separate tasks even though they are interdependent. In this study, we investigate training a single network to perform both tasks jointly. We train the network in a supervised multi-task learning setup, where the speech transcription branch of the network is trained to minimise a phonetic connectionist temporal classification (CTC) loss while the speaker recognition branch of the network is trained to label the input sequence with the correct label for the speaker. We present a large-scale empirical study where the model is trained using several thousand hours of labelled training data for each task. We evaluate the speech transcription branch of the network on a voice trigger detection task while the speaker recognition branch is evaluated on a speaker verification task. Results demonstrate that the network is able to encode both phonetic and speaker information in its learnt representations while yielding accuracies at least as good as the baseline models for each task, with the same number of parameters as the independent models.

Index Terms— Speaker verification, keyword spotting

1. INTRODUCTION

Speech-based personal assistants allow users to interact with devices like phones, watches, speakers, and headphones via speech commands. Usually the speech commands are prefixed with a trigger phrase. Therefore, accurately detecting the trigger phrase is important as it signals the start of a user interaction with a device. Detecting a given phrase involves 2 steps. The first is to decide if the phonetic content in the input audio matches that of the trigger phrase. This process is known as voice trigger detection [1, 2]. The second is to determine whether the speaker’s voice matches the voice of the registered user(s) of the device. This problem is known as speaker verification [3].

Currently, these 2 problems are often considered independently. Voice trigger detection, which is interchangeably known as keyword spotting [4], wake-up word detection [5], or hotword detection [6], is treated as an acoustic modelling problem. The inputs to these models are the acoustic signal and they are trained to either produce a sequence of phonetic labels or to output binary labels indicating the presence or absence of a given trigger phrase. Recent approaches to this problem have explored a variety of neural network architectures [2, 4, 7, 8]. Their primary aim is to recognise the phonetic content (or the trigger phrase directly) in the input audio, with no regard for the identity of the speaker.

On the other hand, speaker verification systems aim to confirm the identity of the speaker by comparing an input utterance with a set of enrolment utterances which are collected when a user sets up their device. This task is done by learning a fixed-dimensional representation or embedding that encodes information only related to the characteristics of the speaker while remaining invariant to the phonetic content of the audio. Given a test recording, the embedding for this recording is compared against the embeddings generated from the enrolment utterances using a suitable distance metric. Speaker verification algorithms can be characterised based on whether the phonetic content in the inputs is limited, which is known as text-dependent speaker verification [9]. Alternatively, text-independent systems operate with no restrictions on the phonetic content [3]. Speaker verification systems are also classified according to the objective function used to train the embedding function. One common approach to learning a speaker embedding is to train a neural network to output correct speaker labels given the input [3, 9, 10]. An alternative strategy is to use the triplet loss [11, 12], where the objective more explicitly encodes the notion that embeddings from the same speaker must be close while embeddings from different speakers should be far apart.

Although these 2 tasks are related, they are treated independently when considering them as engineering problems. We believe that knowledge of the speaker would help determine the phonetic content in the acoustic signal and vice versa, therefore estimating both properties is similar to solving simultaneous equations. In this study, the main research question we try to answer is “can a single network efficiently represent both phonetic and speaker specific information?”? Rather than trying to estimate or exploit the interdependence between the two tasks, we explore whether using a shared/joint network to solve both tasks results in positive inductive transfer between them. From a practical standpoint, being able to share computation between the two tasks can save on-device memory, computation time or latency and the
amount of power/battery consumed. More generally, we are
interested in studying whether a single model can perform
multiple speech understanding tasks rather than designing a
separate model for each task.

This problem has received some attention in the literature
recently. [13] proposes a recurrent architecture that tries to
explicitly encode the interdependence between the phonetic
and speaker recognition branches of the model. [14] proposes
a sequence-to-sequence model for performing joint speaker
diarization and ASR for a limited number of speakers. [15]
investigates the effect of adding or removing speaker informa-
tion while training a speech transcription model, though
the limited size of the dataset prevents thorough evaluation
on a speaker verification task. In this study, we train a joint
network to perform a phonetic labelling task and a speaker
recognition task. Our main contribution is to perform a
large-scale empirical study where the joint model is trained
using over 15,000 hours of labelled training data. We eval-
uate the 2 branches of the model on a voice trigger detection
task and a speaker verification task, respectively. The models
are compared against strong baseline models on challenging
real-world evaluation sets. The results presented demonstrate
that it is possible for a single network to encode both speaker
and phonetic information and yield similar accuracies as the
baseline models without requiring any additional parameters.

2. VOICE TRIGGER DETECTION BASELINE

The baseline architecture for the voice trigger detector is as
follows: we extract 40-dimensional log-filterbanks from the
audio at 100 frame-per-second (FPS). At every step, 7 frames
are spliced together to form symmetric windows and finally
this sequence of windows is sub-sampled by a factor of 3,
yielding a 280-dimensional input vector to the model at a
rate of 33 FPS. The features are input to a stack of 4 bidi-
rectional LSTM layers with 256 units in each layer (Figure
1). This is followed by a fully connected layer and an output
softmax layer over context-independent phonemes and addi-
tional sentence and word boundary symbols, resulting in a
total of 53 output symbols and 6 million model parameters.
This model is then trained by minimising the CTC loss func-
tion [16]. Note that at inference, we want to use the model to
calculate the probability of the trigger phrase phone sequence
given the acoustic evidence, \( P(\text{TriggerPhrasePhoneSeq}|x) \).

This computation can be compactly expressed as a left-to-
right HMM and consequently the probability scores can be
efficiently computed using dynamic programming. The main
attraction of using this setup is the fact that we can use the
same training data as the main ASR without requiring a sepa-
rate training dataset specific to each trigger phrase.

The training data for this model is 5000 hours of anonymised
audio data that is manually transcribed, where all of the
recordings are sampled from intentional voice assistant in-
vocations and are assumed to be near-field. A third of the
training examples are additionally convolved with room im-
pulse responses (RIRs) to simulate reverberant speech. We
use a set of 3000 different RIRs that are internally collected in
a wide range of houses and represent a diverse set of acoustic
conditions. Furthermore, a third of the data is also mixed
with echo residuals to simulate playback from the device
at various levels [17]. The model parameters are optimised
using large-batch stochastic gradient descent (SGD). Each
mini-batch contains 128 utterances and we use 32 GPUs in
parallel resulting in an effective batch size of 4096 examples
per gradient update. We use an initial learning rate of 0.0001
and update the weights using the Adam optimiser.

3. SPEAKER VERIFICATION BASELINE

The inputs to this model are exactly the same as the inputs to
the model described above. The baseline model comprises 2
bidirectional LSTM layers with 256 units each. Rather than
using the activations of the final LSTM hidden state as the
speaker embedding as in [3], we use a simple location-based
attention mechanism [18] to summarise the encoder activa-
tions as a fixed-dimensional vector. We found the attention
mechanism to be particularly effective in the text-independent
setting (c.f. Section 5). Let the activations of the final layer
of the encoder be \( h = (h_1, \ldots, h_T) \) where \( h_t \) is a 512-
dimensional vector and represents the encoder activations at
time-step \( t \) obtained by concatenating the 256-dimensional
activations from the final forward and backward LSTM lay-
ers. At each time-step, we compute a scalar valued score:

\[
s_t = f_{\text{attn}}(h_t, \theta_{\text{attn}}),
\]

where \( f_{\text{attn}} \) is an MLP with 1 hidden layer with 256 units
and a scalar output \( s_t, \theta_{\text{attn}} \) are the weights and biases of the
MLP. The scores at each time-step are normalised:

\[
\alpha_t = \frac{\exp(s_t)}{\sum_t \exp(s_t)},
\]

and the final summary vector is obtained by computing a
weighted sum of encoder activations:

\[
e = \sum_t \alpha_t h_t,
\]

where \( e \) is a 512-dimensional vector. The speaker embedding
is obtained by applying a 128-dimensional linear projection
to the vector \( e \). Note that the embedding model contains a
total of 2.9 million parameters. During training, the embed-
ding layer is followed by a softmax layer over the number of
speakers in the training dataset and the network is trained by
minimising the categorical cross-entropy loss.

During inference, given a test utterance \( x \), the speaker em-
bedding is obtained by removing the final softmax layer and
using the 128-dimensional activations of the previous layer.
A score for the test utterance is then obtained by computing cosine similarities between $x$ and the enrolment utterances:

$$s(x, spk) = \frac{1}{N} \sum_{i=1}^{N} \frac{f(x)^T f(x_{spk})}{\|f(x)\| \|f(x_{spk})\|}$$  

(4)

where $f$ denotes the embedding function, $x$ is a test input, $spk$ is the identifier for a given speaker and $x_{spk}$ denotes the $i$th enrolment utterance for that speaker. Finally, a decision is made to accept or reject the test utterance by comparing the score against a threshold.

The training data for the speaker recognition task comprises 4.5 million utterances sampled from intentional voice assistant invocations. The training set contains 21,000 different speakers, with a minimum of 20 examples and a median of 118 examples per speaker, resulting in over 5700 hours of audio. Note that the training labels only contain the labels of the speaker without any information about the phonetic content in the audio. Each training utterance is of the form “Trigger phrase, payload” and the whole utterance. We found that breaking the utterances up this way results in models that generalise significantly better. The final dataset contains 13 million training examples with over 11,000 hours of labelled training data. We use exactly the same hyperparameters as the voice trigger baseline for the optimiser.

### 4. MULTI-TASK LEARNING

Figure 1 provides an overview of the multi-task learning (MTL) setup. Note that most of the weights in the two baseline systems are in modules with the same structure (biLSTM layers). To perform MTL, we share (tie) corresponding weights in some of those modules. The objective function that is used to optimise the parameters of the joint model is as follows:

$$C_{\text{mtl}}(\theta_{\text{tied}}, \theta_{\text{ct}}, \theta_{\text{spk}}) = C_{\text{ct}}(\theta_{\text{tied}}, \theta_{\text{ct}}) + C_{\text{spk}}(\theta_{\text{tied}}, \theta_{\text{spk}}),$$  

(5)

where $C_{\text{ct}}$ denotes the CTC loss for the voice trigger branch, $C_{\text{spk}}$ is the cross-entropy loss for the speaker recognition task, $\theta_{\text{tied}}$ are the weights of the tied biLSTM layers, $\theta_{\text{ct}}$ are the untied parameters in the voice trigger branch and $\theta_{\text{spk}}$ are the parameters of the speaker verification branch of the model.

We train 3 sets of models. The first is where all 4 biLSTM layers of the encoder are tied for both tasks (6 million parameters). This setup is restrictive since the model is expected to perform 2 different tasks with the same architecture and parameter count as the voice trigger baseline. Furthermore, the model must also learn to represent both phonetic and speaker information using the same activations of the final layer of the encoder. The second model relaxes this constraint by sharing only 3 biLSTM layers in the encoder, with separate final biLSTM layers for the voice trigger and speaker recognition branches (7.6 million parameters). Finally, we train a third model where 2 biLSTM layers have tied weights, with 2 additional biLSTM layers for each branch (Figure 1). Note that the total number of parameters in this third model (9 million parameters) is equal to the sum of the parameters in the voice trigger and speaker baseline models.

The training dataset for these models is formed by concatenating the datasets for the voice trigger and speaker recognition tasks. The resulting dataset contains over 16,000 hours of labelled training data, where 5000 hours of audio have phonetic labels and the remaining examples have speaker labels only. We shuffle the dataset after every training epoch, ensuring that each mini-batch contains examples for both tasks. We use exactly the same optimisation hyper-parameters as before. Somewhat surprisingly, training the joint model did not require any further hyper-parameter tuning. We observed that simply summing up the objective functions for both tasks with unity coefficients resulted in a stable training objective.

### 5. EVALUATION

We evaluate the model described above on 2 tasks, voice trigger detection and speaker verification. Note that we employ a cascaded 2-stage architecture for the detection system [1, 2], where a low-power detector is always running and listening for the trigger phrase. If a detection is made at this stage, the acoustic segment is handed over to larger more complex models that verify both whether the segment contains the trigger phrase and the identity of the speaker. All the models discussed so far are used in this second pass.

For the detection task, we use the voice trigger branch of the model to compute the probability $P(\text{TriggerPhrasePhoneSeq} | x)$ given an input utterance $x$ and this score is compared to a threshold to accept or reject the hypothesis that the input contains the trigger phrase. The model is evaluated on a large
Fig. 2. DET curves for the voice trigger detection task.

Table 1. EERs for the speaker verification task.

| Model  | HS   | HS+Payload | Payload |
|--------|------|------------|---------|
| Baseline | 2.45 | 2.11       | 8.01    |
| 4 Tied Layers | 2.98 | 2.73       | 9.87    |
| 3 Tied Layers | 2.25 | 2.55       | 7.78    |
| 2 Tied Layers | 2.35 | 1.98       | 7.40    |

Our results demonstrate that sharing the first two layers of the model between the speaker and phonetic tasks gives accuracies that are as good as the individual baselines. This result indicates that it is possible to share some of the low-level computation between speech processing tasks without hurting accuracies. We hope to train such unified models to perform a larger combination of speech understanding tasks while achieving positive inductive transfer between tasks. In future work, we plan to train models on a larger set of related speech tasks while exploiting their interdependence.
7. REFERENCES

[1] Apple Machine Learning Blog, “Hey Siri: An On-device DNN-powered Voice Trigger for Apple’s Personal Assistant,” https://machinelearning.apple.com/2017/10/01/hey-siri.html, October 2017.

[2] Siddharth Sigtia, Rob Haynes, Hywel Richards, Erik Marchi, and John Bridle, “Efficient Voice Trigger Detection for Low Resource Hardware,” Proc. INTERSPEECH, pp. 2092–2096, 2018.

[3] Erik Marchi, Stephen Shum, Kyuyeon Hwang, Sachin Kajarekar, Siddharth Sigtia, Hywel Richards, Rob Haynes, Yoon Kim, and John Bridle, “Generalised discriminative transform via curriculum learning for speaker recognition,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5324–5328.

[4] Guoguo Chen, Carolina Parada, and Georg Heigold, “Small-Footprint Keyword Spotting Using Deep Neural Networks,” in 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2014, pp. 4087–4091.

[5] Kenichi Kumatani, Sankaran Panchapagesan, Minhua Wu, Minjae Kim, Nikko Strom, Gautam Tiwari, and Arindam Mandai, “Direct Modeling of Raw Audio with DNNs for Wake Word Detection,” in 2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU). IEEE, 2017, pp. 252–257.

[6] Yiteng Huang, Turaj Zakizadeh Shabestary, Alex Grusenstein, and Li Wan, “Multi-Microphone Adaptive Noise Cancellation for Robust Hotword Detection,” Proc. INTERSPEECH, pp. 1233–1237, 2019.

[7] Tara N Sainath and Carolina Parada, “Convolutional Neural Networks for Small-Footprint Keyword Spotting,” in Sixteenth Annual Conference of the International Speech Communication Association, 2015.

[8] Santiago Fernández, Alex Graves, and Jürgen Schmidhuber, “An Application of Recurrent Neural Networks to Discriminative Keyword Spotting,” in International Conference on Artificial Neural Networks. Springer, 2007, pp. 220–229.

[9] Georg Heigold, Ignacio Moreno, Sanny Bengio, and Noam Shazeer, “End-to-end text-dependent speaker verification,” in 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2016, pp. 5115–5119.

[10] Yi Liu, Liang He, and Jia Liu, “Large Margin Softmax Loss for Speaker Verification.” Proc. INTERSPEECH, pp. 2357–2362, 2019.

[11] Chao Li, Xiaokong Ma, Bing Jiang, Xiangang Li, Xuewei Zhang, Xiao Liu, Ying Cao, Ajay Kannan, and Zhenyao Zhu, “Deep Speaker: An End-to-end Neural Speaker Embedding System,” arXiv preprint arXiv:1705.02304, 2017.

[12] Li Wan, Quan Wang, Alan Papir, and Ignacio Lopez Moreno, “Generalized End-to-end Loss for Speaker Verification,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 4879–4883.

[13] Zhiyuan Tang, Liantian Li, and Dong Wang, “Multi-task Recurrent Model for Speech and Speaker Recognition,” in 2016 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA). IEEE, 2016, pp. 1–4.

[14] Laurent El Shafey, Hagen Soltau, and Izhak Shafran, “Joint Speech Recognition and Speaker Diarization via Sequence Transduction,” Proc. INTERSPEECH, pp. 1943–1948, 2019.

[15] Yossi Adi, Neil Zeghidour, Ronan Collobert, Nicolas Usunier, Vitaliy Liptchinsky, and Gabriel Synnaeve, “To Reverse the Gradient or Not: an Empirical Comparison of Adversarial and Multi-task Learning in Speech Recognition,” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 3742–3746.

[16] Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber, “Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks,” in Proceedings of the 23rd International Conference on Machine Learning (ICML). ACM, 2006, pp. 369–376.

[17] Apple Machine Learning Blog, “Optimizing Siri on HomePod in FarField Settings,” https://machinelearning.apple.com/2018/12/03/optimizing-siri-on-homepod-in-far-field-settings.html, December 2018.

[18] Thang Luong, Hieu Pham, and Christopher D. Manning, “Effective approaches to attention-based neural machine translation,” in Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP), Sept. 2015, pp. 1412–1421.

[19] Roland Auckenthaler, Michael Carey, and Harvey Lloyd-Thomas, “Score normalization for text-independent speaker verification systems,” Digital Signal Processing, vol. 10, no. 1-3, pp. 42–54, 2000.