

Unsupervised Task Discovery in Multi-Task Acoustic Modeling

Josh Meyer

University of Arizona

joshua.richard.meyer@gmail.com

Abstract

The following work focuses on low-resource acoustic model training with Multi-Task Learning (MTL) for Automatic Speech Recognition. The main question of this research is: *How can we automatically discover useful auxiliary tasks to help train a neural network acoustic model?* Past work has already shown that linguist-crafted auxiliary tasks (either via acoustic landmarks or mapping to a source language) can help train more robust acoustic models in low-resource settings. However, to create these tasks the researcher must have access to expert linguistic knowledge. The following study demonstrates that WER in a low-resource setting can improve if the acoustic model is trained with an auxiliary task discovered via k-means clustering. Specifically, I train a Multi-Task DNN acoustic model, such that the model has multiple, separate output layers which represent (1) traditional phonemes defined by a phonetic decision tree or (2) clusters of audio discovered by standard k-means clustering. Given only 1.59 hours of audio, I observed a XXX% relative increase in Word Error Rate when a second task was added during training.

Index Terms: speech recognition, multi-task learning, acoustic modeling

1. Introduction

In the Multi-Task Learning (MTL) framework, data from a related task updates hidden layers in parallel with the target task [1]. A task here is defined as a mapping of data to labels, and as such one can create a new task by creating new labels for existing data. In general it is difficult to create relevant labels for a new classification problem. The current study investigates auxiliary tasks (i.e. new labels) which are not hand-crafted by an expert or human, but automatically discovered from training data via unsupervised clustering (i.e. k-means).

The target language is Kyrgyz, and the data comes from an audiobook provided to the author by the Bizdin.kg project.

2. Background

Past work on MTL for acoustic modeling can be divided into two main categories: monolingual vs. multilingual. Multilingual MTL acoustic modeling involves training a single DNN with multiple output layers, where each output layer represents triphones from one language. Monolingual MTL acoustic modeling involves designing multiple tasks for a single language, where each task is linguistically relevant (eg. triphones vs. monophones vs. graphemes). Multilingual MTL aims for domain transfer, but monolingual MTL aims for robust generalization from the training data.

The earliest examples of multilingual MTL for ASR can be found in [2] and [3]. They were interested in improving performance on all languages, not just one target language. During IARPA's Babel program, bottleneck MRASTA feature extraction was developed for low-resource languages, which relies on

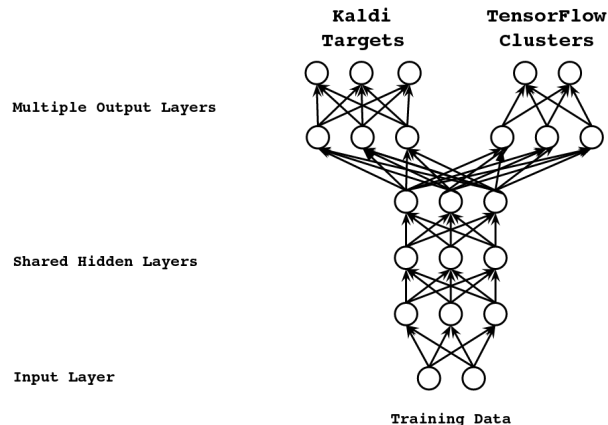


Figure 1: *Multi-Task Acoustic Model Architecture.* Audio features are extracted via standard Kaldi scripts and then imported into TensorFlow. Standard k-means clustering is performed in TensorFlow, and the cluster identities are then exported back into Kaldi as targets for an auxiliary task. The final Multi-Task acoustic model is trained within Kaldi.

multi-task learning [4]. More recently, [5] studied the effect of adding data from a single, well-resourced language to some low-resourced language.

With regards to monolingual MTL, research has aimed to find tasks (from the same language) which are phonetically relevant to the main task [6]. The aim being to improve generalization to new data. Both [7] and later [8] looked at a very similar approach, defining additional auxiliary tasks in MTL via broad, abstract phonetic categories for English. With regards to low-resource languages, [9] and later [10] created extra tasks using graphemes or a universal phoneset as extra targets.

The current work falls into the Monolingual line of research on Multi-Task Learning for acoustic modeling.

3. Experiments

3.1. Data

The speech corpus used in the following experiments comes from an audiobook of a female speaker of Kyrgyz. A total of 1.59 hours of transcribed speech were used in training, and a held out 15 minutes were used in testing.

3.2. Model Building

All models are trained in Kaldi as `nnet3` Time-Delay Neural Networks (TDNNs) [11, 12]. The main neural net run script used in this paper can be found at [www.github.com/JRMeyer/multi-task-kaldi/blob/master/mtk/run_nnet3_multitask.sh](https://github.com/JRMeyer/multi-task-kaldi/blob/master/mtk/run_nnet3_multitask.sh).

The main GMM alignment script can be found at www.github.com/JRMeyer/multi-task-kaldi/blob/master/mtk/run_gmm.sh.

During GMM alignment, monophones were allotted 1,000 Gaussian components, and trained over 25 iterations of EM. These monophones were then expanded into context-dependent triphones via a phonetic decision tree, with a maximum of 2,000 leaves & 5,000 Gaussians. The resulting tied-state triphones are then trained over 25 iterations of EM. Given the alignments from the GMM-HMM models, a 5-layer, 500-dimensional TDNN is trained over 2 epochs of backprop on a single GPU instance.

The auxiliary task from TensorFlow is implemented as a separate output and penultimate layer. All other hidden layers of the TDNN are trained in parallel. A declining learning rate was used, with an initial $\alpha_{initial} = 0.0015$ and a final $\alpha_{final} = 0.00015$. A *ReLU* activation function was used at every layer.

During testing, *only* the main task is used. This highlights the purpose of the extra task: to force the learning of robust representations in the hidden layers during training; the auxiliary task serves as “training wheels” which are removed once the net is ready.

3.2.1. Baseline Model

The Single-Task baseline model has an identical architecture to the Multi-Task models without the additional task (5 hidden layers, 1024-dimensional layers, ReLU activations, same linear objective function).

3.2.2. Auxiliary Task Discovery

The new labels for the auxiliary task were discovered as such:

- Kaldi Feature Extraction
 - 13 PLP features extracted via 25ms Hamming windows at a 10ms shift
 - Resulting vectors spliced to have context of 16 frames to the left and 12 frames to the right (i.e. 29 frames per training example)
- TensorFlow k-means Clustering
 - CMVN normalization applied to each training example
 - Pre-set number of clusters discovered via TensorFlow’s standard k-means clustering
 - For each training example, its discovered cluster is assigned as new target label
- Mapping Kaldi targets onto TensorFlow clusters
 - Given all training examples for a Kaldi target label, the most commonly assigned TensorFlow cluster is chosen as new target label. In this way, all training examples assigned the same label in Kaldi will share the same cluster from TensorFlow, however, the key addition is that multiple targets from Kaldi may be mapped onto a single TensorFlow cluster.

By forcing the neural net to recognize higher levels in the English source tree, the net will learn representations which are more abstract, and therefore more likely to be relevant to another language.

3.3. Preliminary Results

All results come from performance on the same held-out 30-minute section of Kyrgyz audiobook. Decoding is performed with a bigram backoff language model trained on a Wikipedia Kyrgyz dump, and contains, 103,998 unigrams and 56,6871 bigrams. The bigram language model, lexicon, and main-task decision tree are built into a standard decoding graph (ie. a Weighted Finite State Transducer) in the traditional Kaldi pipeline.

The experimental results are shown in Table (1) as percent Word Error Rate (WER) relative to the baseline model. All experiments show improvement over the baseline. Each column has in bold the model which performed best (the bottom row has also the bolded best average weighting).

Table 1: Word Error Rates (WER%)

| | Amount of Training Data | |
|-----------------------------------|-------------------------|------------|
| | 1.59 hours | 15 minutes |
| STL Baseline | 49.56 % WER | |
| + 250 TensorFlow Clusters | % WER | |
| + 500 TensorFlow Clusters | 47.90 % WER | |
| + 1000 TensorFlow Clusters | 49.07 % WER | |

4. Discussion

5. Acknowledgements

I’d like to thank Dan Povey for answering my (oftentimes naive) questions on the kaldi-help Google Group.

I’d like to also thank Chorobek Saadanbekov and Murat Jumashev for making the Kyrgyz audiobook available to me through the Bizdin.kg group.

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant No. (DGE-1746060). Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors(s) and do not necessarily reflect the views of the National Science Foundation.

6. References

- [1] R. Caruana, "Multitask learning," *Machine Learning*, vol. 28, no. 1, pp. 41–75, Jul 1997. [Online]. Available: <https://doi.org/10.1023/A:1007379606734>
- [2] J.-T. Huang, J. Li, D. Yu, L. Deng, and Y. Gong, "Cross-language knowledge transfer using multilingual deep neural network with shared hidden layers," in *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*. IEEE, 2013, pp. 7304–7308.
- [3] G. Heigold, V. Vanhoucke, A. Senior, P. Nguyen, M. Ranzato, M. Devin, and J. Dean, "Multilingual acoustic models using distributed deep neural networks," in *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*. IEEE, 2013, pp. 8619–8623.
- [4] Z. Tuske, D. Nolden, R. Schluter, and H. Ney, "Multilingual mrasta features for low-resource keyword search and speech recognition systems," in *Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on*. IEEE, 2014, pp. 7854–7858.
- [5] F. Grézl and M. Karafiát, "Boosting performance on low-resource languages by standard corpora: An analysis," in *Spoken Language Technology Workshop (SLT), 2016 IEEE*. IEEE, 2016, pp. 629–636.
- [6] P. Bell and S. Renals, "Regularization of context-dependent deep neural networks with context-independent multi-task training," in *Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on*. IEEE, 2015, pp. 4290–4294.
- [7] M. L. Seltzer and J. Droppo, "Multi-task learning in deep neural networks for improved phoneme recognition," in *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*. IEEE, 2013, pp. 6965–6969.
- [8] Z. Huang, J. Li, S. M. Siniscalchi, I.-F. Chen, J. Wu, and C.-H. Lee, "Rapid adaptation for deep neural networks through multi-task learning," in *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.
- [9] D. Chen, B. Mak, C.-C. Leung, and S. Sivasdas, "Joint acoustic modeling of triphones and trigraphemes by multi-task learning deep neural networks for low-resource speech recognition," in *Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on*. IEEE, 2014, pp. 5592–5596.
- [10] D. Chen and B. K.-W. Mak, "Multitask learning of deep neural networks for low-resource speech recognition," *IEEE/ACM Trans. Audio, Speech and Lang. Proc.*, vol. 23, no. 7, pp. 1172–1183, Jul. 2015. [Online]. Available: <http://dx.doi.org/10.1109/TASLP.2015.2422573>
- [11] D. Povey, A. Ghoshal, G. Boulianne, L. Burget, O. Glembek, N. Goel, M. Hannemann, P. Motlicek, Y. Qian, P. Schwarz *et al.*, "The kaldi speech recognition toolkit," in *IEEE 2011 workshop on automatic speech recognition and understanding*, no. EPFL-CONF-192584. IEEE Signal Processing Society, 2011.
- [12] V. Peddinti, D. Povey, and S. Khudanpur, "A time delay neural network architecture for efficient modeling of long temporal contexts," in *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.