Unsupervised Task Discovery for Multi-Task Acoustic Modeling

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Abstract

- *Multi-Task Learning works (good for low-resource languages)*
- *However, tasks are hard to make*
- *Better to discover tasks automatically*
- *Experiment with k-means on MFCCs*
- *Data == 1.5 hours of Kyrgyz audio-book*
- *Initial Results Promising*

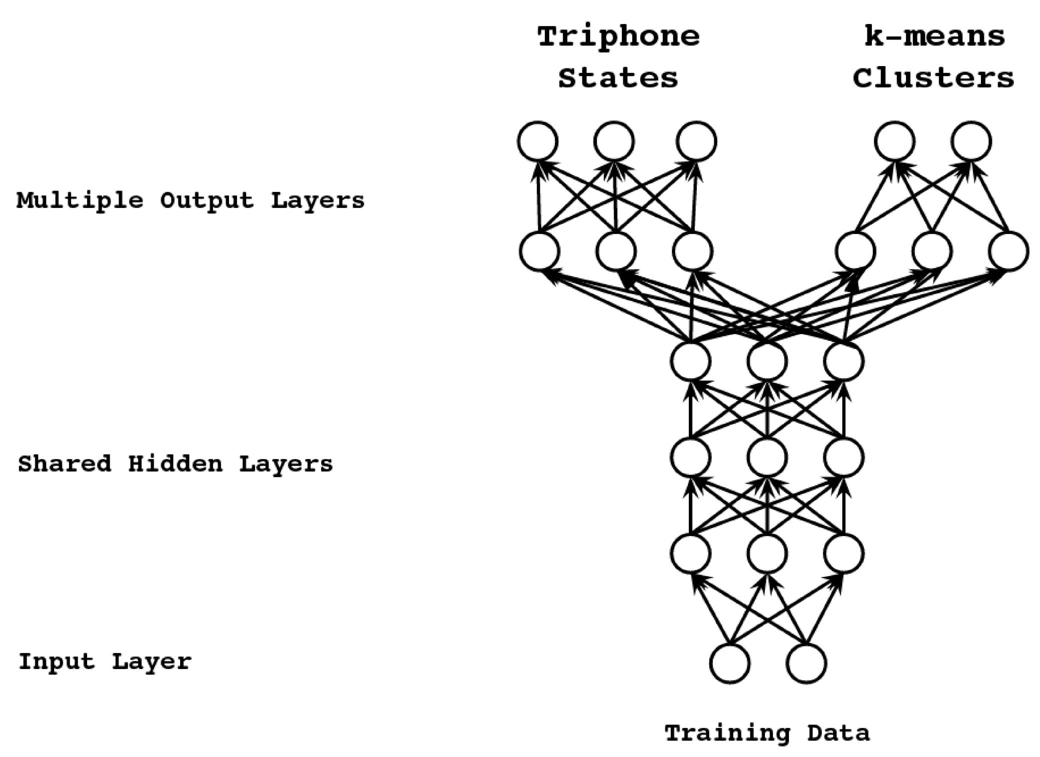

Figure 1: Multi-Task Learning Architecture

1. Background

- Multi-Task Learning in Acoustic Modeling
  - Multilingual
    - new language == new task
    - e.g. English vs. Kyrgyz
  - Monolingual
    - new linguistic encoding == new task
    - e.g. vowels vs. consonants; monophones vs. triphones

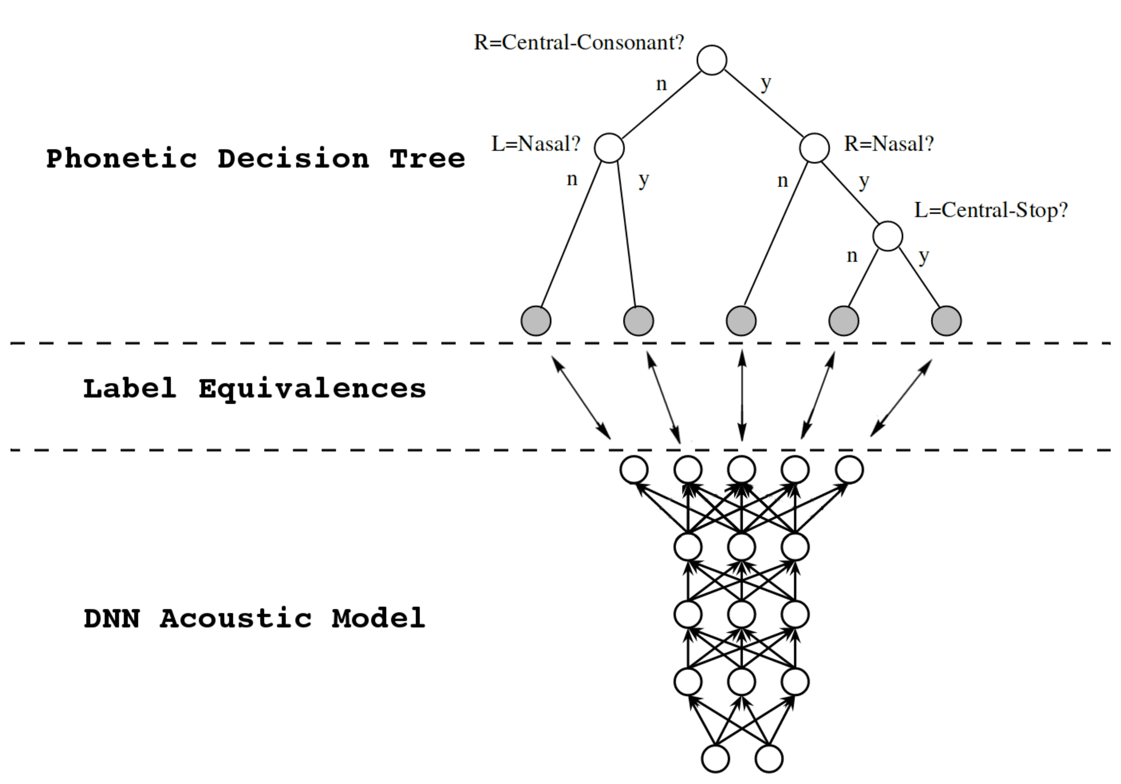

Figure 2: Label Correspondance of Decision Tree / DNN

2. Alignment

- Feature Extraction
  - 13 PLP features, 25ms Hamming windows, 10ms shift, 16 frame left-context & 12 frame right-context, CMVN
- GMM Alignment
  - Monophones: 1,000 Gaussians, 25 iterations EM // Triphones: 2,000 leaves & 5,000 Gaussians, 25 iterations EM

3. Clustering

- k-means Clustering
  - A set number of clusters is discovered via TensorFlow's standard k-means clustering.

4. Mapping Triphone States → Clusters

- All training examples aligned to triphone state are mapped to most common k-means cluster.

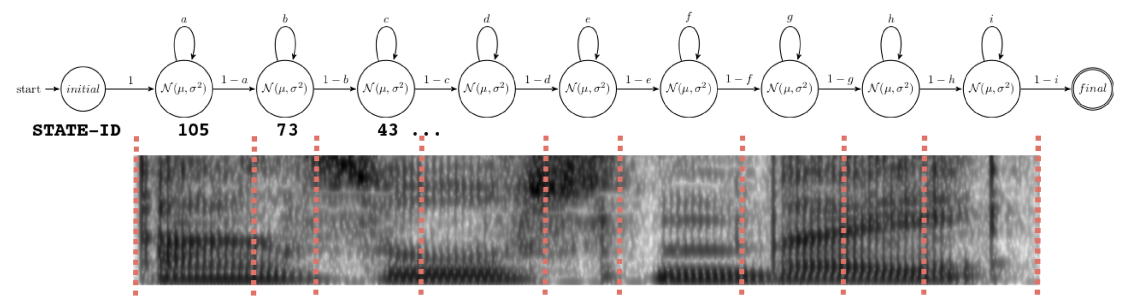

Figure 3: GMM-aligned training examples

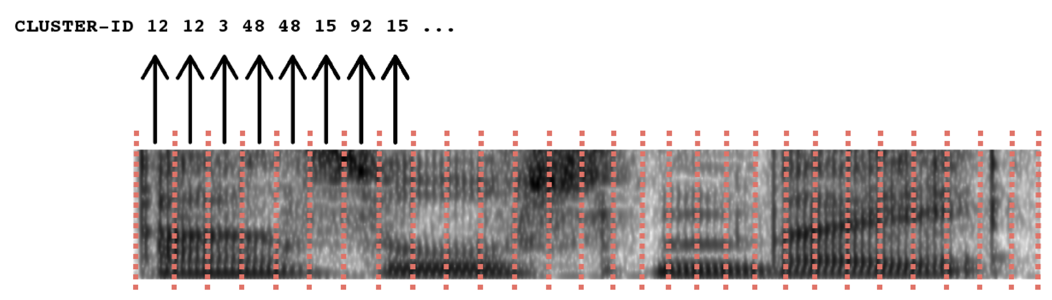

Figure 4: k-means clustered training examples

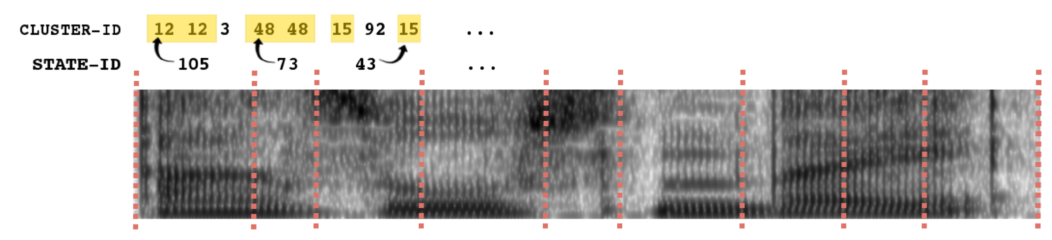

Figure 5: GMM-aligned training examples

5. Cluster Contents

- 672 leaves in Kaldi and 1024 clusters in TF
- 185 new labels after mapping
  - 123 / 185 are interpretable
- 84 / 185 contain only one phoneme
  - 9 / 84 contained > 1 triphone of phoneme
- 101 / 184 contain mixed phonemes
  - 39 / 101 only vowels or only consonants

Table 1: Discovered intelligible Phoneme Clusters

Vowels		Consonants	
a j	a u	k r	g n m
a o	a ih	k p	s sh ch
e j	e ih	r ng	t k s p
e y	o u	d ch	m ng
u ih y	u ih	t k	t k h
i e y	o ih	d z	t k s
a e oe j ih	j ih	l z	t ch d
a ih o u y		n p	t k zh b
			t g b s sh z zh

6. Multi-Task DNN Training Set-up

- DNN Acoustic model training
  - Multi-Task Time-Delay Neural Network
  - 5-epochs, 11 hidden layers, *ReLU* activations
  - $\alpha_{initial} = 0.0015 \rightarrow \alpha_{final} = 0.00015$
  - Each task has penultimate + ultimate output layer

Figure 6: Model Accuracy During Training (Simple Loss)

7. Testing Setup

- k-folds cross-validation ($k == 5$)
  - 511 utterances for train
  - 100 utterances for test
- Decoded with 1-gram LM

8. Results: Traditional Weighting Scheme

- Loss = $((1-\alpha) * MAIN + \alpha * AUX)$
- WER better than Baseline in 4/9 experiments

Table 2: WER% for Traditional Weighting Scheme

	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$
Single Task Baseline		57.55 ± 1.82	
+ 256 clusters	57.93 ± 1.63	57.04 ± 1.58	57.66 ± 1.24
+ 1024 clusters	57.69 ± 3.78	**56.99** ± 3.08	57.60 ± 0.79
+ 4096 clusters	57.25 ± 2.87	58.07 ± 1.35	57.45 ± 0.32

9. Results: Simple Weighting Scheme

- Loss = $(MAIN + \alpha * AUX)$
- WER better than Traditional Loss
- WER better than Baseline in 6/9 experiments

Table 3: WER% for Simple Weighting Scheme

	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$
Single Task Baseline		57.55 ± 1.82	
+ 256 clusters	57.33 ± 2.49	58.02 ± 2.09	57.18 ± 0.56
+ 1024 clusters	57.74 ± 3.06	**56.88** ± 1.33	57.13 ± 1.55
+ 4096 clusters	57.56 ± 2.53	57.49 ± 3.17	57.31 ± 1.31

10. Discussion

- Good auxiliary tasks exist (we just need to find them)
- Initial Results show small improvements, given good hyper-parameters
- Clustering in high-dimensional feature space isn't great
  - Find better projections: LDA, source DNN activations (from well-resourced lang)
- Big net overfits to both tasks
  - add more tasks
  - use smaller net

11. Acknowledgements

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