PHONOTACTIC LANGUAGE RECOGNITION USING I-VECTORS AND PHONEME POSTERIOGRAM COUNTS

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# Introduction

- Current main approaches to LID
  - Acoustic-based: i-vectors, JFA, SVMs, or GMMs
  - Phonotactic
- Phonotactic systems:
  - PRLM, PPRLM: LMs created using different phonetic ASR
  - Lattice-based soft-counts: Created from phone lattices
    - Zero counts (i.e. data sparseness)
    - Limited by the number of phonemes and n-gram order
    - Dimensionality reduction: PCA or n-gram selection
  - Using i-vectors through Subspace Multinomial Models (SMMs)
    - We propose a new feature vector that performs better than softcounts

#### **1.** Compute Posterior Probabilities



 In the example, we consider only three phonemes and bigrams. In our experiments, they were 33 and we used trigrams.

# **2.** Compute Posterior Probs



Find the phoneme boundaries using Viterbi algorithm

Can be seen as incorporation of a-priori information

Average the posterior probs over the phone boundaries

 Smoothes the posterior probs and avoids the high-correlation of within-phoneme posteriors

#### 3. Create N-gram Posterior Probs



- Outer product with the posteriogram of the previous phones
- Assume that the frames of the averaged posteriogram are statistically independent,
  - Therefore we have joint probabilities for sequences of phonemes

#### 4. N-gram Counts via N-gram Posterior-Probs



- Sum up all matrices to obtain n-gram soft counts
- Obtain feature super-vector for creating next the phonotactic i-vectors using SMMs

#### Subspace Multinomial Models

- Allows extraction of low-dimensional vectors of coordinates in total variability subspace (i.e. i-vectors)
- The log-likelihood of data D for a multinomial model with C discrete events is determined by

$$\log p(D) = \sum_{n=1}^{N} \sum_{c=1}^{C} \gamma_{nc} \log \varphi_{nc}$$

 Where γ<sub>nc</sub> is the count for n-gram event c at utterance n, and φ<sub>nc</sub> is the probability of a multinomial distribution defined by the subspace model

# i-vectors from SMM

$$\varphi_{nc} = \frac{\exp(m_{c} + t_{c}w_{n})}{\sum_{i}^{C}\exp(m_{i} + t_{i}w_{n})}$$

 Where t<sub>c</sub> is the c-th row of subspace matrix T (Extractor), and w<sub>n</sub> is the i-vector

- An i-vector for a single utterance is estimated numerically by maximizing the likelihood (ML)
- Matrix T is trained numerically using ML by iteratively optimizing T and re-estimating the ivectors for all training utterances
- Then we use these i-vectors as feature input for training a discriminative LID classifier
  - Multiclass logistic regression

# **Experimental Setup**

- NIST LRE 2009 database
  - 50K segments for training (~119h), 38K segments for dev (~153h) and 31K sentences for test (~125h)
  - 23 languages, test on 3, 10, and 30 s conditions
  - Results given using C<sub>avg</sub> metric
- Acoustic i-vector system
  - 7 MFCC + 49 SDCs, CMN/CVN, 2048 Gaussians -> i-vectors of 400 dimensions
- Comparisons with:
  - Lattice-based soft-counts with i-vectors (size 600)
  - Lattice-based soft-counts with PCA (reduction to 1000 dimensions)
- Fusion: Multiclass logistic regression
  - Acoustic and Phonotactic

# **Results on NIST LRE 2009**



## **Conclusions and Future Work**

- Advantages of the new features
  - Avoid data sparseness (i.e. robustness)
  - Results outperforms a similar system based on lattice soft-counts with i-vectors
    - 8,16% relative on 30 s condition
  - Fusion with acoustic i-vectors are also better
    - 10% relative on 30 s condition
- Future Work: Apply discriminative n-gram selection techniques to reduce the vector size
  - Avoids low frequency n-gram counts
  - Allows using high n-gram orders

# ...Thanks for your attention...

# **Comments or Questions?**