

Unsupervised Word Discovery from Speech using Bayesian Hierarchical Models

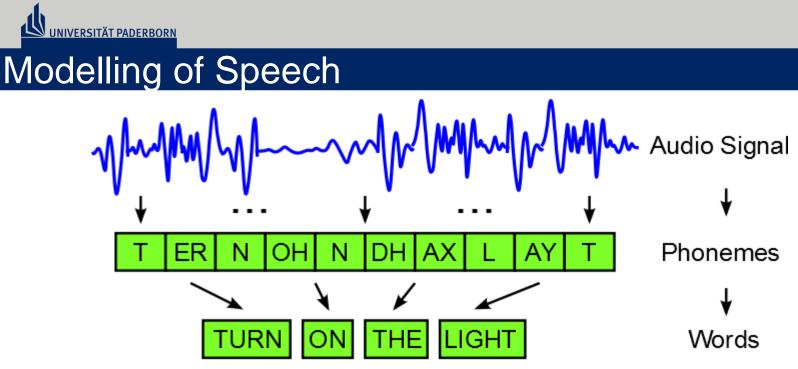
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Computer Science, Electrical Engineering and Mathematics

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- Sequential
- Hierarchical
 - Audio
 - Phonemes
 - Words
- Increasing abstraction with each layer





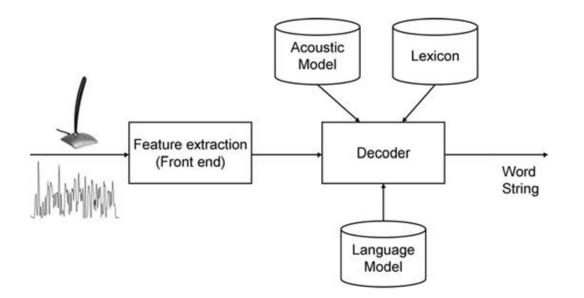
Unsupervised Learning

- Labeled speech data needed to train recognition system
 - Transcription in terms of the spoken words
 - Lexicon to map words to phoneme sequences
- Labeled data not always available
 - Costly to obtain
 - So called low resource languages
 - Zero resource
 - Languages without written form
 - Endangered languages
 - Speech changes constantly
- Learn a language like a child

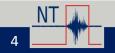




Speech recognition

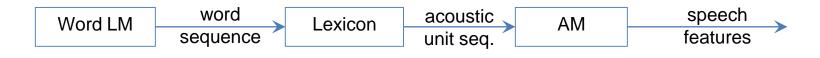


- Components of traditional speech recognition system
 - Acoustic model
 - Lexicon
 - Language model





Generative model of speech

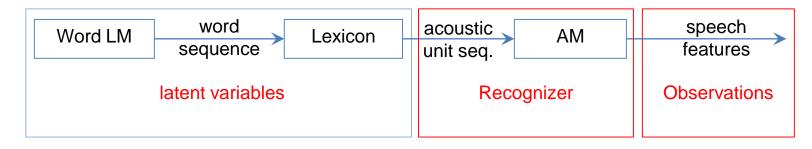


- Language model generates sequence of words
- Lexicon maps words to phoneme sequences
- Acoustic model emits speech features

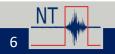




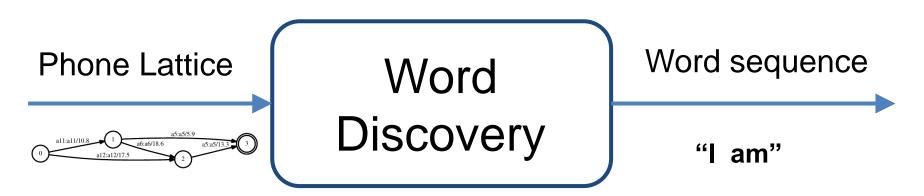
Generative model of speech



- Language model generates sequence of words
- Lexicon maps words to phoneme sequences
- Acoustic model emits speech features
- For the remainder of the presentation we assume an already trained acoustic model
 - Represent input as graph of possible phoneme sequences
 - Learn language model and lexicon







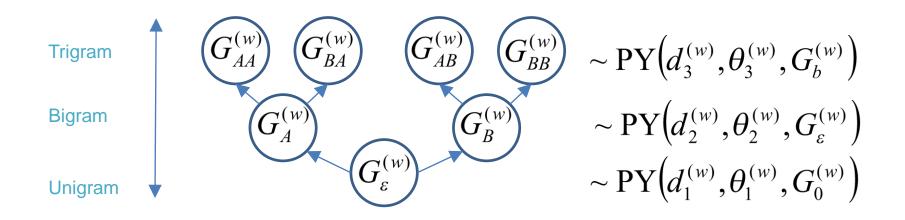
- Goal: Segment the Phone lattice into words
- Approach:
 - Exploit that the sequence of units is more predictable within words than at word boundaries
 - Iteratively alternate between word segmentation and language model estimation
 - Use Nested Hierarchical Pitman-Yor Language Model

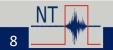


• Bayesian interpolated n-gram Language Model with back off:

$$\Pr(w|\mathbf{u}) = \frac{c_{\mathbf{u}w\cdot} - d_{|\mathbf{u}|}t_{\mathbf{u}w}}{\theta_{|\mathbf{u}|} + c_{\mathbf{u}\cdot\cdot}} + \frac{\theta_{|\mathbf{u}|} + d_{|\mathbf{u}|}t_{\mathbf{u}\cdot}}{\theta_{|\mathbf{u}|} + c_{\mathbf{u}\cdot\cdot}}\Pr(w|\pi(\mathbf{u}))$$

- Hierarchy of Pitman-Yor processes
- Base measure $G_0^{(w)}$ of unigram: zero-gram (uniform distribution)
- Inference performed with Gibbs Sampling

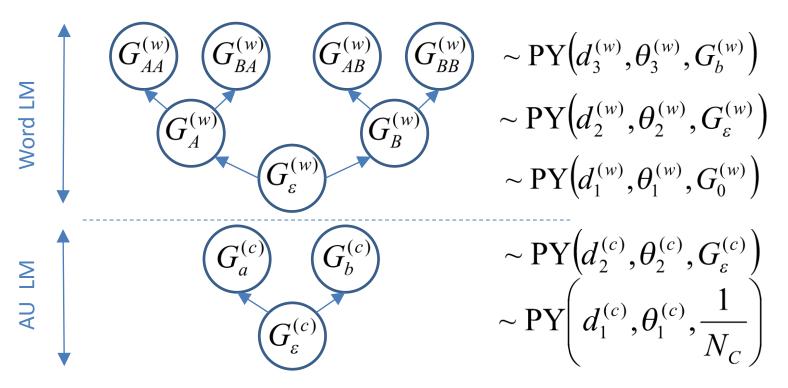


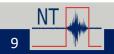


NHPYLM

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- Idea: Words consist of units (Characters, Phones, Acoustic Units)
- Model unit n-gram probabilities with another HPYLM
- Replace word LM zerogram with resp. unit sequence likelihood
- Result: Able to learn words from unit sequences

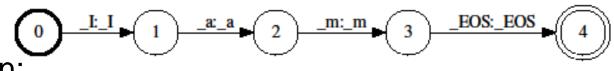




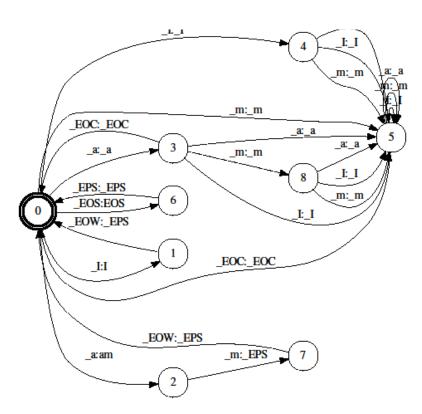


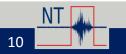
Finite State Machine based Implementation

• Input sequence:



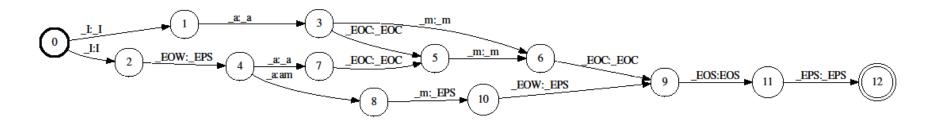
Lexicon:

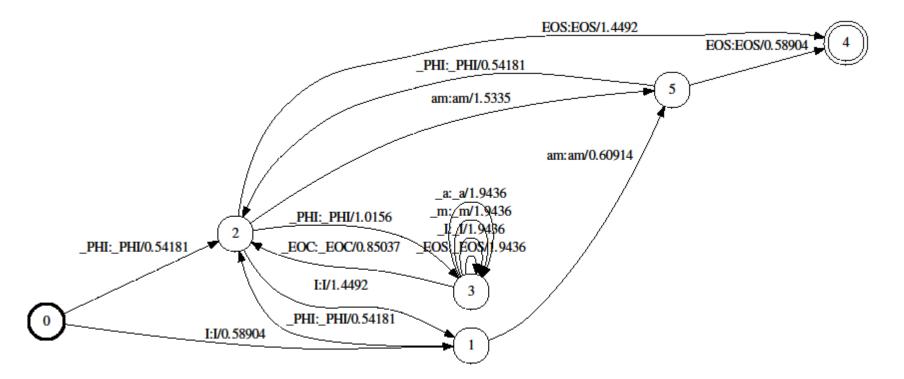


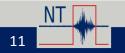




Segmentations and Language Model



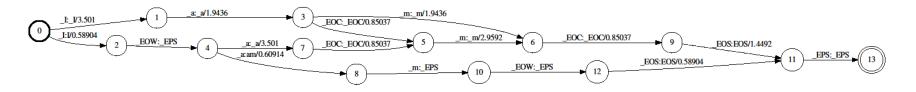






Weighted Segmentations

• Weighted possible Paths



- Learning is done using Gibs Sampling
 - Forward filtering / Backward sampling
- Iterate between sampling of possible Path and Language model Estimation

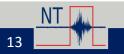




Experimantal Results

- Use English Recognizer to decode Xitsonga speech
 - ZeroSpeech 2015 challenge Data
 - Type (Lexicon) F-Score
 - Token (Segmentation) F-Score

English		Xitsonga	
Туре	Token	Туре	Token
24.0	25.0	5.1	3.7

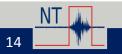




Conclusion and Outlook

- Learning from untranscribed data is possible
 - Learn: Language model and Lexicon
 - But: Noisy input deteriorates the results

- Still open problems:
 - How to deal with recognition errors
 - Consider pronunciation variants
 - Integrate Acoustic model learning







Vielen Dank für ihre Aufmerksamkeit

Fragen?

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