Increasing speaker invariance in unsupervised speech learning by partitioning probabilistic models using linear siamese networks

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Why unsupervised speech recognition?

- Speech recognition traditionally supervised
  - Need transcription in addition to audio
  - Very costly to develop data
  - Lack of quality data for most of the world's languages
- Unsupervised recognition: Learn from only audio, without transcription
  - Easier to develop speech systems for low-resource languages
  - Useful for linguistic research
  - Could model language acquisition of infants

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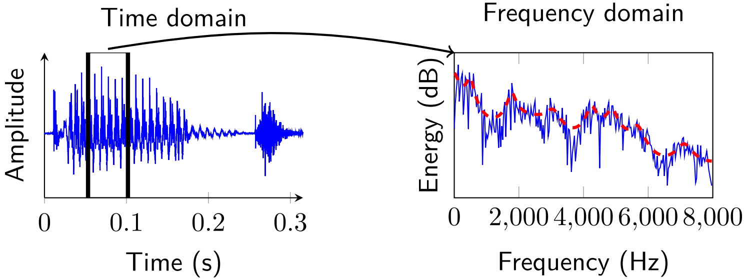
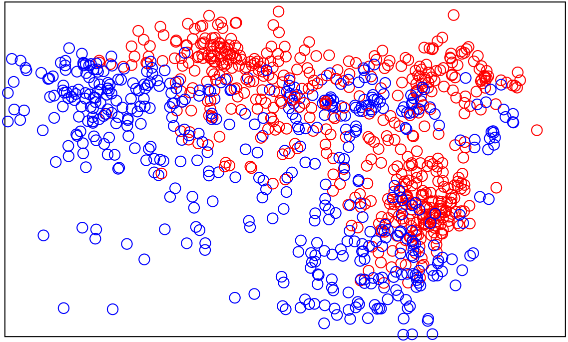
Representation of speech in speech recognition

- Waveform not optimal as a representation of speech
- Instead: Frequency content of short sections of the signal
- Further processing: Filter banks, cosine transform
- Repeat while moving the window to generate frames



Challenges in unsupervised speech recognition

- Speaker variation
- Segmentation
- No knowledge of what sounds exist in the language



Learning speaker-invariant representations

- Standard representations of speech are speaker dependent
- First step: Find speaker-invariant representations
  - Sounds of the same type should be similar
  - Sounds of different types should be dissimilar
  - Not concerned with categorising sounds
- Track 1 of Zero Resource Speech Challenge[1]

[1] Maarten Versteegh et al. (2015). 'The Zero Resource Speech Challenge 2015'. In: *Proc. of Interspeech*.

Previous work

- Deep autoencoder[2]
- Contrastive autoencoder[3]
  - "Auto"encode frame to other frame of same type
- Dirichlet process GMM clustering[4]
  - Surprisingly performant

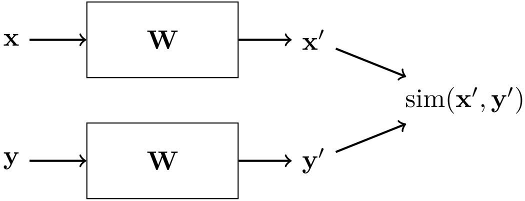
[2] Leonardo Badino et al. (2015). 'Discovering Discrete Subword Units with Binarized Autoencoders and Hidden-Markov-Model Encoders'. In: *Proc. of ISCA*.

[3] Daniel Renshaw et al. (2015). 'A comparison of neural network methods for unsupervised representation learning on the Zero Resource Speech Challenge'. In: *Proc. of Interspeech*.

[4] Hongjie Chen et al. (2015). 'Parallel Inference of Dirichlet Process Gaussian Mixture Models for Unsupervised Acoustic Modeling: A Feasibility Study'. In: *Proc. of Interspeech*.

Siamese networks for representation learning[5]

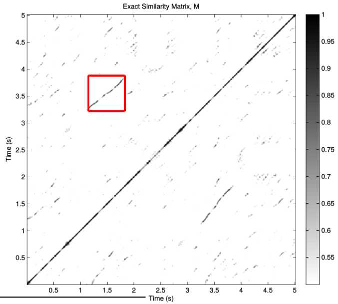
- Input: Pairs of same-class and different-class frames
- Adjust weights to make same-class frames more similar



[5] Gabriel Synnaeve et al. (2014). 'Phonetics embedding learning with side information'. In: *Proc. of IEEE SLT*. IEEE, pp. 106–111.

Finding same-class frames[6]

- Wish to find same-class frame pairs without supervision
- Simple clustering yields speaker-dependent units
- Idea: Patterns are easier to find at larger time scales



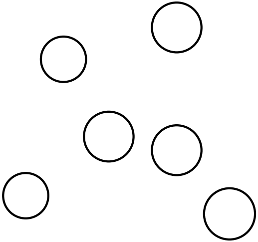
[6] Figure taken from Jansen and Van Durme (2011)

Proposed method – motivation

- Term discovery only covers a fraction of the data
  - Would like to make more efficient use of all data
- Large neural networks are prone to overfitting and difficult to interpret
- Idea: Use the whole data to find representations that are speaker dependent, but that can be used with simpler models
- Use a term discovery data to make these representations more speaker invariant

Proposed method

- Infer a probabilistic model from the whole data
- The model will find speaker-dependent phonetic classes
- Use same-class and different-class frame pairs to merge the phonetic classes
- The classes are described using probabilities → merging is simple addition



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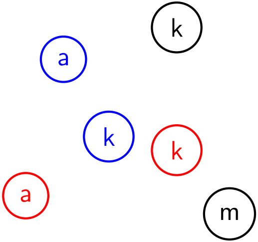

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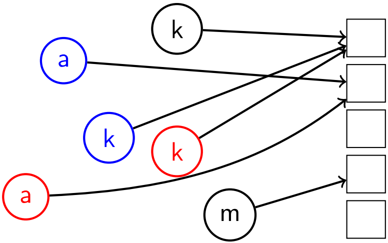

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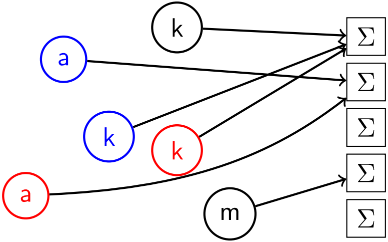

Proposed method (cont.)

- Represent input as a probability vector $\mathbf{x}$
  - Each element is the probability of a latent class
- Merging the classes is done using a linear transform: $\mathbf{xW}$
- $\mathbf{W}$ describes a proper partitioning of the input iff:
  1. Each element in $\mathbf{W}$ is either 0 or 1
  2. Each row in $\mathbf{W}$ contains exactly one 1
- We instead constrain $\mathbf{W}$ as follows:
  1. Each element is positive
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- Output of the model is a lower-dimensional probability vector

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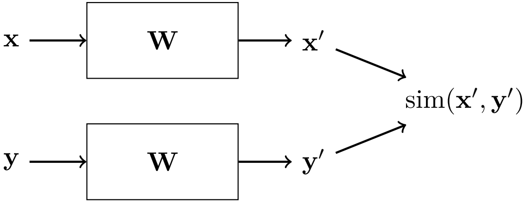

Loss function

- The output is a probability vector
- We can measure similarity using a statistical divergence measure
- Here: The root Jensen-Shannon divergence

$$L(\mathbf{W}; \mathbf{x}, \mathbf{y}) = \sqrt{JS(\mathbf{xW} || \mathbf{yW})}$$

- Minimize if $\mathbf{x}$ and $\mathbf{y}$ are the same speech sound; maximize otherwise
- Need to balance same-class and different-class losses over a minibatch

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Entropy penalty for encouraging sparsity

- Merging corresponds to partitioning the speaker-dependent classes
- However, $\mathbf{W}$ as defined is not a proper partitioning
- Using an entropy penalty on the model output we can encourage $\mathbf{W}$ to be an approximate partitioning

$$L_H(\mathbf{W}; \mathbf{x}, \mathbf{y}) = H(\mathbf{x}\mathbf{W}) + H(\mathbf{y}\mathbf{W})$$

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- Implicitly makes the model sparse

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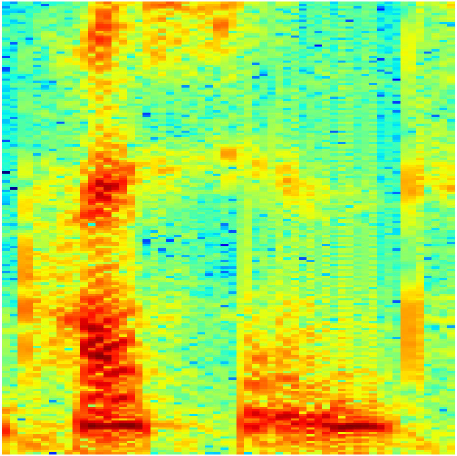
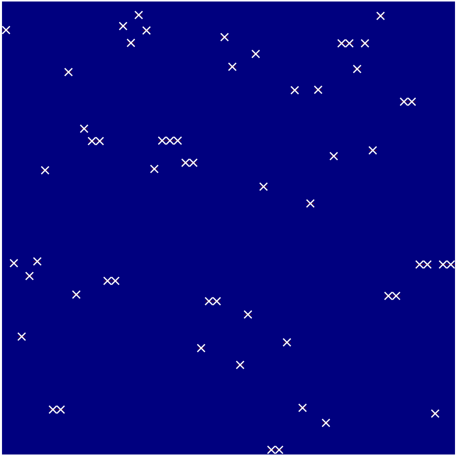
Discretisation

- The trained model can be discretised
- Set largest element on each row to 1
- Set all other elements to 0
- Yields a proper partitioning

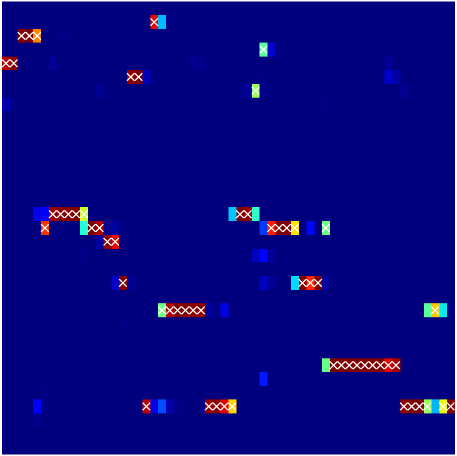
Spectrogram features



GMM features (input)



Merged GMM features (output)



Data

- Two corpora: One of casual English, and one of read Xitsonga
- The data is clustured using 1024-component GMMs
- For each frame we extract posterior probabilities from the GMM
- The proposed model is trained with 64 outputs

Minimal-pair ABX

- The evaluation is done using the minimal-pair ABX task
- Three utterances: A, B and X
- Either A or B is the same category as X
- Representing frames using the output of the model, the utterance most similar to X is chosen

Results

	English		Xitsonga	
Model	Within	Across	Within	Across
GMM posteriors	12.3	23.8	11.4	23.2
Proposed model	12.8	19.8	14.0	23.2
Binary $\mathbf{W}$	12.0	19.3	12.7	21.9
ABnet[7]	12.0	17.9	11.7	16.6
DPGMM + LDA[8]	10.6	16.0	8.0	12.6

[7] Roland Thiolliere et al. (2015). 'A hybrid dynamic time warping-deep neural network architecture for unsupervised acoustic modeling'. In: *Proc. of Interspeech*.

[8] Michael Heck et al. (2016). 'Unsupervised Linear Discriminant Analysis for Supporting DPGMM Clustering in the Zero Resource Scenario'. In: *Procedia*

Discussion

- The model significantly decreases the dimensionality of the input
- At the same time, it empirically improves the speaker invariance of the representation
- Worse performance for Xitsonga – sensitive to dimensionality?
- The model has few parameters, making it fast to train and robust against overfitting
- Can use probability vectors from any model as input

Future work

- Other models for generating the probability vectors
- Alternative loss functions

Thank you for listening!