Features for Factored Language Models for Code-Switching Speech

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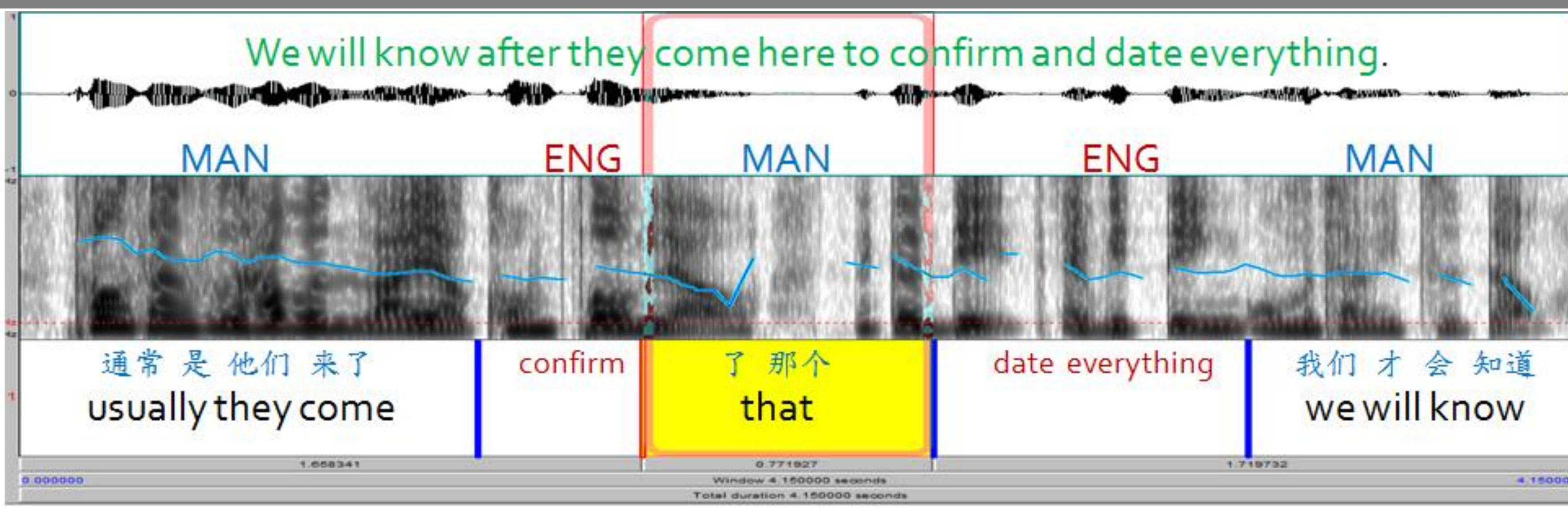

Outline

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- Factored Language Models
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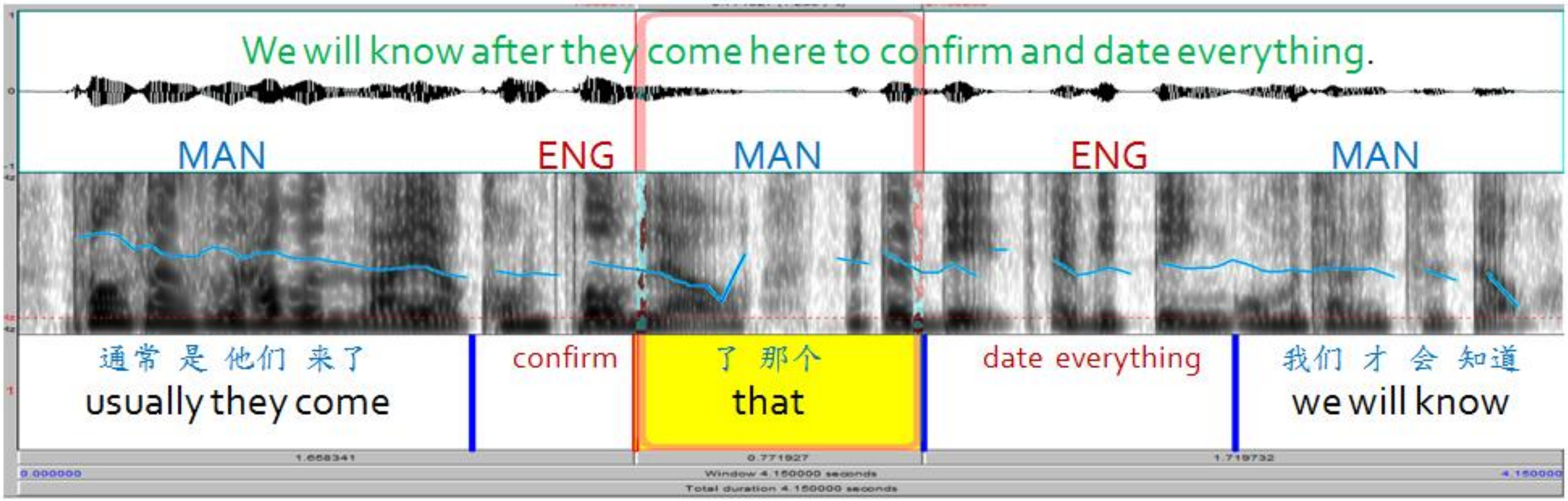
  - Summary

Motivation

- Code-Switching (CS) = speech with more than one language
- Exists in multilingual communities or among immigrants



Challenges:
multilingual models and CS training data necessary

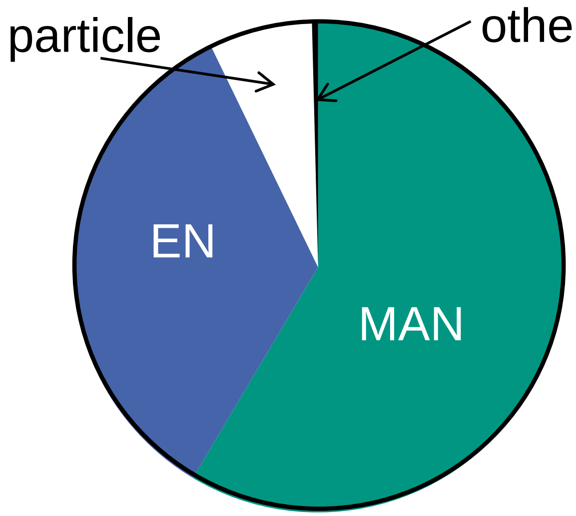
SEAME corpus

- SEAME = South East Asia Mandarin-English
- Conversational speech, recorded from Singaporean and Malaysian speakers by [1]

Challenges

- much CS per utterance (∅: 2.6)
- short monolingual segments (mostly less than 1 sec, 2-4 words)
- not much training data for LM (575k words)

Language distribution



[1] Lyu, D.C. et al.,2010
Originally used: research project 'Code-Switch' (NTU and KIT)

Main contributions

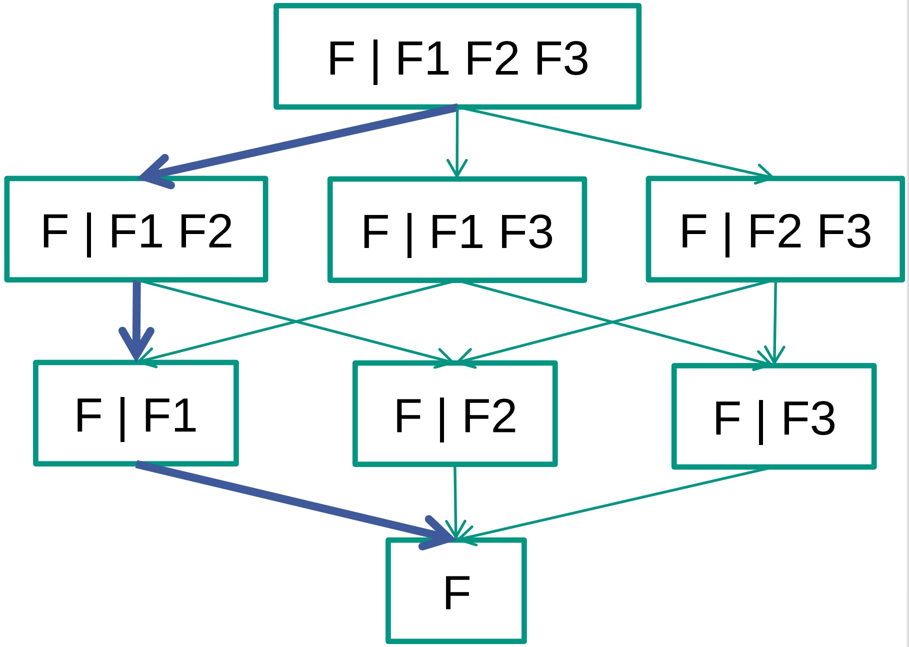
- Investigation of different features for Code-Switching speech
- Integration of factored language models into a dynamic one-pass decoder

Factored Language Models (FLMs) [2]

- Idea: word = feature bundle

$$w_t \equiv \{ f_t^1, f_t^2, \ldots, f_t^K \}$$

- Good e.g. in the case of
  - Rich morphology
  - Few training data
    => applicable to CS task
- Generalized backoff



[2] Bilmes, J. and Kirchhoff, K., 2003

Features: Words, POS, LID

Model	PPL dev	PPL eval
Baseline (3-gram)	268.39	282.86
POS	260.70	267.86
LID	263.24	267.63
POS + LID	**257.62**	**264.20**

- Problems:
  - POS tagging of CS speech: challenging
  - Accuracy of POS tagger: unknown

→ different clustering method may be more robust

Features: Brown Word Clusters

- Clusters based on word distributions in text [3]
  - minimize average mutual information loss
- Best number of classes in terms of PPL: 70

Model	PPL dev	PPL eval
Baseline (3-gram)	268.39	282.86
POS + LID	257.62	264.20
Brown clusters	257.17	265.50
Brown clusters + POS	**249.00**	**255.34**
Brown cl + POS + LID	251.39	259.05

- So far: clusters based on syntax or word distributions
  ➔ next step: semantic features

[3] Brown, P.F. Et al. ,1992

Features: Open Class Words

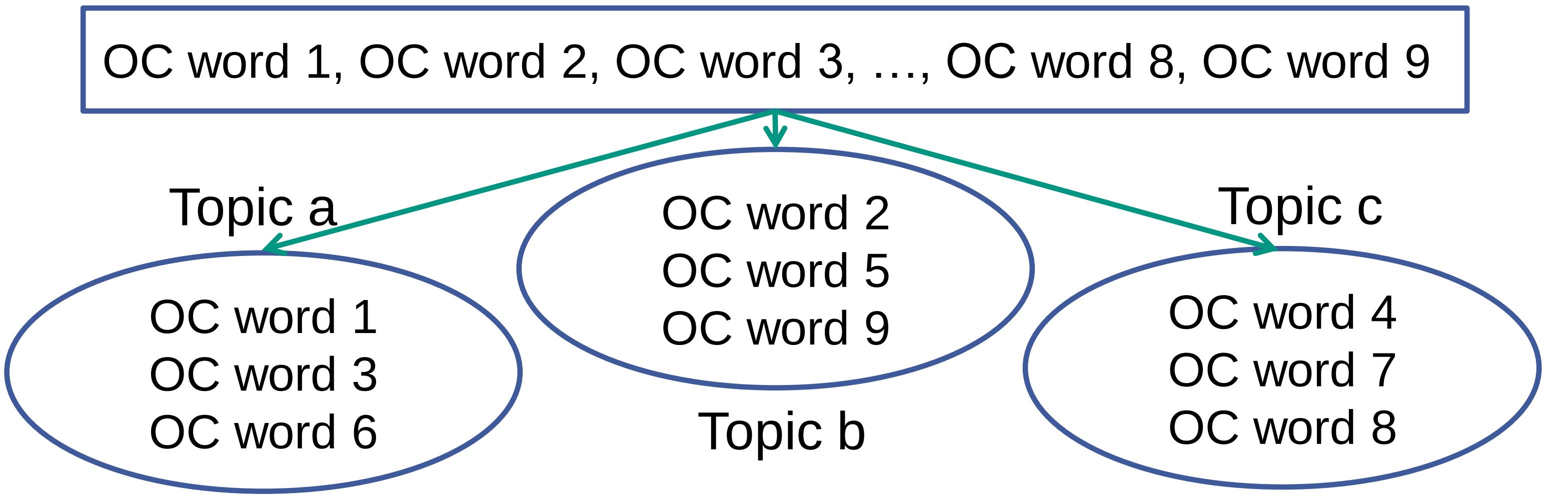
- Definition: content words, e.g. nouns, verbs, adverbs
  - “open” because class can be extended with new words, e.g. “Bollywood”

  ➔ open class words indicate semantic of sentence

Model	PPL dev	PPL eval
Baseline 3-gram	268.39	282.86
Brown clusters + POS	249.00	255.34
Last oc word per speaker + Brown clusters + POS	**247.18**	**252.37**

Features: Open Class Word Clusters

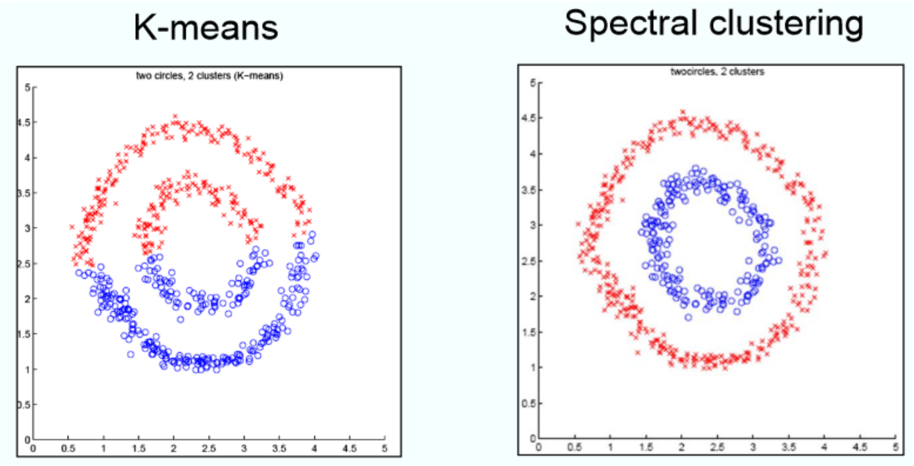
- Idea:



- Semantic clusters in comparison to distribution based clusters (oc Brown clusters)

Features: Semantic OC Word Clusters

- Clustering of open class word vectors
  - RNNLMs learn syntactic and semantic similarities [4]
  - RNNLMs represent words as vectors
  - ➔ apply clustering to these word vectors
    - k-means clustering
    - spectral clustering



[4] Mikolov, T. et al., 2013

Features: Semantic OC Word Clusters

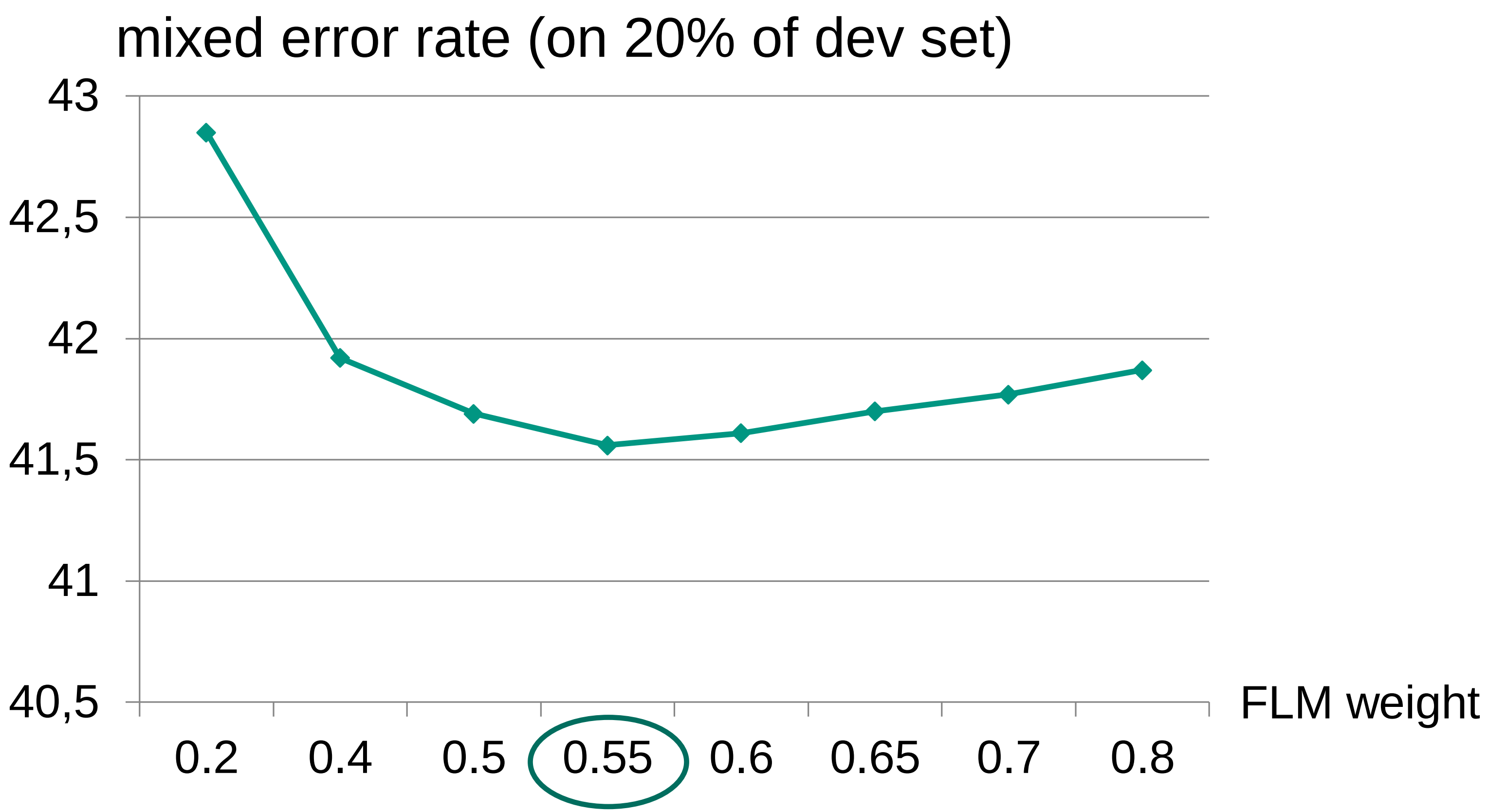
- Experiments with different
  - Clustering methods
    - Brown, k-means, Spectral Clustering
  - Monolingual and bilingual clusters
    - Monolingual Clusters
      - Based on English and Mandarin Gigaword data (2005)
    - Bilingual Clusters
      - Based on CS text
      - Mixed lines of Gigaword data
  - different numbers of clusters

➔ Lowest perplexity (247.24, but unclustered oc words: 247.18):

- Spectral Clustering
- Bilingual Clusters
- 800 OC word clusters

FLMs: Decoding Experiments

- Interpolation weight of FLM and n-gram



FLMs: Decoding Experiments (2)

- Decoding results

Model	MER dev	MER eval
Baseline 3-gram	39.96%	34.31%
POS	39.47%	33.46%
POS + LID	39.66%	33.30%
Brown clusters	39.45%	33.93%
Brown clusters + POS	**39.30%**	33.60%
Brown clusters + POS + LID	39.39%	33.16%
OC words + Brown clusters + POS	39.33%	**33.15%**
OC clusters + Brown clusters + POS	**39.30%**	33.16%

Conclusion

- Summary
  - Best features in terms of FLM perplexity:
    words + POS + Brown clusters + oc words
  - Relative PPL reduction of up to 10.8% (eval)
  - Best features in terms of MER:
    words + POS + Brown clusters (+ oc clusters)
  - Relative MER reduction of up to 3.4% (eval)

THANK YOU FOR YOUR ATTENTION!

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