Focusing Language Models For Automatic Speech Recognition

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Outline

- Problem definition
- Auxiliary data selection
  - TFxIDF
  - Proposed method
  - Perplexity based method
- Computational issues
  - TFxIDF vs proposed method
- Experiments
- Discussion

Problem definition

- Given a general purpose text corpus and a given speech to transcribe
  - Build a LM which is focused on the particular (unknown) topic of the speech
  - No need for instantaneous, but should be quick
- Approach:
  - Perform a first ASR pass
  - Use recognition output to select text data "similar" to the context
  - Build a focused language model
  - Use the focused language model in the next ASR pass

Recognition setup

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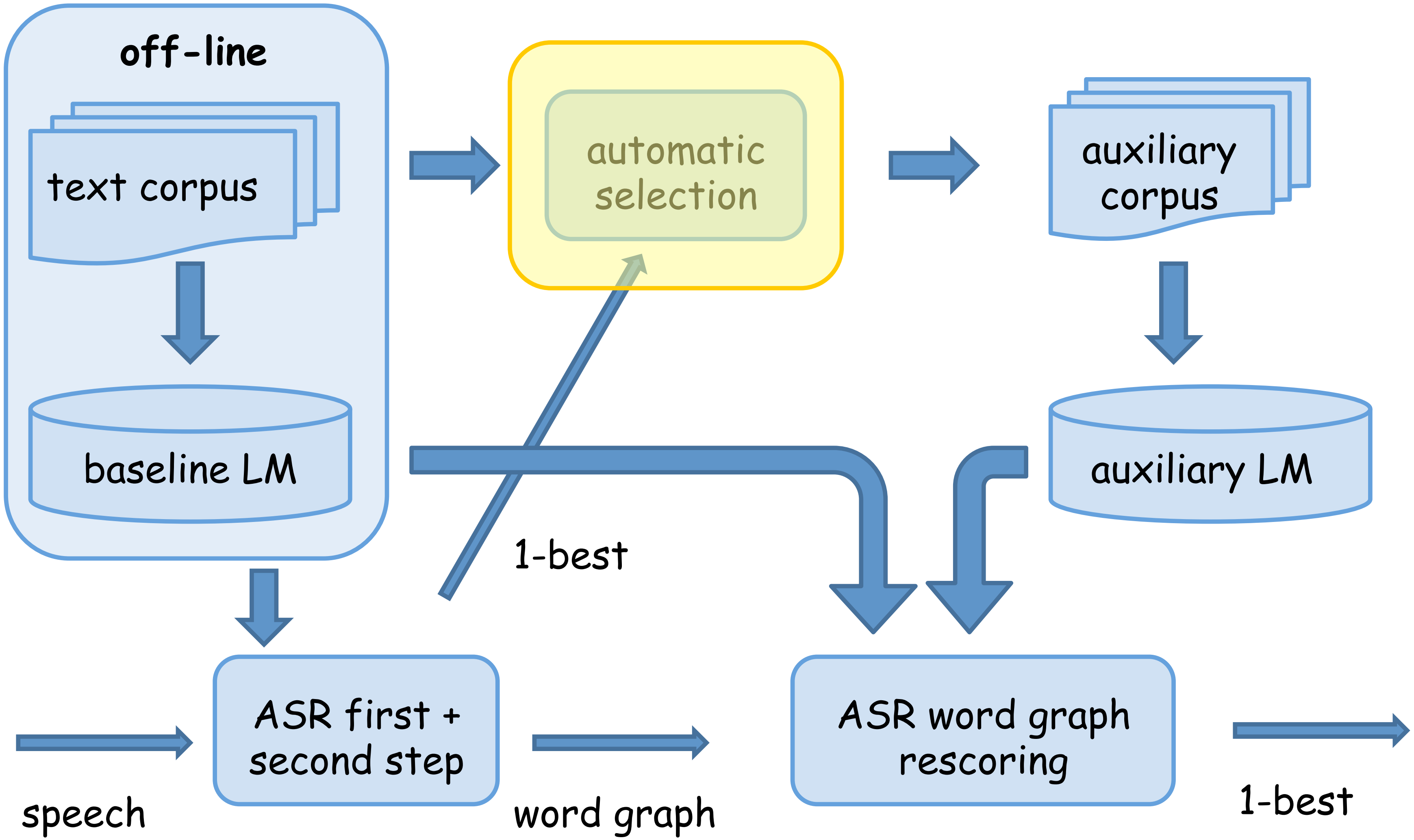
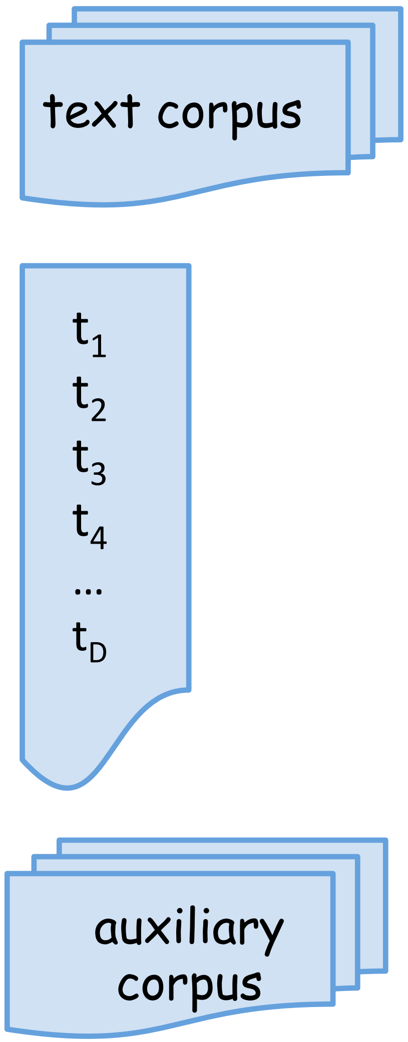


terminology



- text corpus
  - composed by **N** rows (N documents)
  - average length of a document: **Lc**
- dictionary
  - composed by t_d terms, $1 \le d \le D$
- auxiliary corpus
  - composed by rows of the text corpus, size: **K** words
- speech to recognize
  - TED talks, average length: **Lt**

Auxiliary data selection

- rationale:
  - score each row in the text corpus against ASR output
  - sort rows according to score
  - select the first rows → auxiliary corpus (having size K)

- 3 approaches implemented and compared:
  - TFxIDF
  - Proposed method
  - Perplexity based method

- domain specific data (TED LM)

Auxiliary data selection: TFxIDF

- for each talk ***i*** and for each word t_d compute:

$$c^i[t_d] = (1 + \log(tf_d^i)) \log(\frac{D}{df_d}) \quad 1 \le d \le D$$

tf_d^i = frequency of term t_d inside talk

df_d = # of documents in the corpus containing t_d

- **compute the same for each row R^n in the corpus,** $1 \le n \le N$
- **estimate a similarity score:**

$$s(C^i, R^n) = \frac{C^i \cdot R^n}{|C^i||R^n|}$$

Auxiliary data selection: Proposed method

- sort words in dictionary according to frequency
- discard most frequent words (< D_1 = 100)
  - they don't carry semantic information
- discard most rare words (> D_2 = 200K)
  - too rare to help, include typos
- replace words in corpus by their index in dictionary
- sort indices in each row to allow quick comparison
- estimate a similarity score:

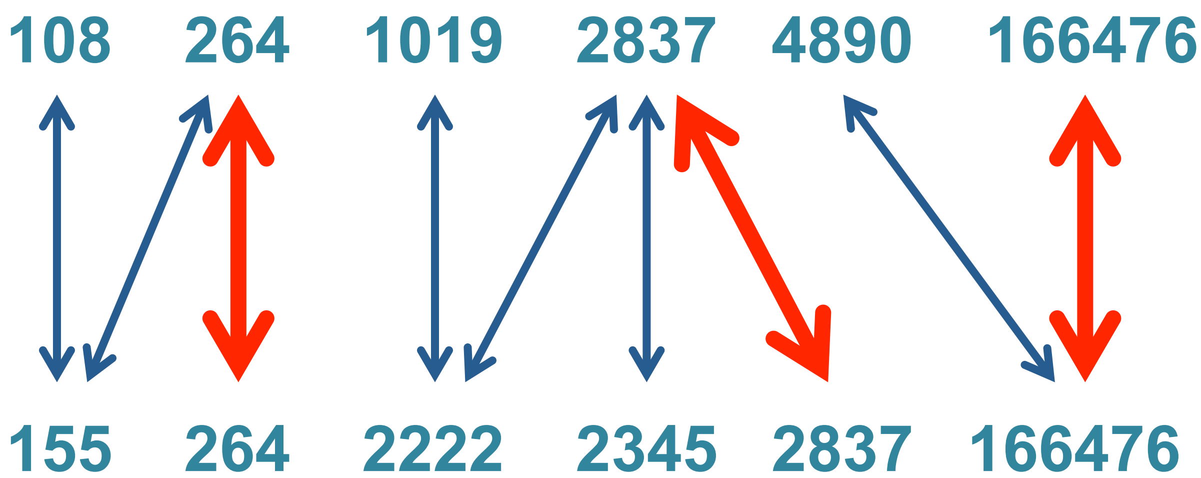
$$s'(C'^{i}, R'^{n}) = \frac{\mathrm{common}(C'^{i}, R'^{n})}{\dim(C'^{i}) + \dim(R'^{n})}$$

Auxiliary data selection: Proposed method

- example:
  - I would like your advice about rule one hundred forty three concerning inadmissibility
  - 47 54 108 264 2837 63 1019 6 12 65 24 4890 166476
  - 108 264 2837 1019 4890 166476
    (like your advice rule concerning inadmissibility)
  - 108 264 1019 2837 4890 166476

Auxiliary data selection: Proposed method

- similarity score computation:
  - the lower index increment



score = 3 / 12

Auxiliary data selection: Perplexity based method

- train a 3-gram LM using ASR output
- estimate perplexity for each row in the corpus
- use perplexity as a similarity score

Auxiliary data selection: Run time computational complexity

- corpus size: **N** (5.7M) rows, average row length **L** (272)
- dictionary size: **D** (1.6M) (D_2=200K)

	TFxIDF	Proposed method
Arithmetic operations	O(2 x N x L)	O(N x L / 2)
Memory requirements	O(D + N x L)	---

Training data

- text corpus
  - google news
  - 5.7 M documents, 1.6 G words
  - 272 words per document
  - LM for rescoring:
    - 4-gram backoff LM, modified shift
    - 1.6M unigrams, 73M bigrams, 120M 3-grams and 195M 4-grams.
  - FSN for first & second step:
    - 200K words, 37M bigrams, 34M 3-grams, 38M 4-grams.

Test data

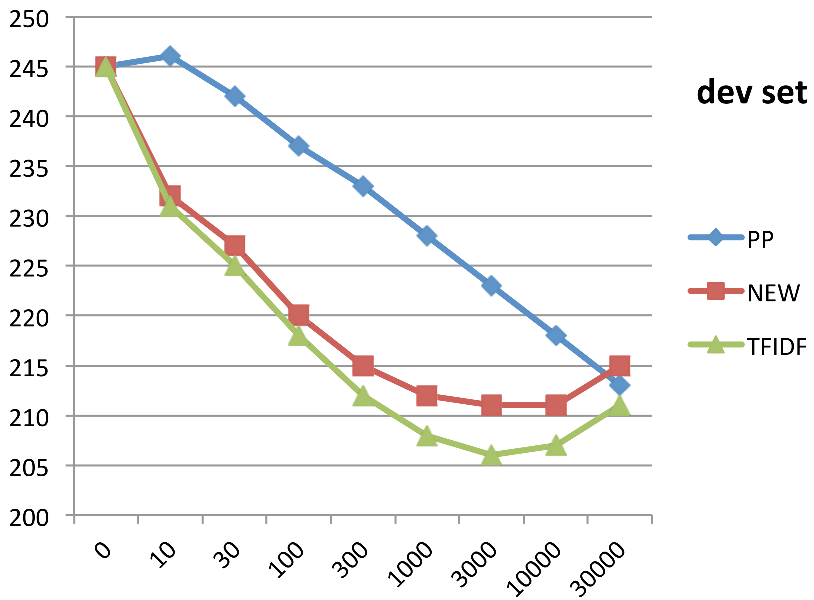
- TED talks (test sets of IWSLT 2011)
- auxiliary corpus and auxiliary LM computed for each talk

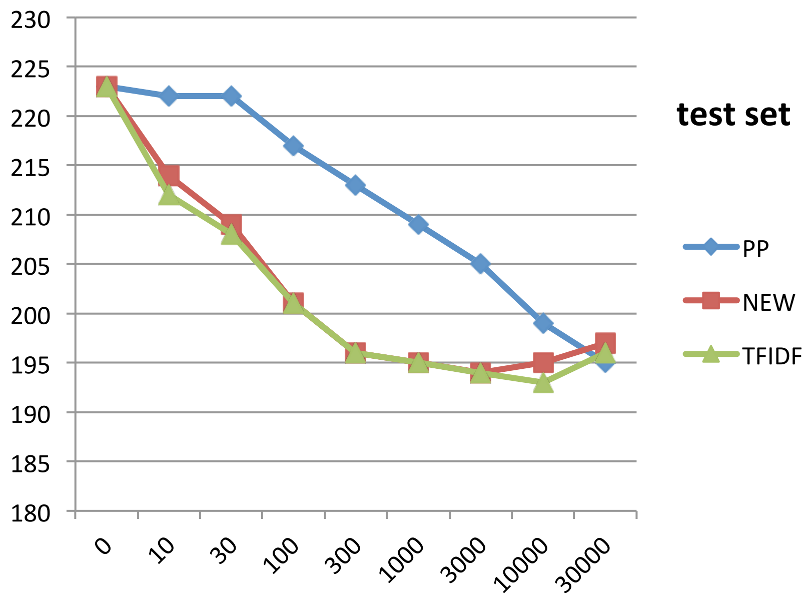
	dev-set (19 talks)	test-set (8 talks)
#words	44505	12431
(min,max,mean)	(591,4509,2342)	(484,2855,1553)

- performance are reported as a function of K, the number of words used to train the auxiliary LMs

Results

- **Perplexity as a function of K**
  - **0 means no interpolation**





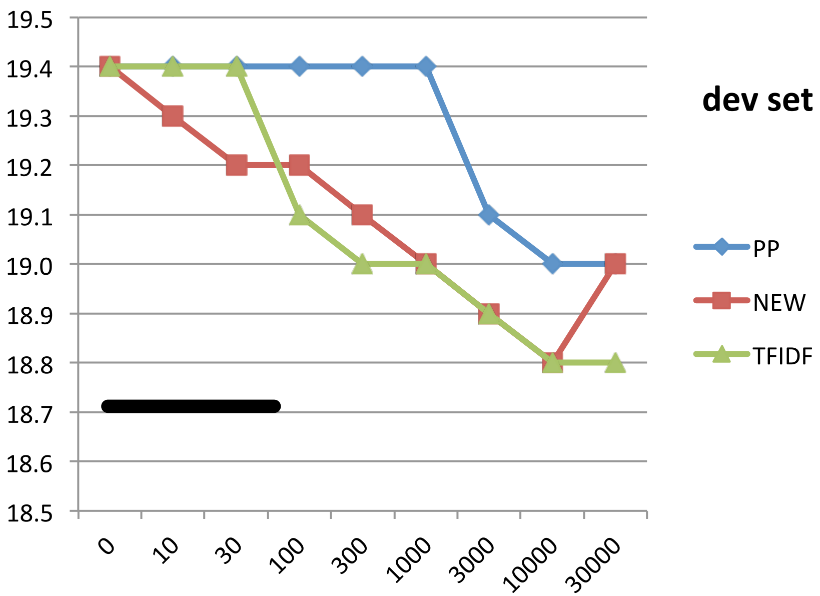
K is expressed in Kwords

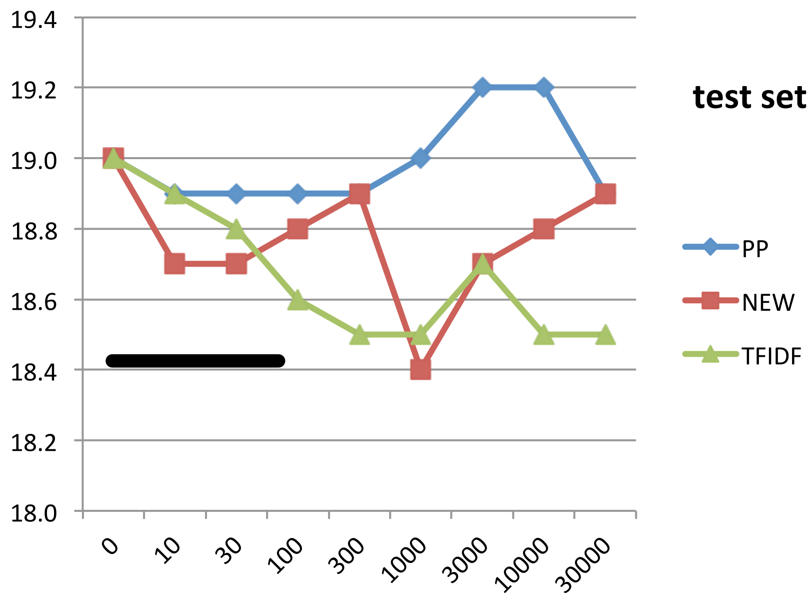
- **Perplexity interpolating the baseline LM with a domain specific LM (trained on ted2011 text, 2 Mwords):**

dev set: 158 **test set: 142**

Results

- **WER as a function of K**
  - **0 means no interpolation**





K is expressed in Kwords

- **WER interpolating the baseline LM with a domain specific LM (trained on ted2011 text, 2 Mwords):**

dev set: 18.7 **test set: 18.4**

Conclusion

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- Method for focusing LMs without using in-domain data
- Comparison between the proposed method and TFxIDF
  - similar performance
  - less demanding computational requirements
- Comparable results if using in-domain data
  - in this setting…
- Future work:
  - how to add new words (to reduce OOV?)
  - instantaneous LM focusing

Thank you for the attention

LM interpolation

- LM probability associated to every arc of the word graph:

$$P[w \mid h] = \sum_{j=1}^{J} \lambda_j P_j[w \mid h]$$

- J = number of LMs to combine
- λ_j = weights estimated to minimize the overall perplexity on a development set

The interpolation weights, i base and i aux, associated to the two LMs (LMbase and Lmi aux) are estimated so as to minimize the overall LM perplexity on the 1-best output (the same used to build the ith query document), of the second ASR decoding step.