The CSTR System for Multilingual and Code-Switching ASR Challenges for Low Resource Indian Languages

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Subtask 1 System Overview

Acoustic Model

- CNN-TDNN with language specific outputs
- Trained with LF-MMI
- Multilingual pre-training
- Monolingual fine-tuning

Language Model

- Language specific 3-gram and RNN LMs
- Training data + CommonCrawl data

Youtube Crawling

To increase the training data size we crawl Youtube videos by searching for the most common trigrams.

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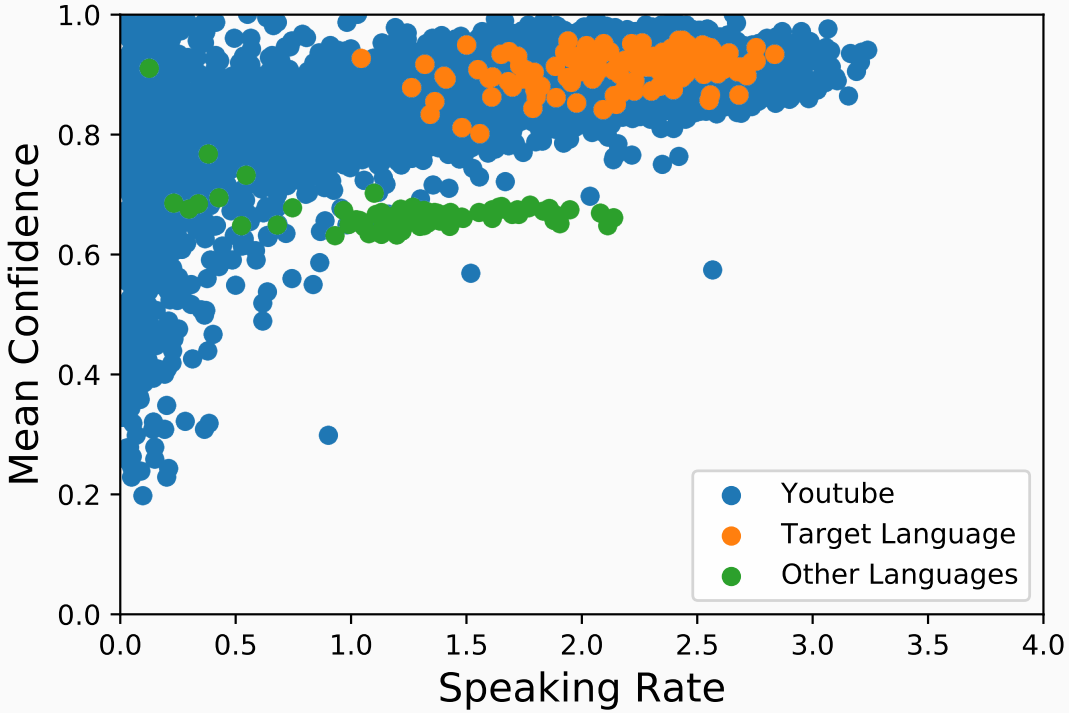
We filter videos using mean confidence and speaking rate.



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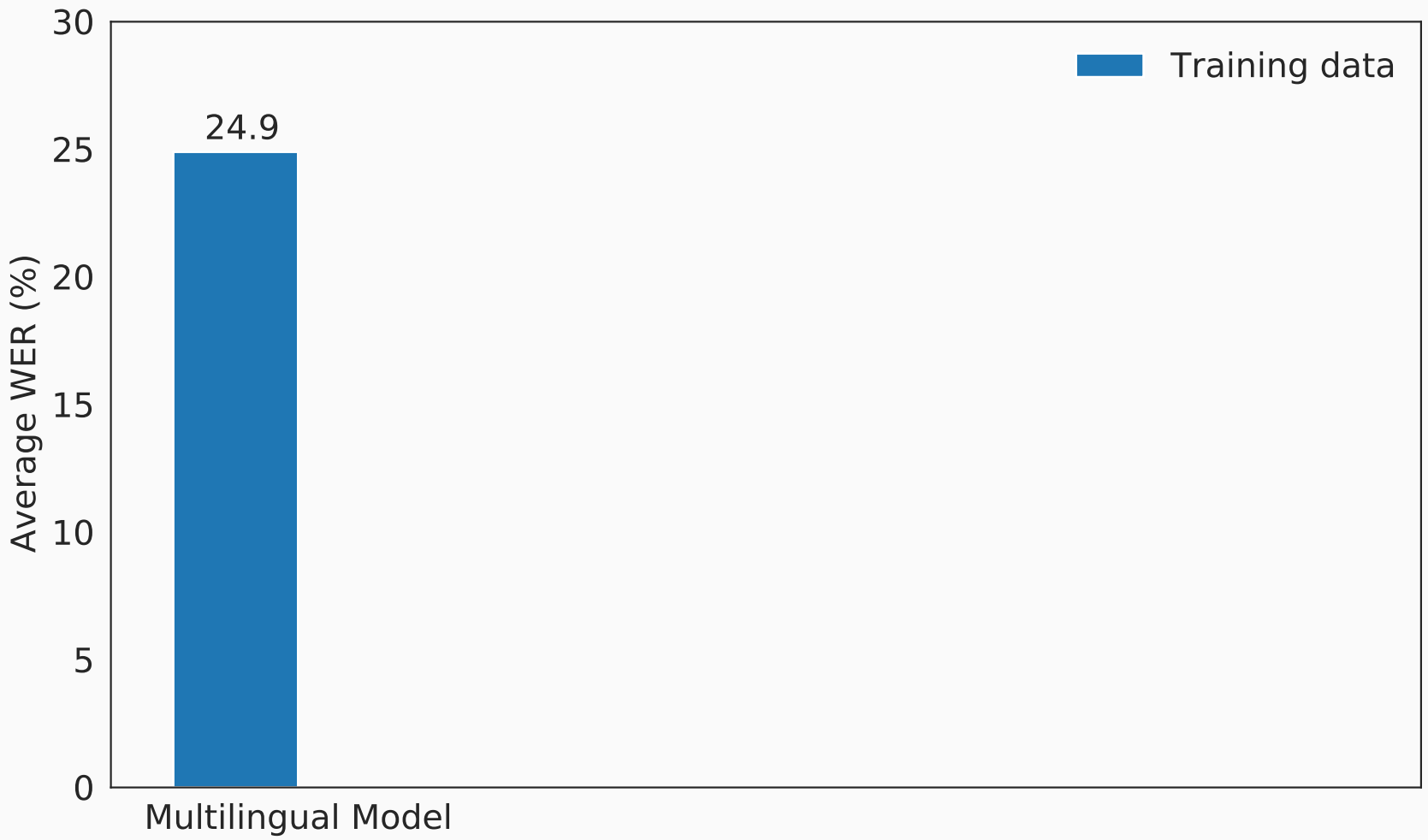
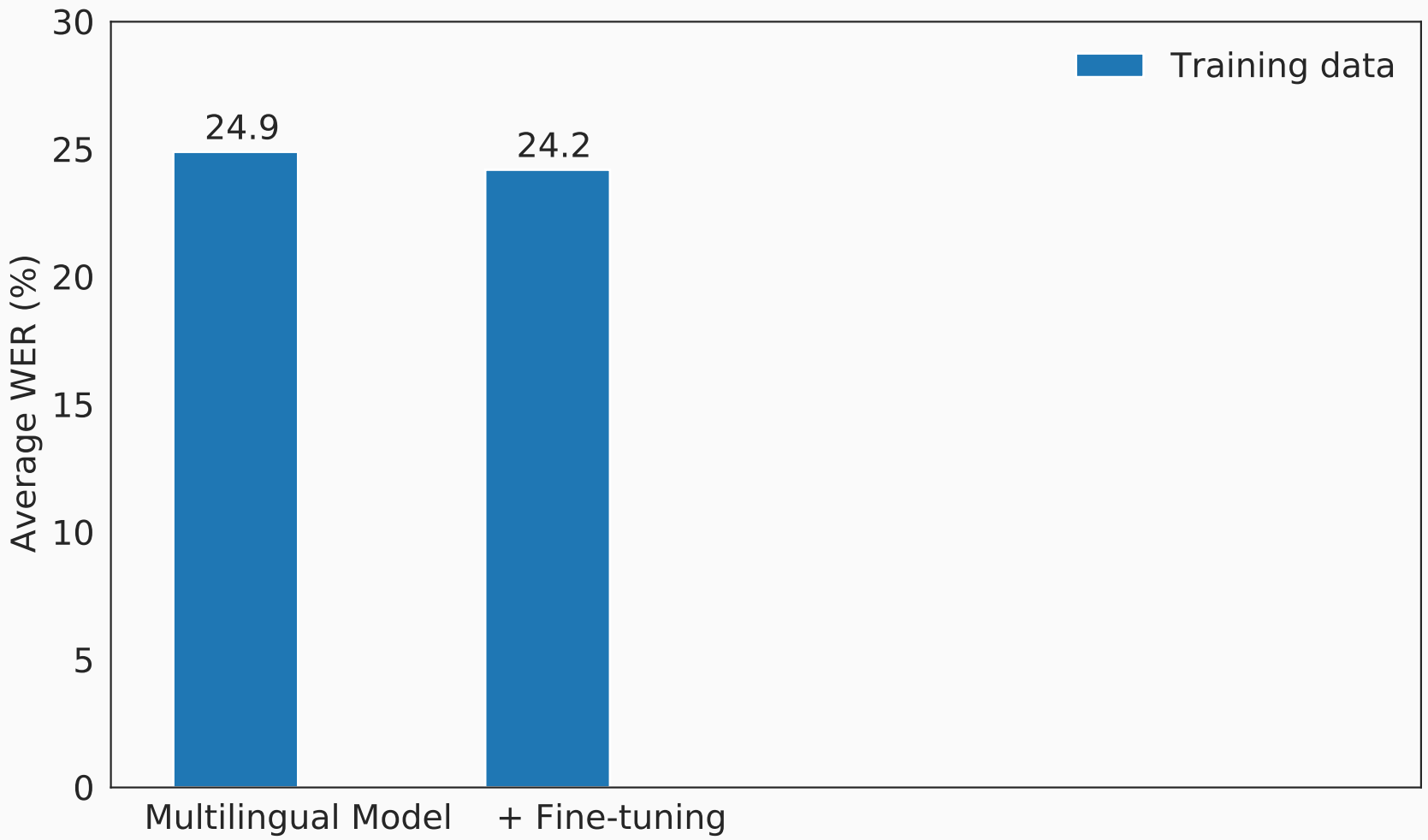
- We decode the videos with a seed model.
- We use the decoded output as labels for training.

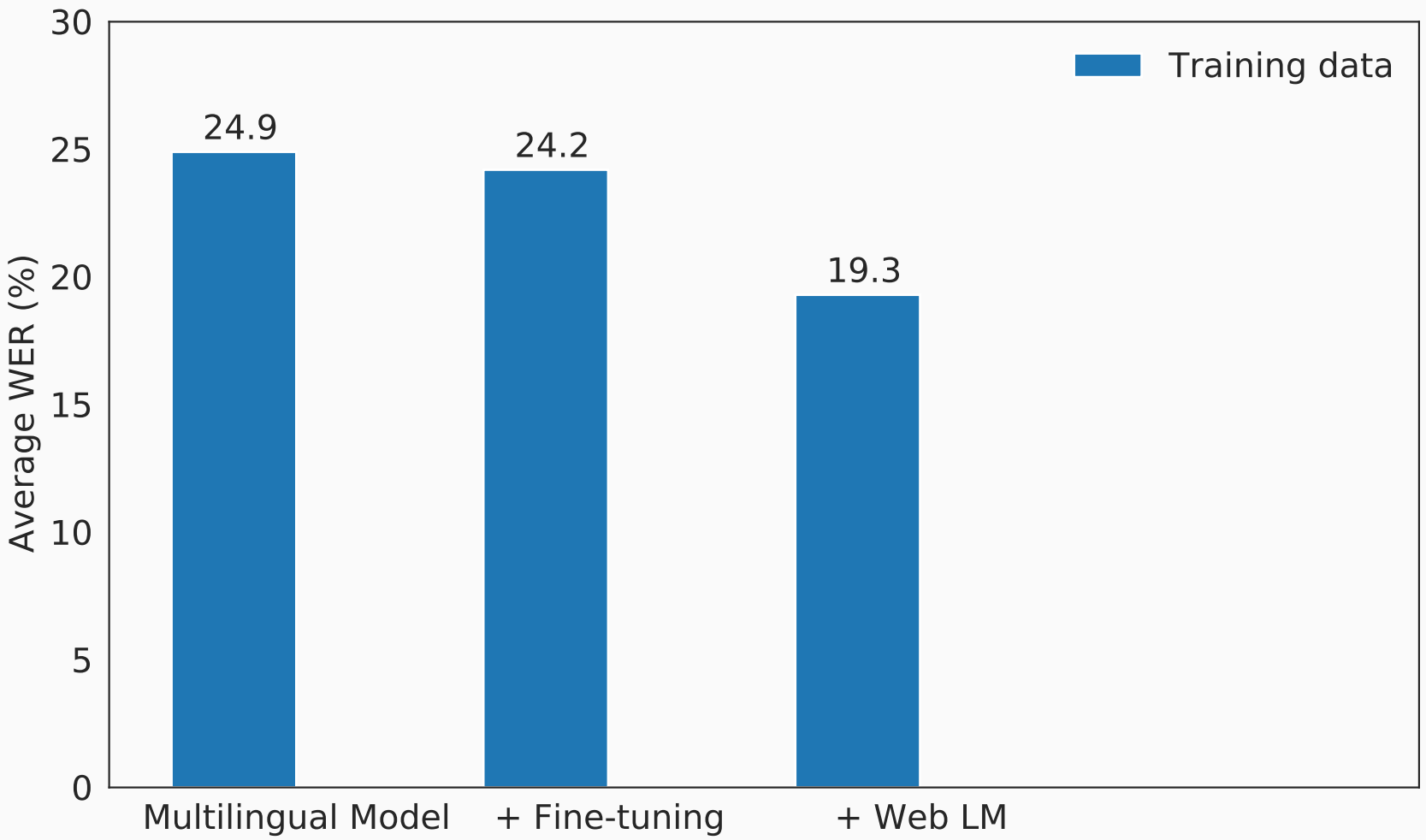
Results


30
25
20
15
10
5
0
Average WER (%)
24.9
Training data
Multilingual Model

Results


30
25
20
15
10
5
0
Average WER (%)
Training data
24.9
24.2
Multilingual Model
+ Fine-tuning

Results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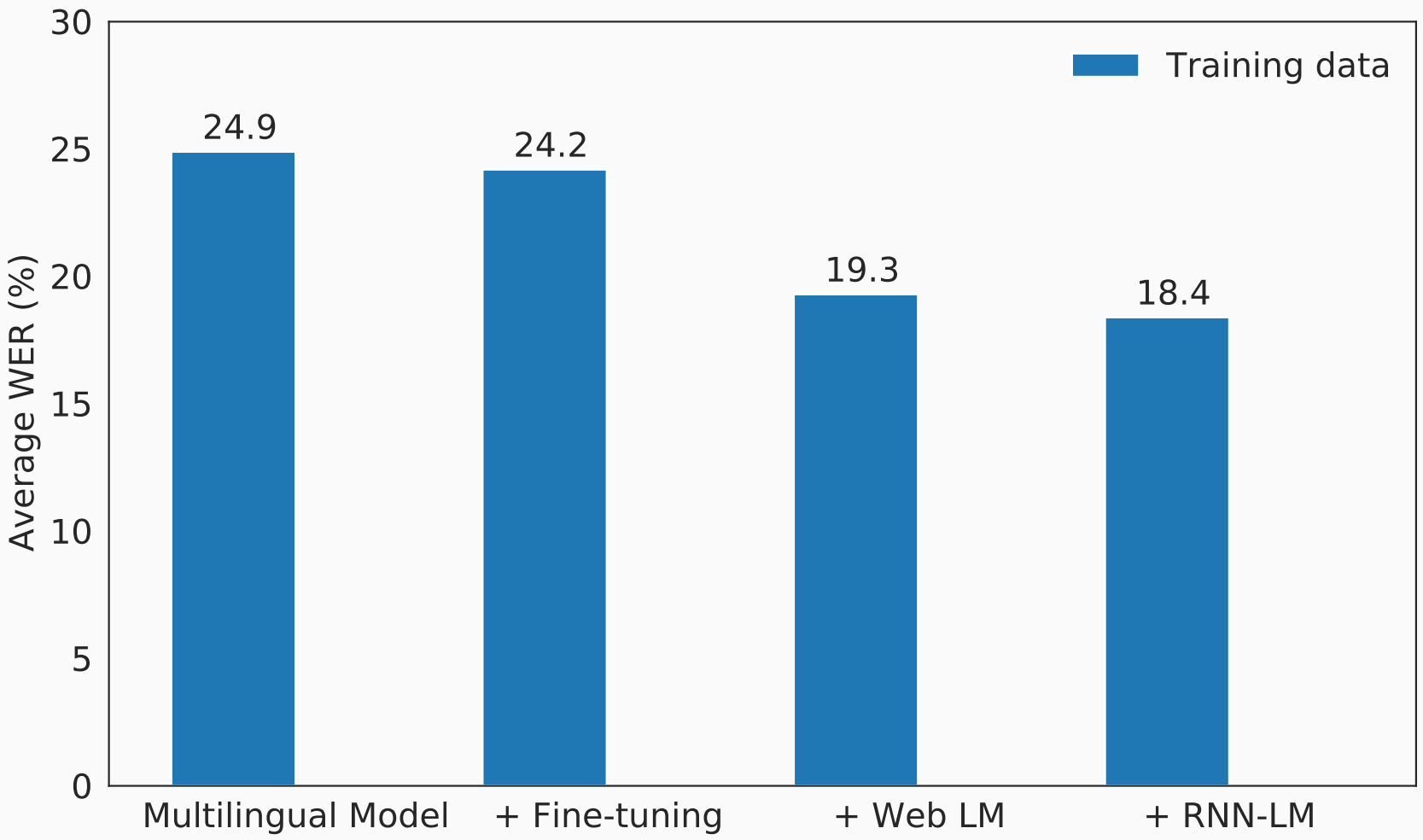
Average WER (%)
Training data
24.9
24.2
19.3
Multilingual Model
+ Fine-tuning
+ Web LM

Results


Training data
Average WER (%)
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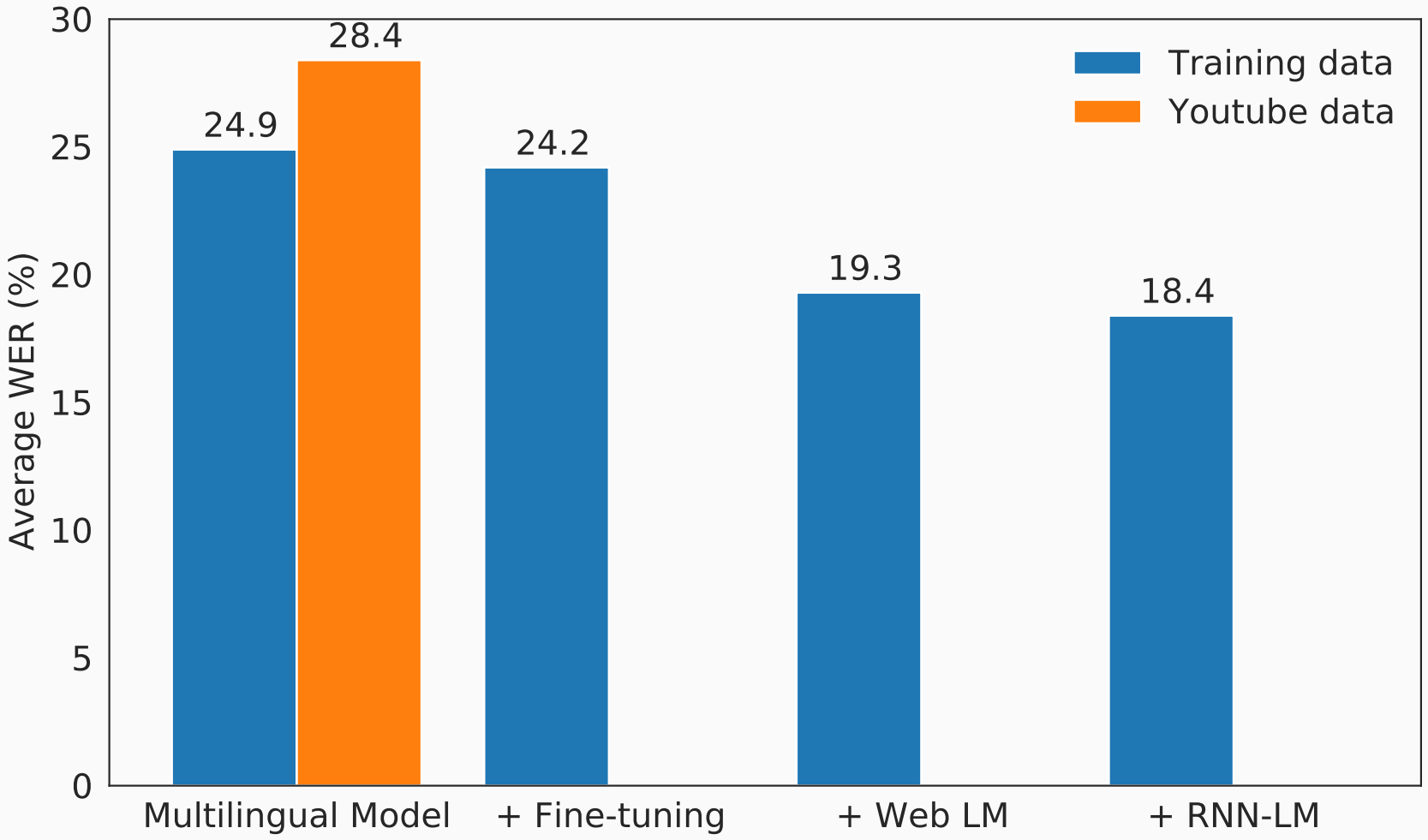
24.2
19.3
18.4
Multilingual Model
+ Fine-tuning
+ Web LM
+ RNN-LM

Results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Training data
Youtube data
Multilingual Model
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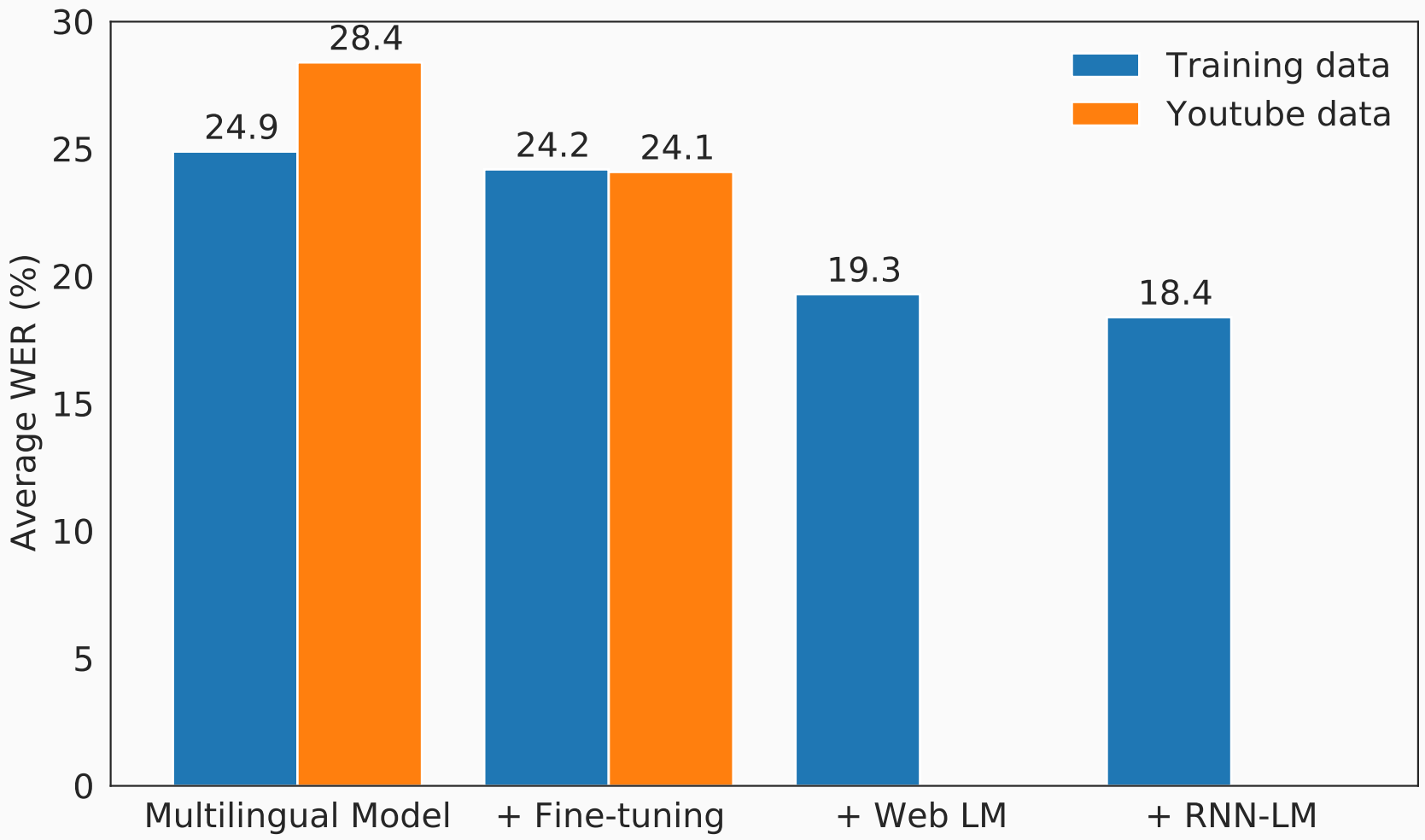
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Training data
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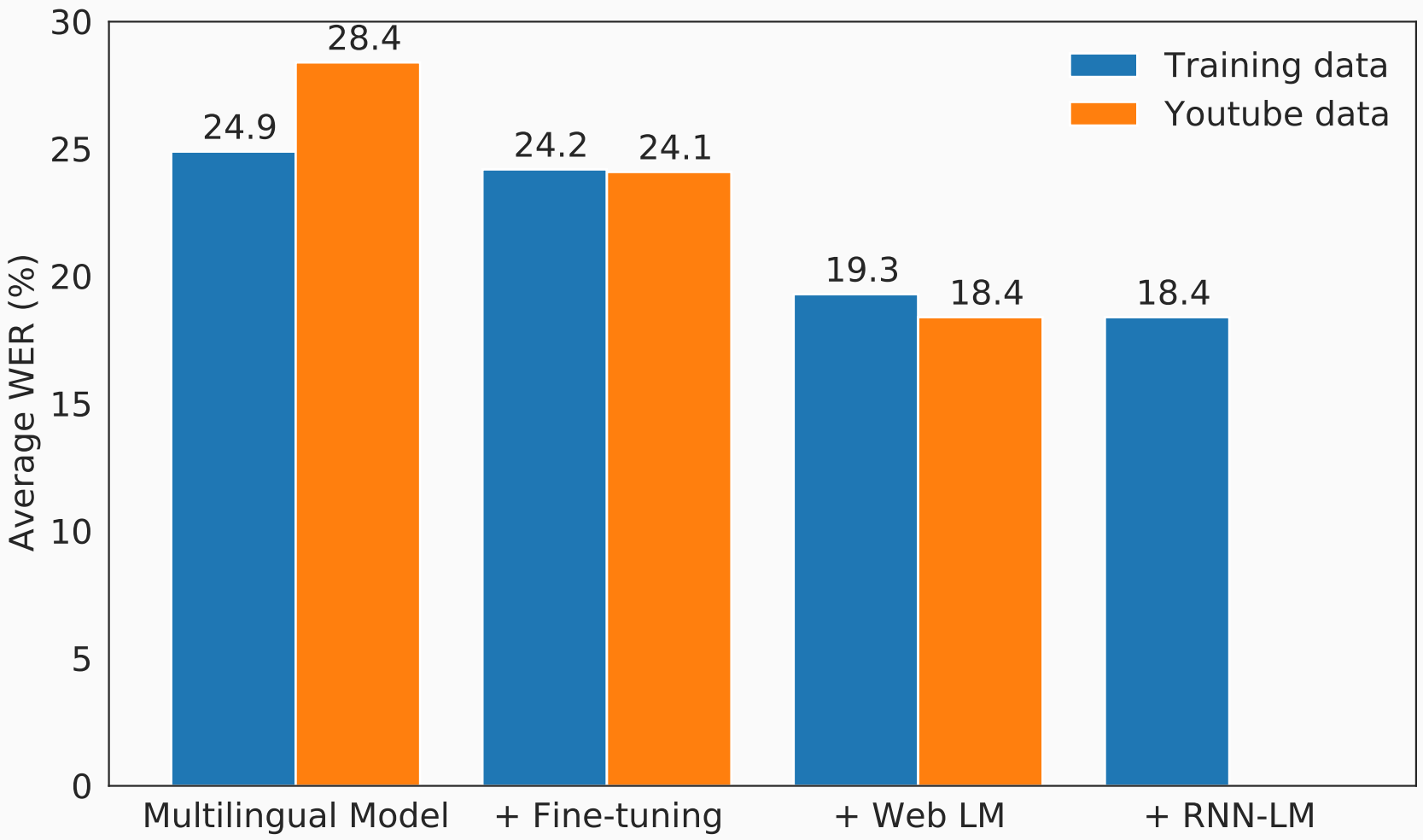
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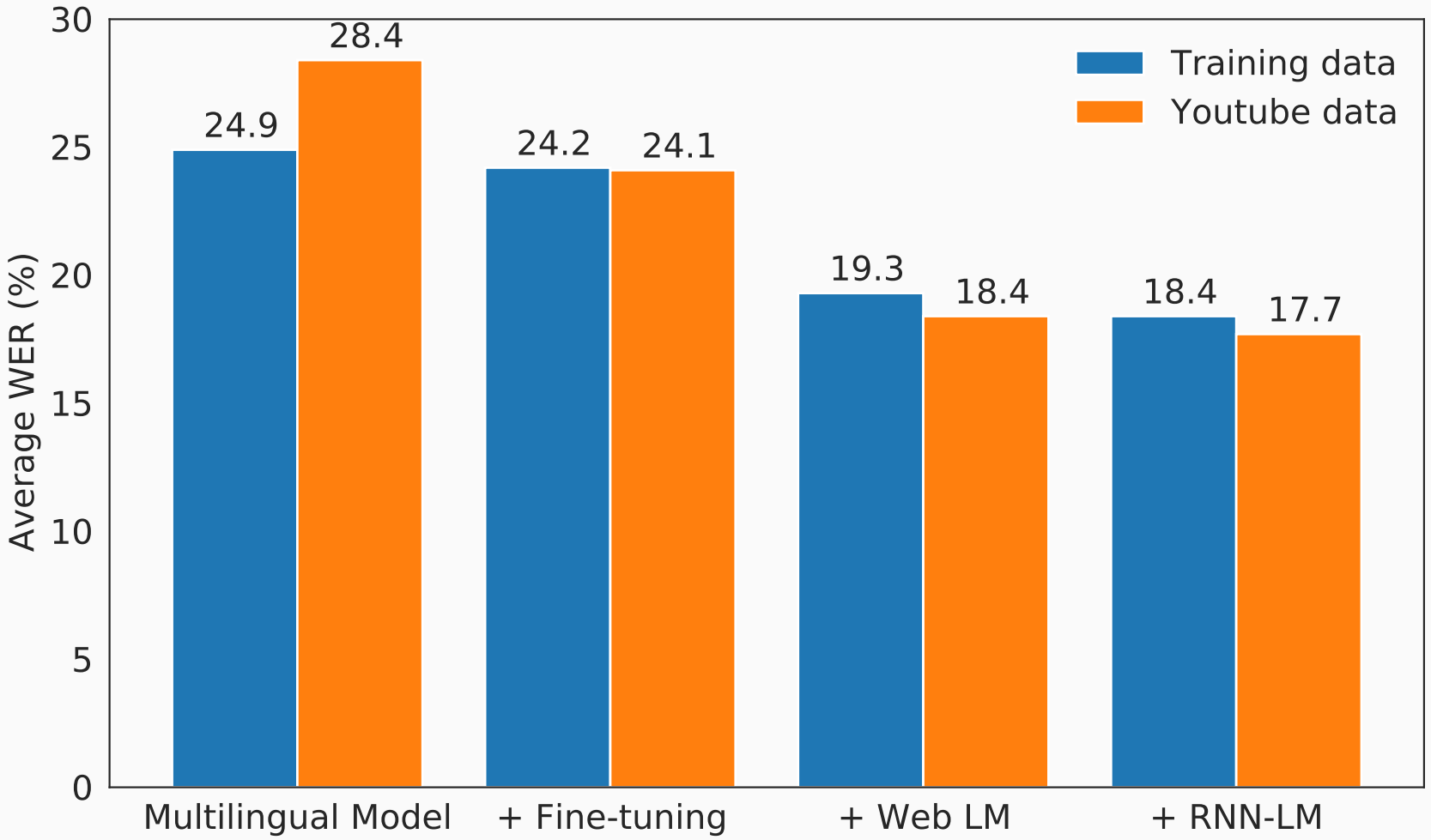
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Language Identification

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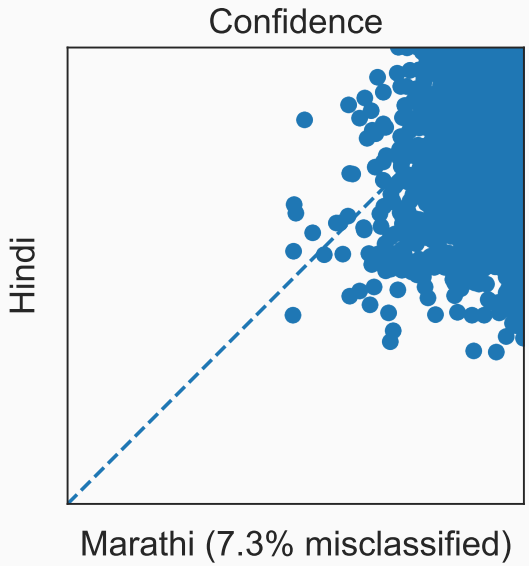

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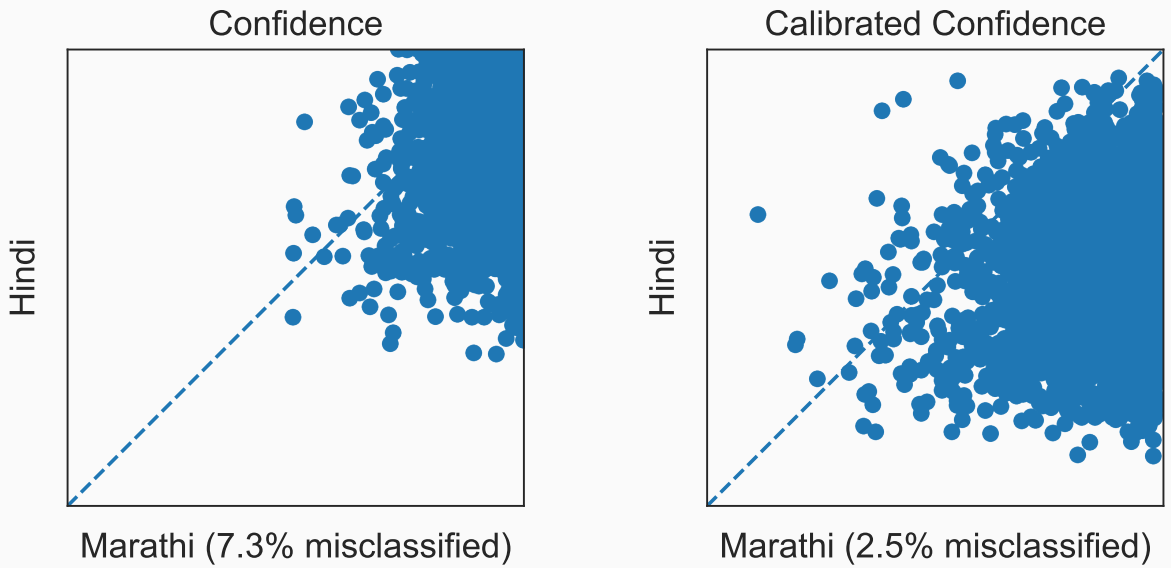

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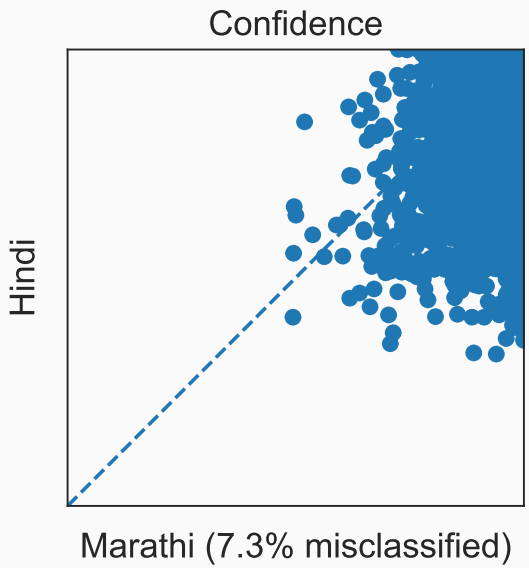

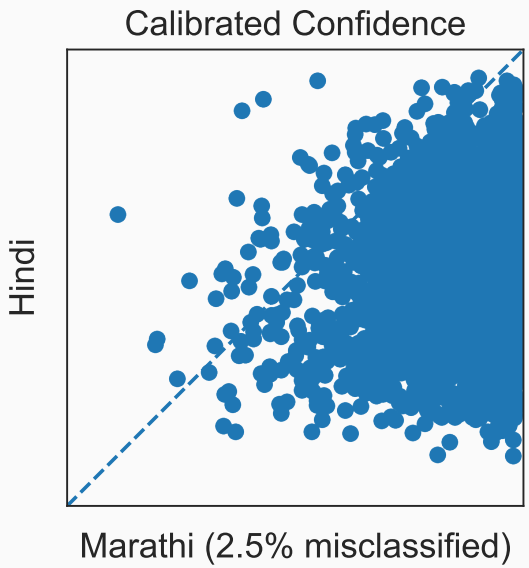

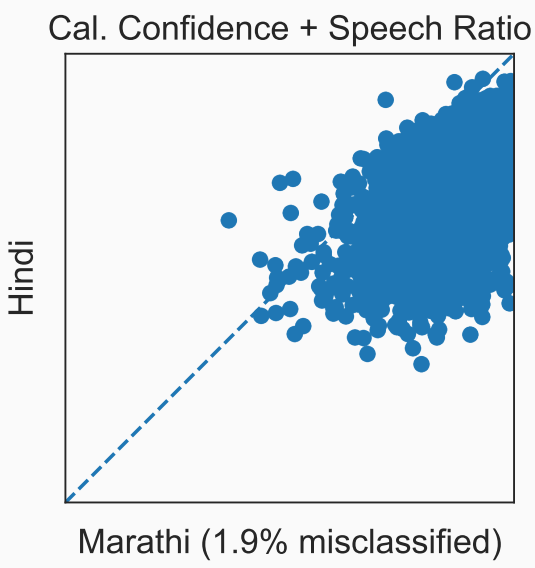

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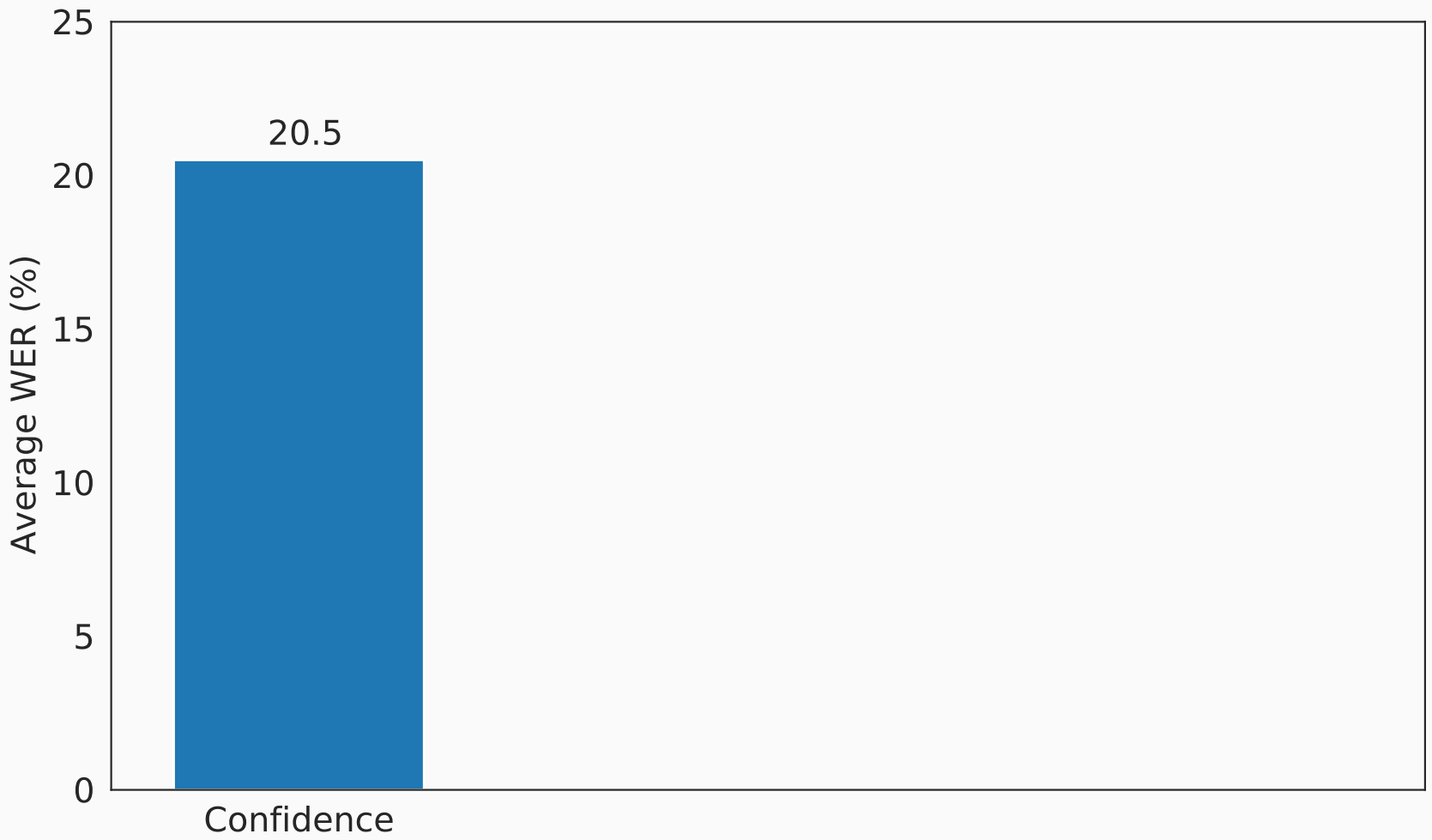

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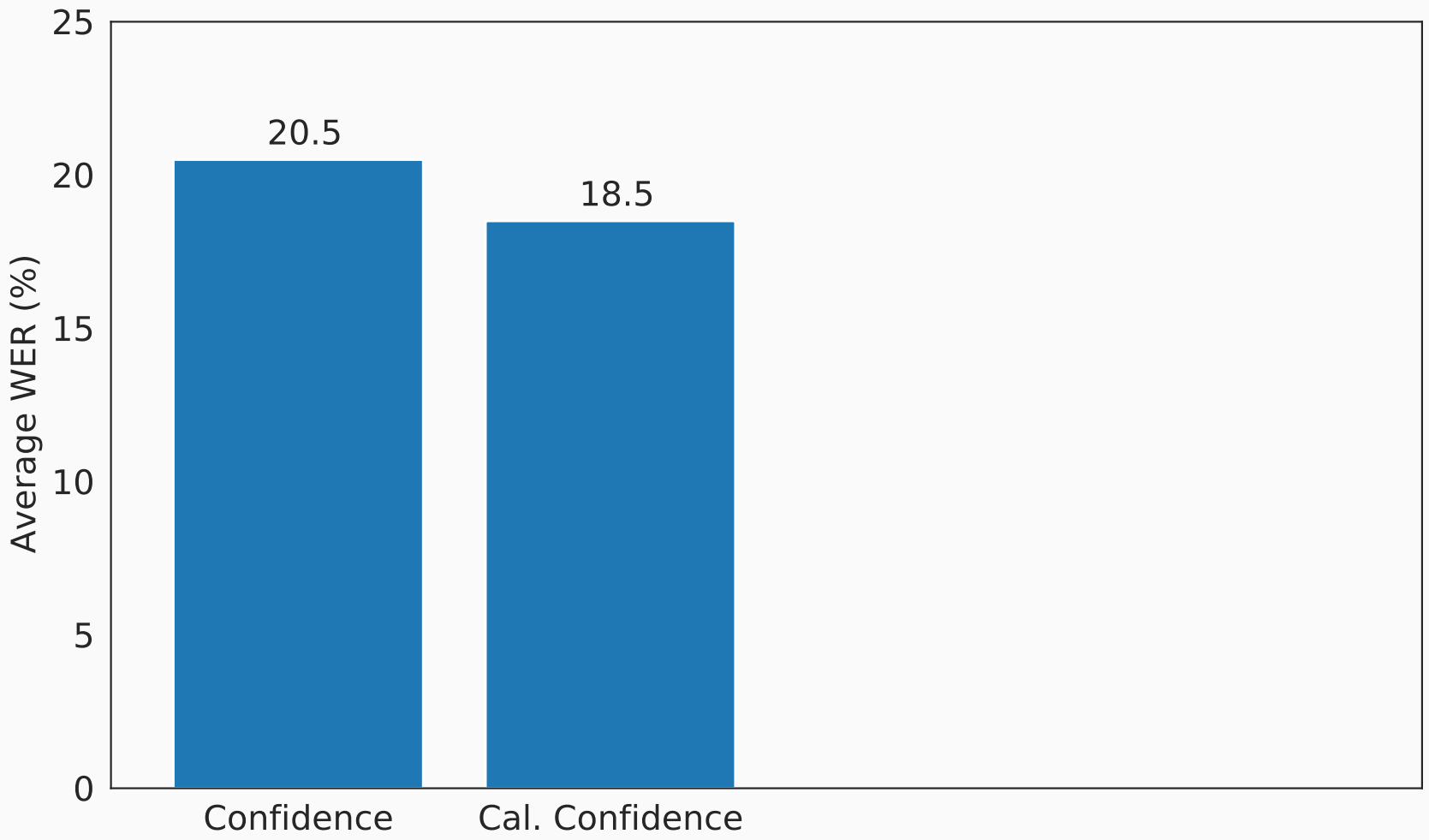

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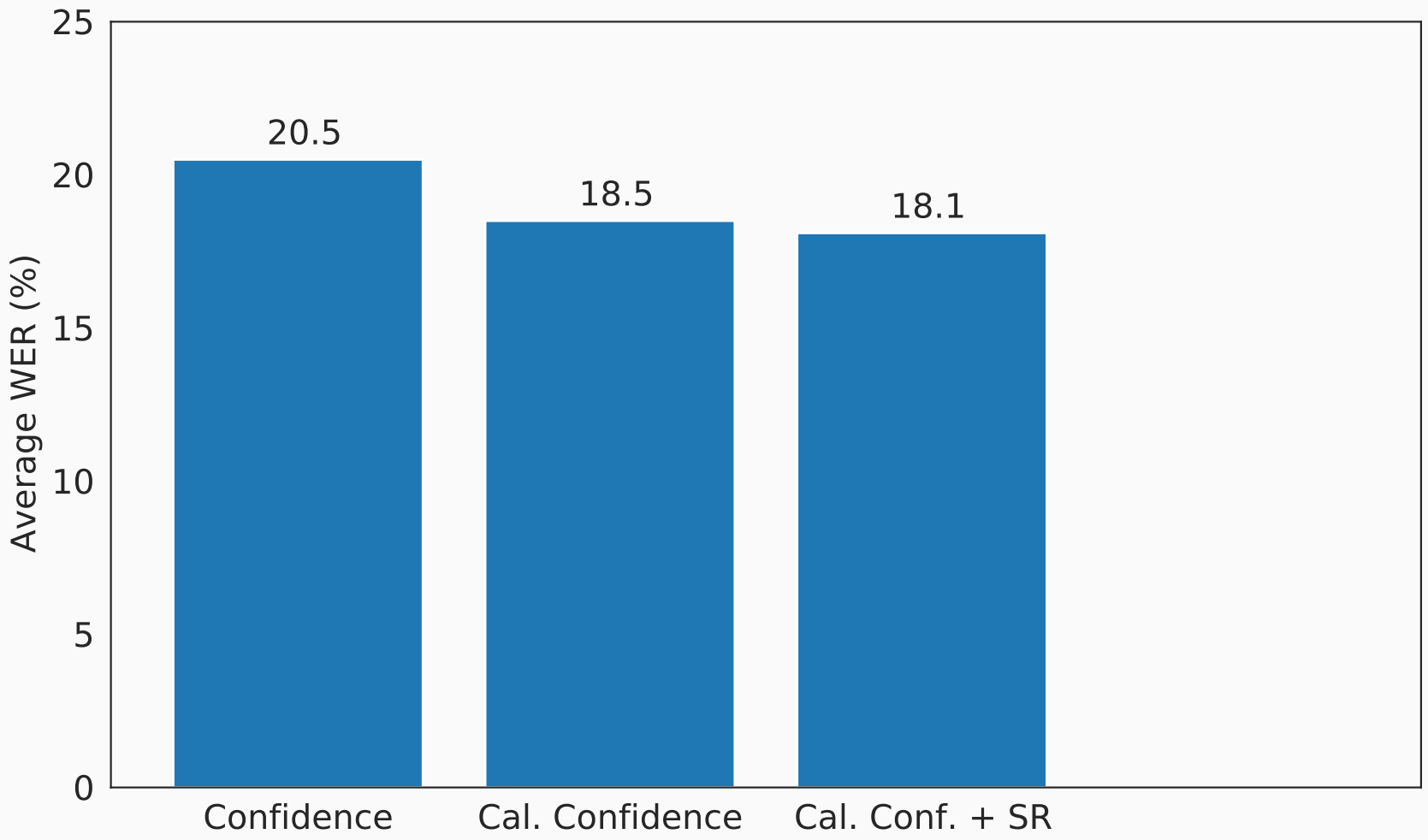

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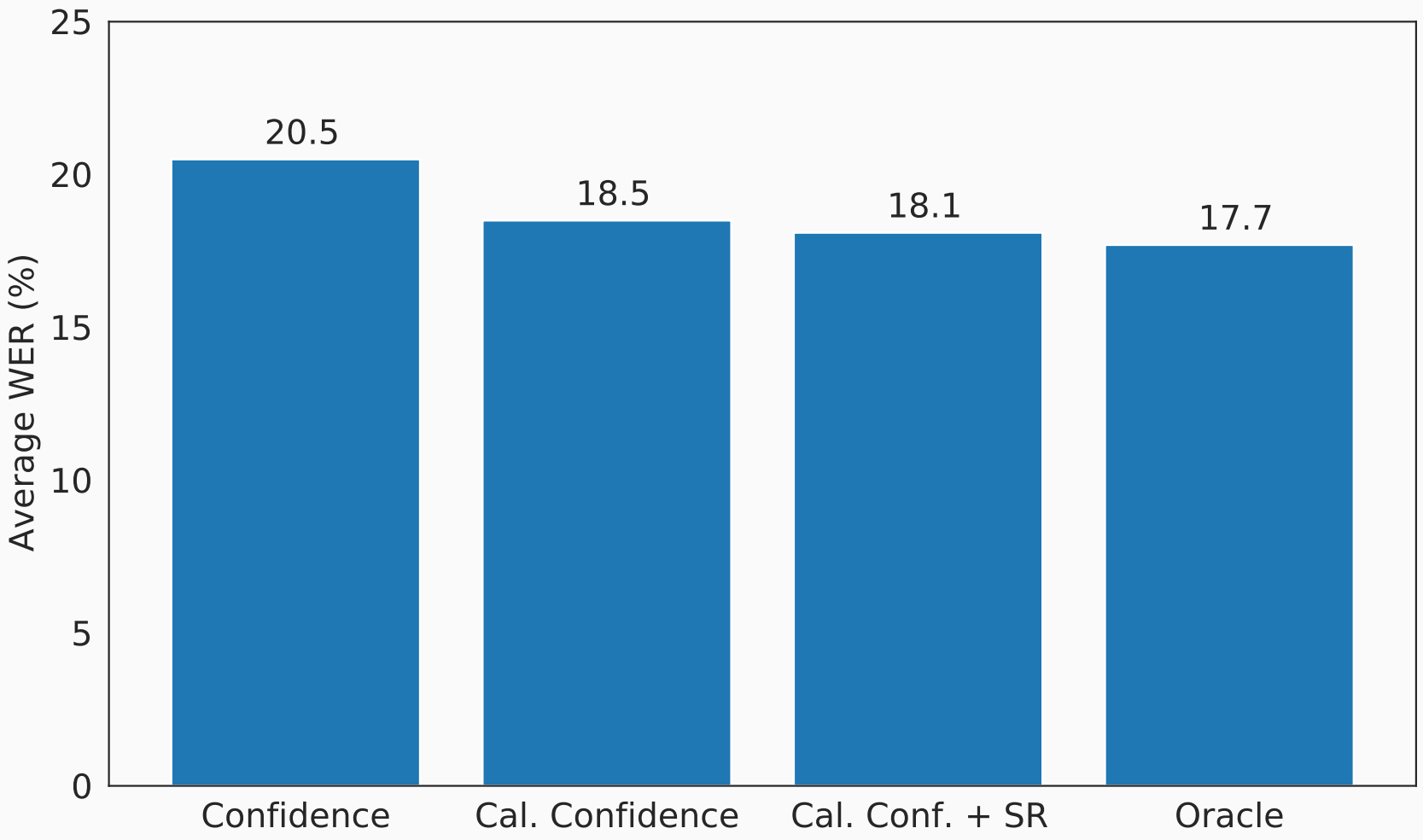

ASR models for low-resource languages can be trained with standard Kaldi recipes and crawled text/audio data.

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Confidence-based language identification works well, but is very expensive for deployment.

Subtask 2 System Overview

Acoustic Model

- CNN-TDNN with language specific outputs
- Multilingual training with LF-MMI

Language Model

- 3-gram, RNN-LM
- Data:
  - Training data
  - Hindi/Bengali CommonCrawl data
  - English SpokenTutorial.org subtitles

Lexicon

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hello	HH AH L OW
world	W ER L D
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दुनिया	द ु न ि य ा

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- To use the same units we trained a phone matcher using automatically crawled Wikipedia data.

Training the Phone Matcher

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David

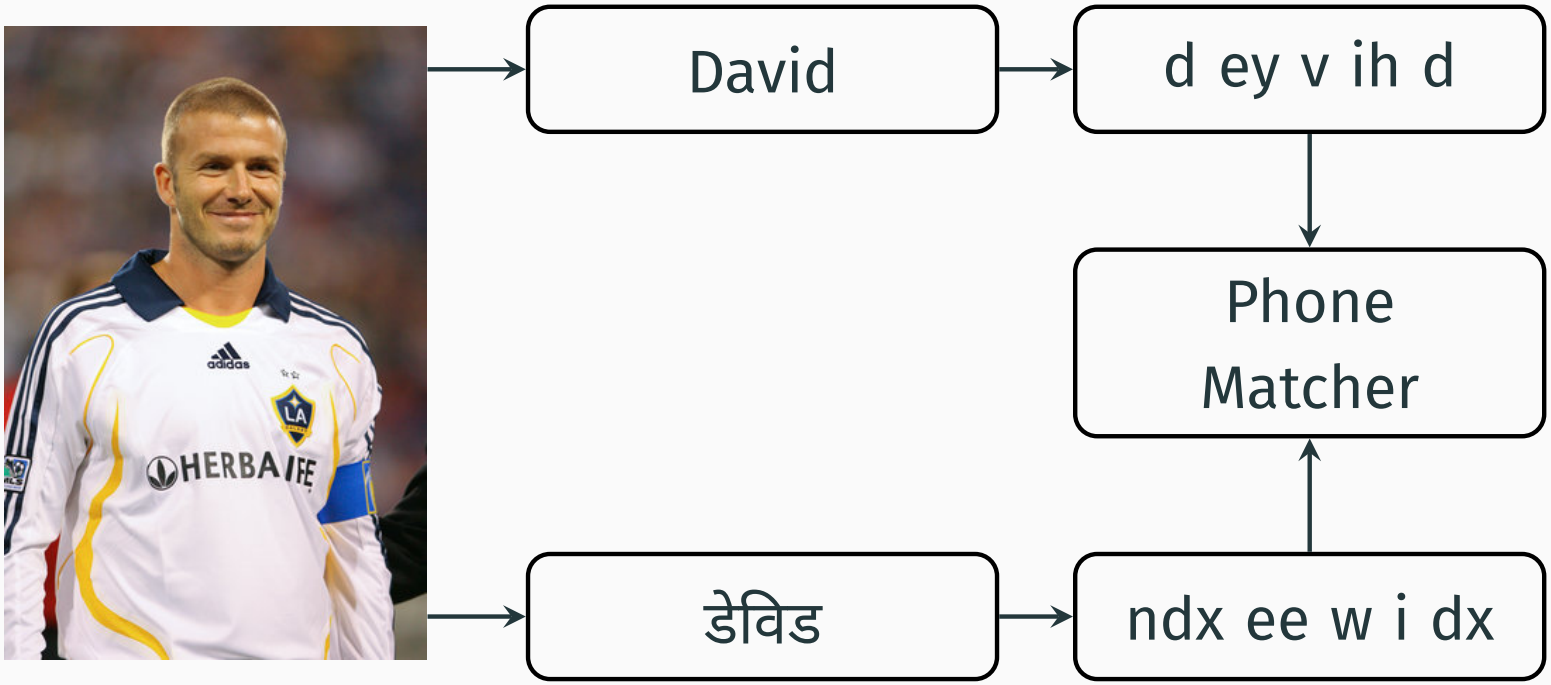
डेविड

Training the Phone Matcher

David → d ey v ih d

डेविड → ndx ee w i dx

Training the Phone Matcher



Language Modeling

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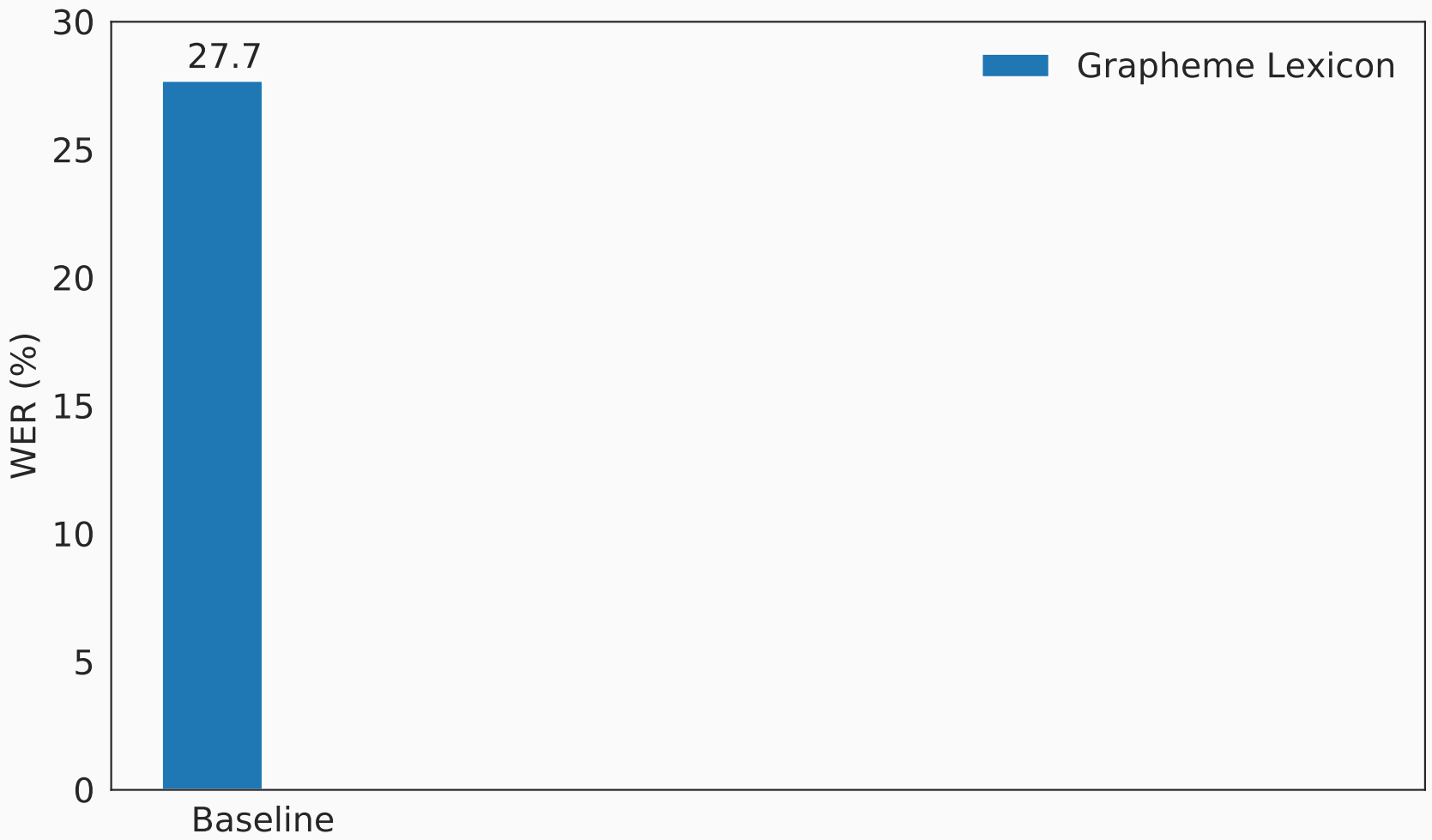
The final language model was a mixture of language models trained on:

- Training data
- CommonCrawl data
- English SpokenTutorial.org subtitles

Interpolation weights were estimated on the dev data.

Hindi-English Results



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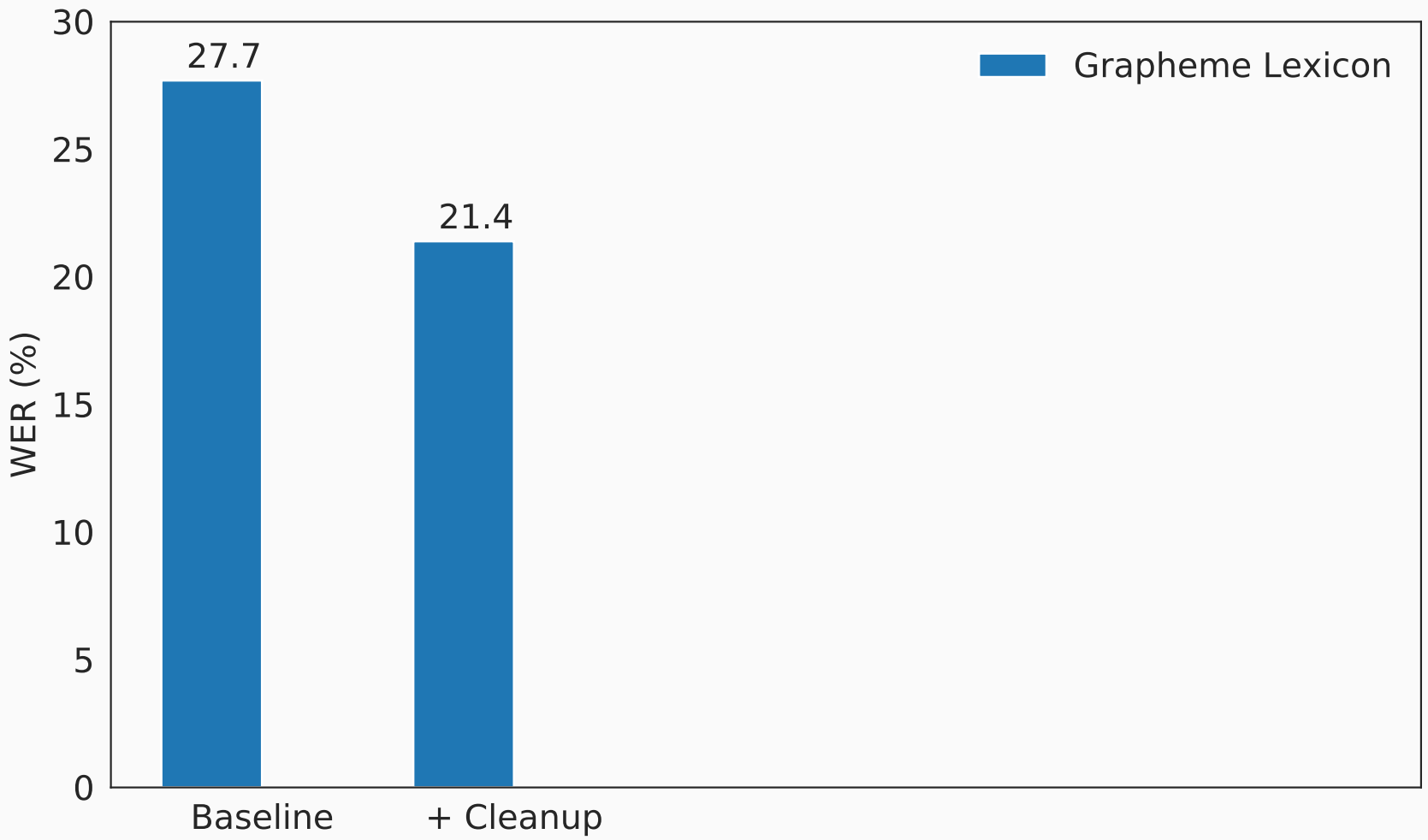

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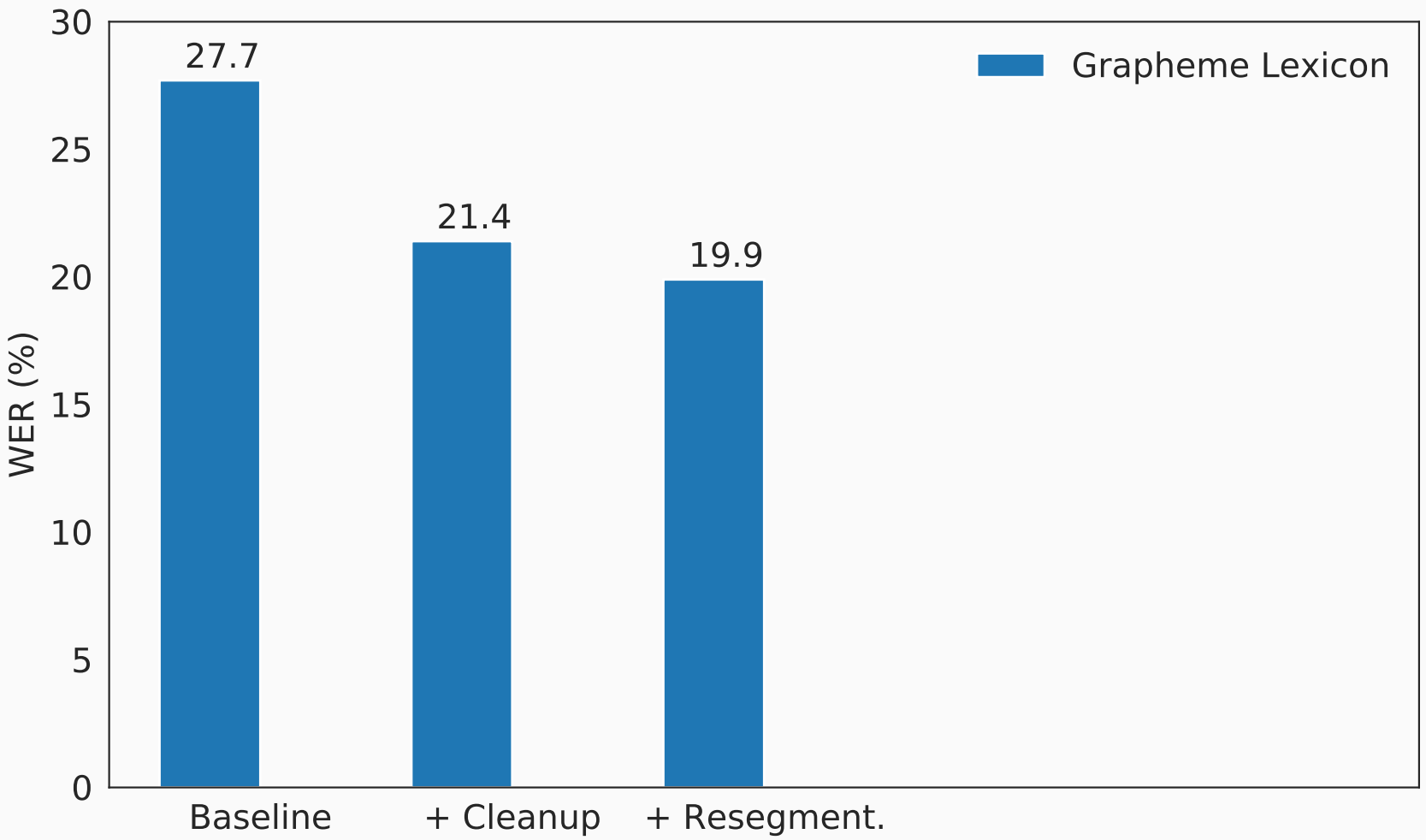

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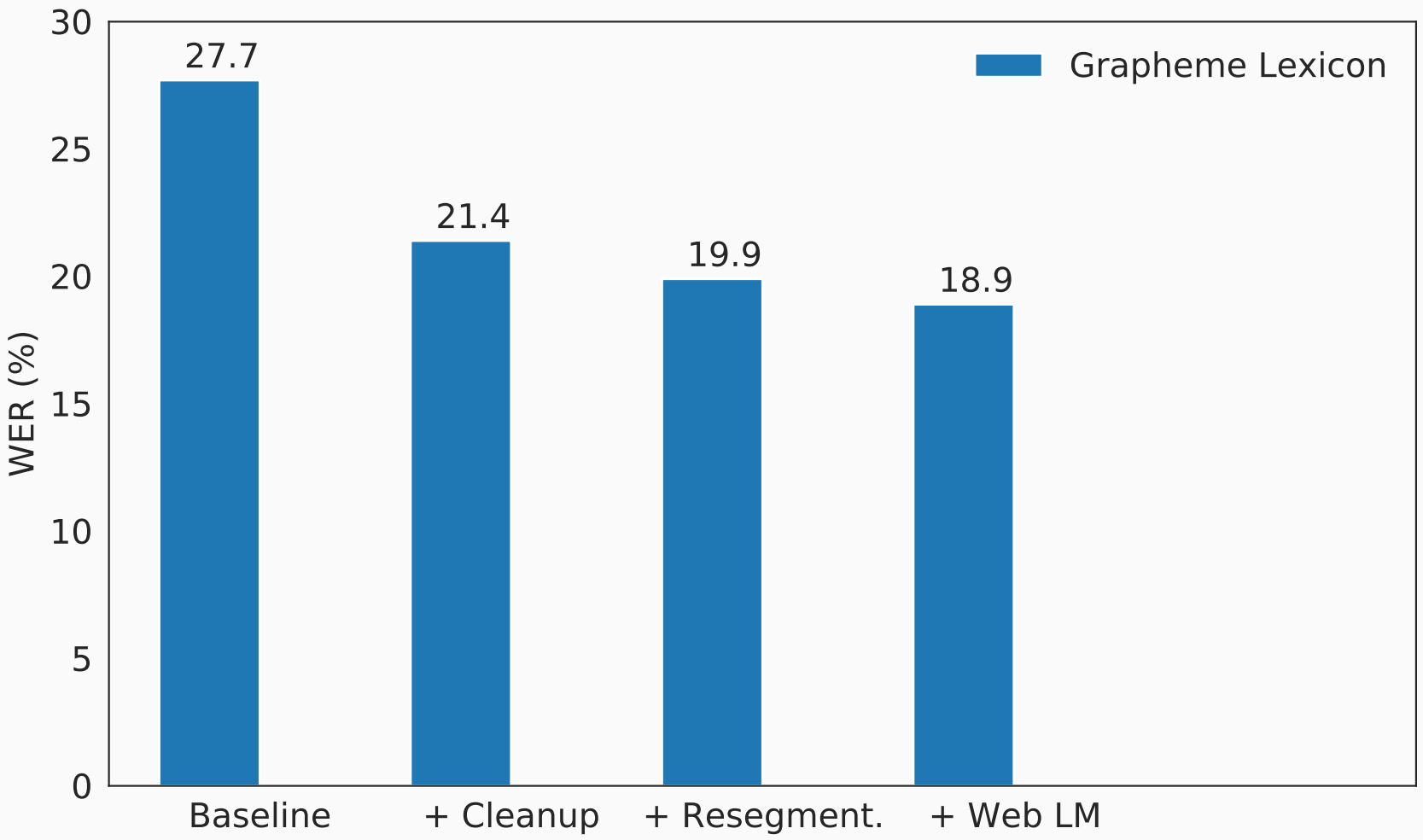

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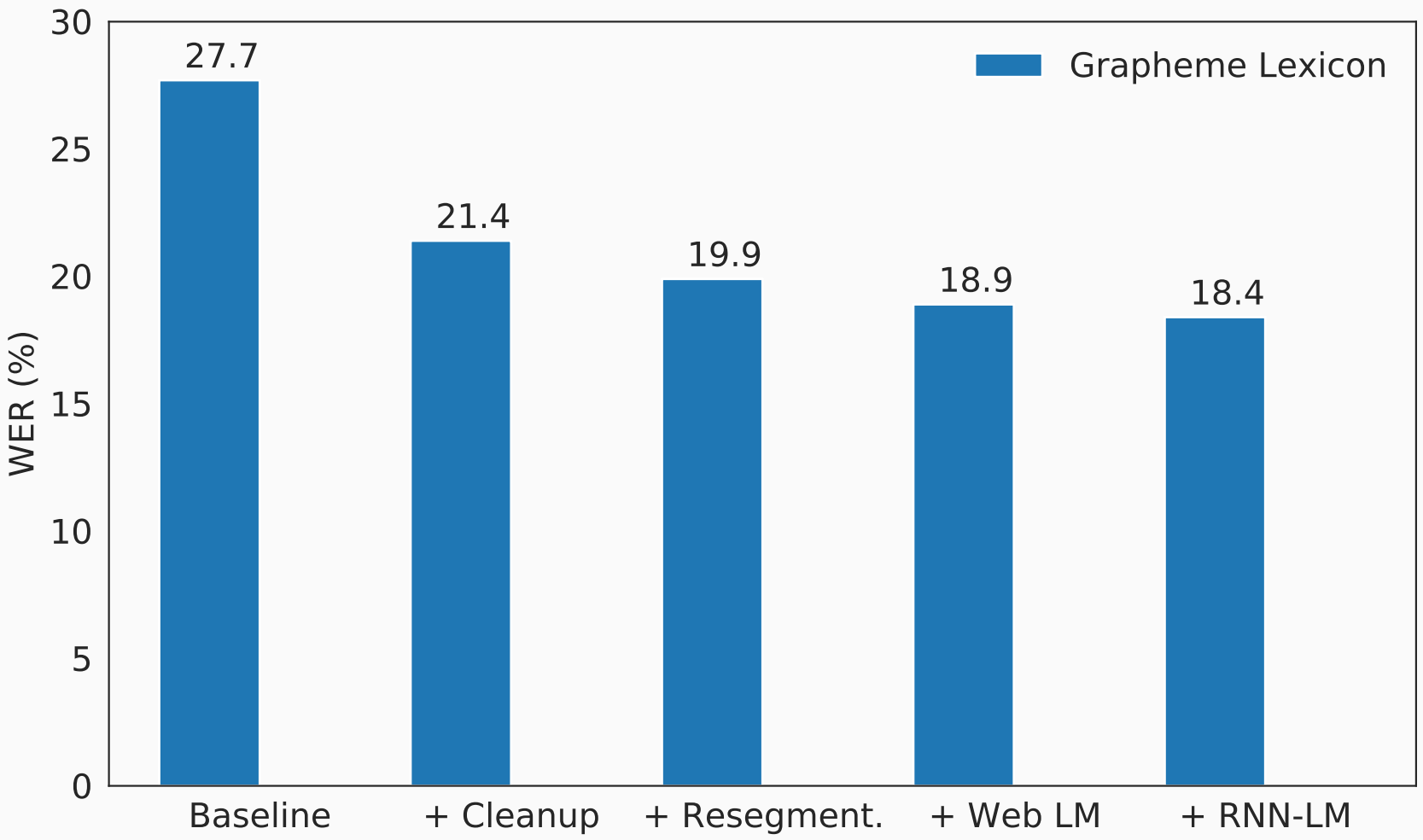

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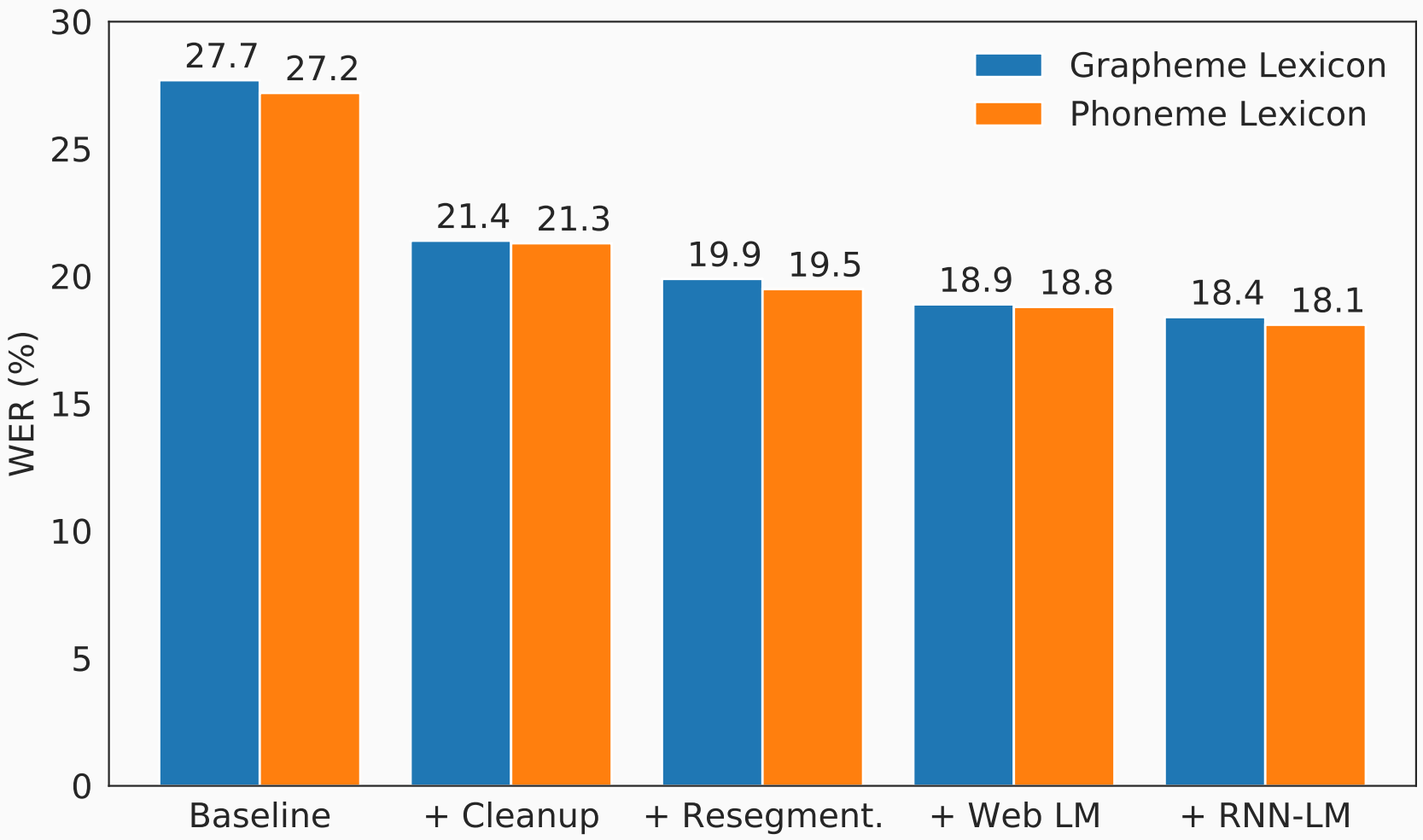
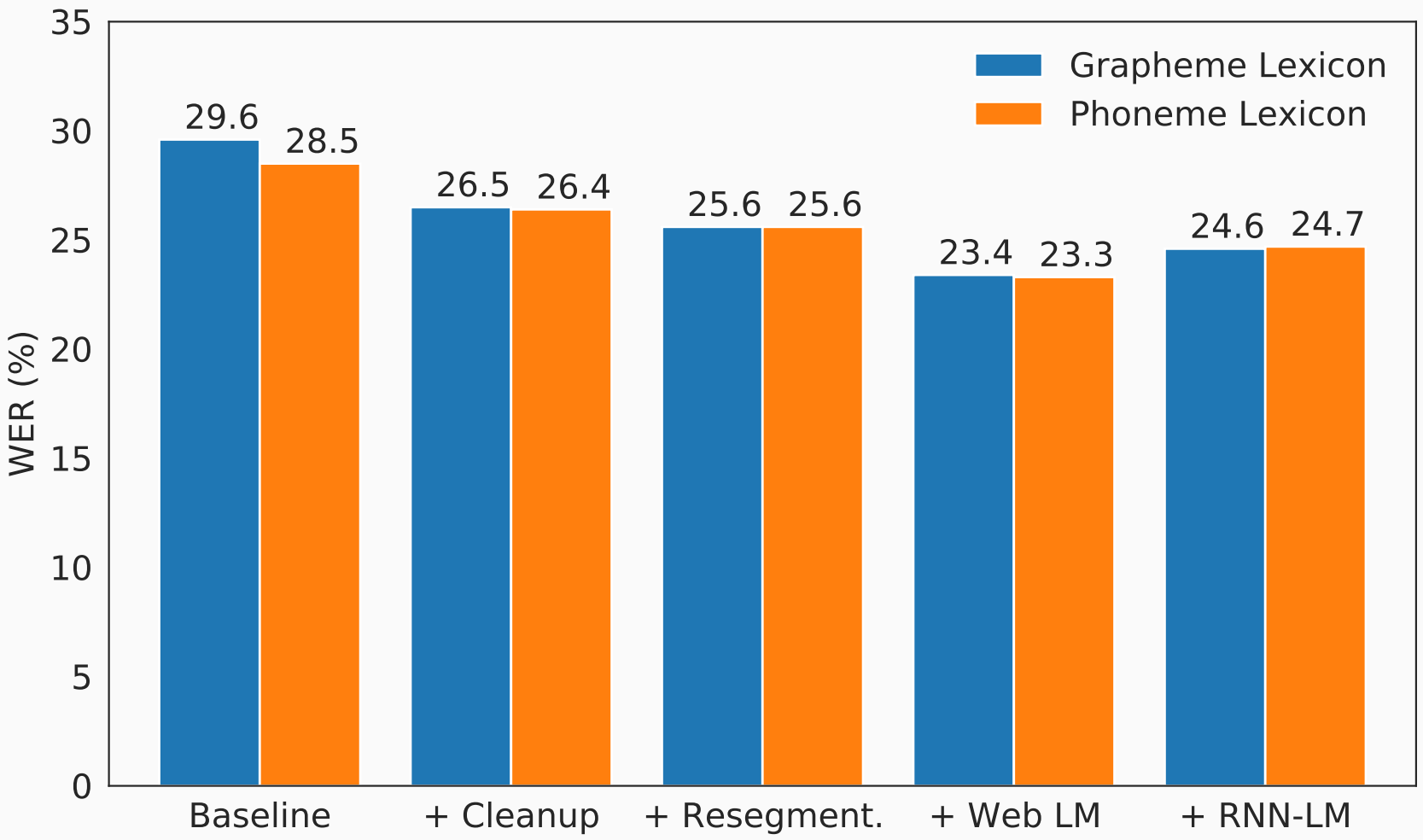


Bengali-English Results



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It is not clear that naively mixing language models would work in more challenging code-switching conditions.