wav2vec: Self-supervised learning of speech representations

Facebook AI Research


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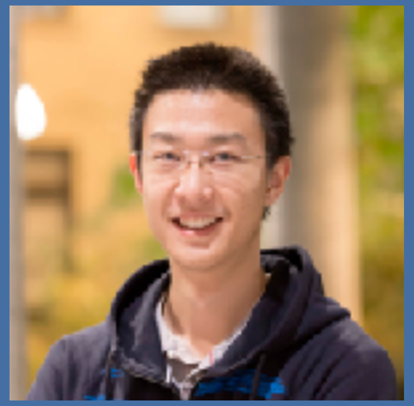
Henry Zhou


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Paden Tomasello


Ronan Collobert


Gabriel Synnaeve

Supervised Machine learning

( , **cat**)

potential train/test mismatch 

Need to annotate lots of data!

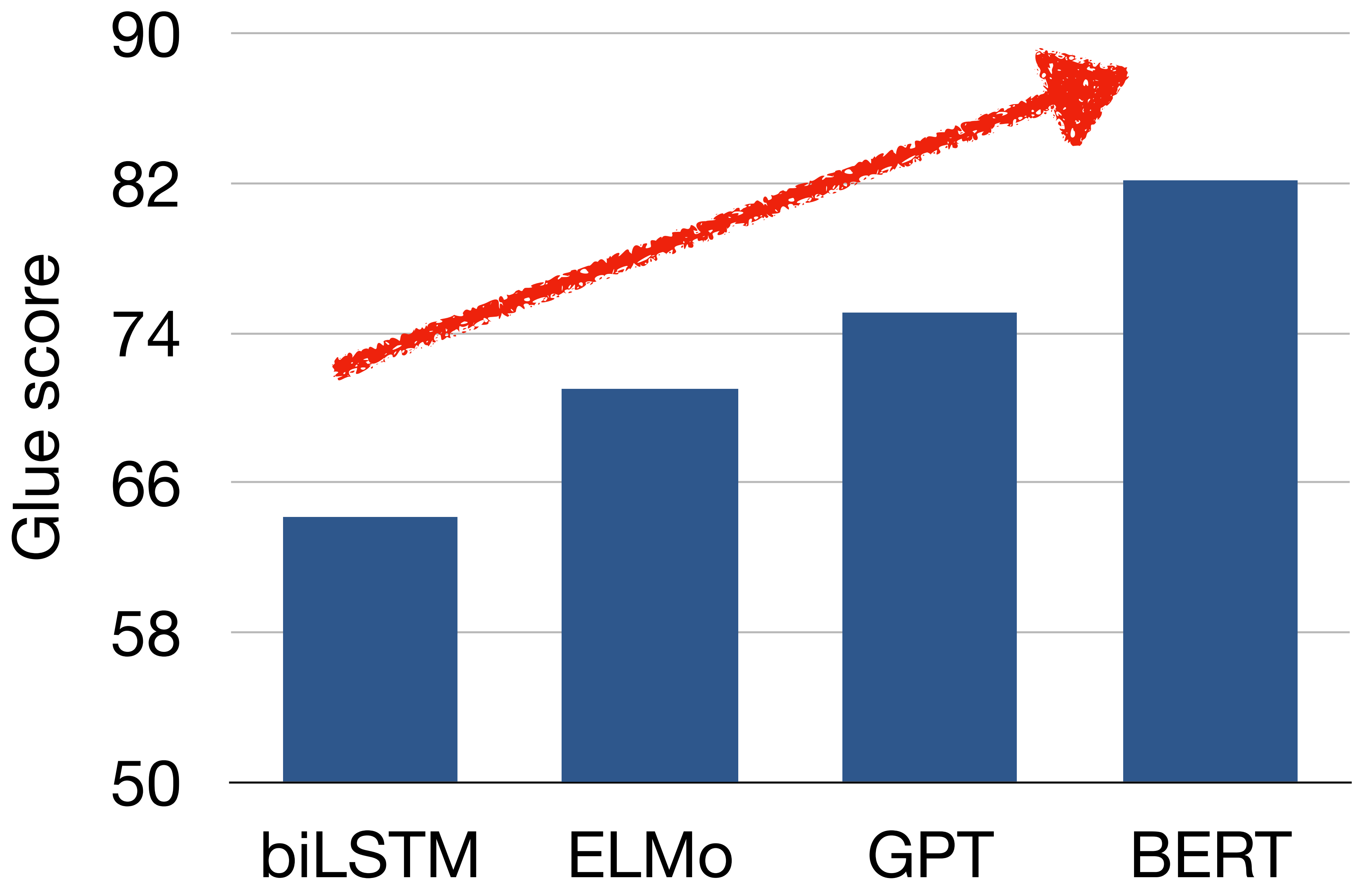
Training speech recognition models

I like black tea with milk

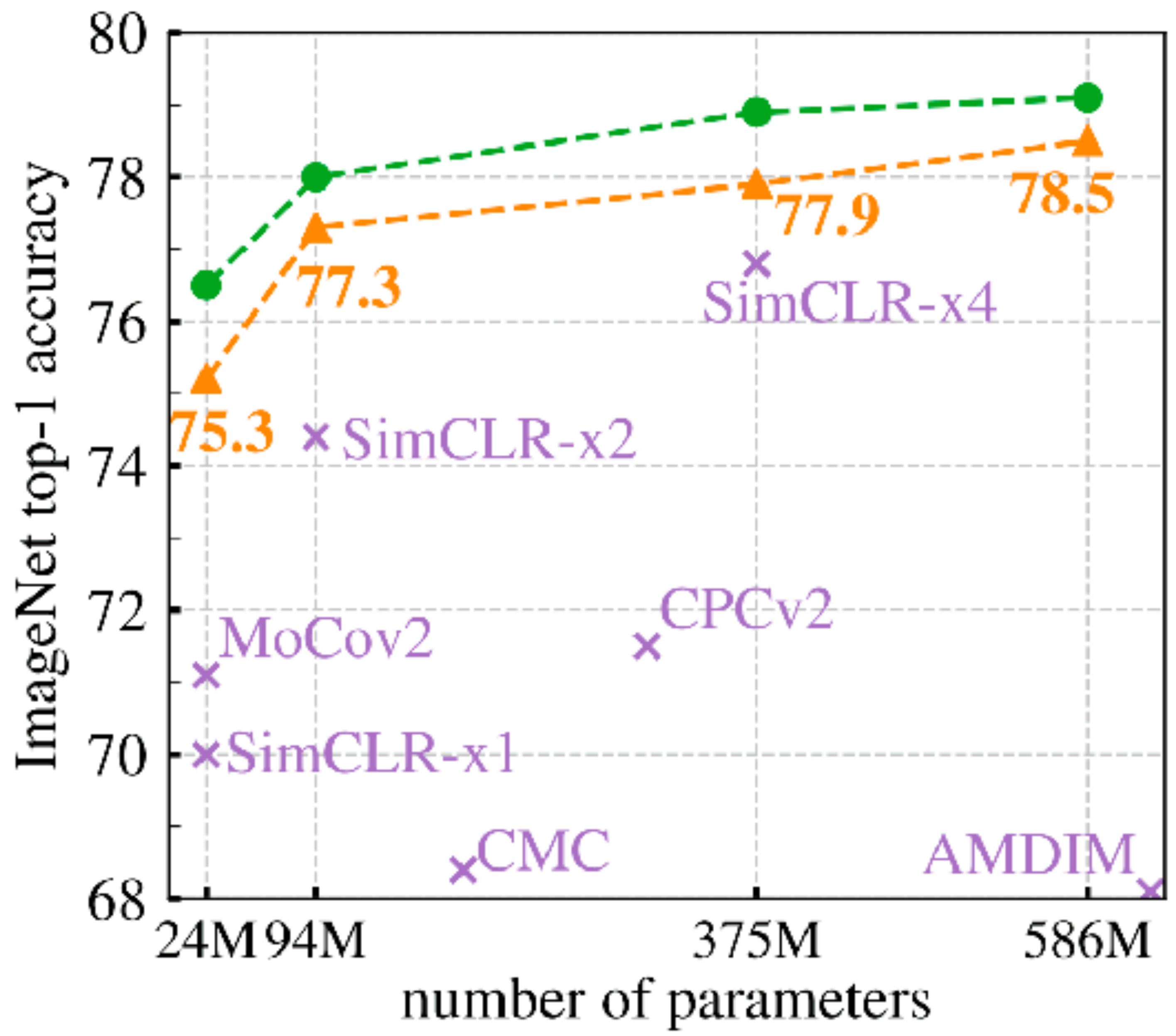
- Train on 1,000s of hours of data for good systems.
- Many languages, dialects, domains etc.

Meanwhile in other fields

Pre-training in NLP



Pre-training in Computer Vision

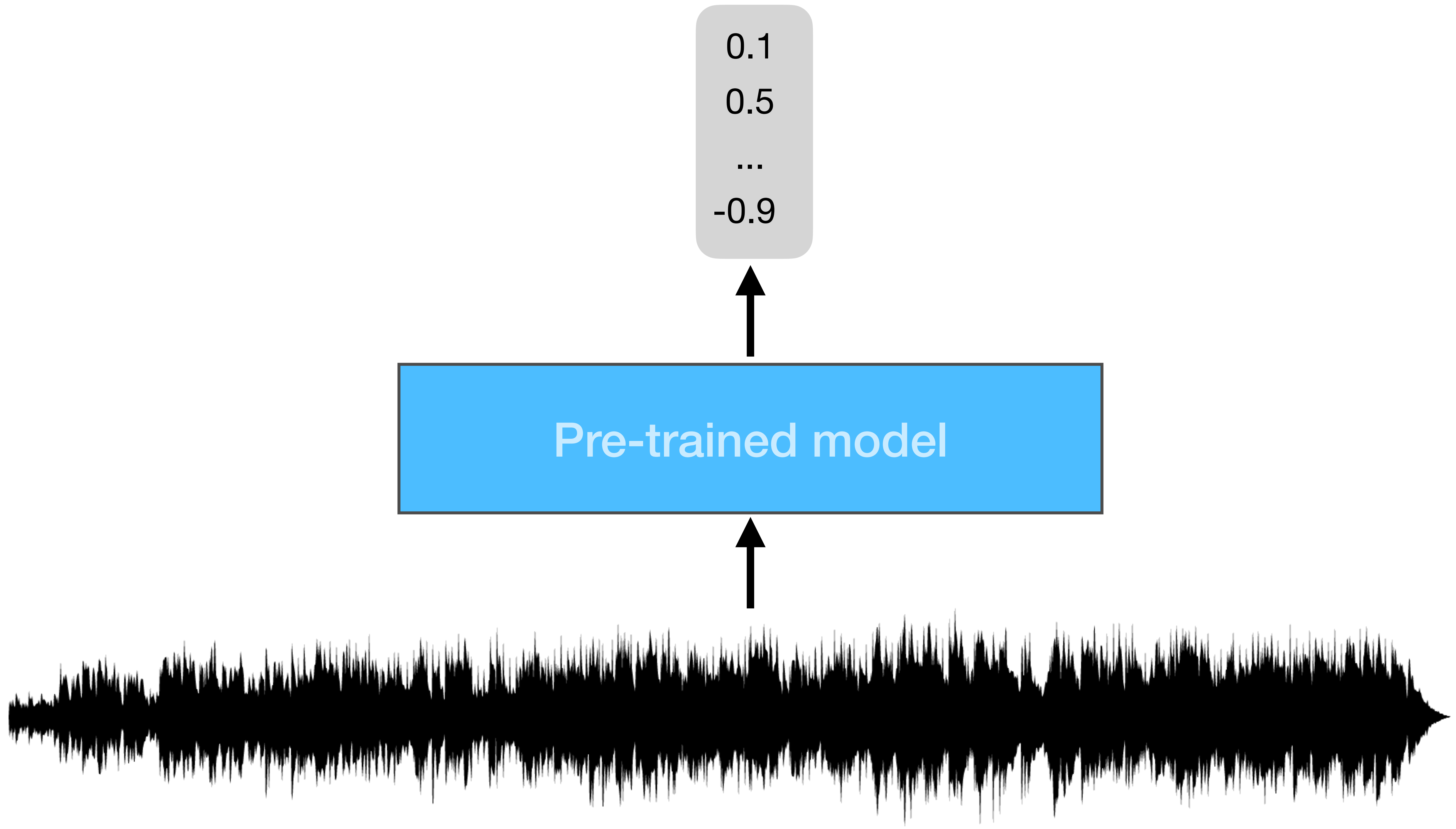


Thanks to Priya Goyal for sharing the vision graph.

Unsupervised / Self-supervised Pre-training

- Learn good representations **without labels**
- NLP: Predict occluded parts of sentence
- Vision: make representations invariant to augmentations

Learning good representations of audio data
from unlabeled audio


0.1
0.5
...
-0.9
Pre-trained model

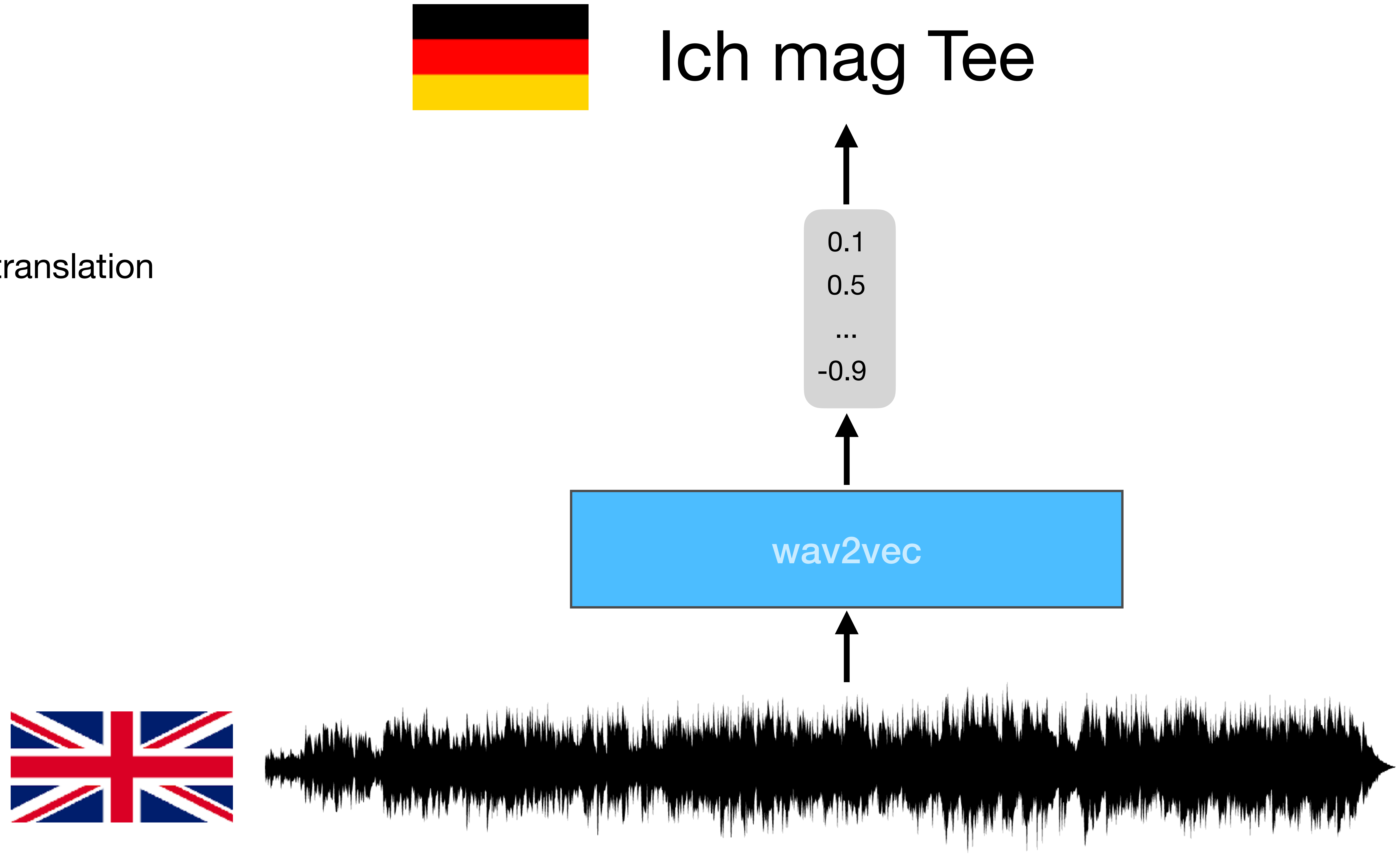
I like tea

0.1
0.5
...
-0.9

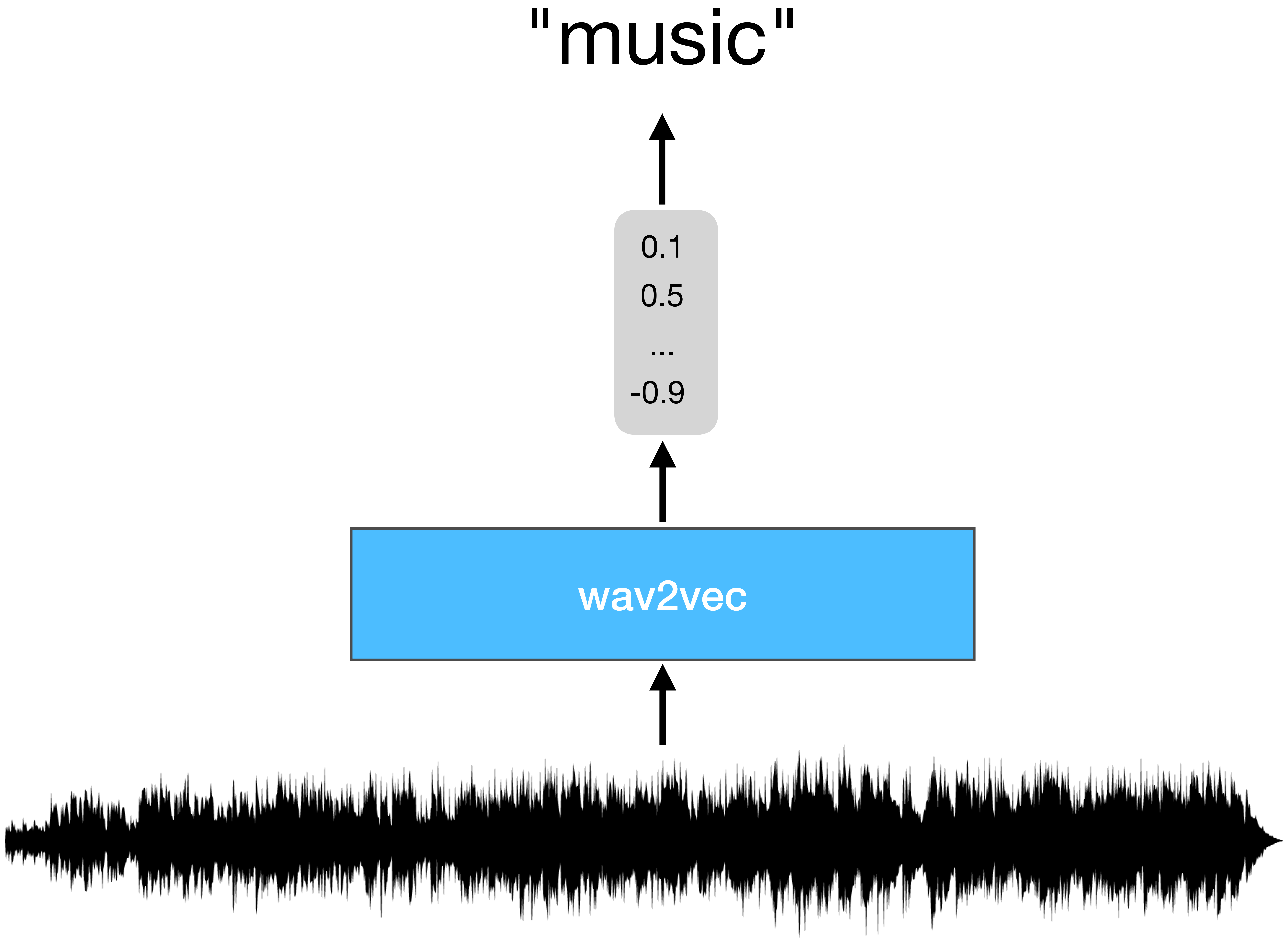
Pre-trained model

Speech recognition

Speech translation



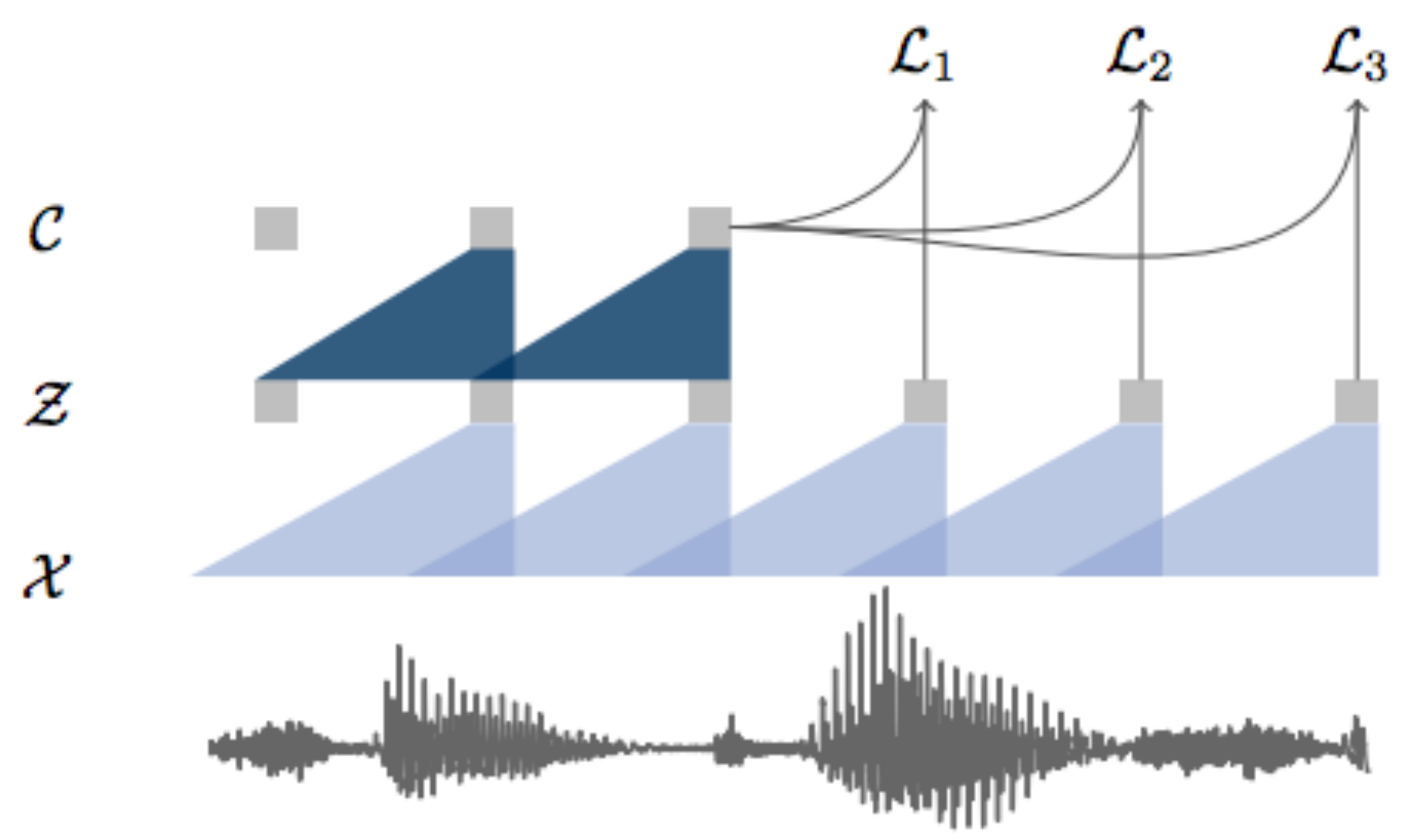
Audio event detection



This talk

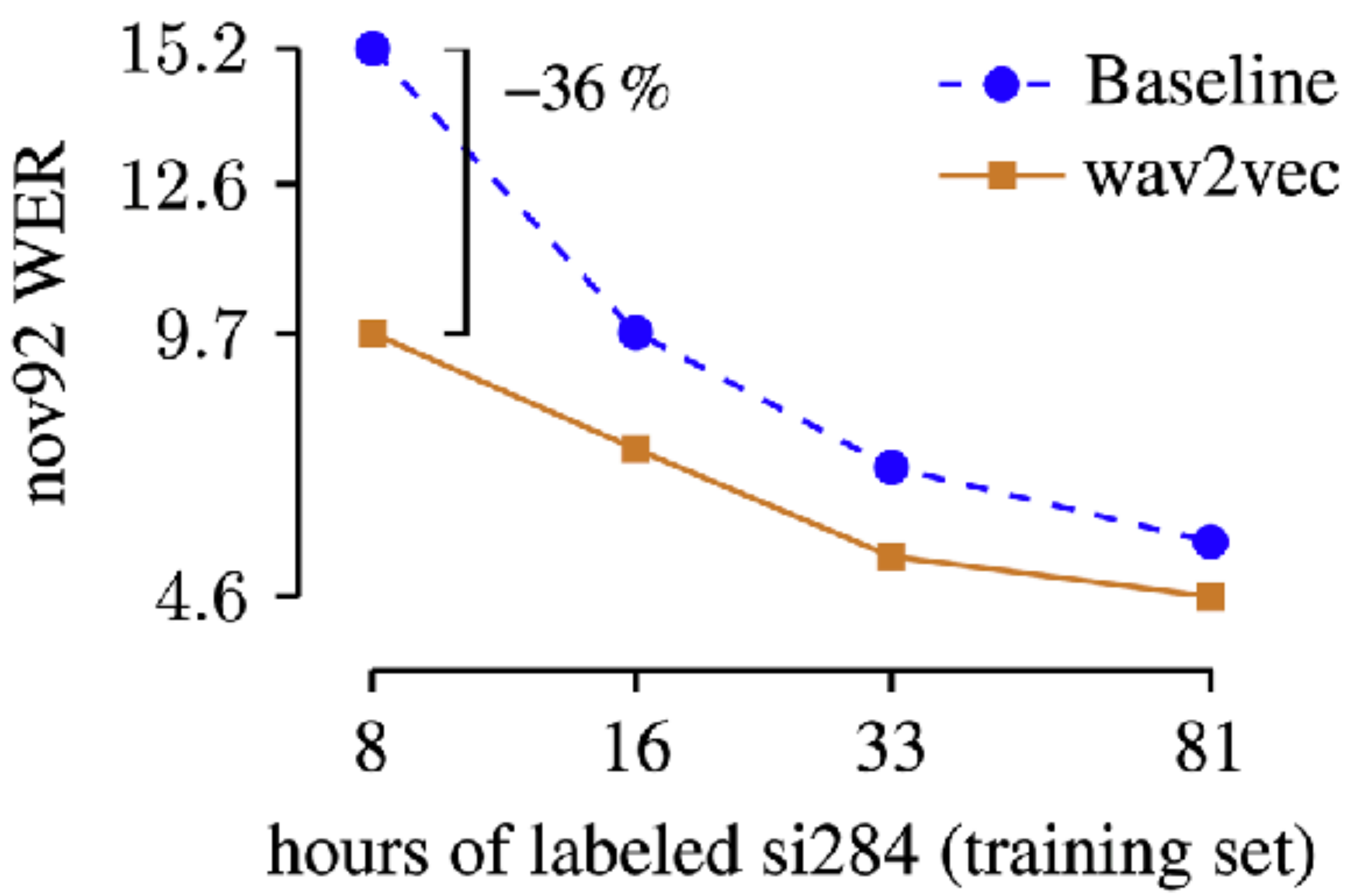
- Summary of past 2 years of our work on SSL for speech
- Speech systems with 10 minutes of labeled data
- Multilingual pre-training transfers across languages

wav2vec: Latent speech audio representations

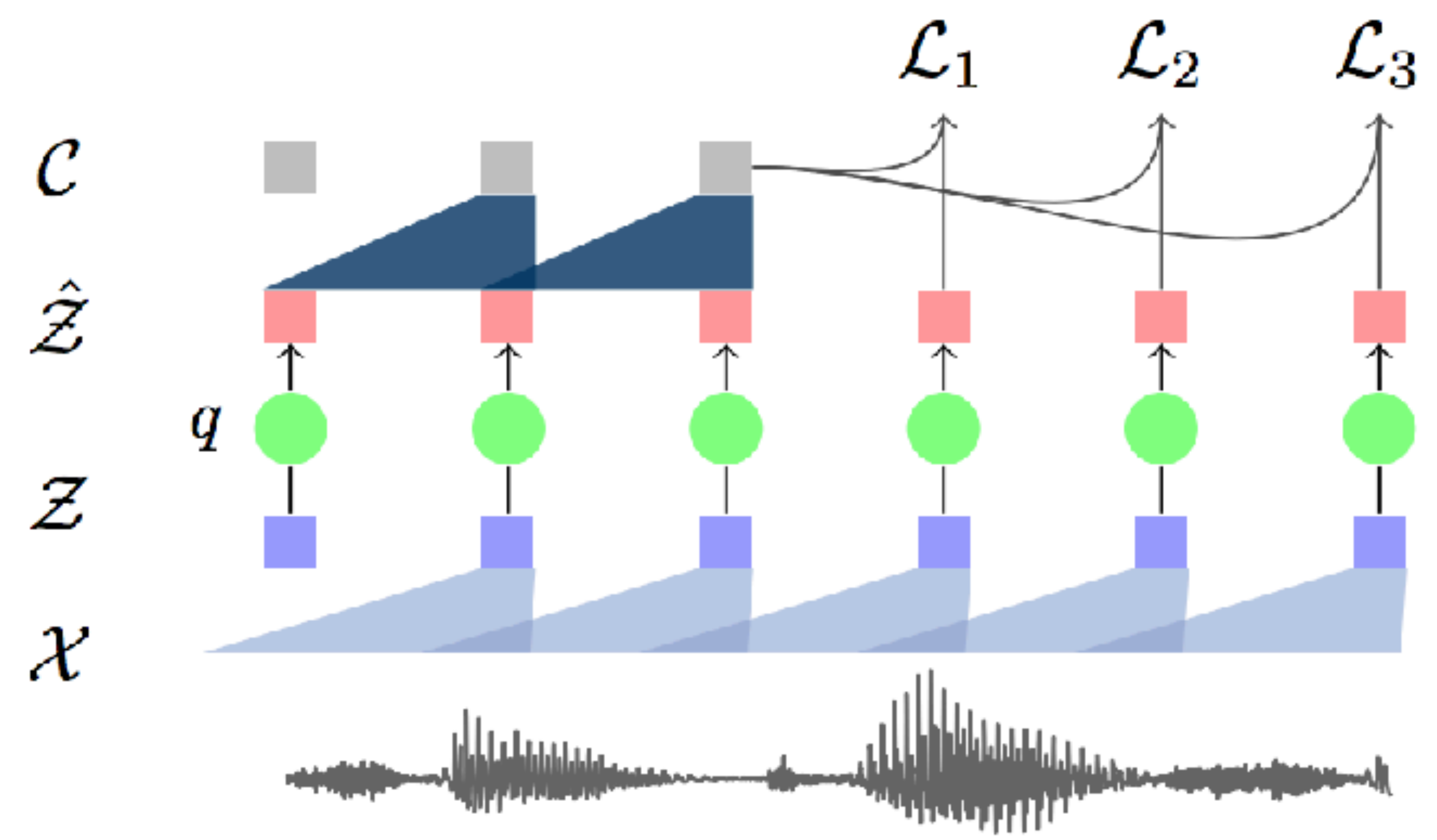


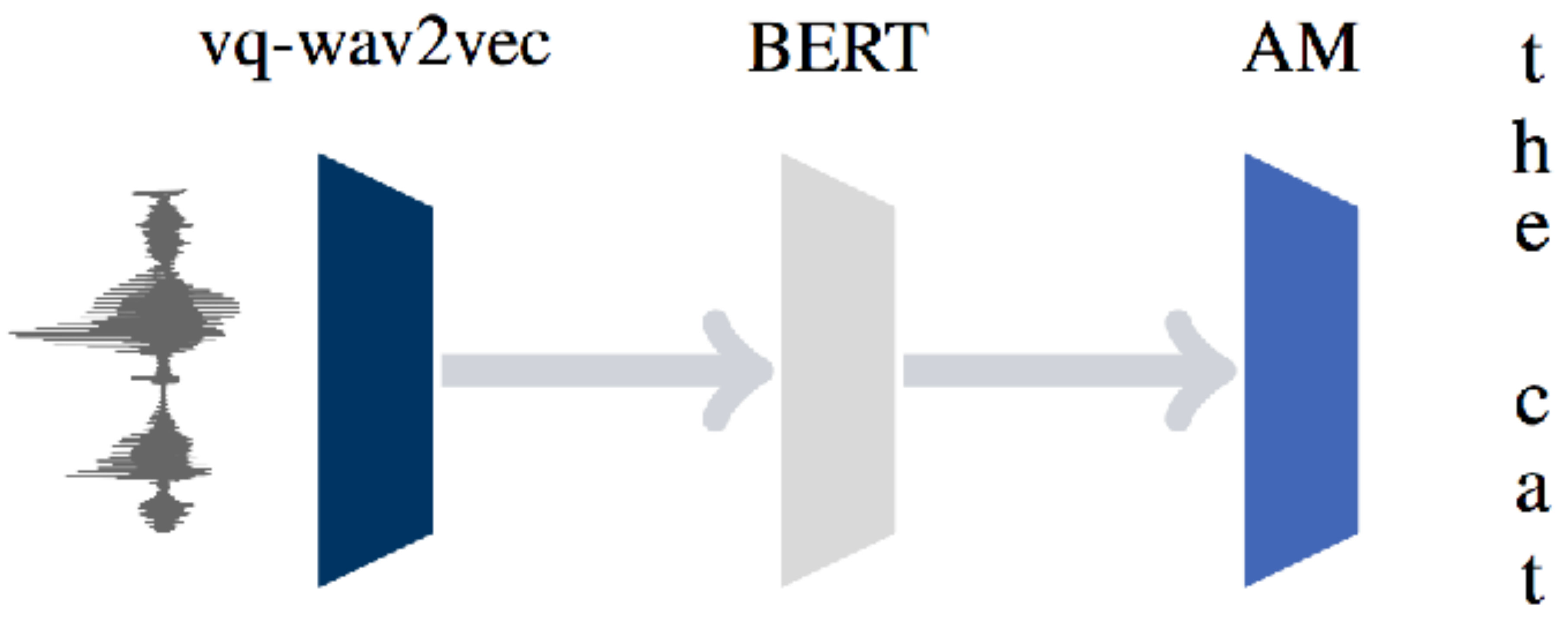
wav2vec

- Fully convolutional
- Binary cross entropy loss
- Representations used to improve ASR tasks



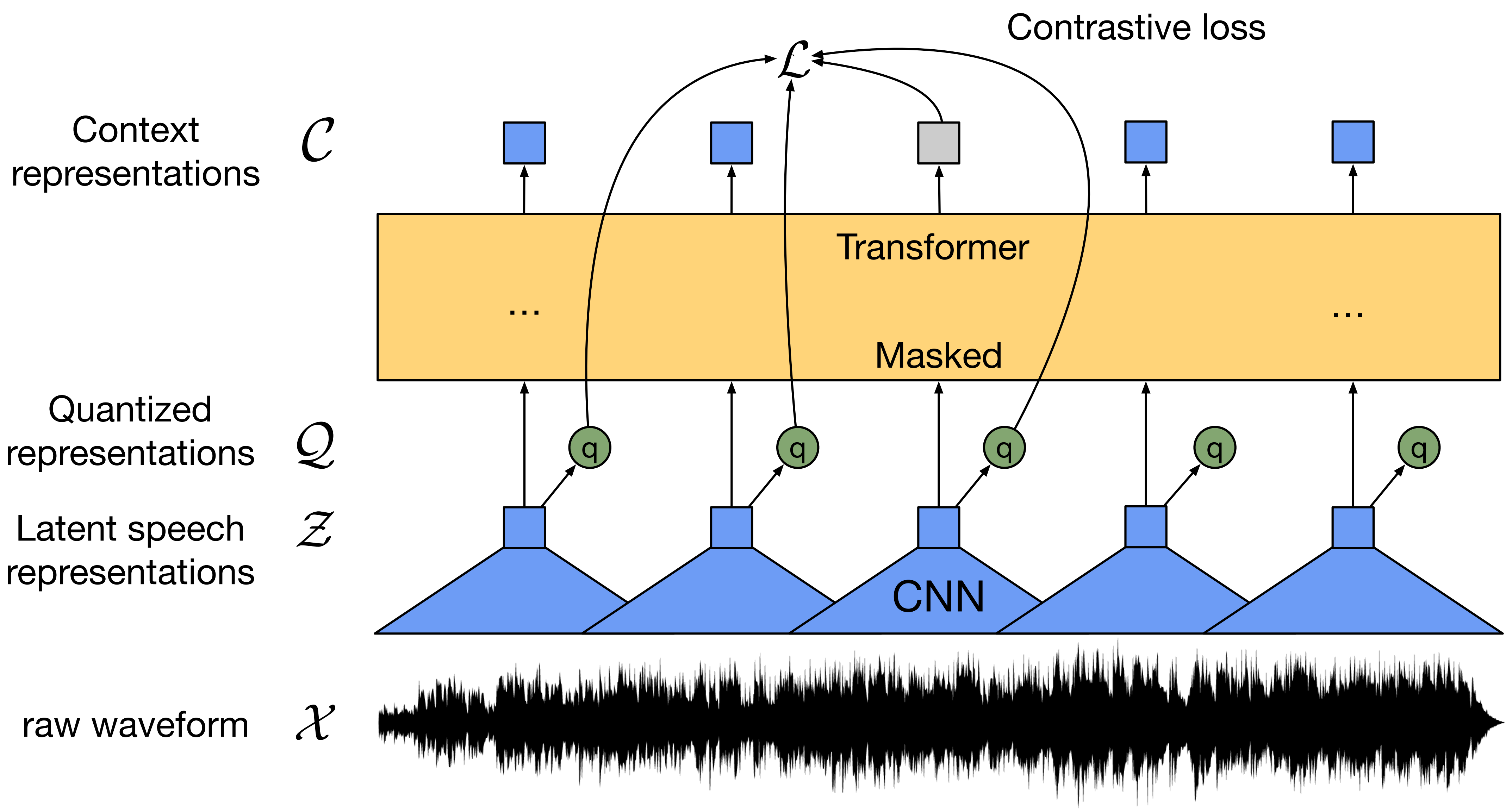
vq-wav2vec: Learning discrete latent speech representations





- Vector quantize to discover **discrete latent speech representations**
- Learn **contextualized representations** on top of quantized speech
- Product quantization of discrete units
- Quantization via Gumbel and K-means
- VQ enables use of NLP-style models
- Different to vq-vae: context in latent space prediction vs. data reconstruction

wav2vec 2.0



- Joint VQ & context representation learning
- Bi-directional contextualized representations
- Contrastive task
- Vector quantized targets
- Fine-tuned on labeled data

Objective

Cosine similarity

Context representation

Discrete latent
speech representation

$$\mathcal{L}_m = -\log \frac{\exp(sim(\mathbf{c}_t, \mathbf{q}_t)/\kappa)}{\sum_{\tilde{\mathbf{q}} \sim \mathbf{Q}_t} \exp(sim(\mathbf{c}_t, \tilde{\mathbf{q}})/\kappa)}$$

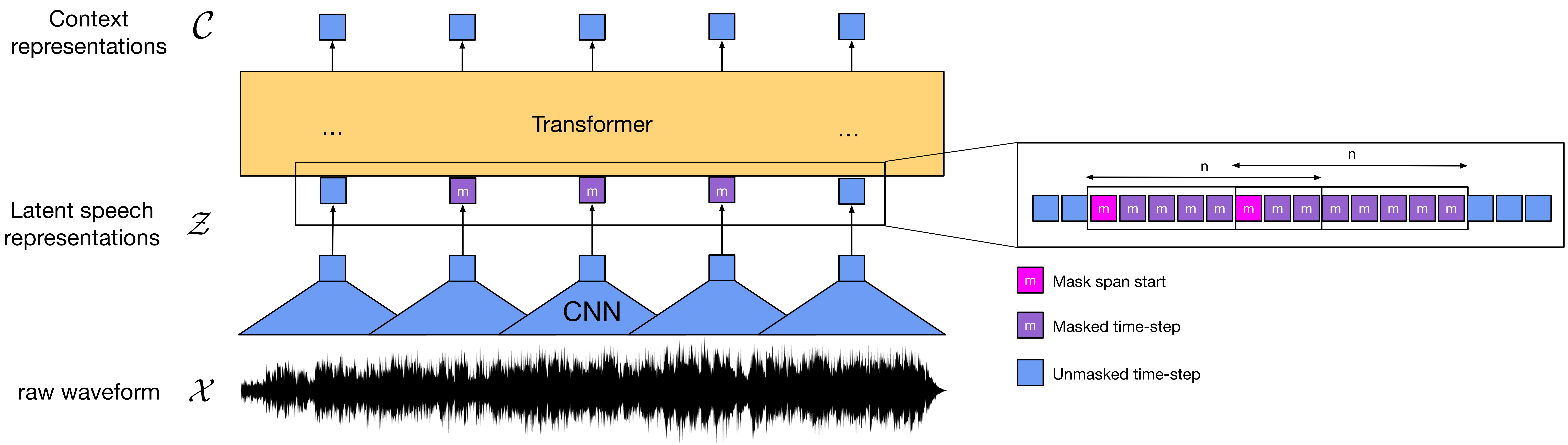
Negative samples

Temperature

Codebook diversity penalty to encourage more codes to be used

Masking

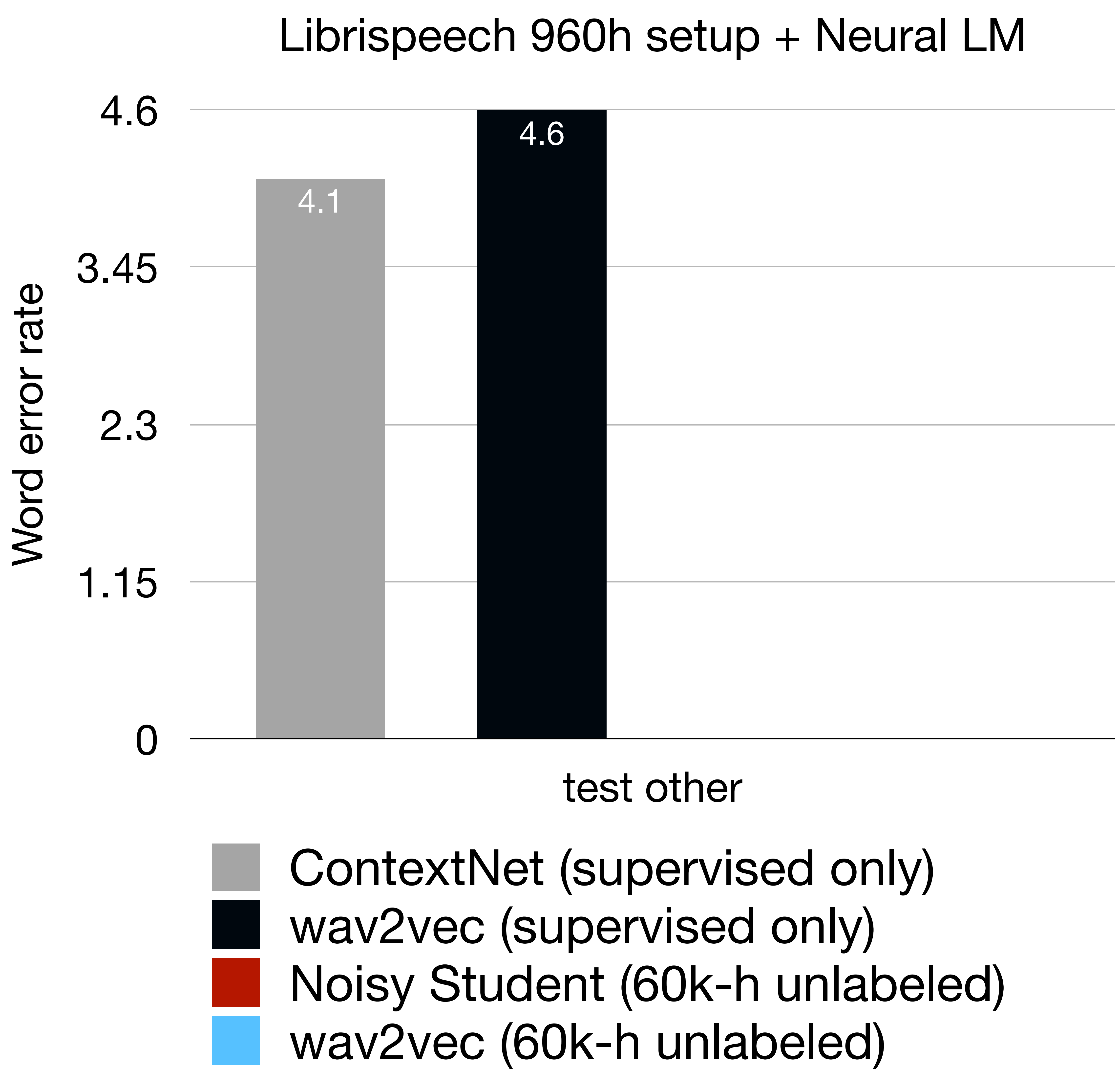
- Sample starting points for masks without replacement, then expand to 10 time-steps
- Spans can overlap
- For a 15s sample, ~49% of the time-steps masked with an average span length of ~300ms



Fine-tuning

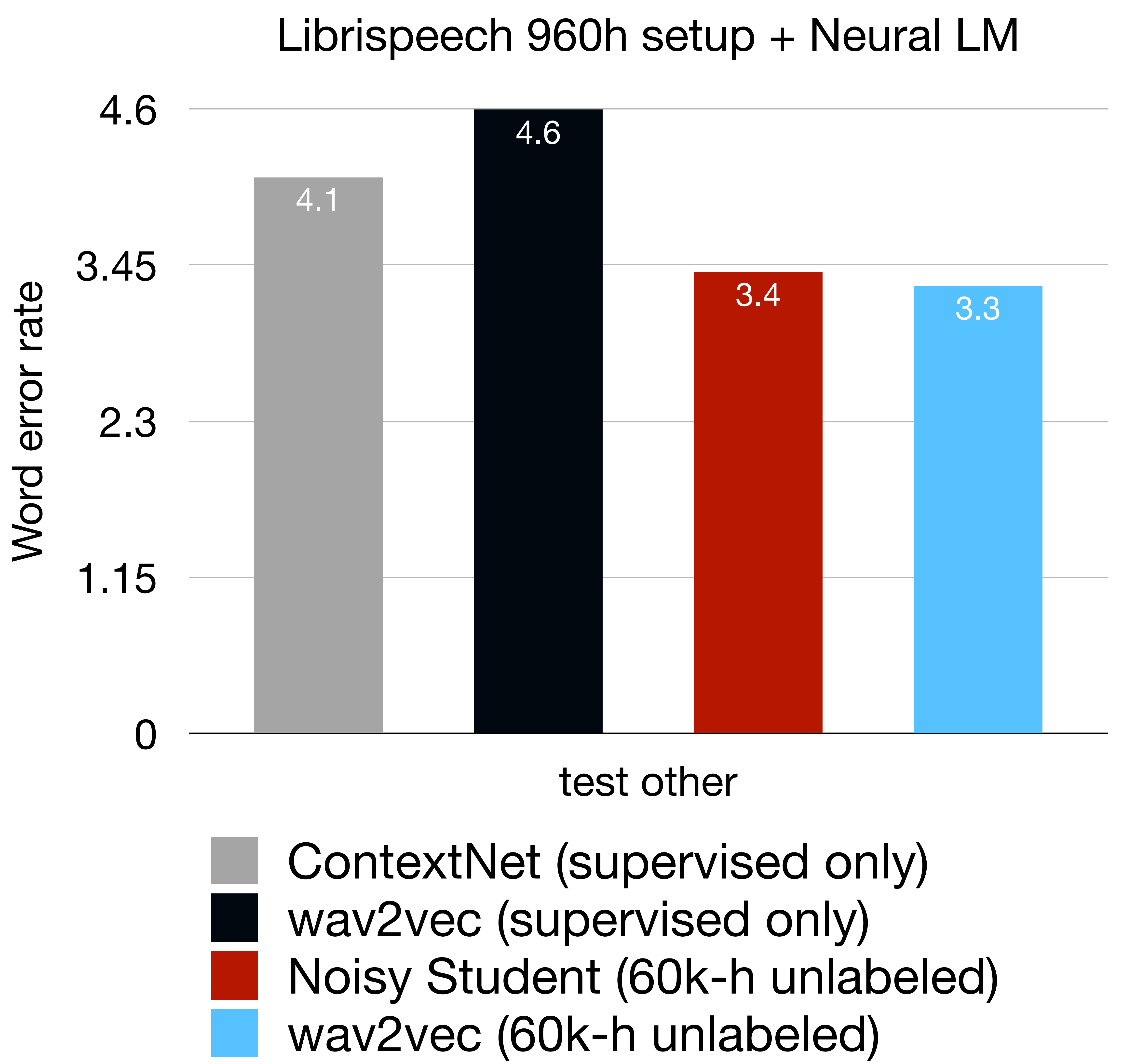
- Add a single linear projection on top into target vocab and train with CTC loss with a low learning rate (CNN encoder is not trained).
- Use modified SpecAugment in latent space to prevent early overfitting
- Uses wav2letter decoder with the official 4gram LM and Transformer LM

Results



Librispeech 960h setup + Neural LM
Word error rate
4.6
3.45
2.3
1.15
0
4.1
4.6
test other
ContextNet (supervised only)
wav2vec (supervised only)
Noisy Student (60k-h unlabeled)
wav2vec (60k-h unlabeled)

Results



Librispeech 960h setup + Neural LM
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4.6
3.45
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1.15
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4.1
4.6
3.4
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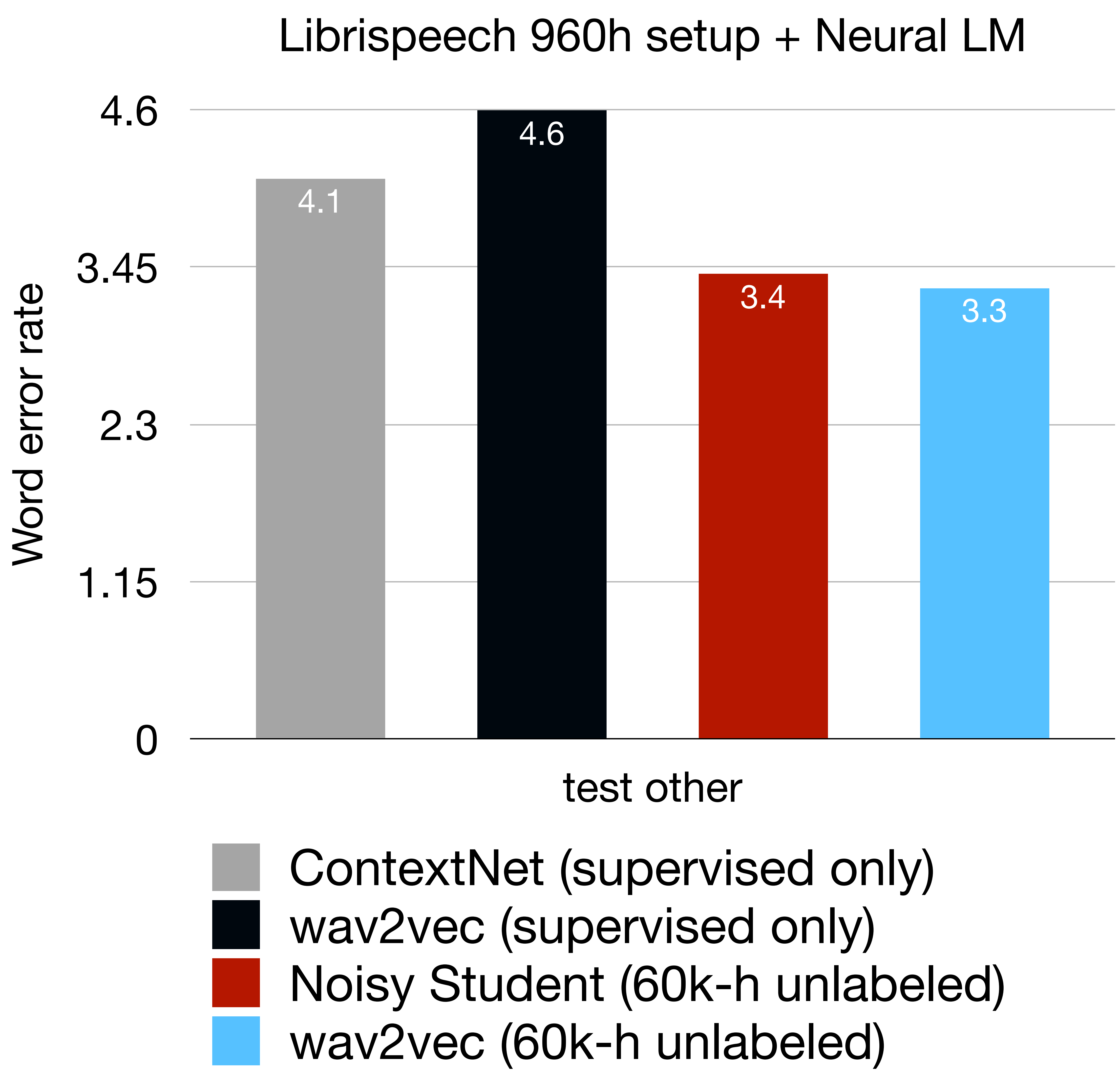
Results



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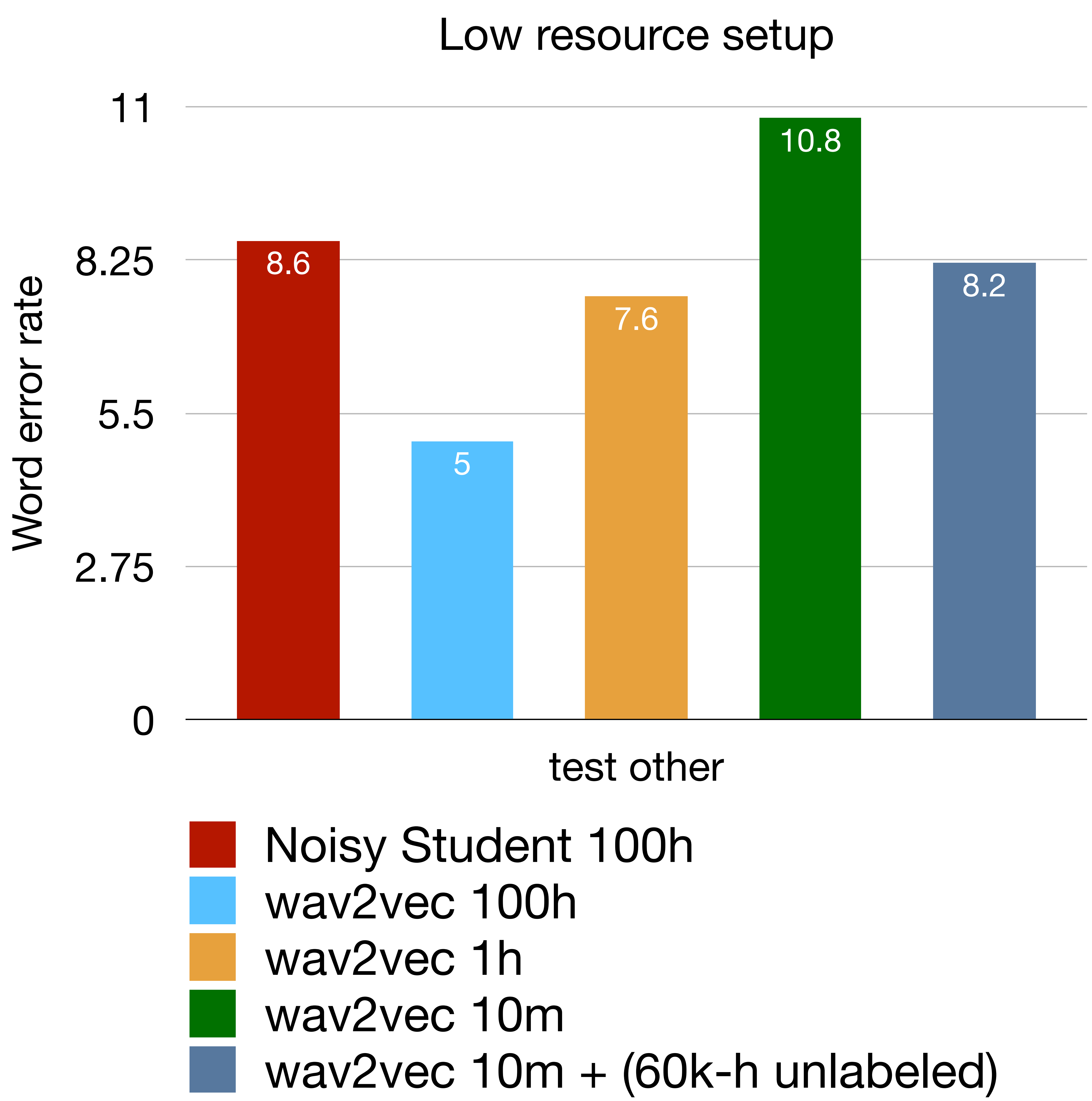
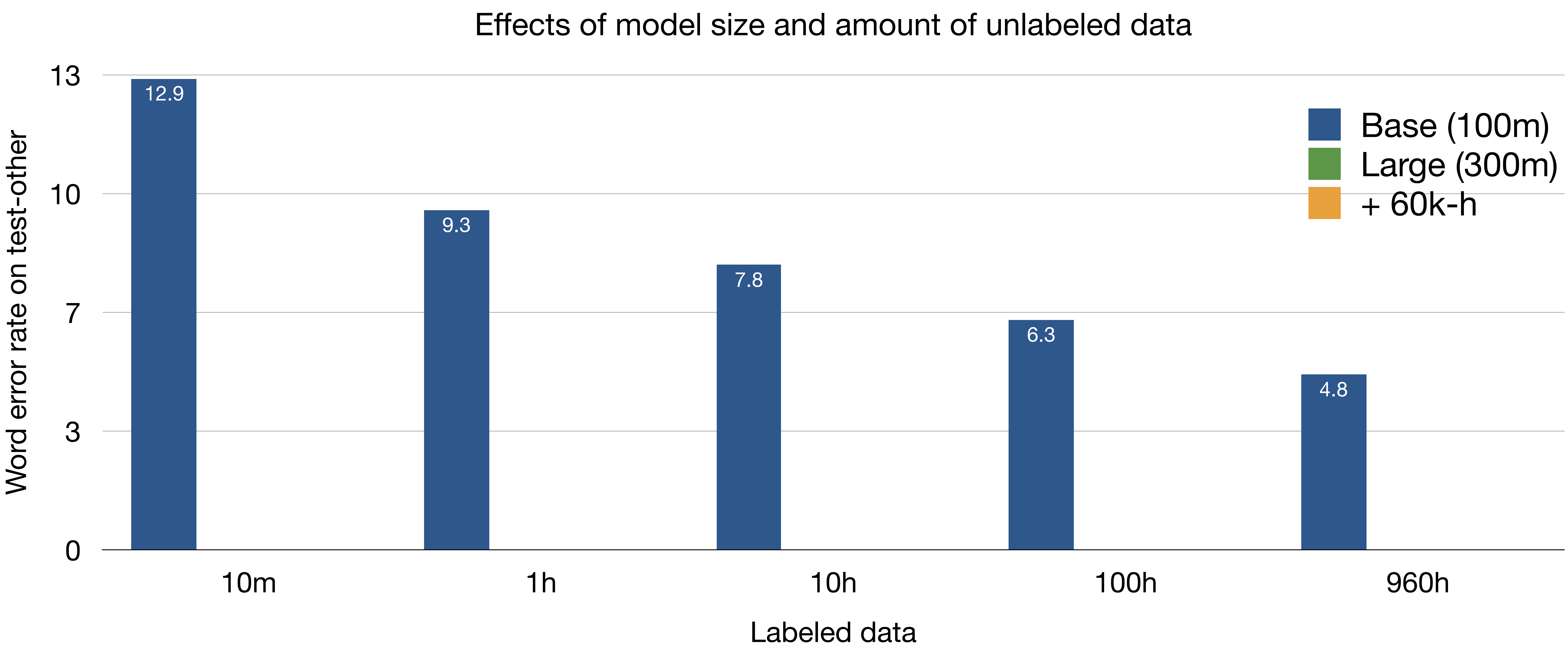


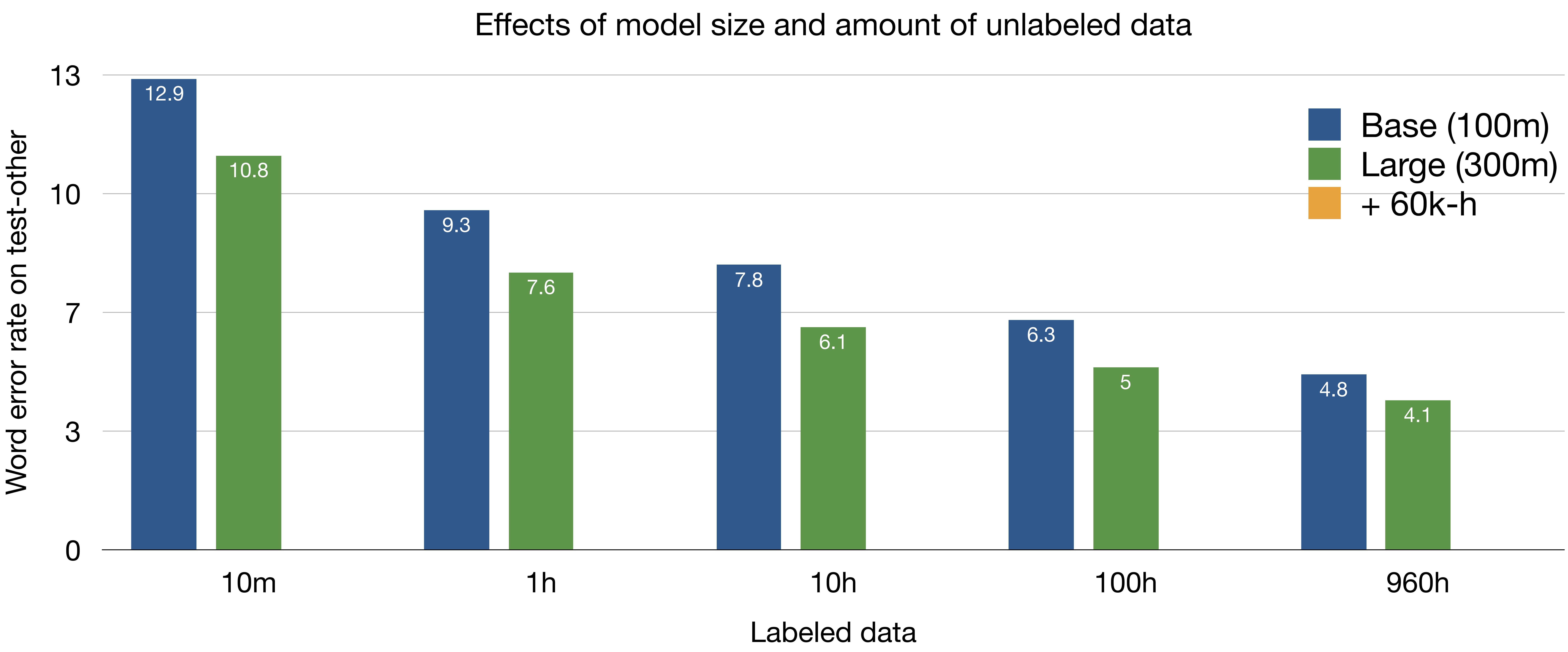
Low resource setup
Word error rate
11
8.25
5.5
2.75
0
8.6
5
7.6
10.8
8.2
test other
Noisy Student 100h
wav2vec 100h
wav2vec 1h
wav2vec 10m
wav2vec 10m + (60k-h unlabeled)

Results



Effects of model size and amount of unlabeled data
Word error rate on test-other
13
10
7
3
0
12.9
9.3
7.8
6.3
4.8
10m
1h
10h
100h
960h
Labeled data
Base (100m)
Large (300m)
+ 60k-h

Results



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Labeled data
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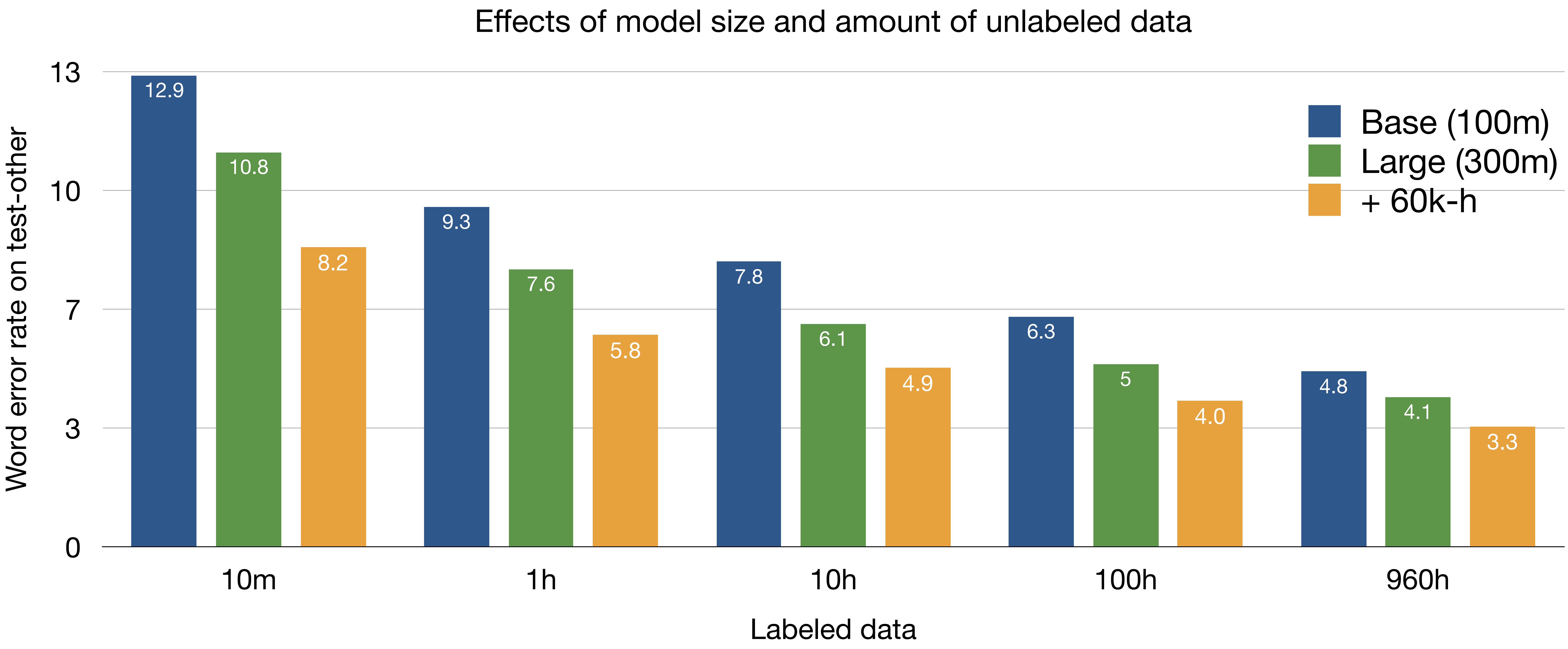
Results



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7.6
5.8
7.8
6.1
4.9
6.3
5
4.0
4.8
4.1
3.3
Base (100m)
Large (300m)
+ 60k-h
10m
1h
10h
100h
960h
Labeled data

Examples (10 min labeled data)

HYP (no LM): she SESED and LUCHMAN GAIVE A SENT won by her GENTAL argument
HYP (w/ LM): she ceased and LUCAN gave assent won by her gentle argument
REF: she ceased and lakshman gave assent won by her gentle argument

HYP (no LM): but NOT WITH STANDING this boris EMBRAED him in a QUIAT FRENDLY way and CISED him THRE times
HYP (w/ LM): but NOT WITHSTANDING this boris embraced him in a quiet friendly way and kissed him three times
REF: but notwithstanding this boris embraced him in a quiet friendly way and kissed him three times

Pre-training and self-training

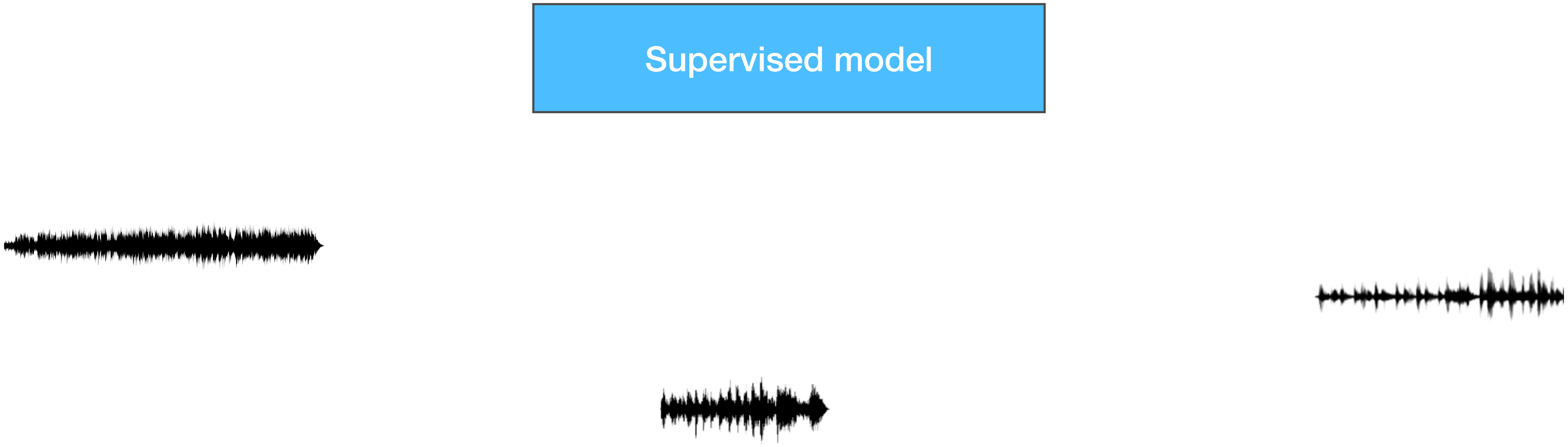
Pre-training and self-training

- Self-training very successful in speech recognition: generate pseudo-labels

Supervised model

Pre-training and self-training

- Self-training very successful in speech recognition: generate pseudo-labels



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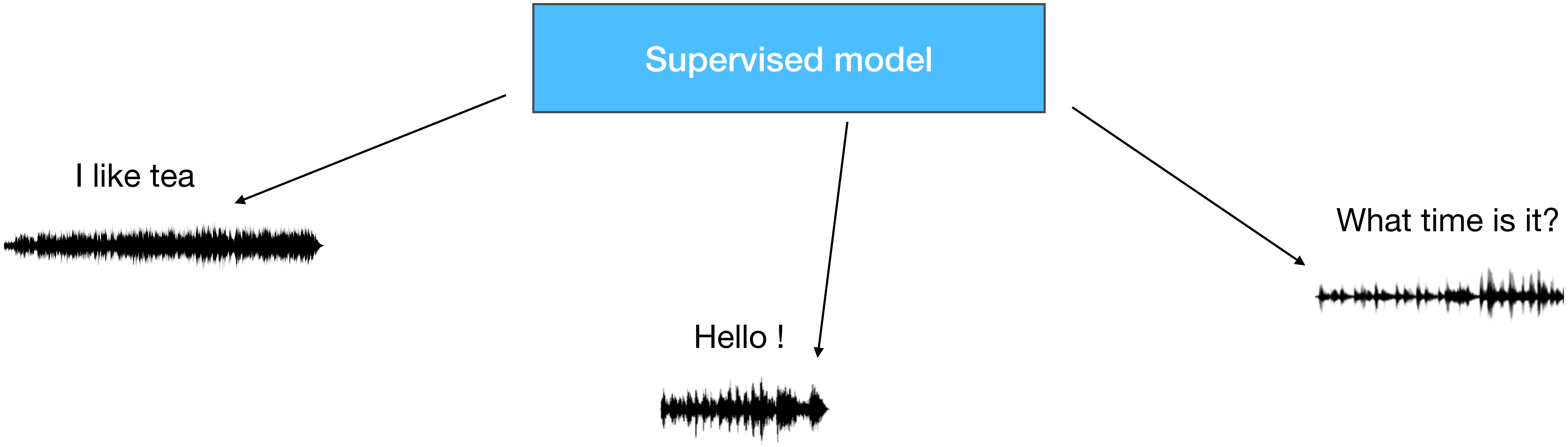
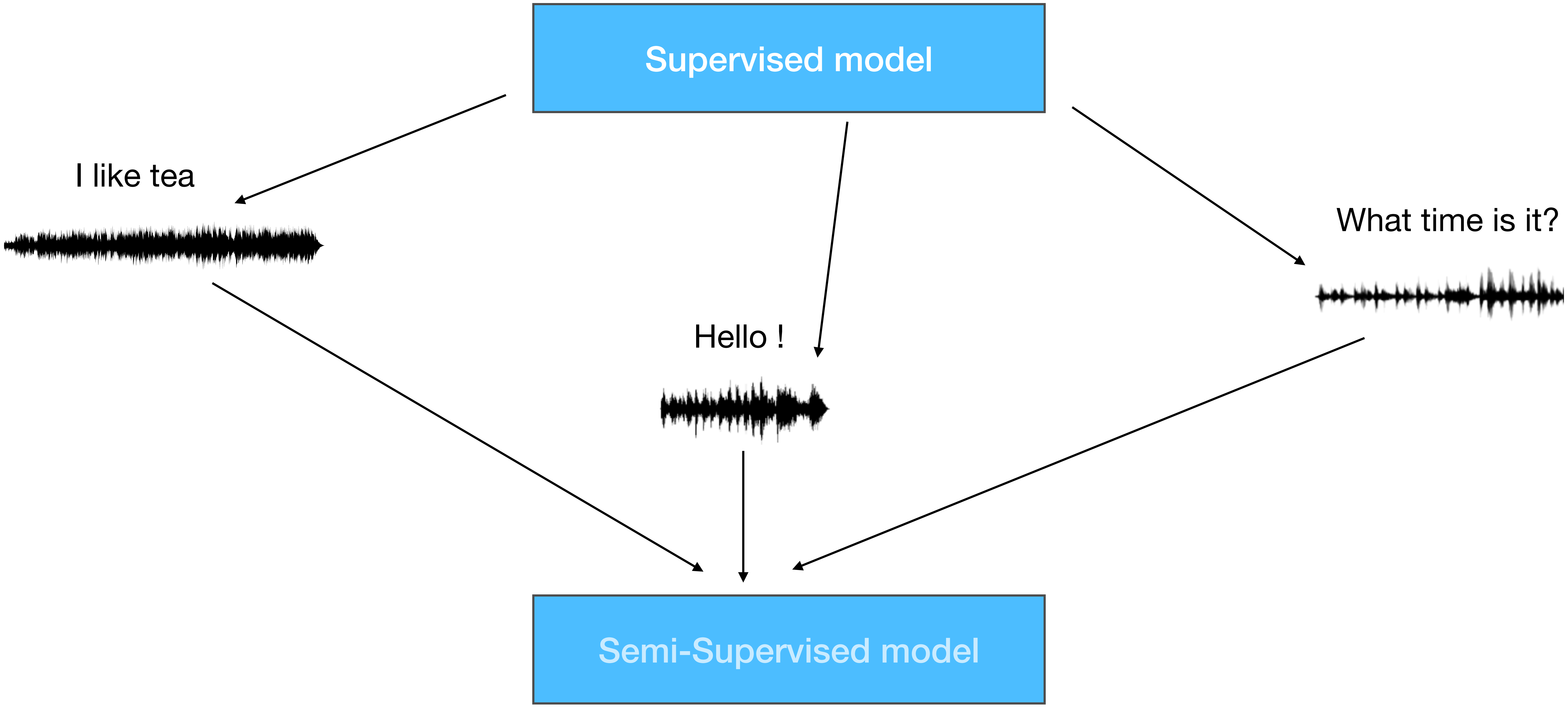


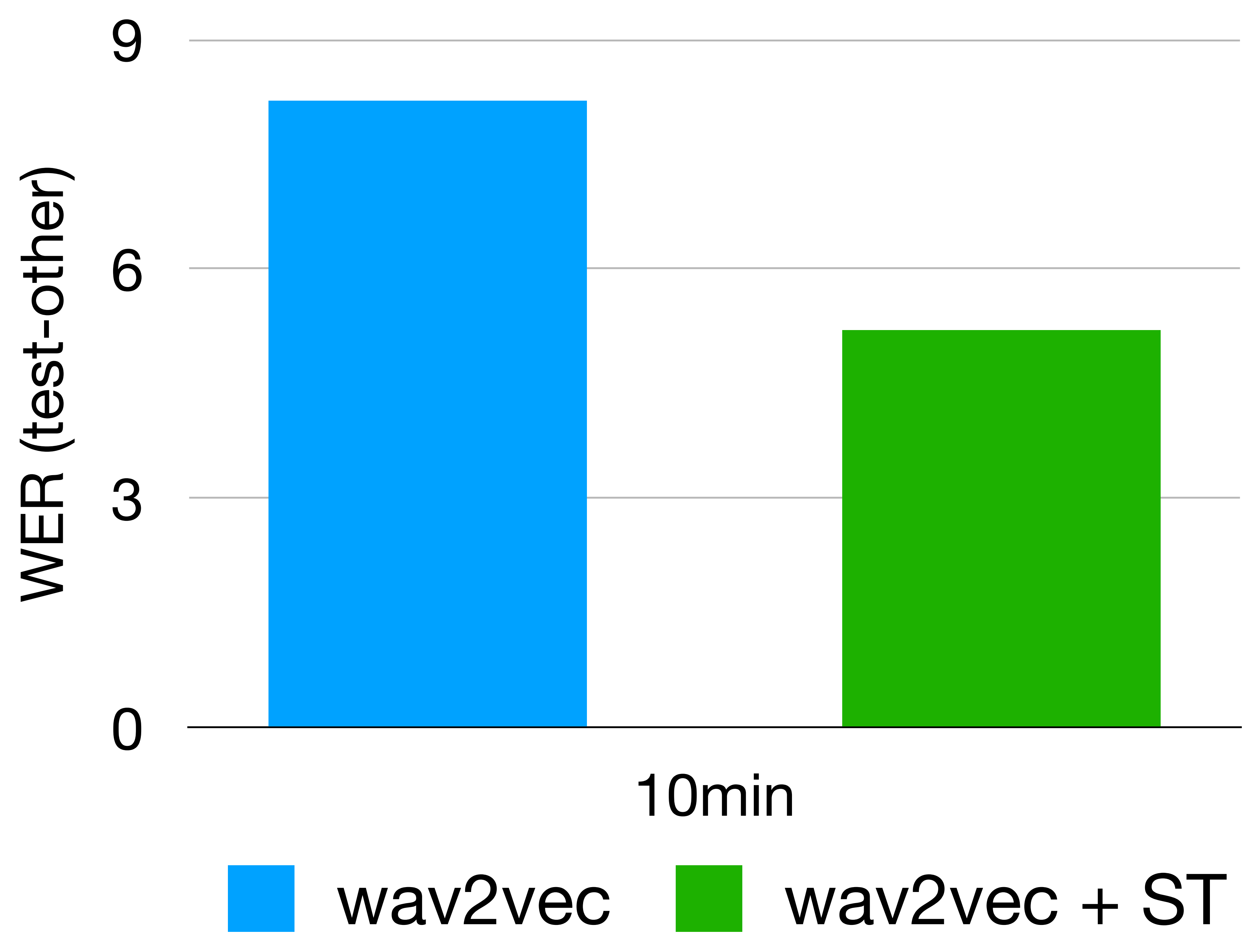
Pre-training and self-training

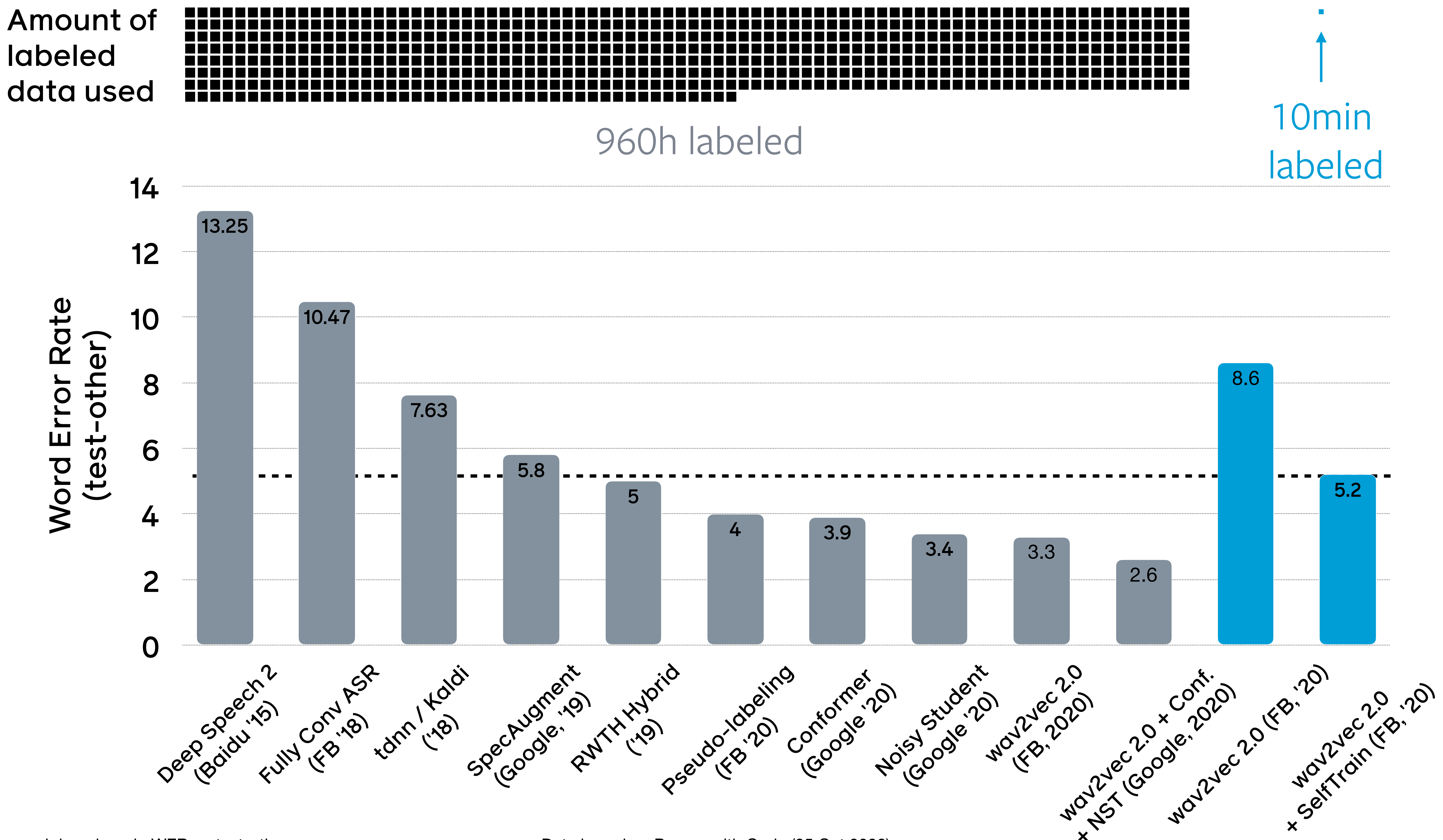
- Self-training very successful in speech recognition: generate pseudo-labels



Pre-training and self-training

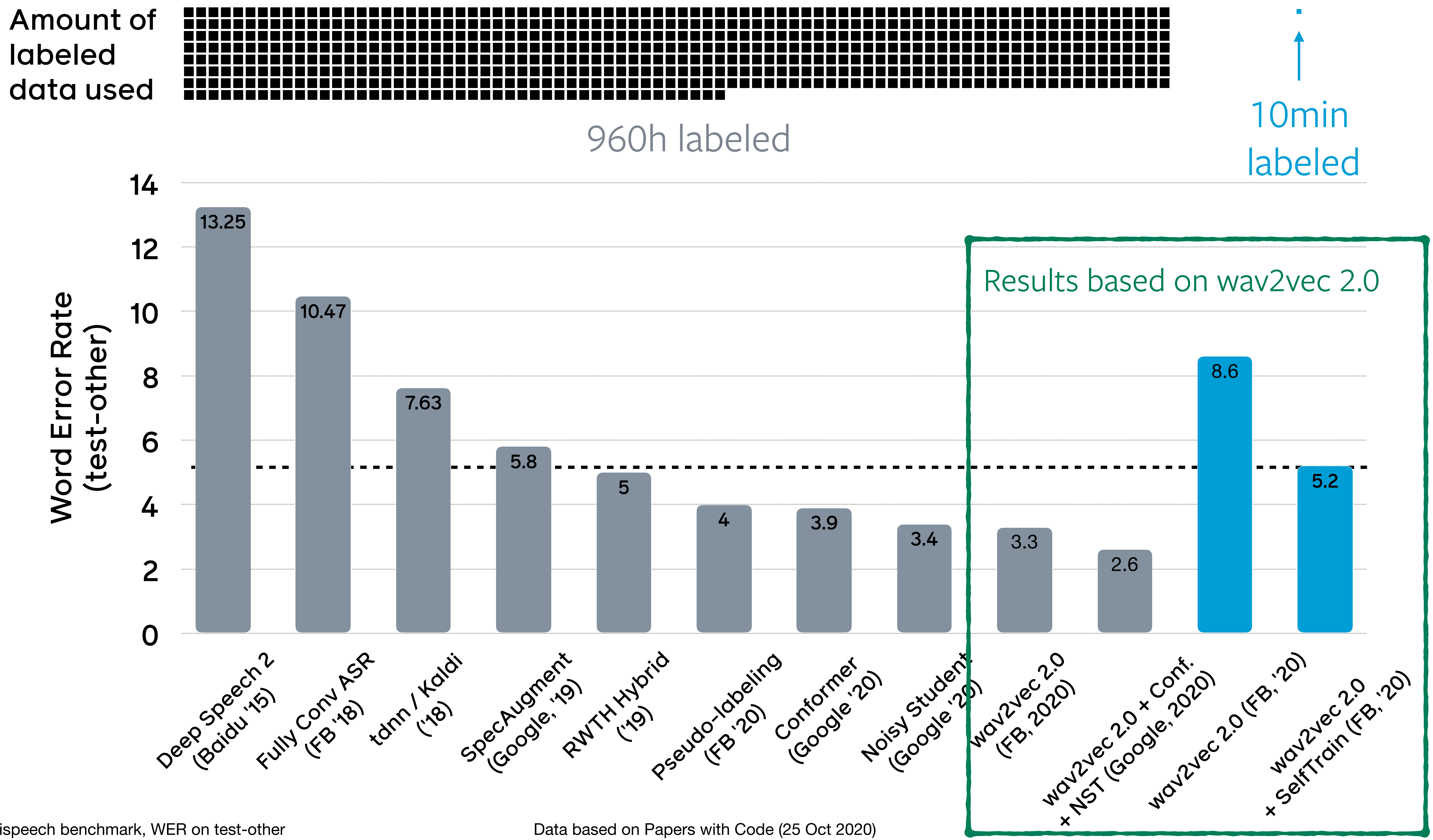
- Self-training very successful in speech recognition: generate pseudo-labels
- Do both have the same effect?
- Recipe: pre-train on the unlabeled data, pseudo-label, fine-tune pre-trained model





Librispeech benchmark, WER on test-other

Data based on Papers with Code (25 Oct 2020)



Librispeech benchmark, WER on test-other

Data based on Papers with Code (25 Oct 2020)

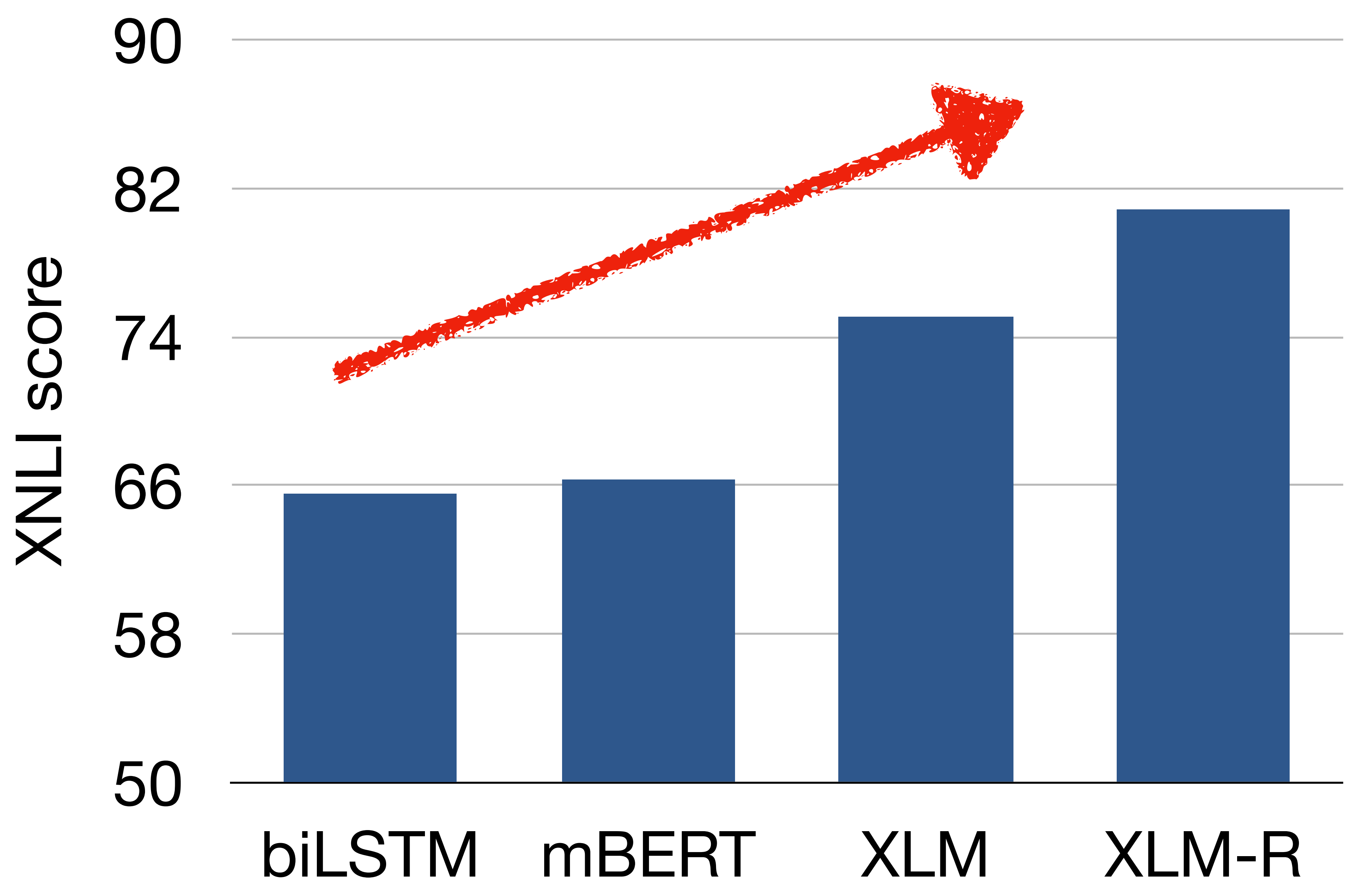
XLSR: cross lingual speech representation learning with wav2vec

Why *cross-lingual* self-supervised learning

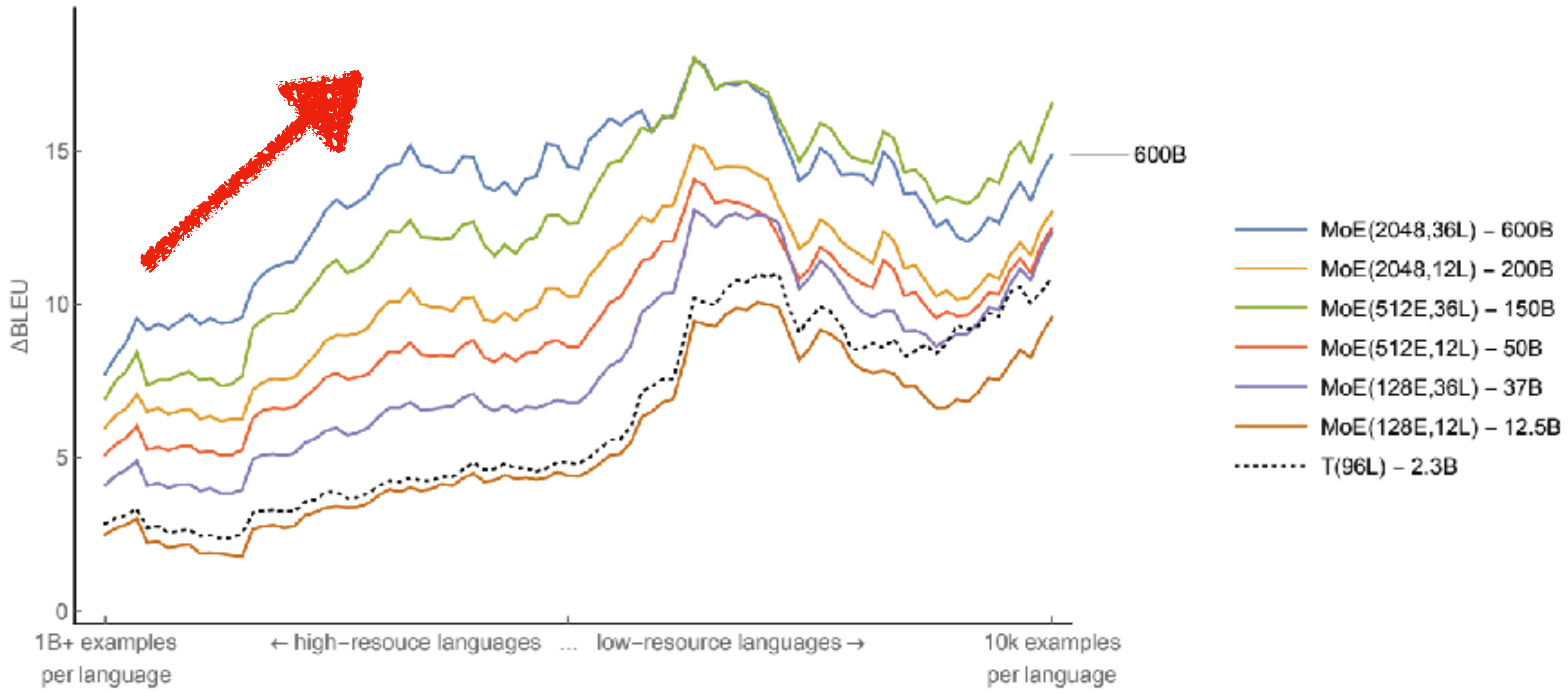
- Little labeled data -> little unlabeled data
- Leverage unlabeled data from high-resource languages
- To improve performance on low-resource languages
- One model for each of the 6500 languages, for each domain? No.
- Instead: one pertained model for all languages

Meanwhile in multilingual research

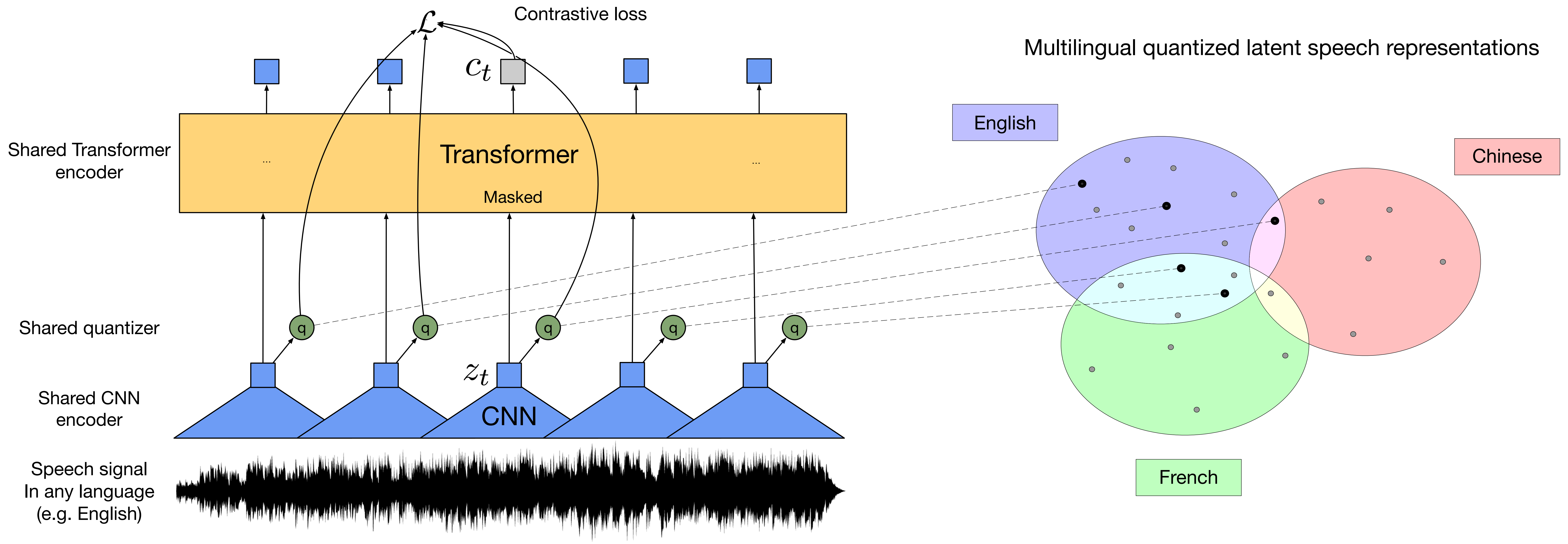
Cross-lingual understanding (XLU)



Multilingual machine translation



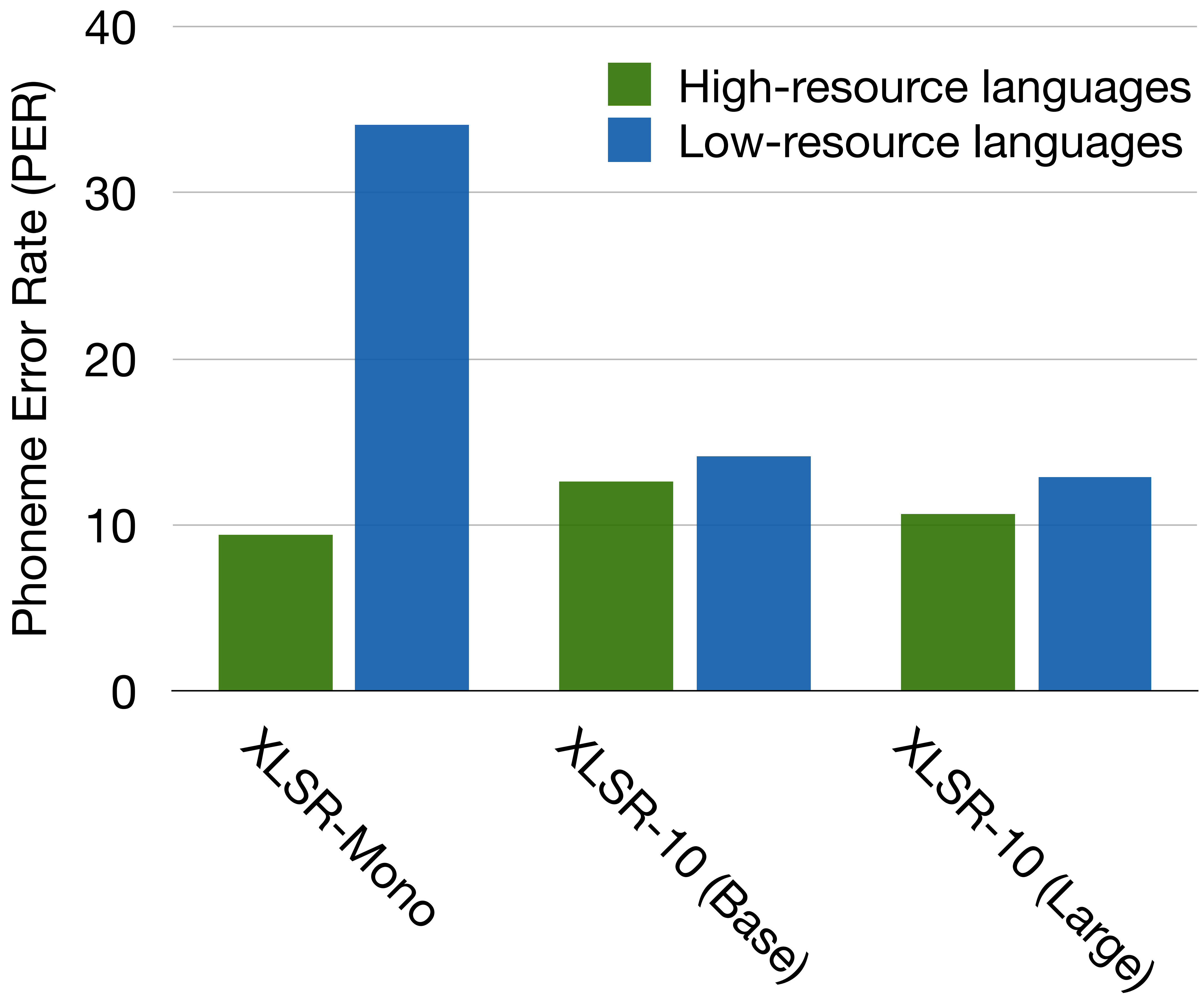
XLSR: cross lingual speech representation learning with wav2vec



XLSR: Results - cross-lingual transfer

XLSR significantly outperforms previously published approaches on CommonVoice/BABEL

CommonVoice results:



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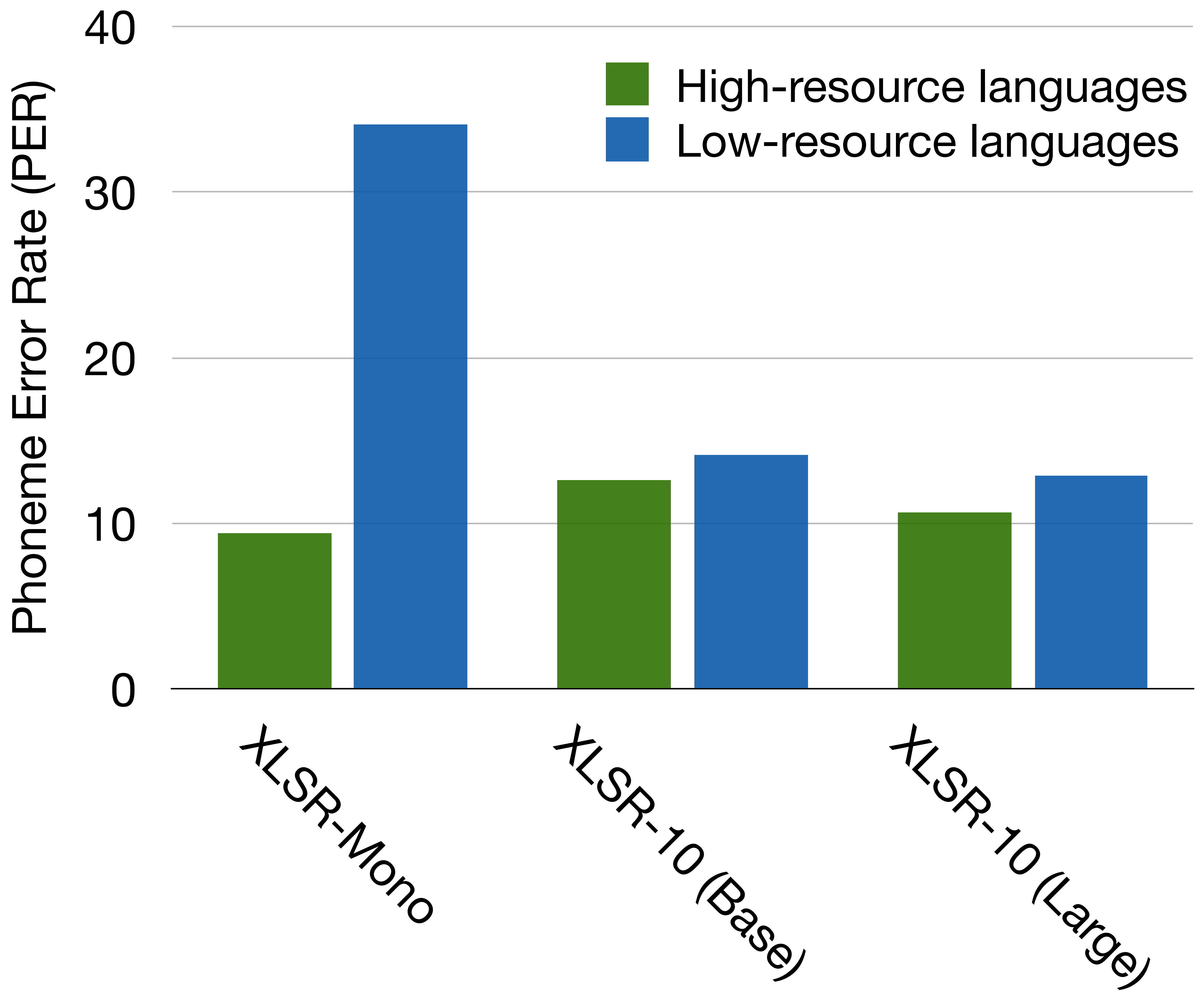
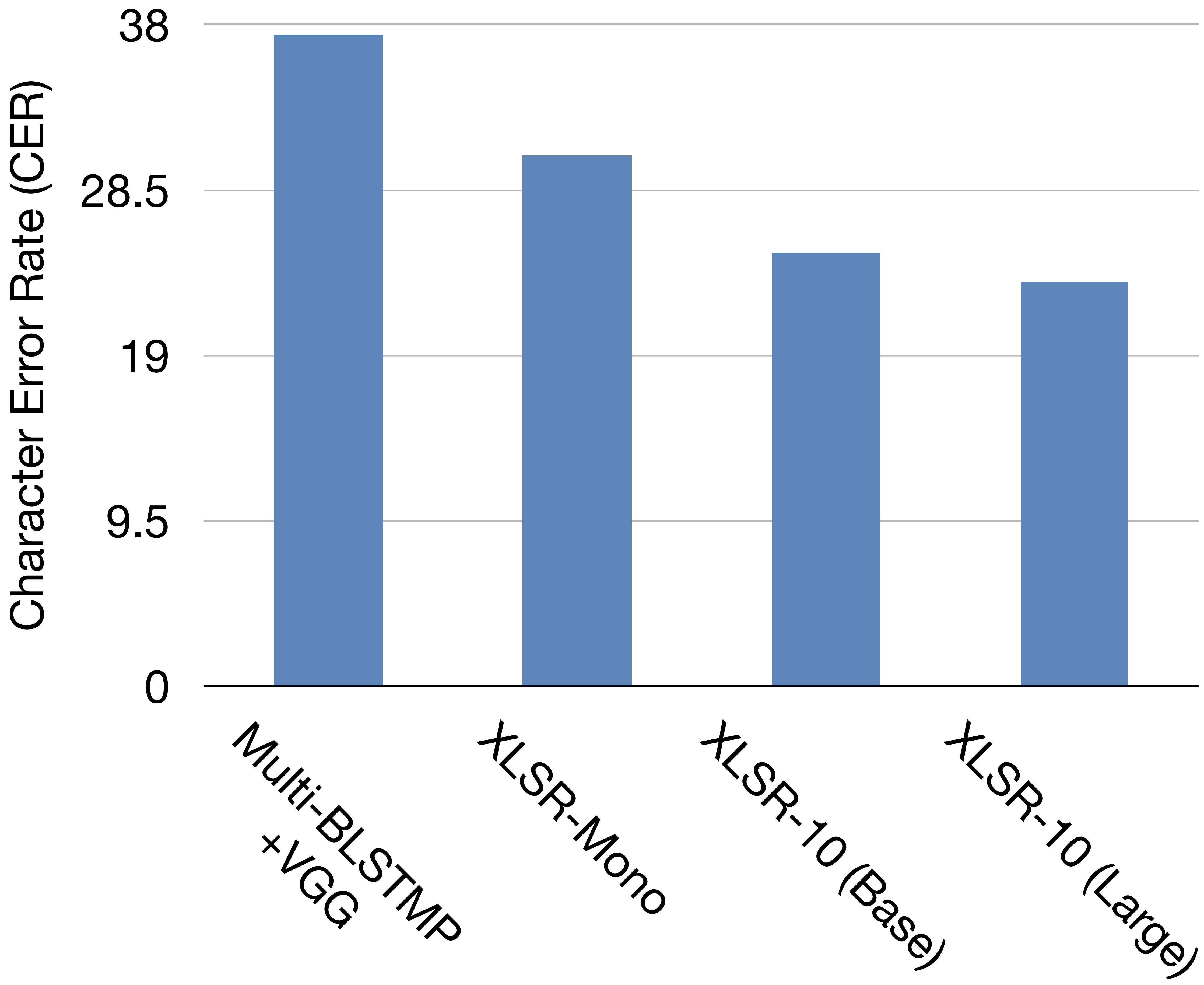


BABEL (average) results:



XLSR: Results - multilingual fine-tuning

Multilingual finetuning leads to *one model for all languages* with little loss in performance

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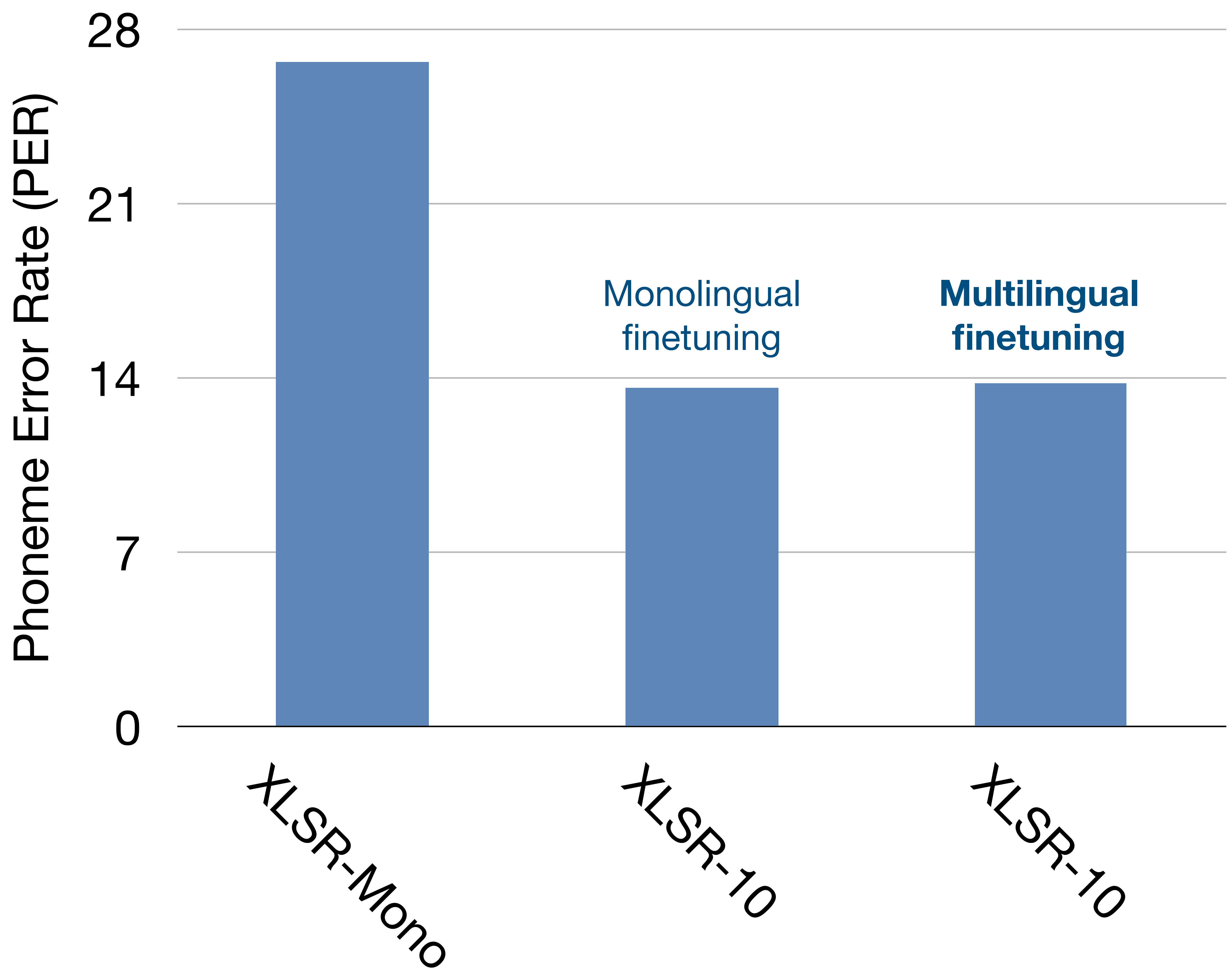
CommonVoice results:



XLSR: Results - impact of language similarity

Language similarity plays an important role in cross-lingual transfer

Similar higher-resource language data helps the most for low-resource language

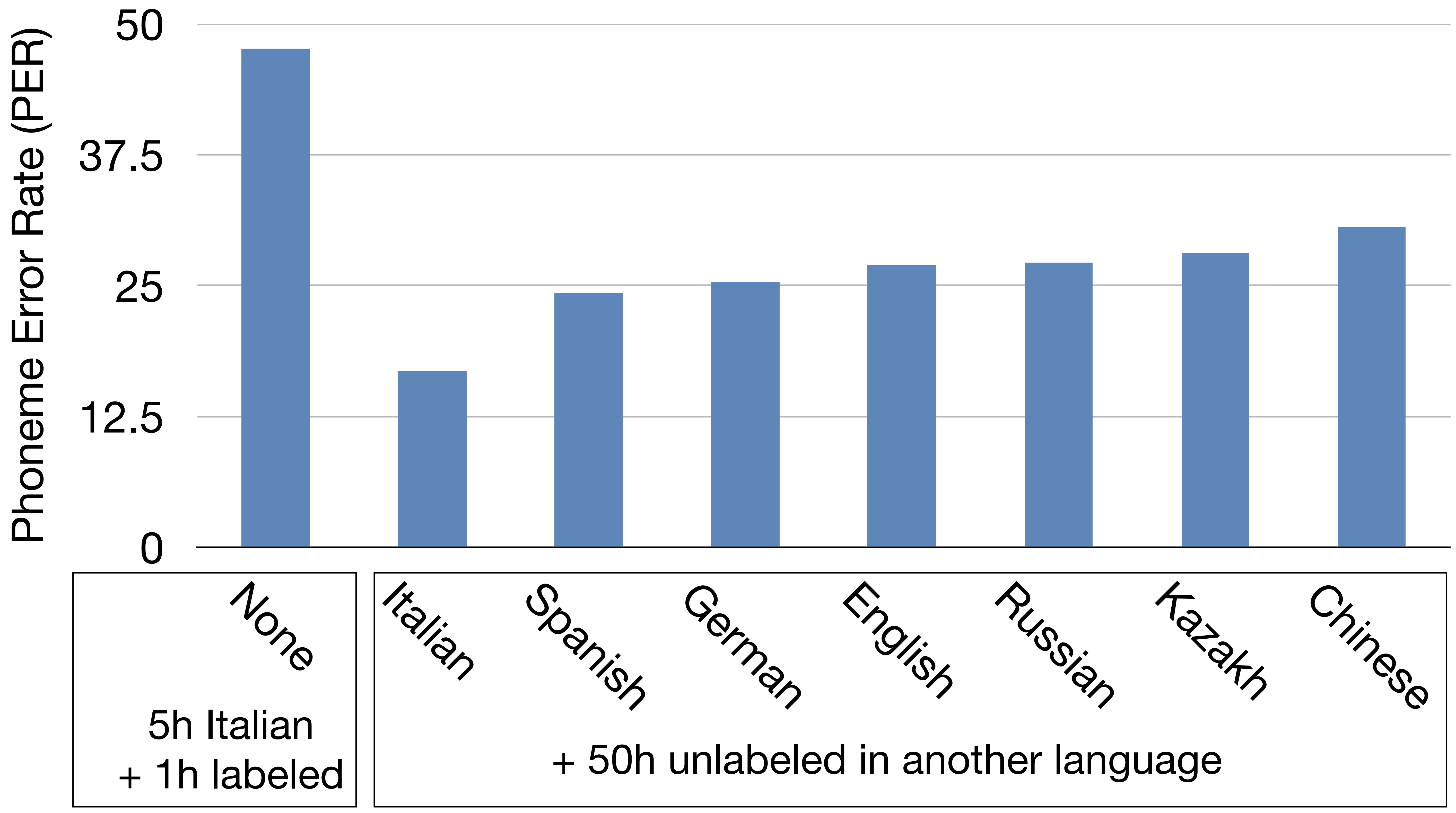
5h Italian
+ 1h labeled

+ 50h unlabeled in another language

XLSR: Results - impact of language similarity

Language similarity plays an important role in cross-lingual transfer

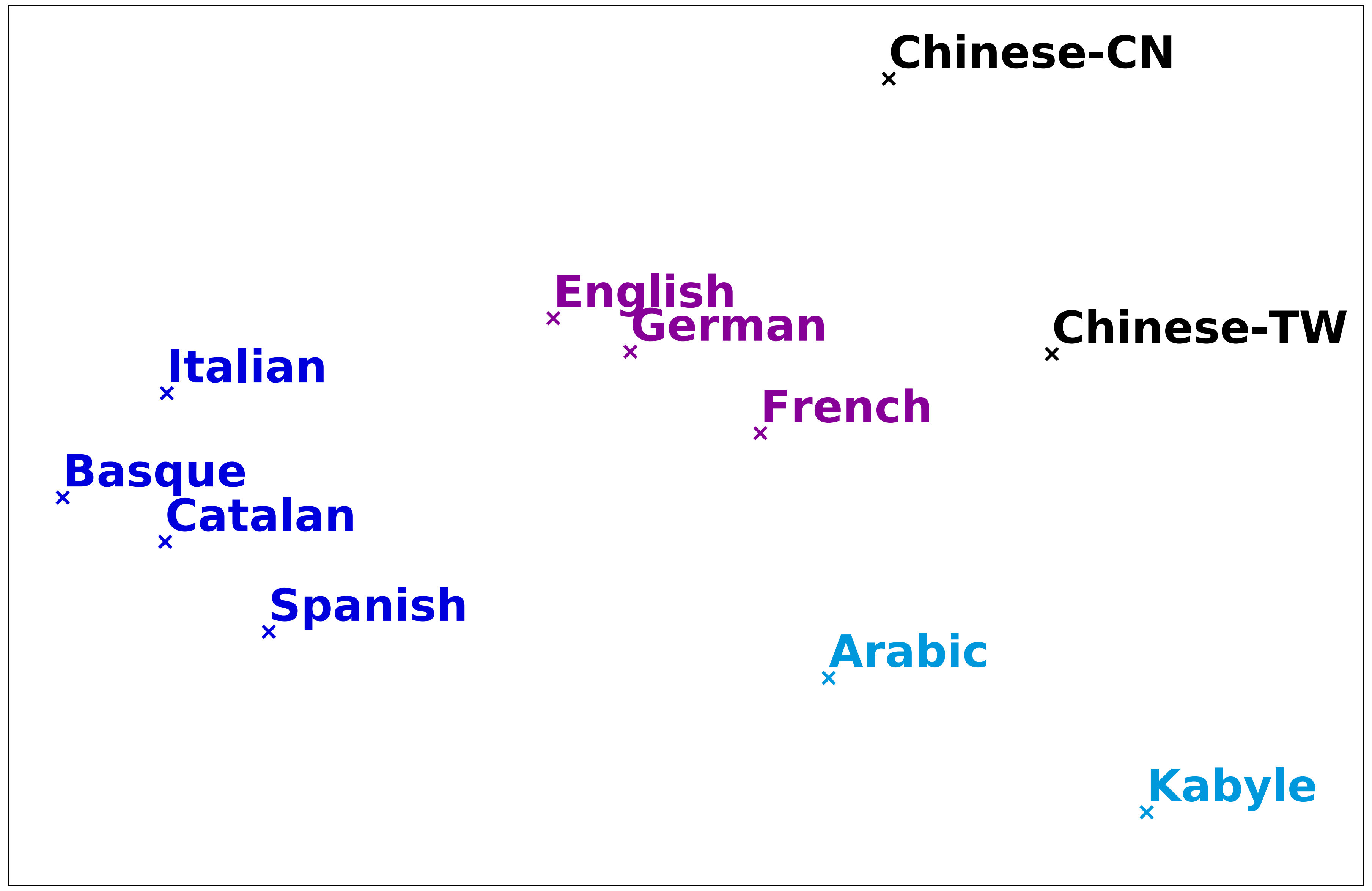
Similar higher-resource language data helps the most for low-resource language

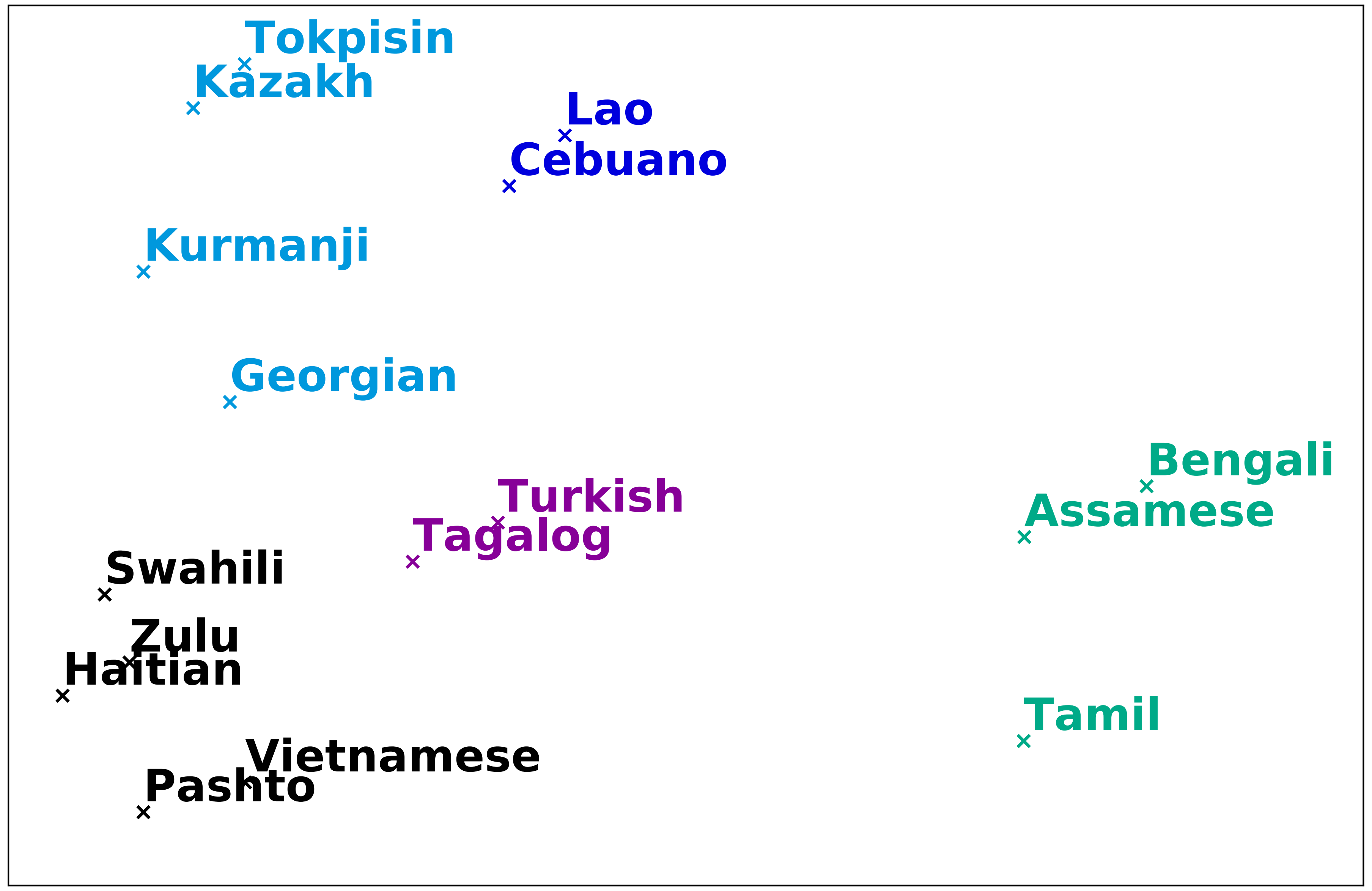


XLSR: Analysis of discrete latent speech representations

PCA visualization of latent discrete representations from the multilingual codebook

Similar languages tend to share discrete tokens and thus cluster together





Conclusion

- For the first time, pre-training for speech works very well in both low-resource and high-resource setup.
- Cross-lingual training improves low-resource languages.
- Pre-training and self-training are complementary.
- Using only 10 minutes (48 utterances) of transcribed data rivals best system trained on 960h from 1 year ago.
- Code and models are available in the fairseq GitHub repo + Hugging Face.

FAIRSEQ

Future directions

- What is learnt at different layers?
- Learning representations at different granularities.
- Can we learn ASR systems without any supervision at all?
- Can we generate speech with the learned representations?

Thank you


Alexei Baevski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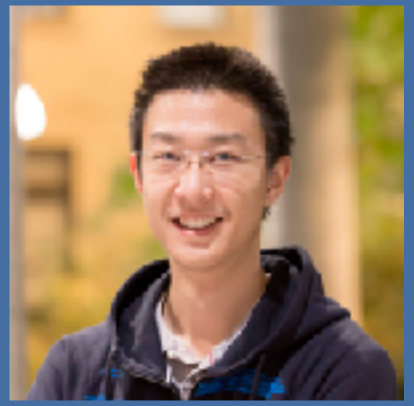
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