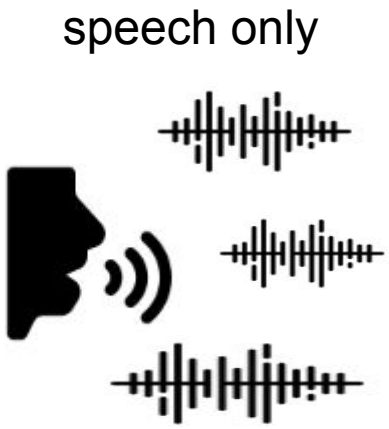
# REBORN: Reinforcement-Learned Boundary Segmentation with Iterative Training for Unsupervised ASR

Liang-Hsuan Tseng, En-Pei Hu, Cheng-Han Chiang, Yuan Tseng,
Hung-yi Lee, Lin-shan Lee, Shao-Hua Sun


# What is Unsupervised ASR (UASR)?

Learning a speech recognition system without any labeled data.



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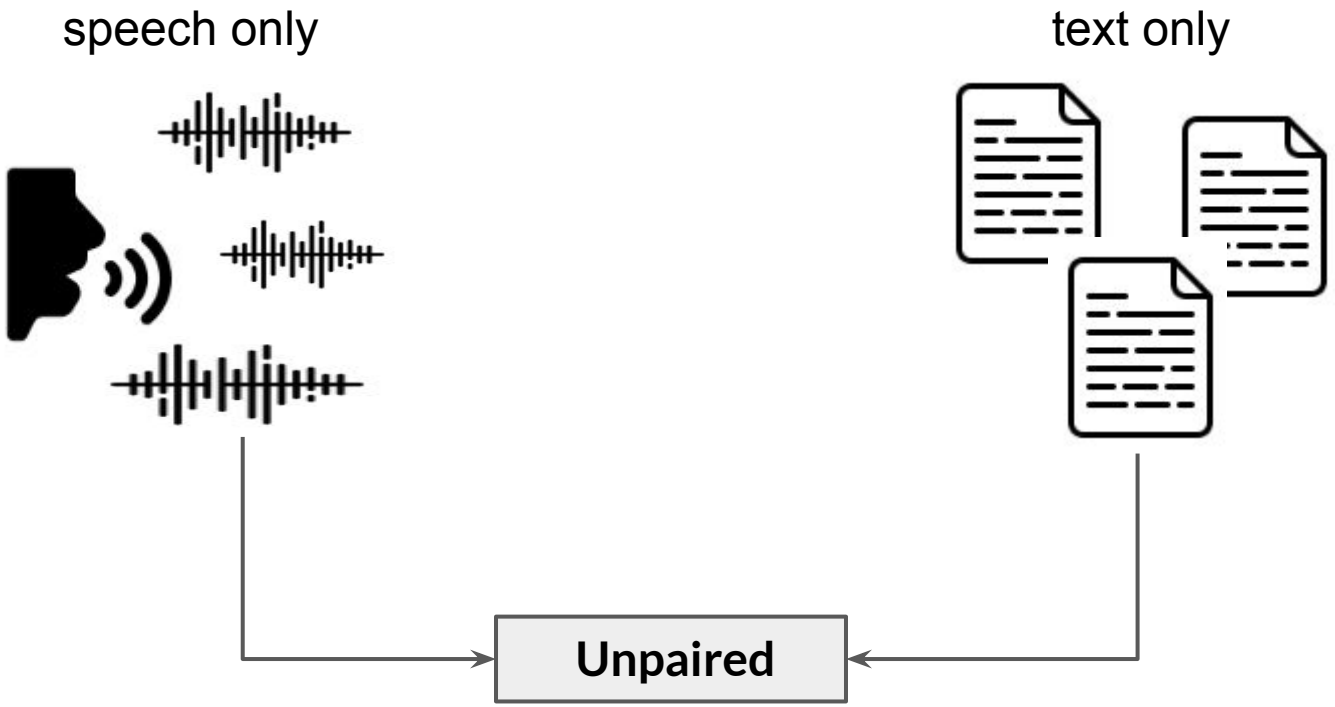

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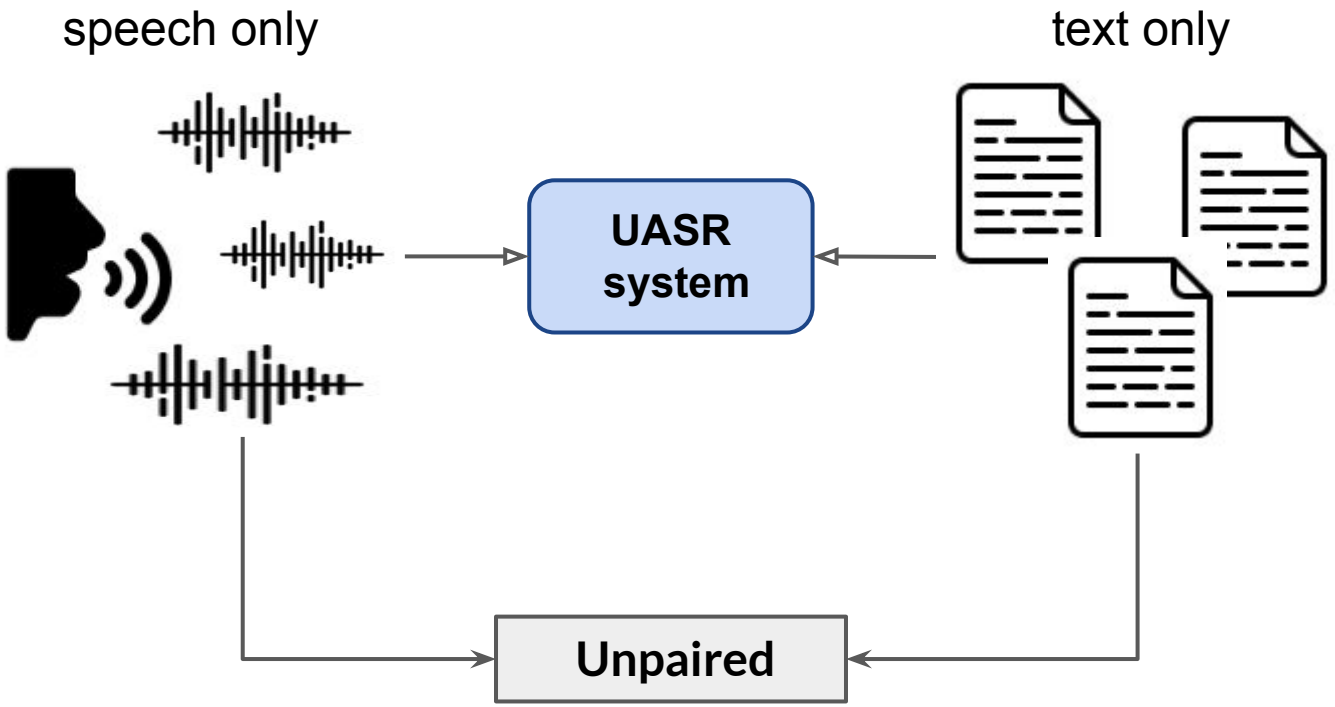

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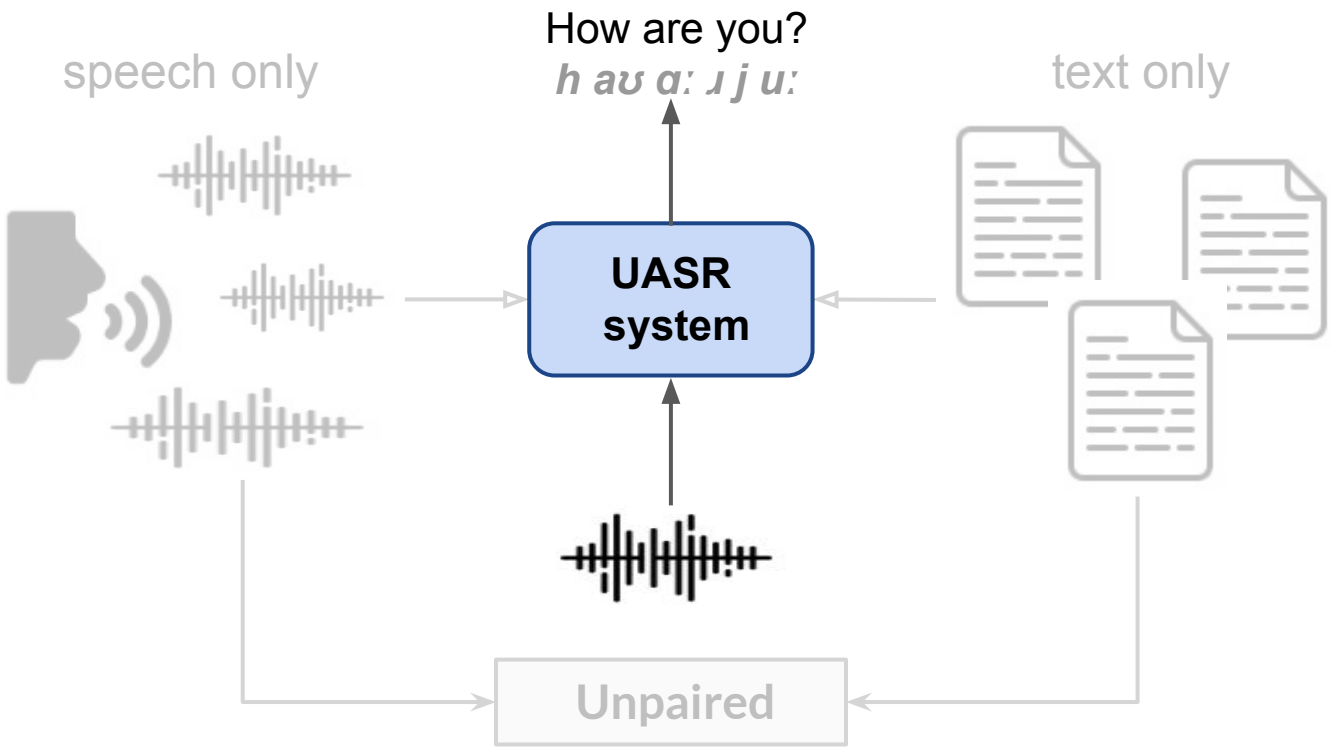

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Speech and text are different!

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*continuous*

d i s c r e t e

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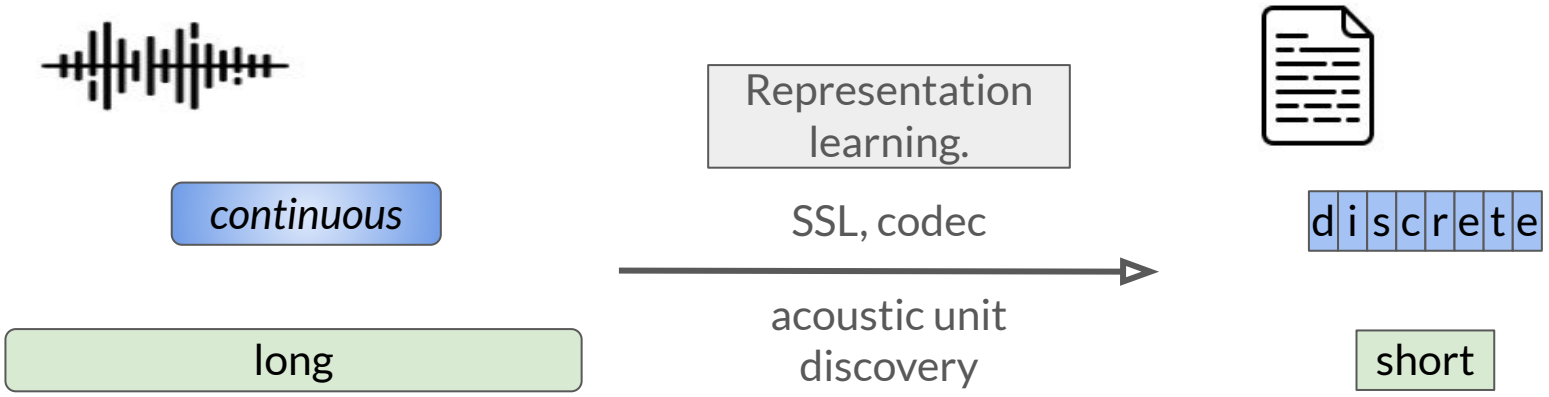

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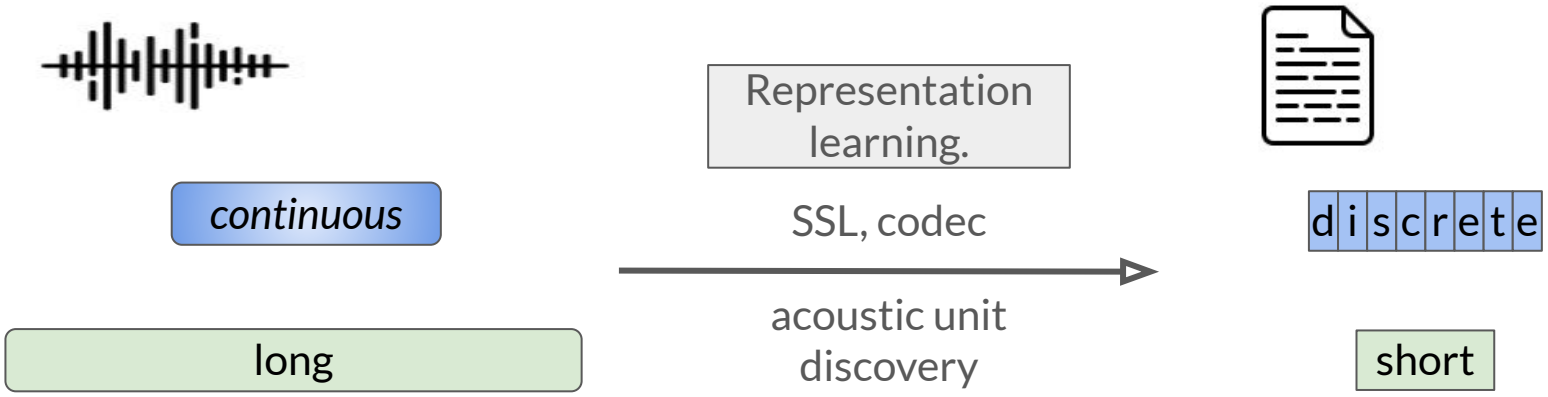


UASR aims to ***match the distribution*** from speech to text with **unpaired** data only!

# Segmentation is what we need

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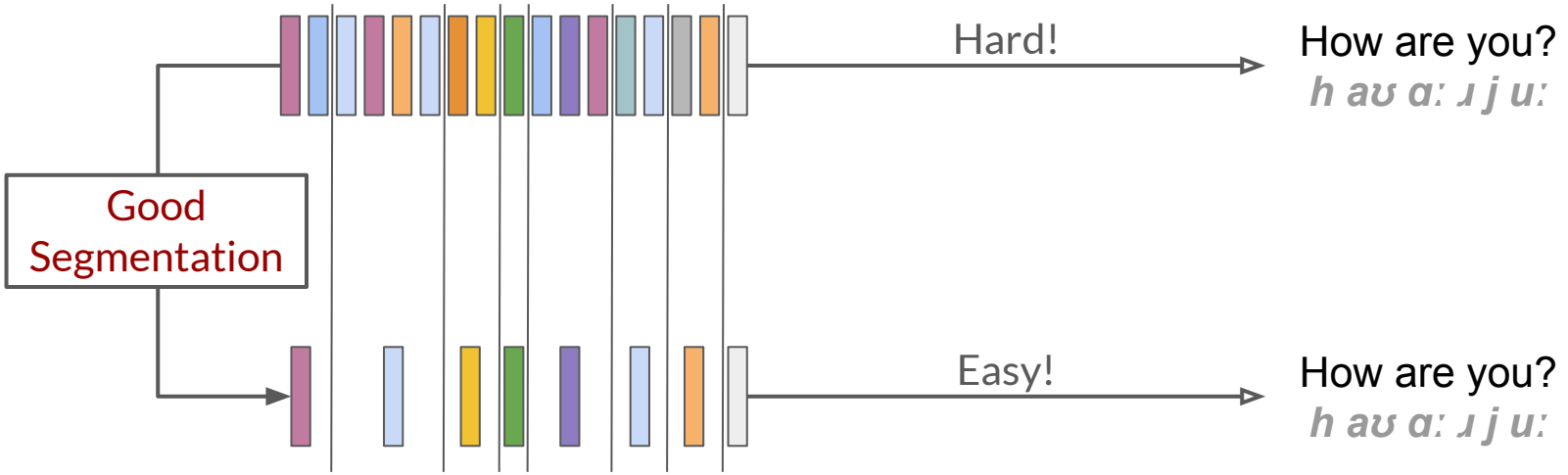
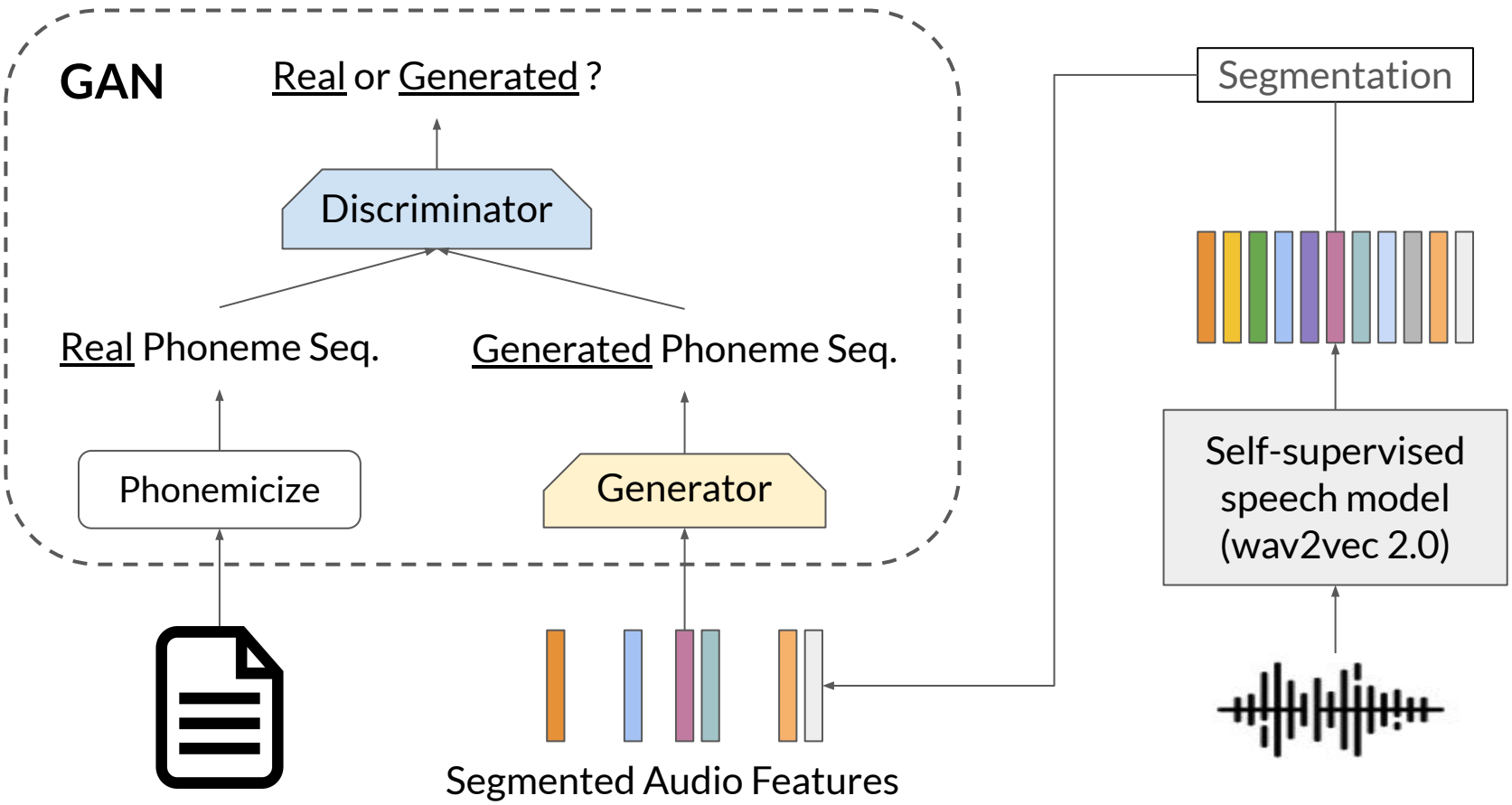
⇒ **Segmentation!**




The distribution matching problem would be easier given a ***good segmentation***.

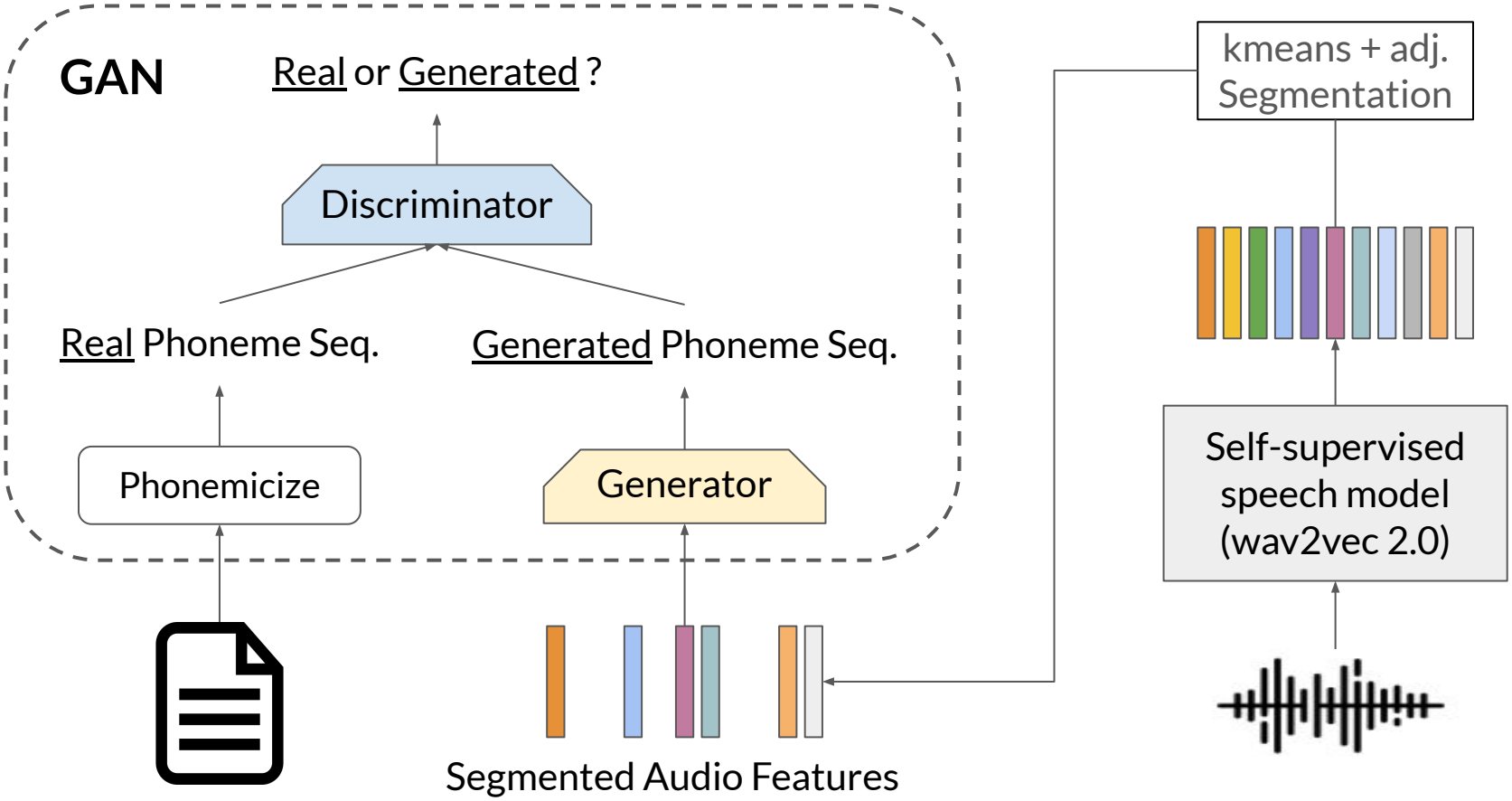
# *k*-means-based segmentation: wav2vec-U

Feature extrator: wav2vec 2.0



# *k*-means-based segmentation: wav2vec-U

Feature extrator: wav2vec 2.0; Segmentation: k-means + adjacent



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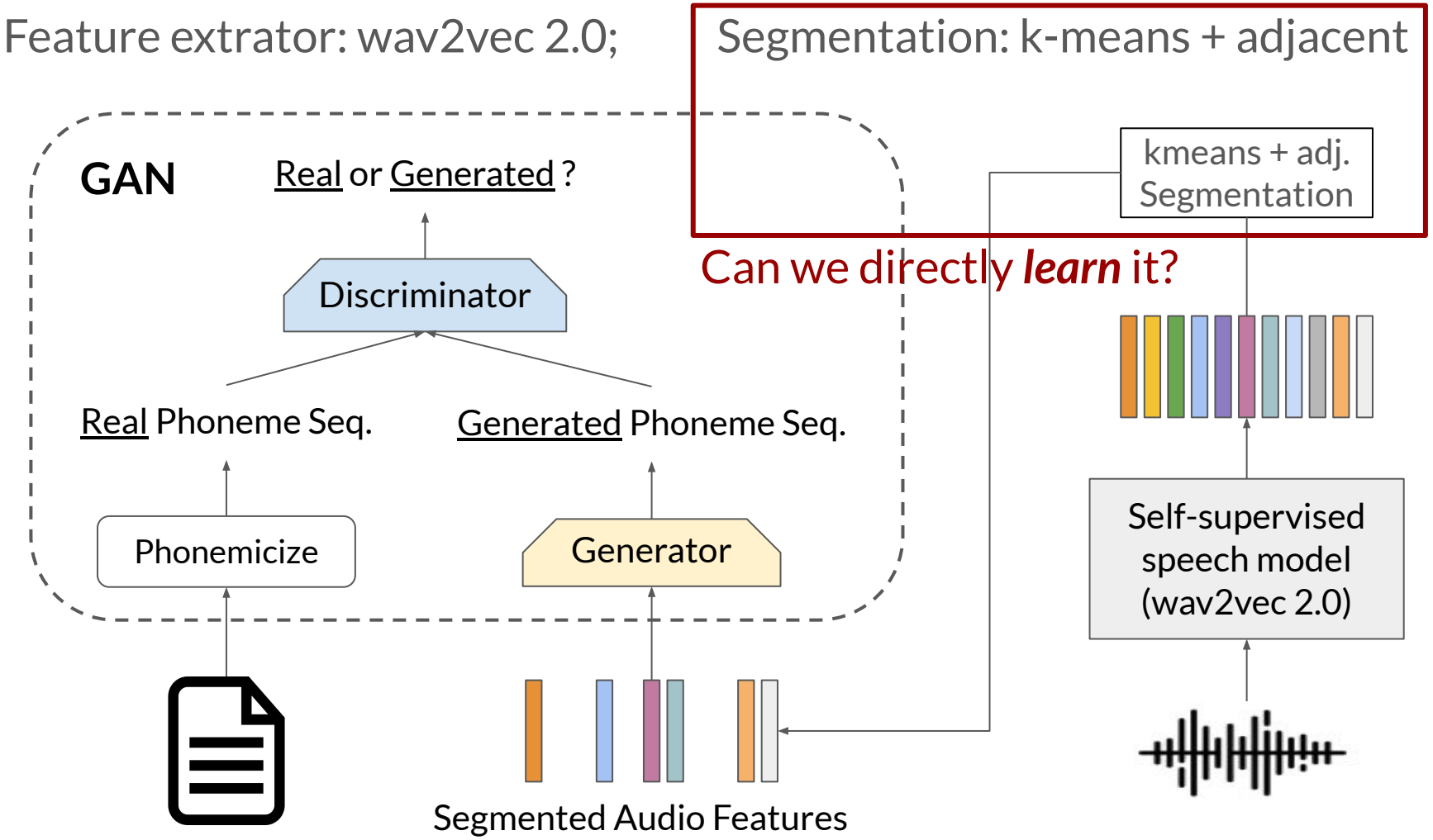

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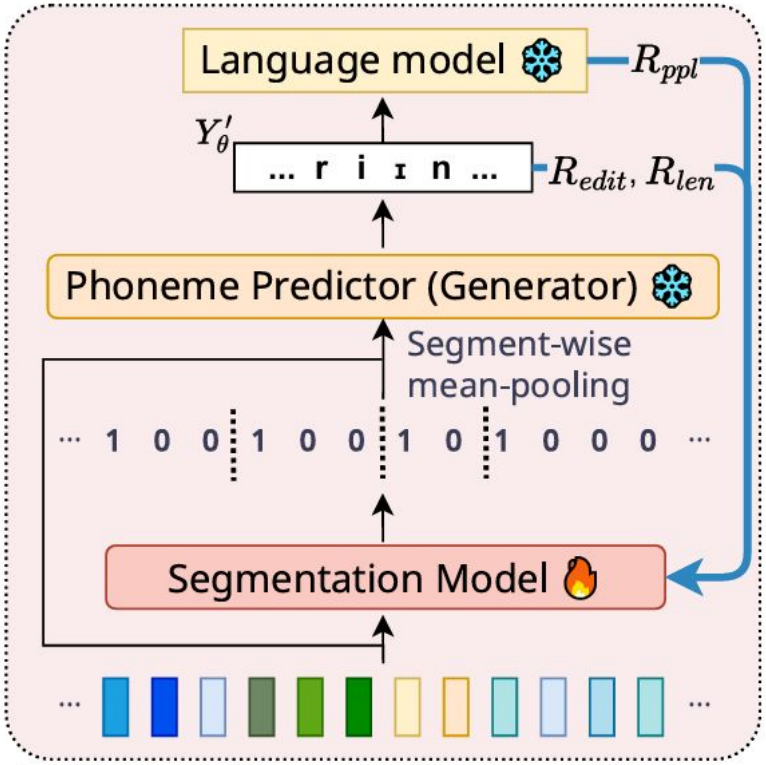
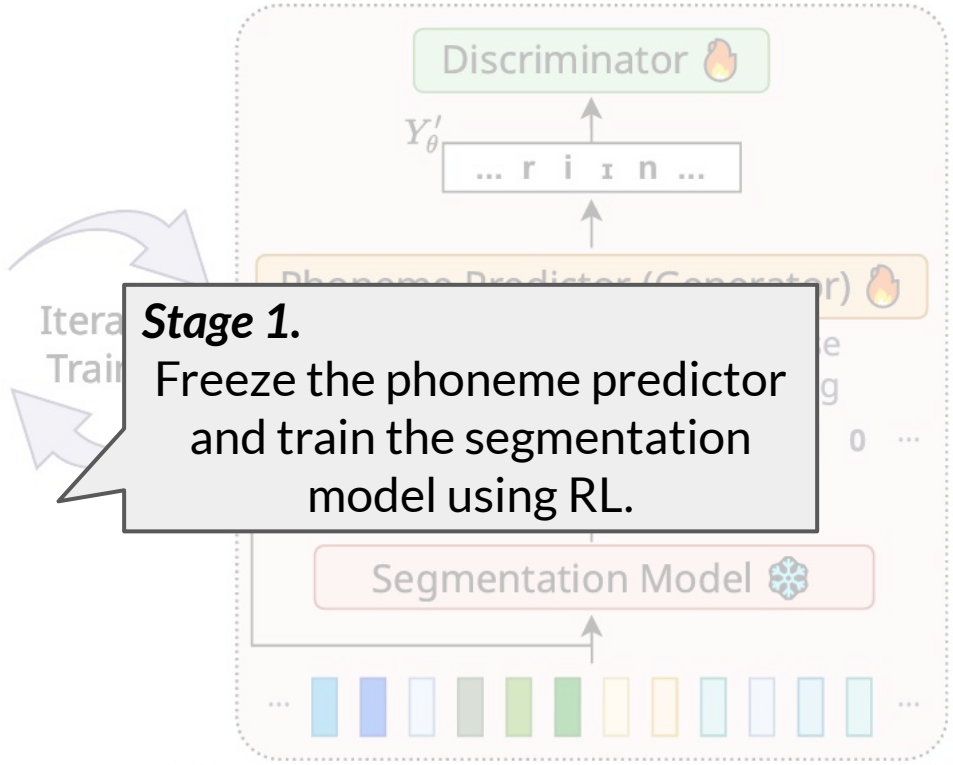


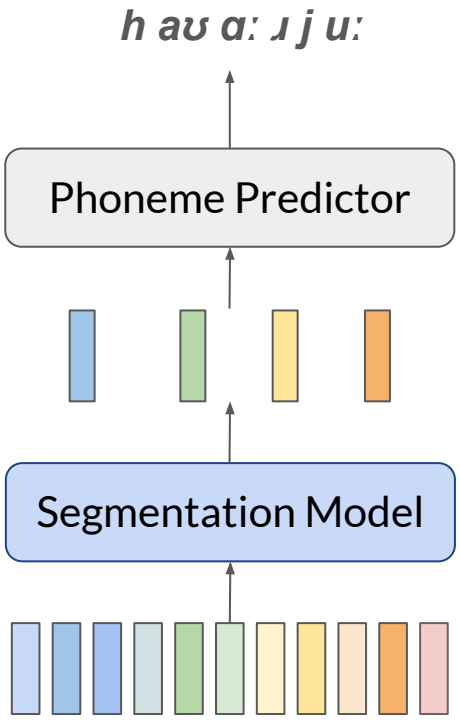

(a) Stage 1: Segmentation model training




(b) Stage 2: Phoneme prediction model training

# Using RL to learn the segmentation model

What we want is a segmentation that can yield a ***better transcription***.



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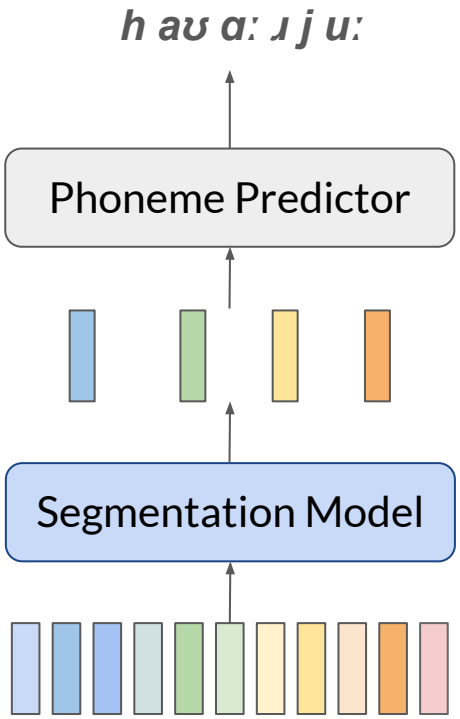

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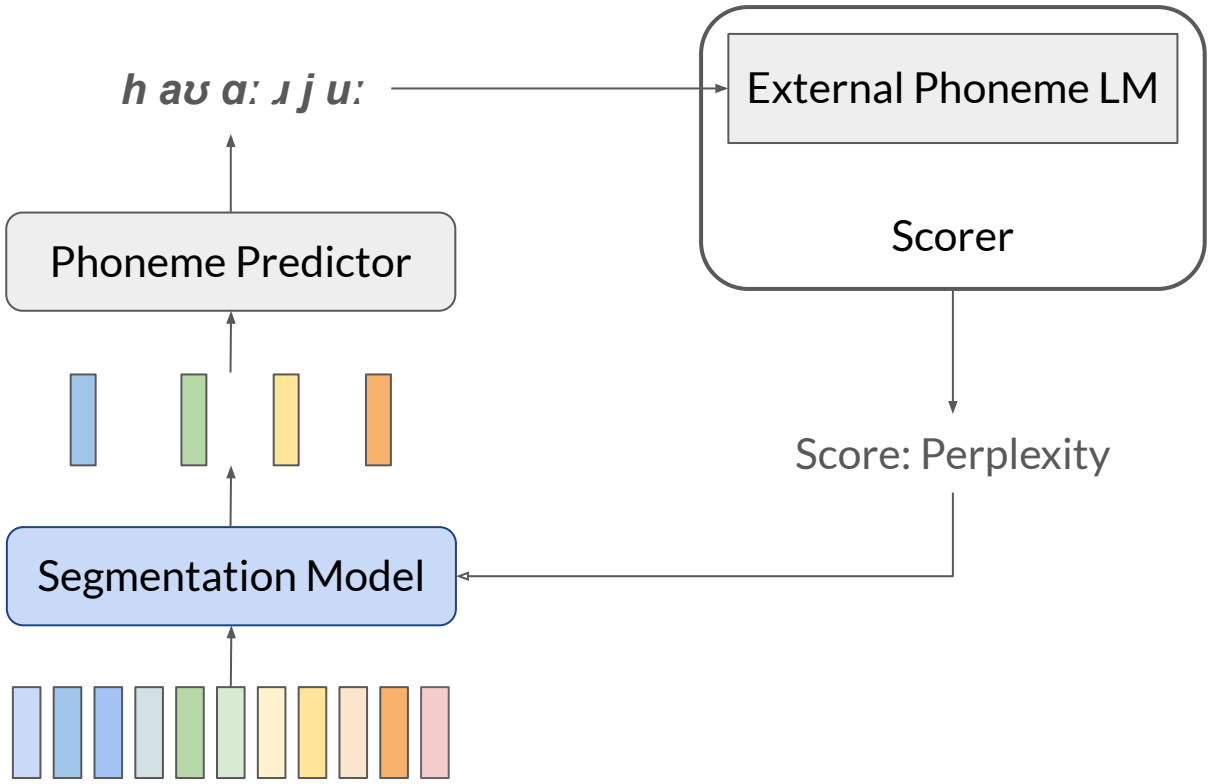

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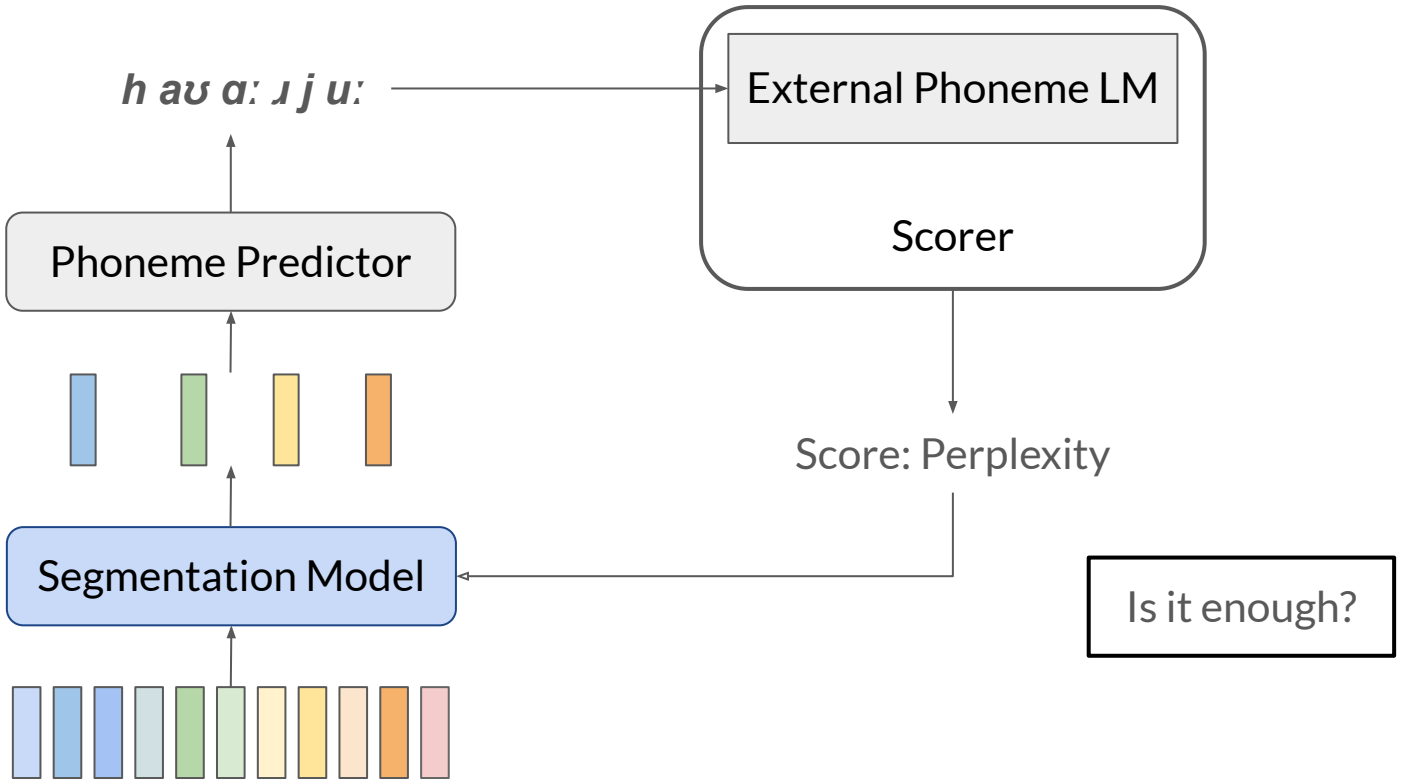

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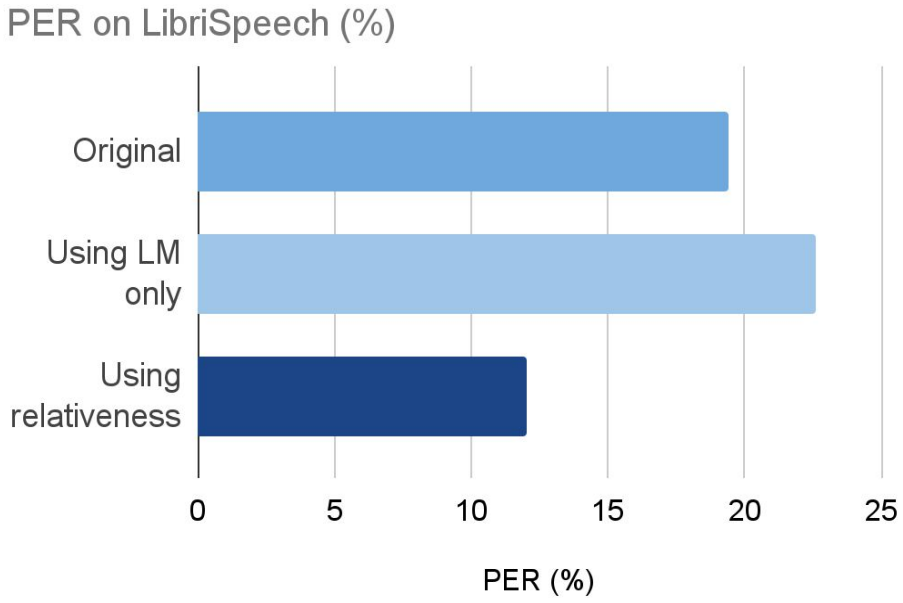

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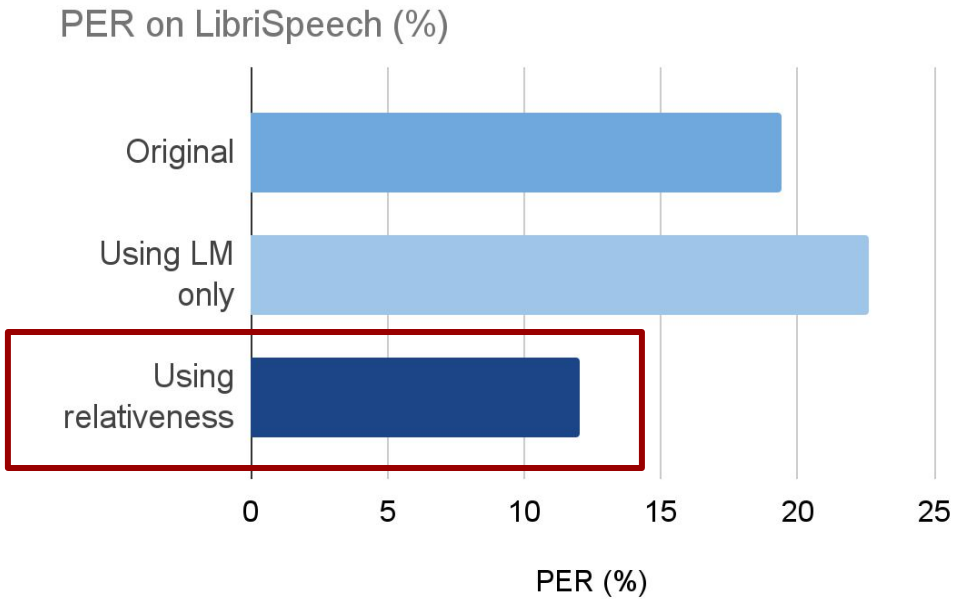
We discover that the concept of using relativeness is essential for our RL rewards.



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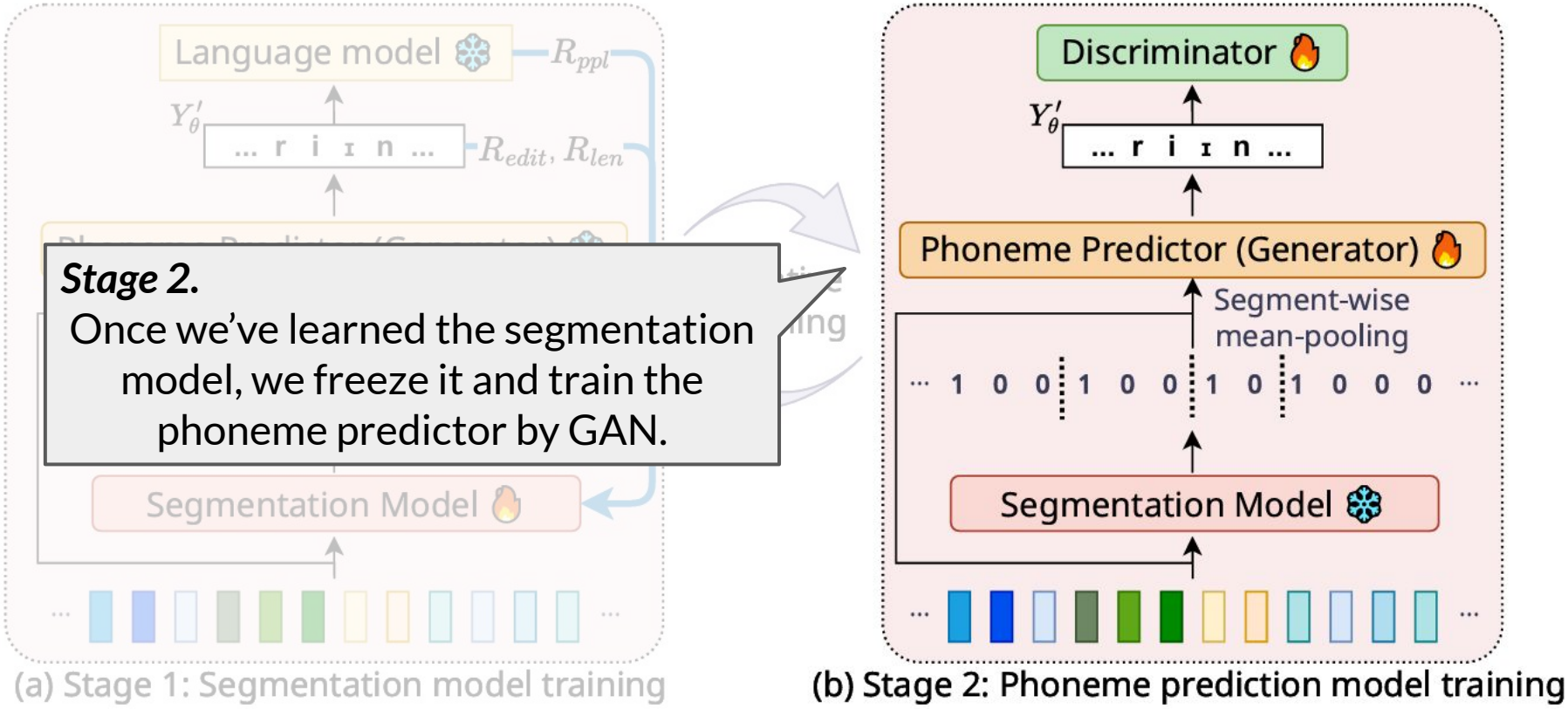


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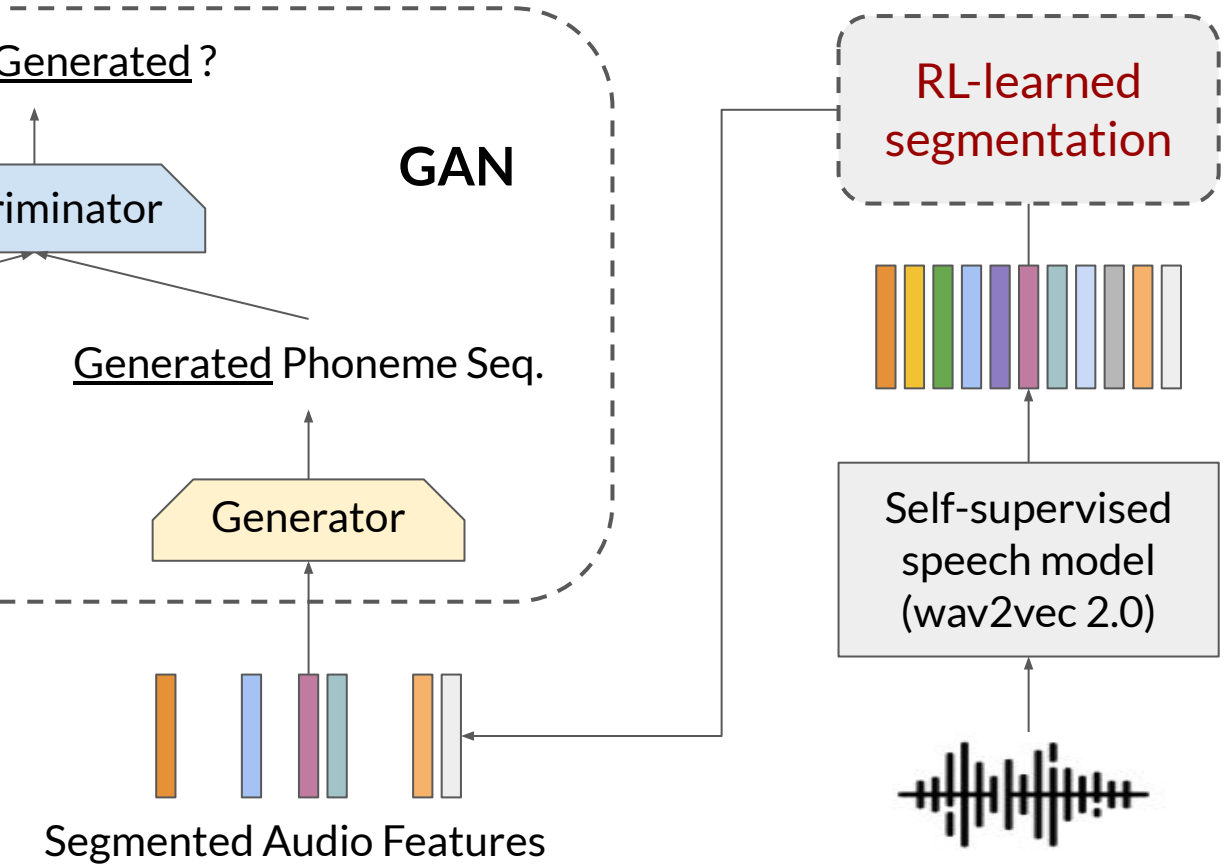
(b) Stage 2: Phoneme prediction model training

# Improving the phoneme predictor further

Can we directly use the new RL-learned segmentation for the stage 2 GAN training?



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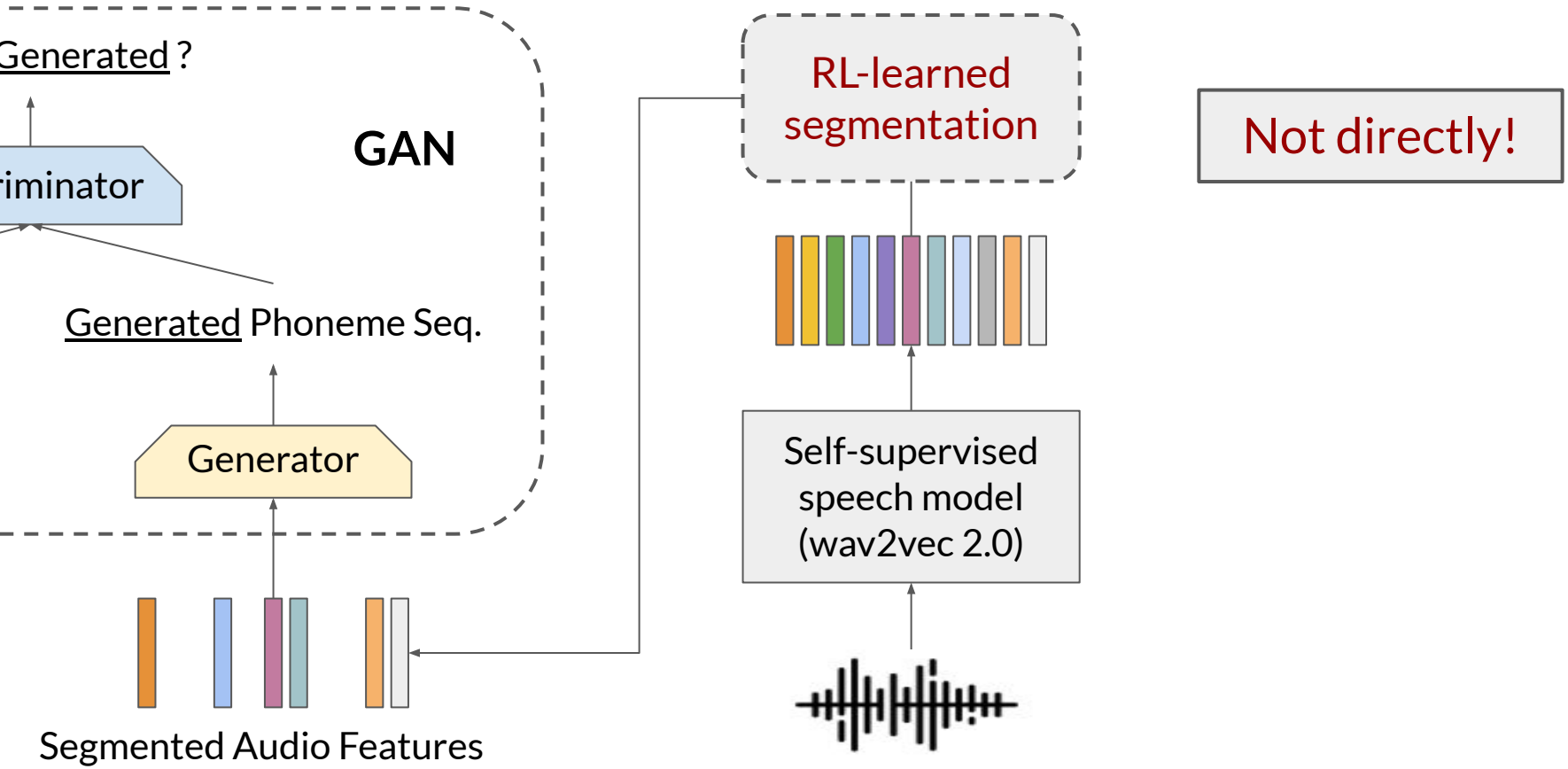
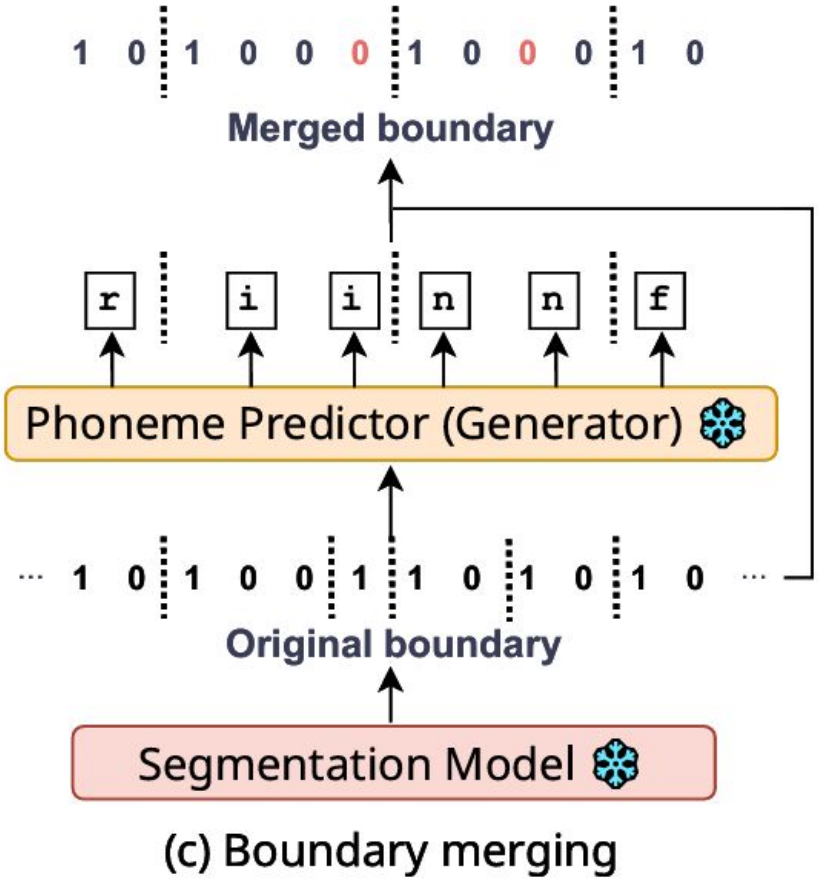


# Introducing boundary merging

We merge the segments yielding consecutive phoneme predictions.

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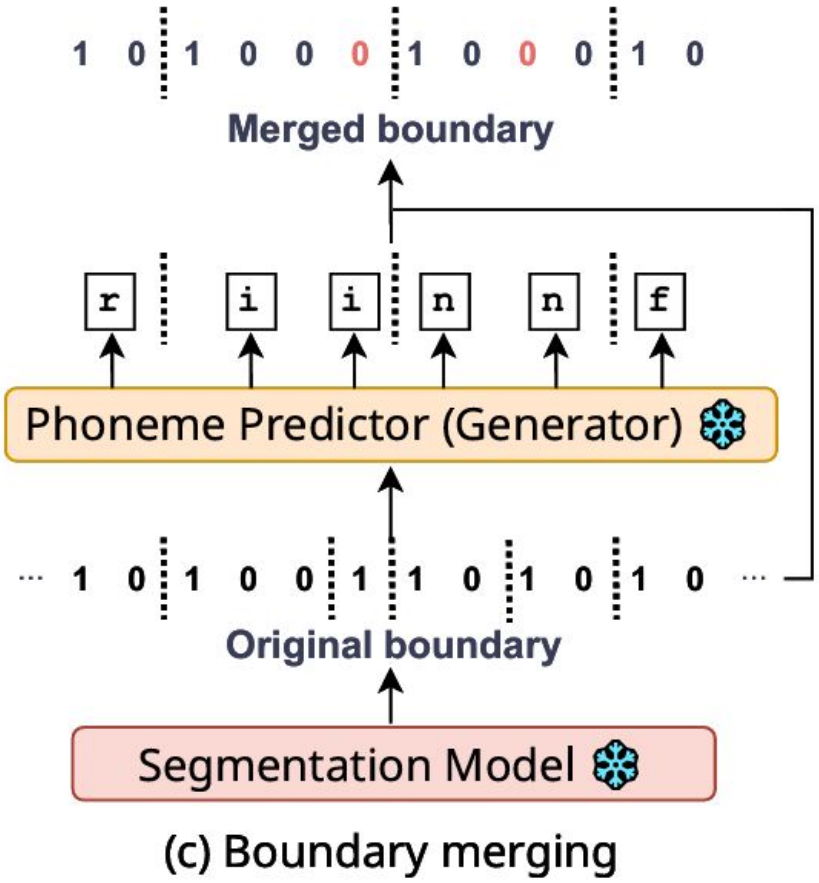


(c) Boundary merging

The amount of segments decreases, the GAN training is more stable and can yield better performance.

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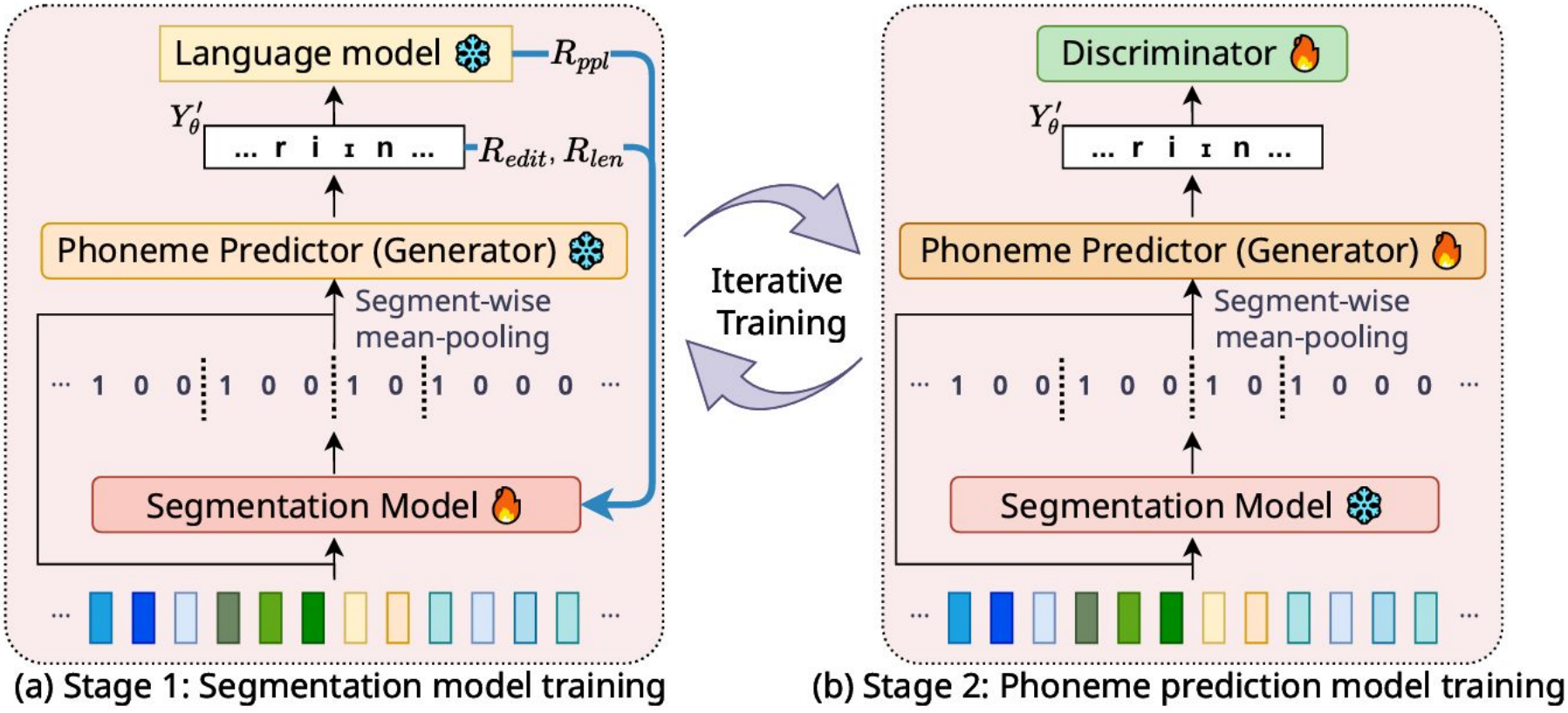


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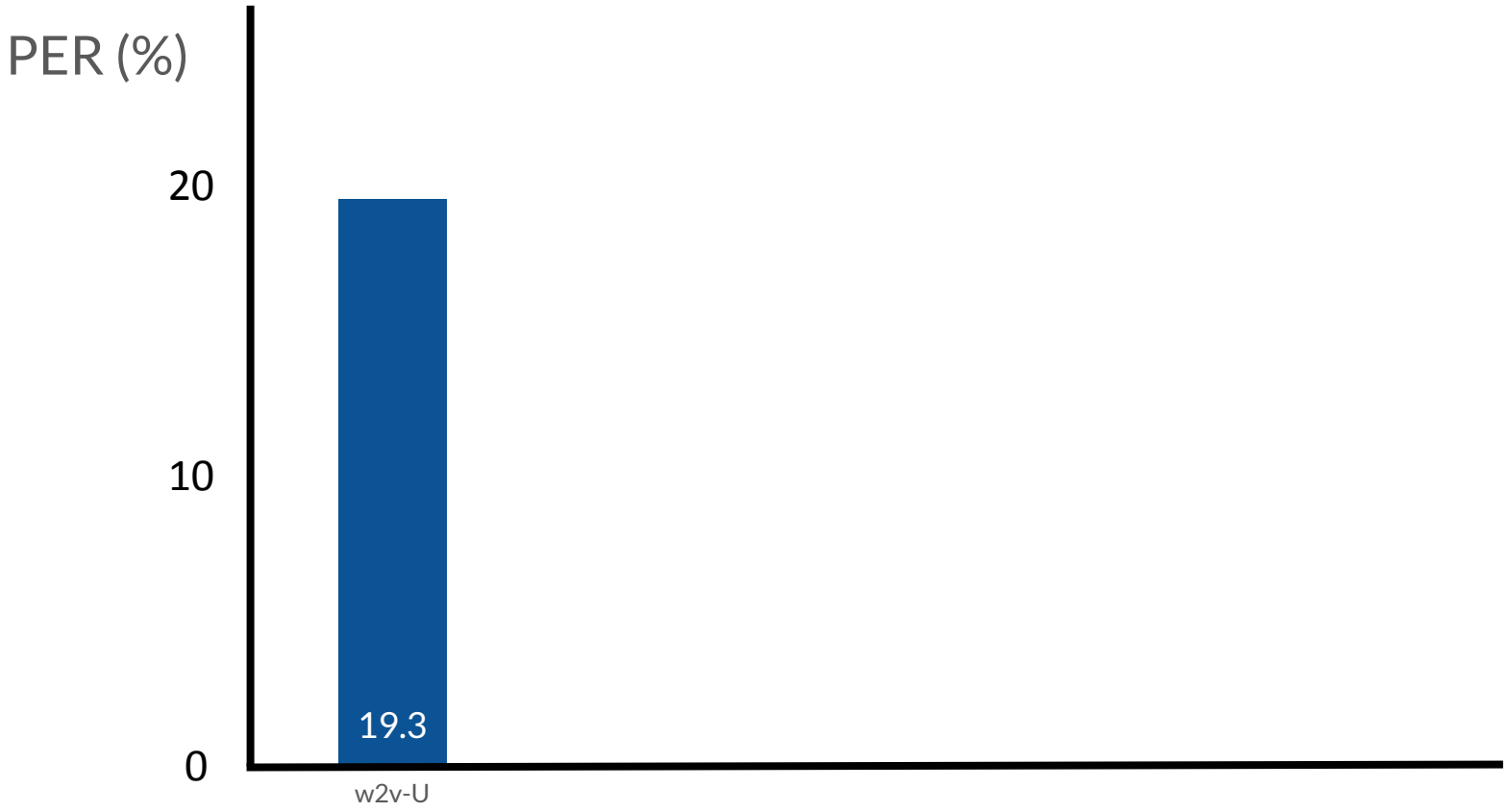
# Result on LibriSpeech

Evaluation metric: PER (%), the lower the better. Training data: 100 hours



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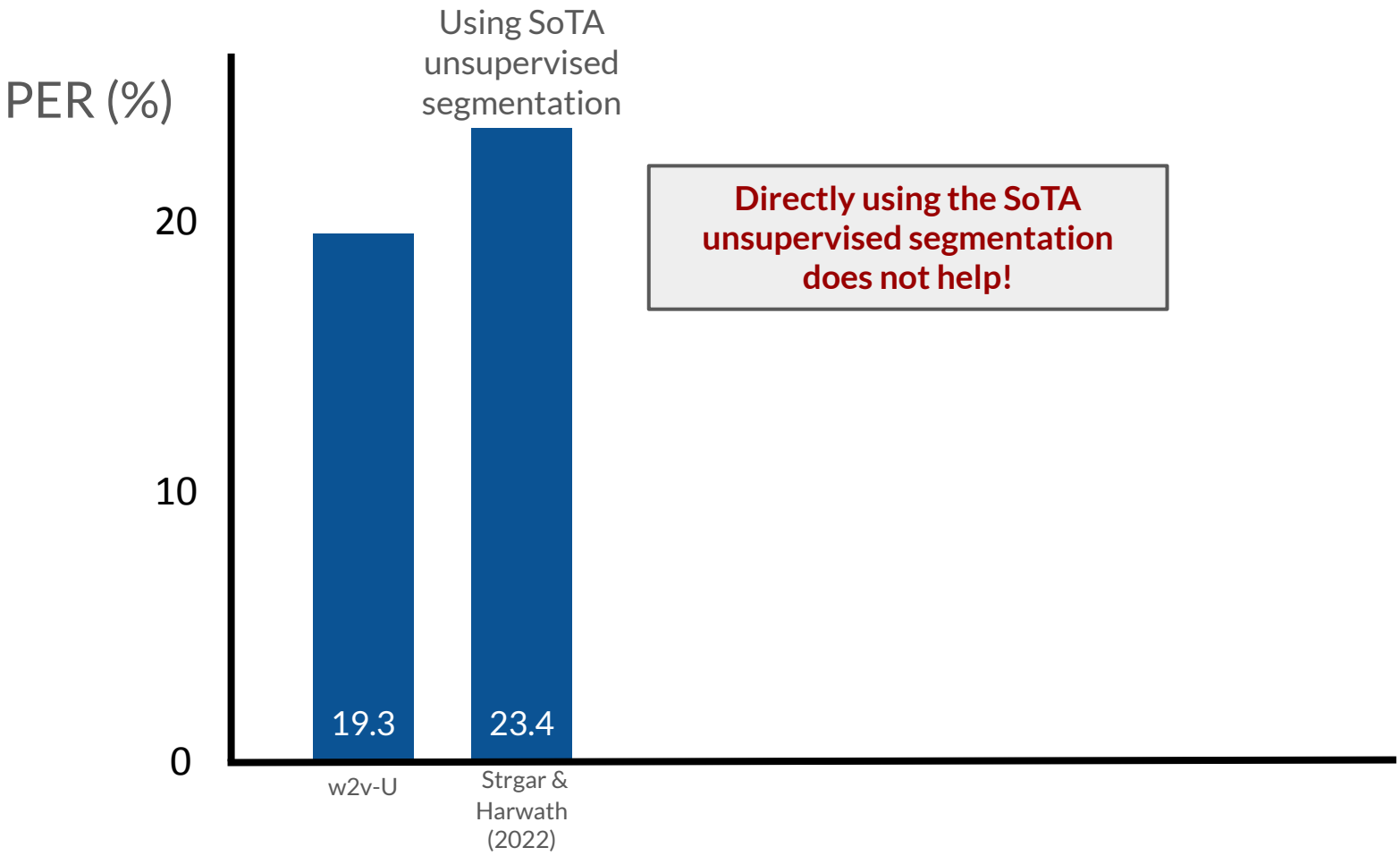

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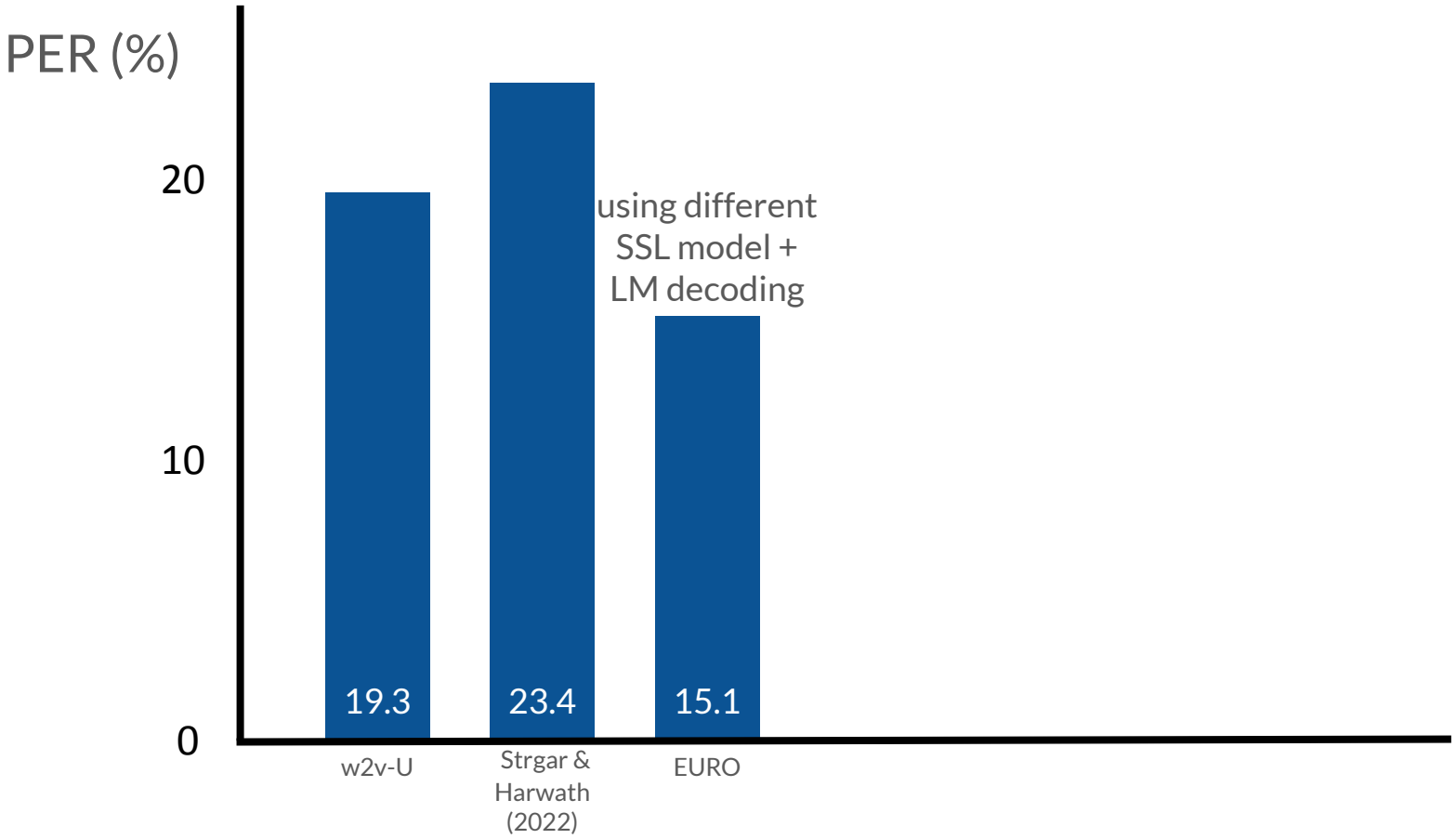

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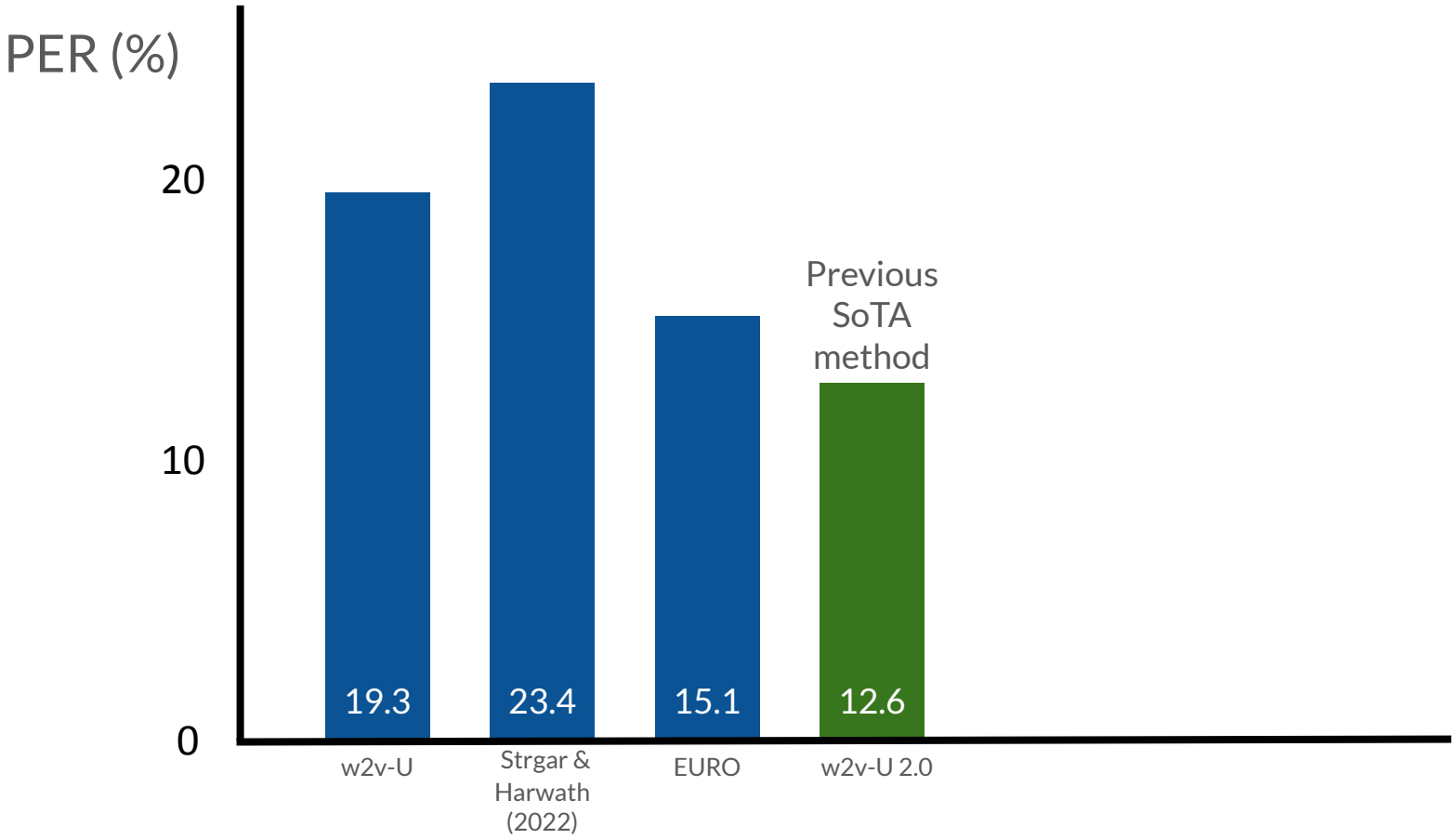

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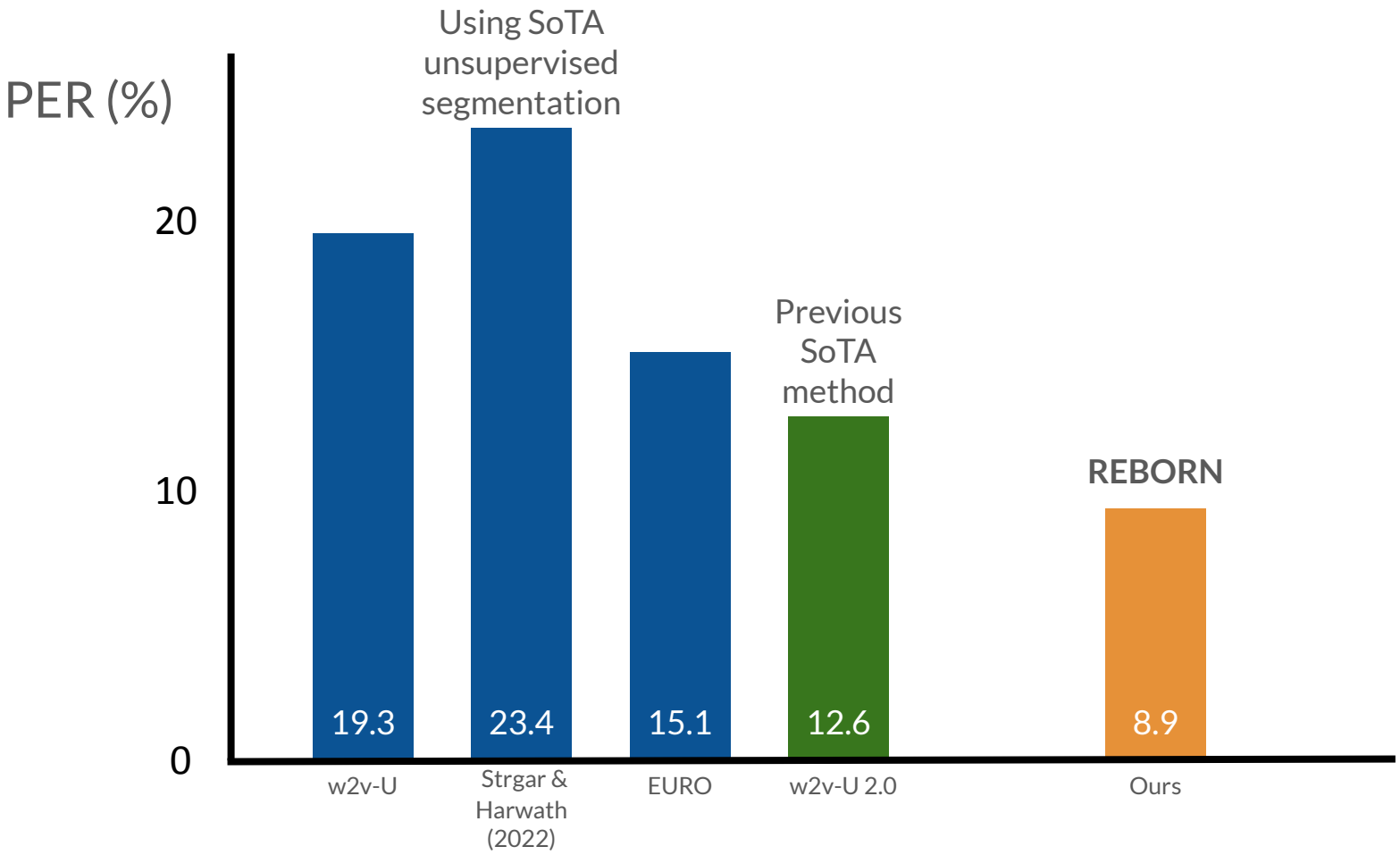

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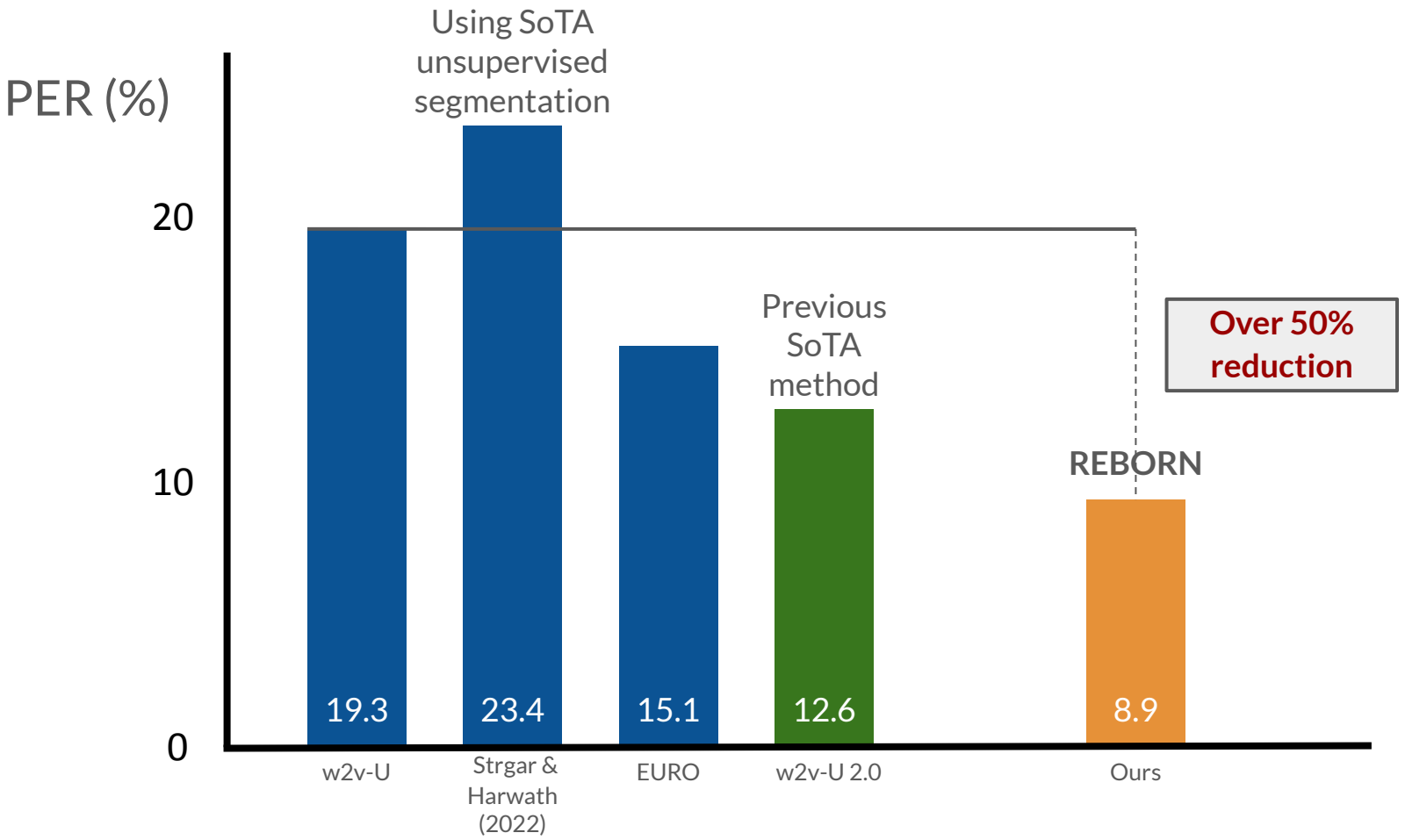

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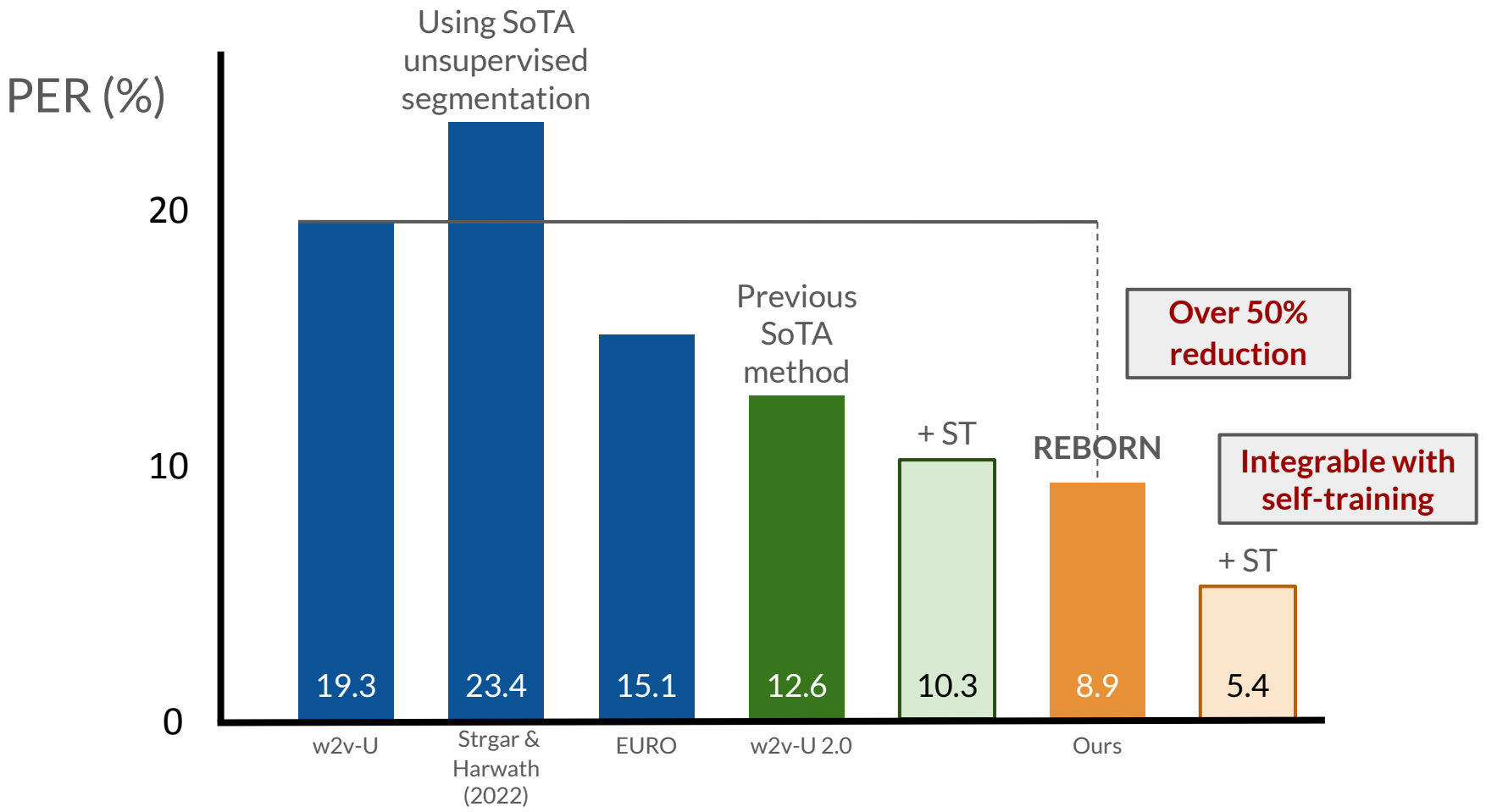
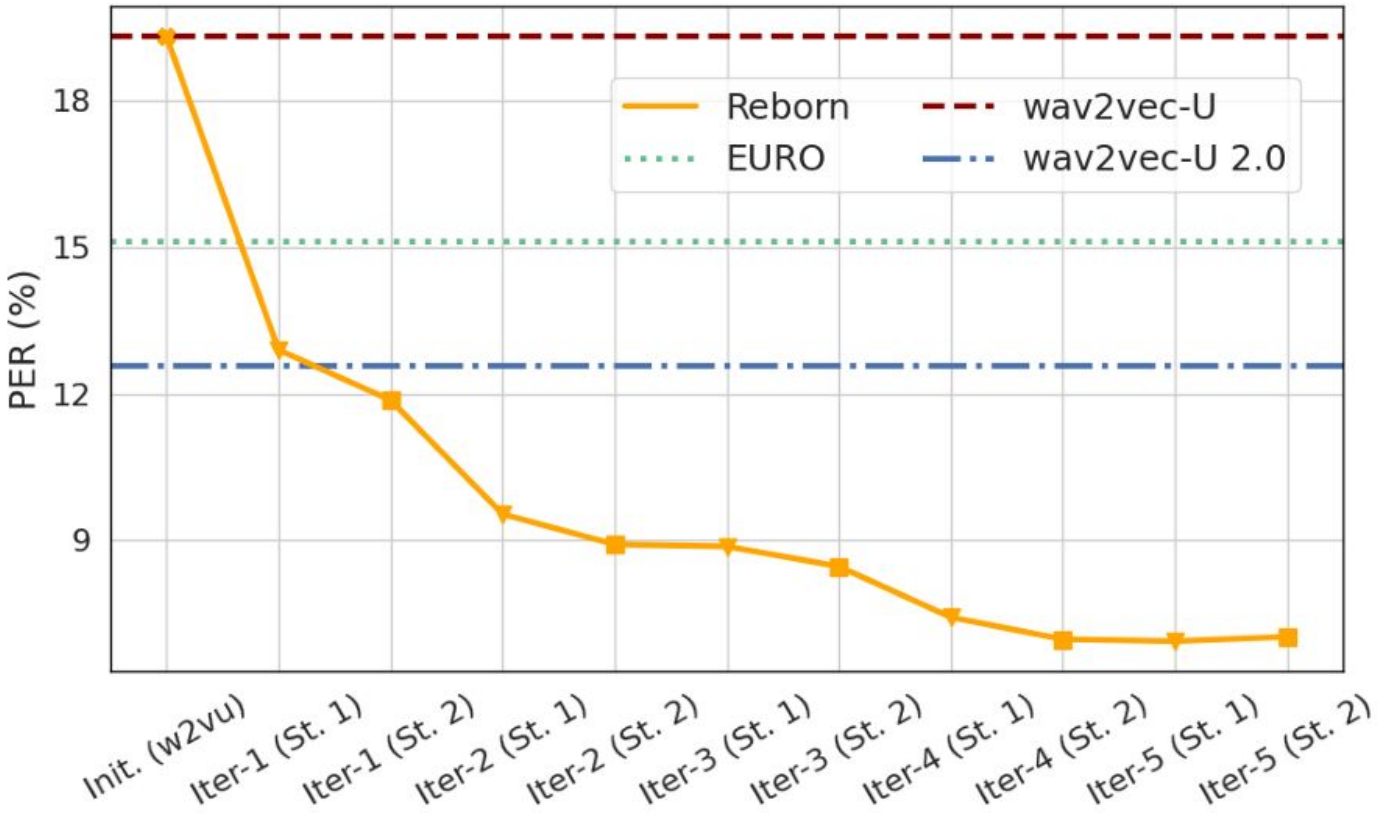


# Result of iterative training

REBORN has large performance improvements in the early iterations, and can still gradually improve afterward.



# REBORN generalizes well to other languages

We conduct experiment on Multi-lingual LibriSpeech across 6 languages.

REBORN achieves the best performance on 5 of them.

| Approach | WER (%) ↓ | | | | | | |
|---|---|---|---|---|---|---|---|
| | de | nl | fr | es | it | pt | Avg. |
| wav2vec-U† | 32.5 | 40.2 | 39.8 | 33.3 | 58.1 | 59.8 | 44.0 |
| wav2vec-U* | 33.9 | 38.1 | 37.7 | 33.1 | 51.8 | 59.4 | 42.3 |
| wav2vec-U 2.0‡ | 23.5 | 35.1 | 35.7 | 25.8 | 46.9 | **48.5** | 35.9 |
| REBORN | **20.9** | **26.9** | **28.2** | **24.7** | **39.9** | 51.5 | **32.0** |

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- We find out that **relativeness is the key** in our reward design.
- We establish an iterative learning framework that can **polish the segmentation model and phoneme predictor in turn**.
- Our method generates **excellent or even SoTA performance** on multiple datasets across different languages.

# Thank you!