Hierarchical Prosody Modeling for Non-Autoregressive Speech Synthesis

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SLT 2021

國立臺灣大學
National Taiwan University

Highlight

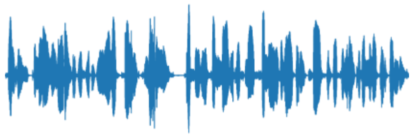
Highlight

Non-Autoregressive Text-to-Speech (NATTS)

Text Input | **NATTS Model** | **Synthesized Speech**

Computer talks. →

→



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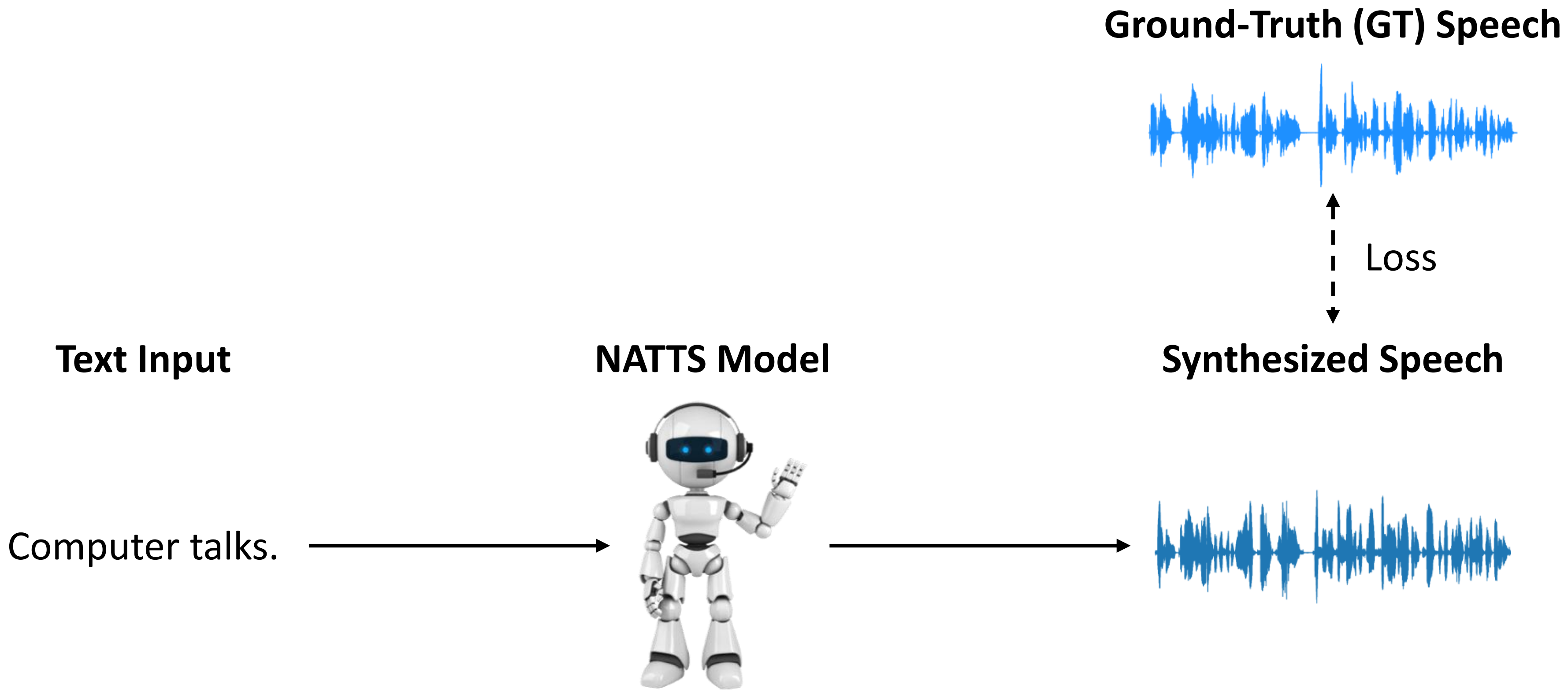

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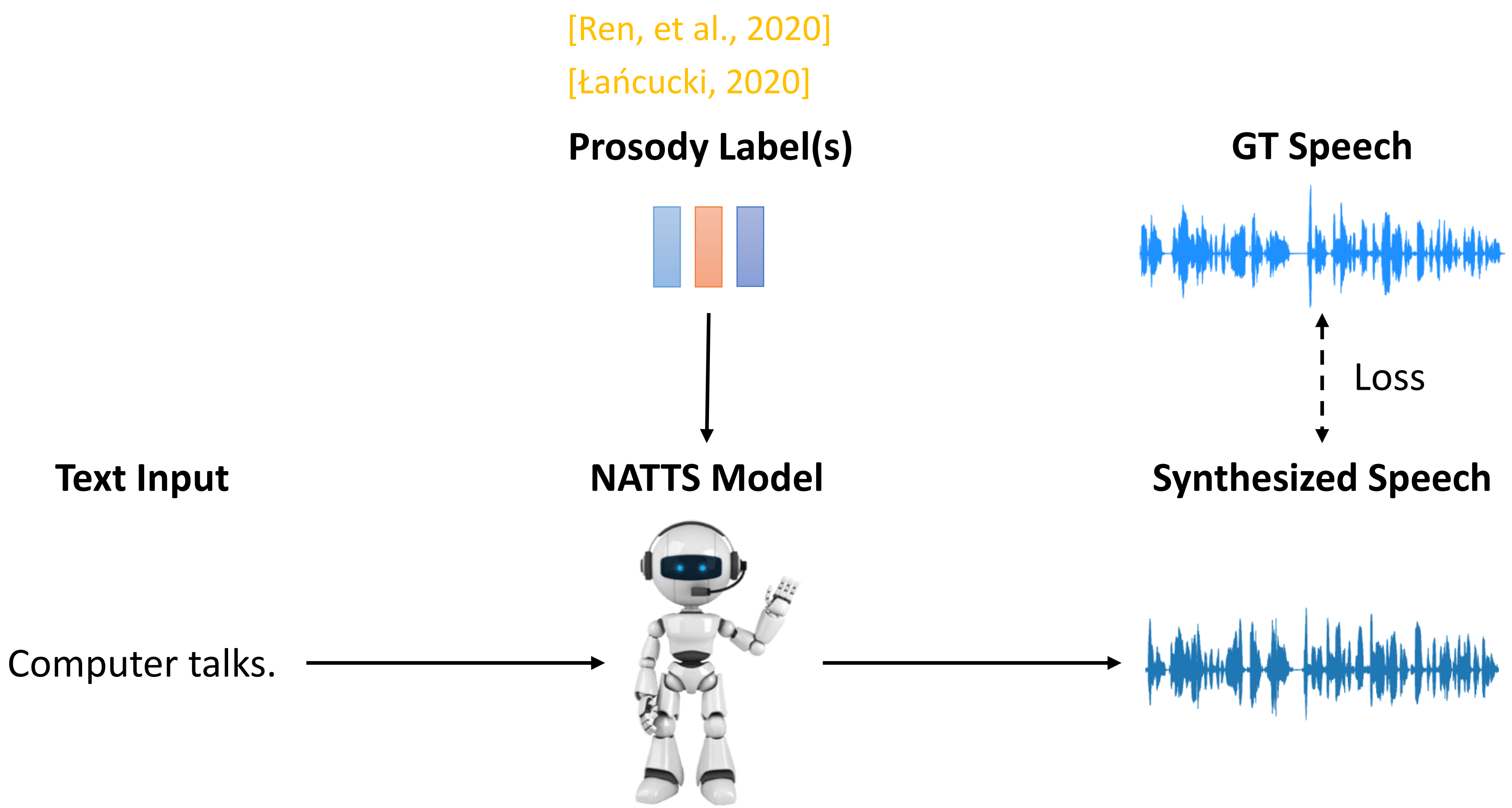
Prosody Modeling in NATTS



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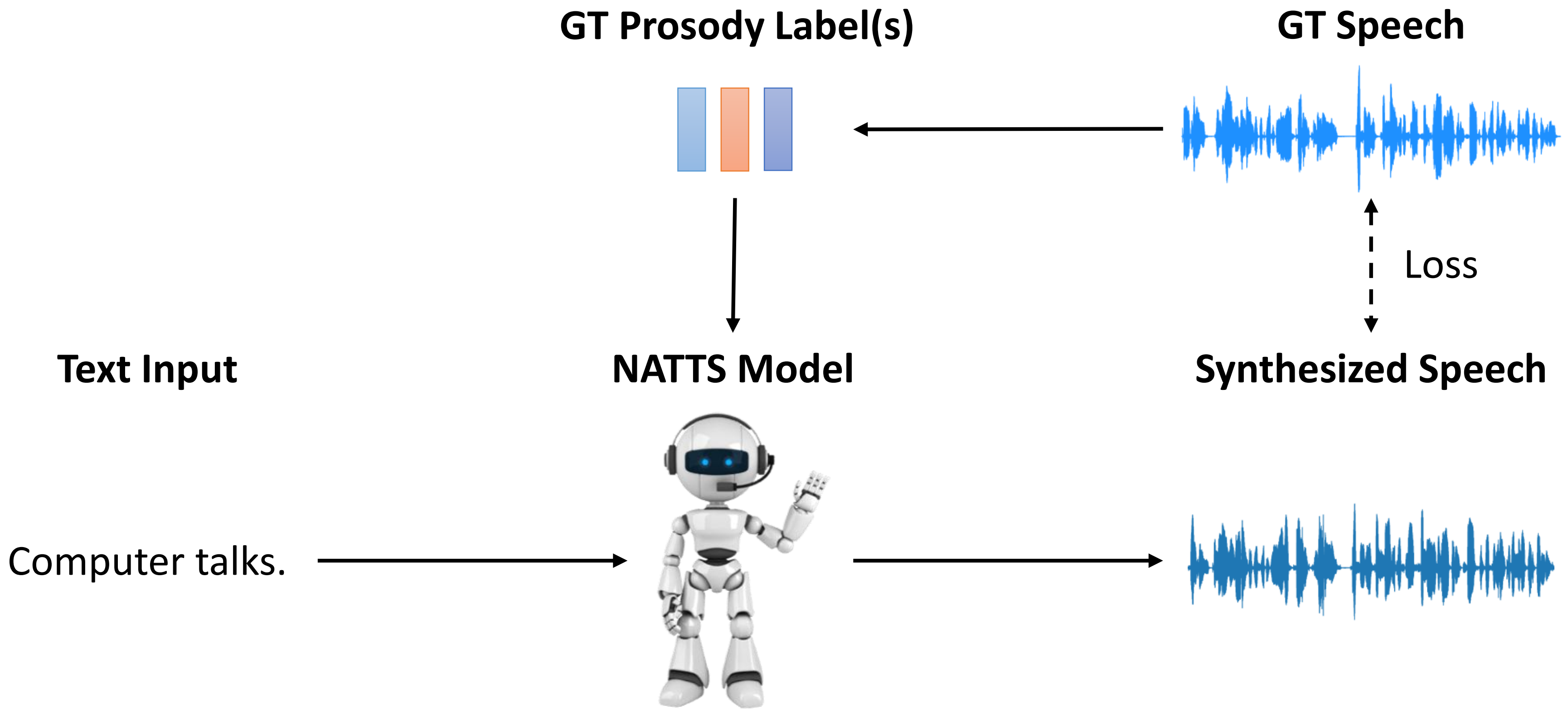
Prosody Modeling in NATTS

Training

[Ren, et al., 2020]

[Łańcucki, 2020]



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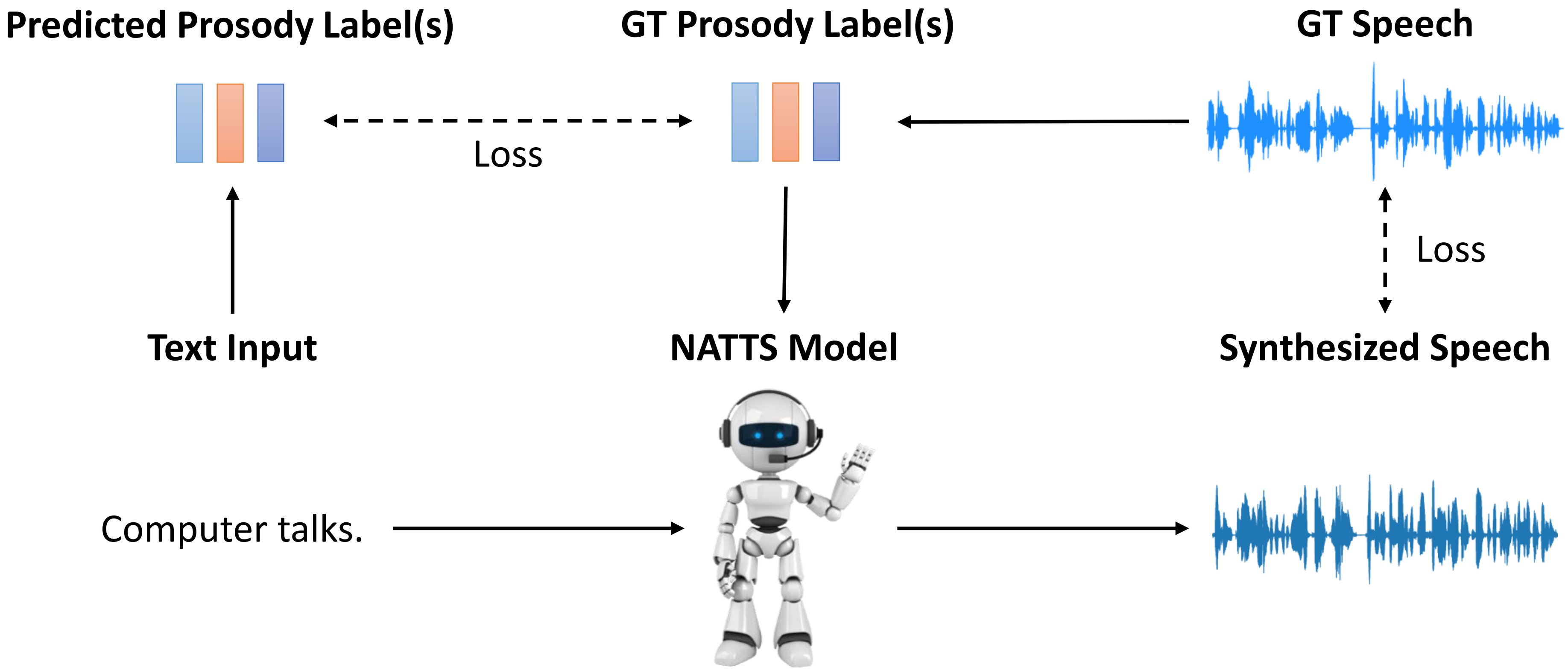

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Prosody Modeling in NATTS

Inference

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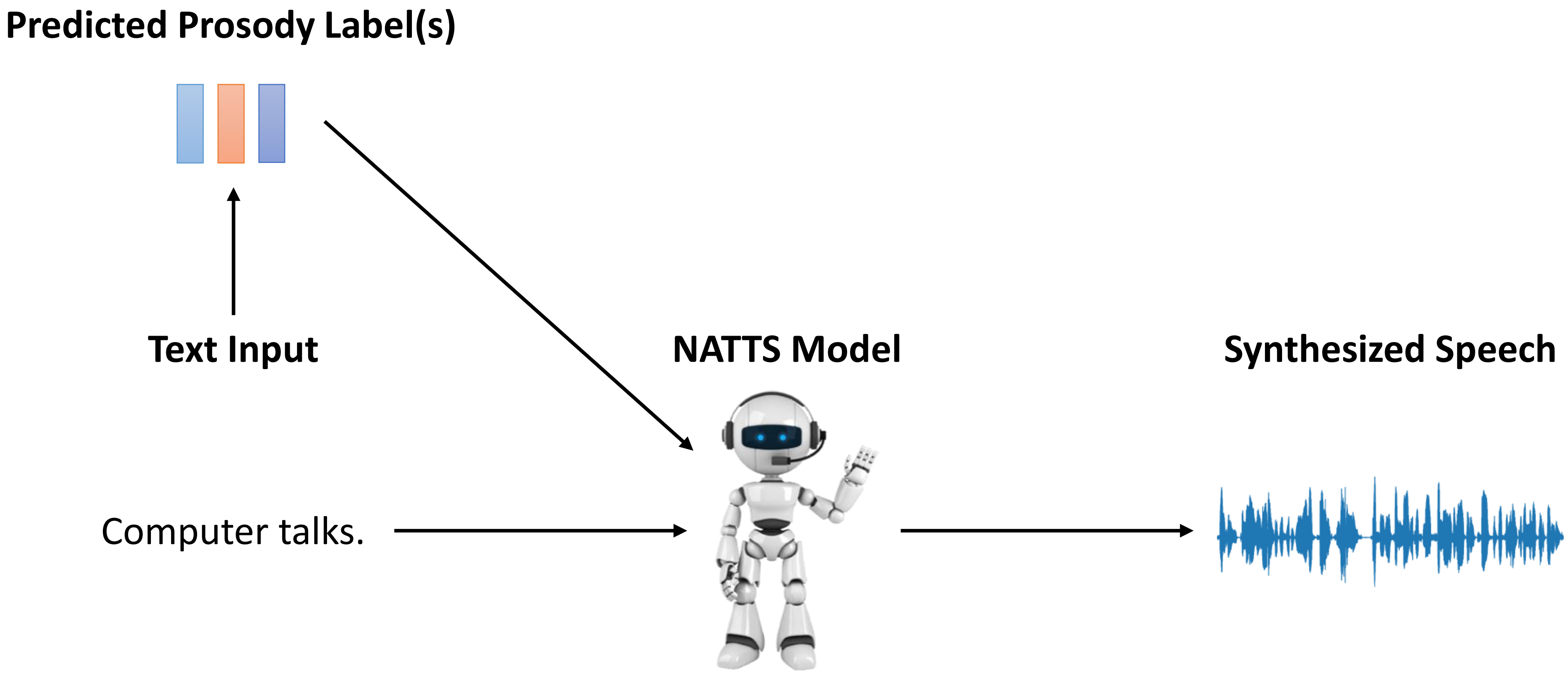
[Łańcucki, 2020]



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Proposed – Hierarchical Prosody Modeling for NATTS

Inference

Text Input

Computer talks.

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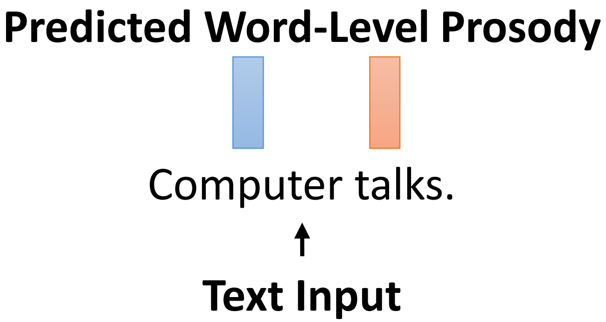

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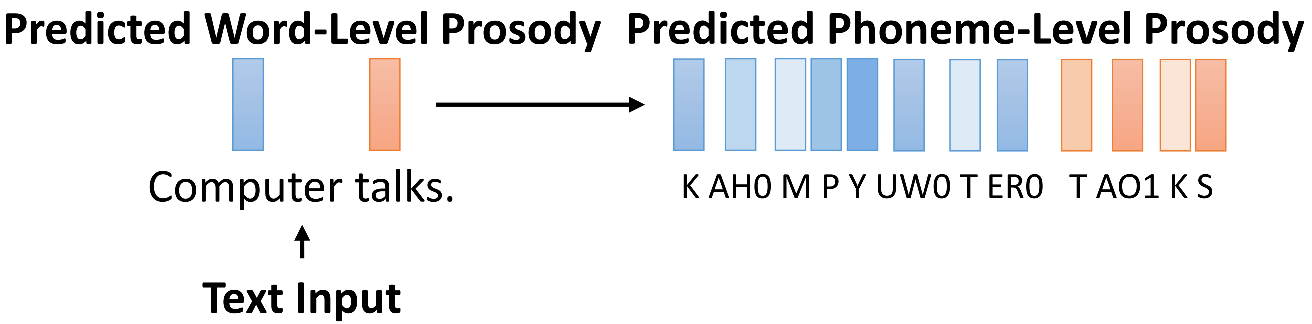

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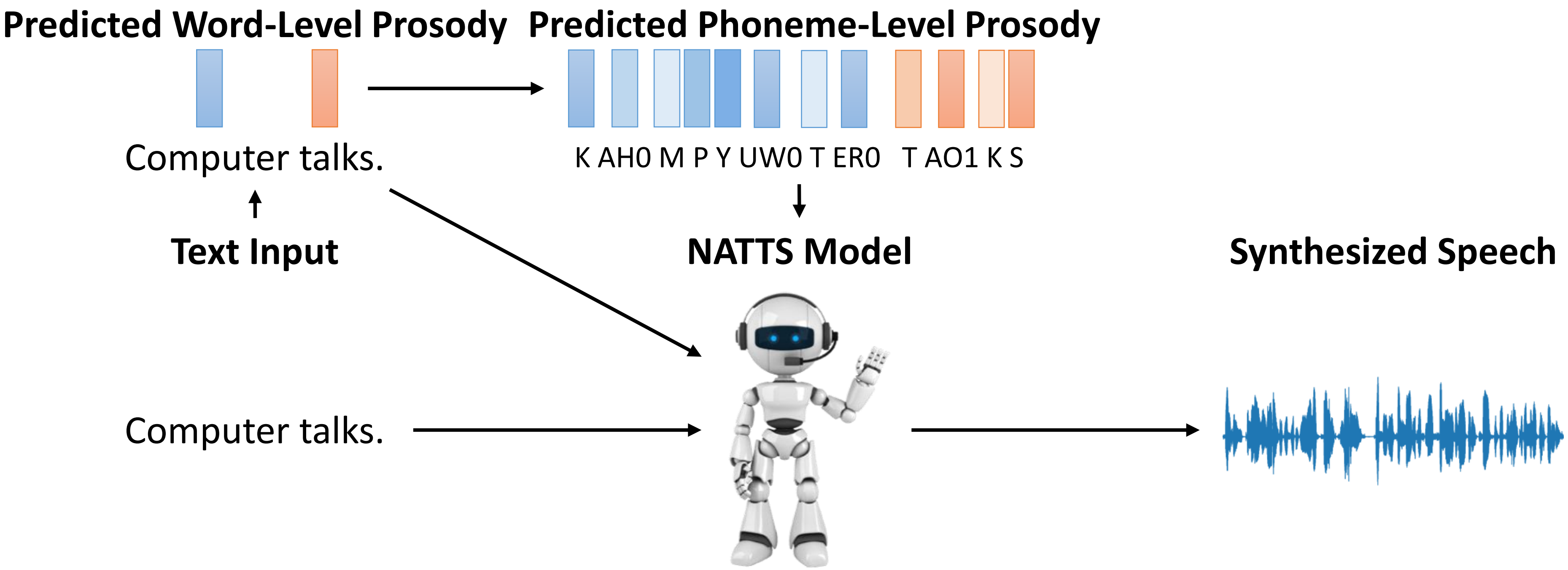

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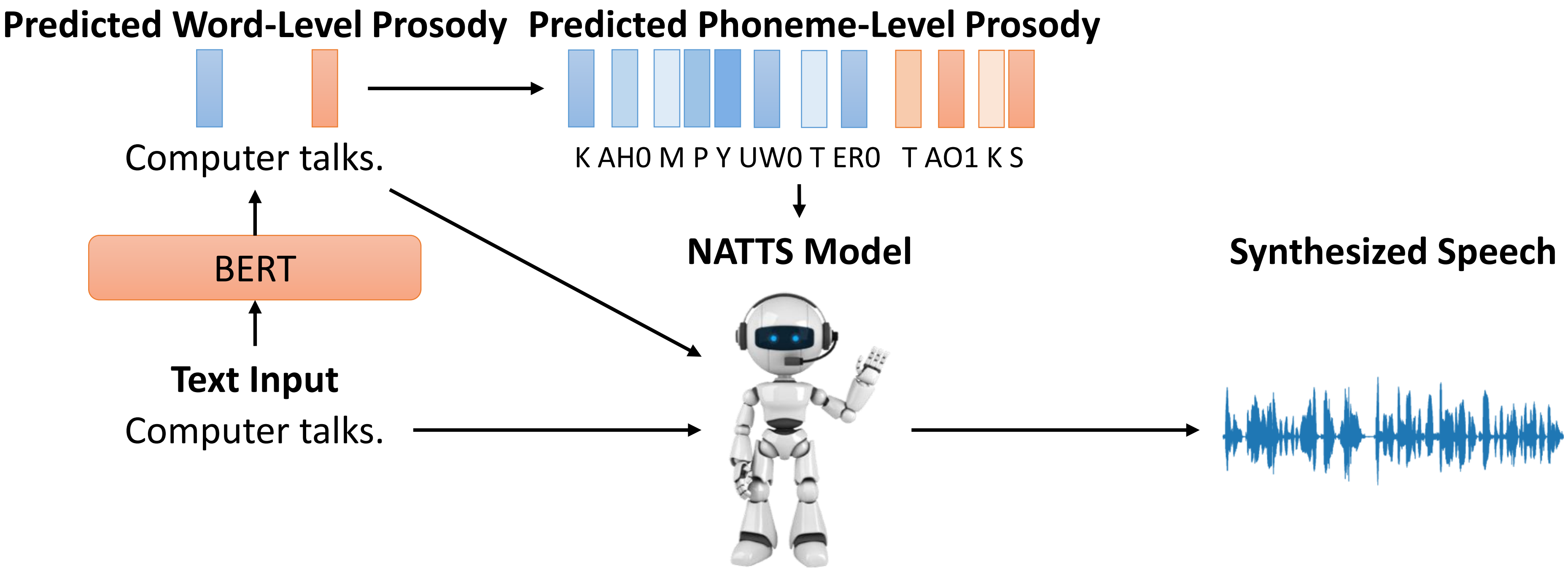


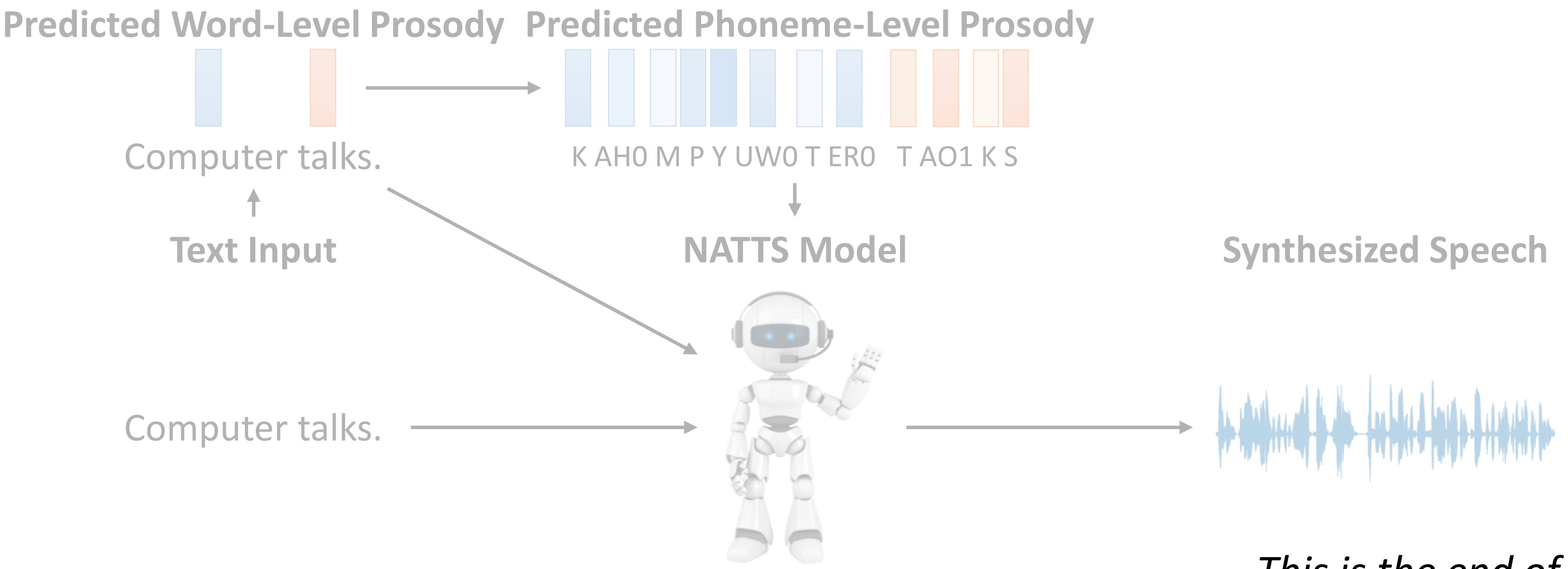
Highlight

Contribution

Prosody Naturalness

Audio Quality

Hierarchical > Non-Hierarchical > No Prosody Modeling

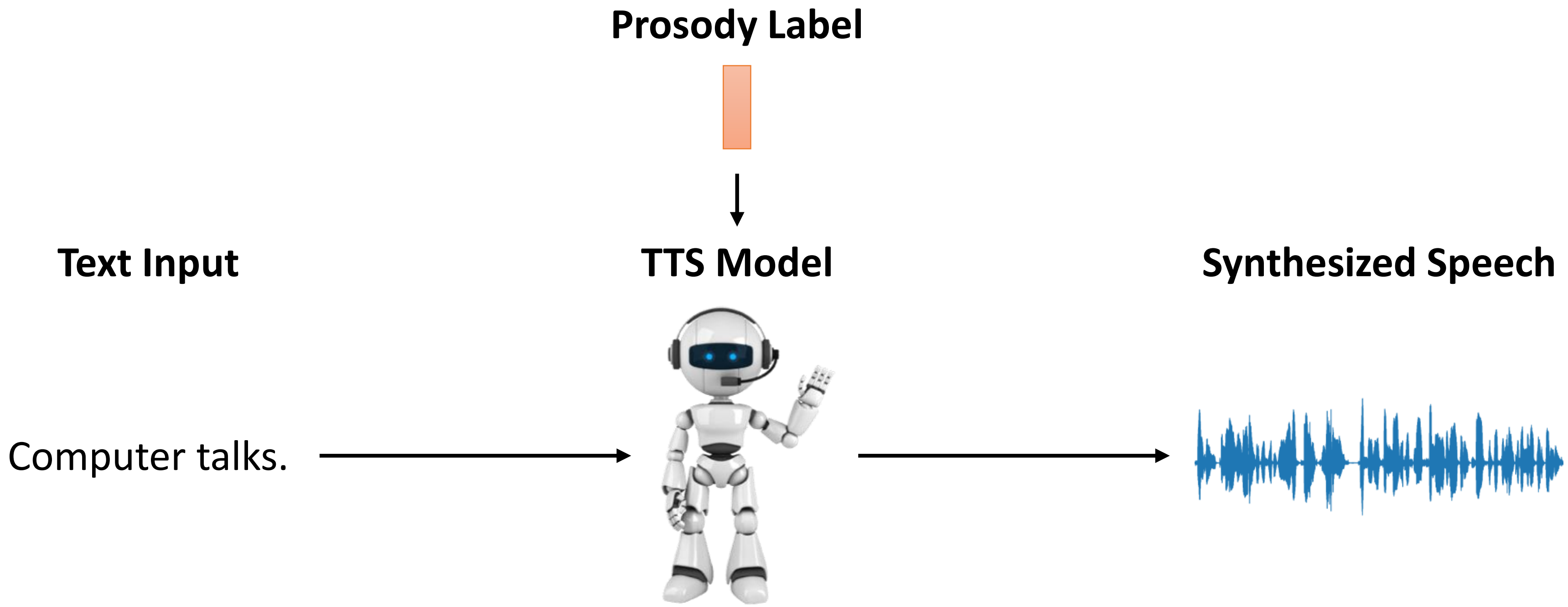


This is the end of my highlight

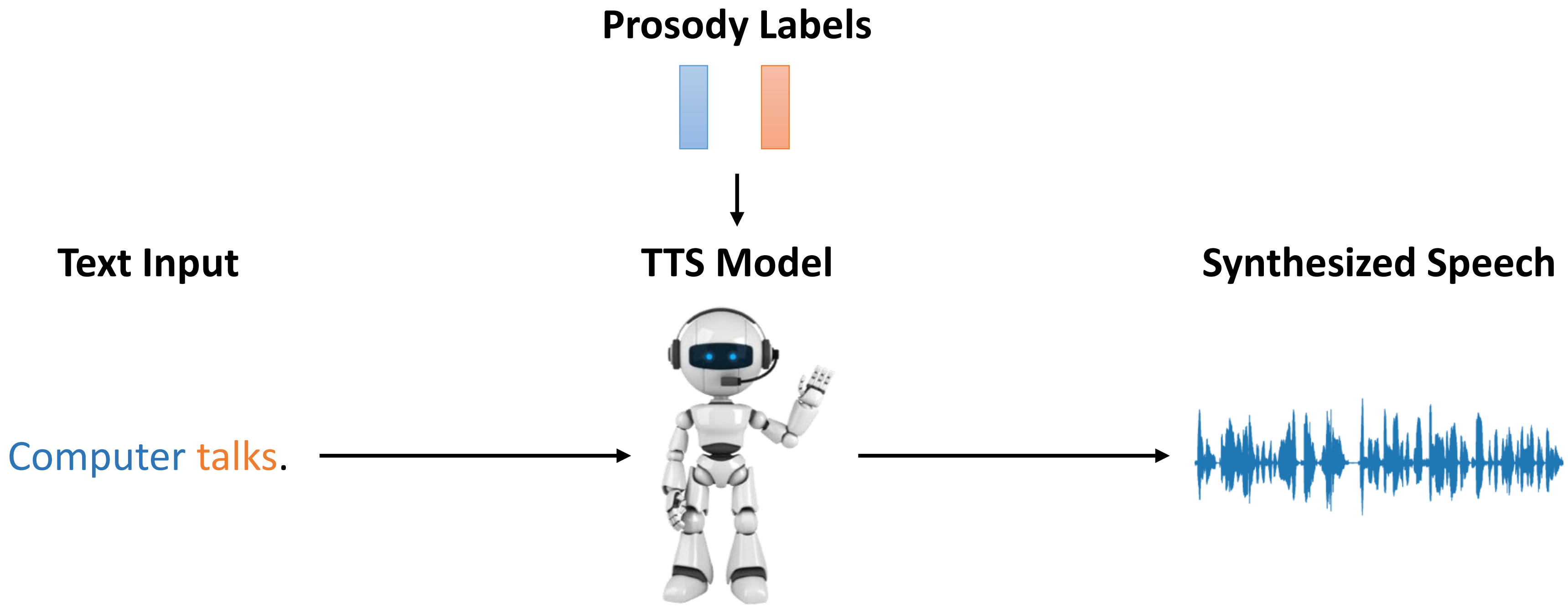
Motivation

Global Prosody Modeling

- E.g. GST-Tacotron [Wang, et al., ICML'18]



Fine-Grained Prosody Modeling [Lee, et al., ICASSP’19]



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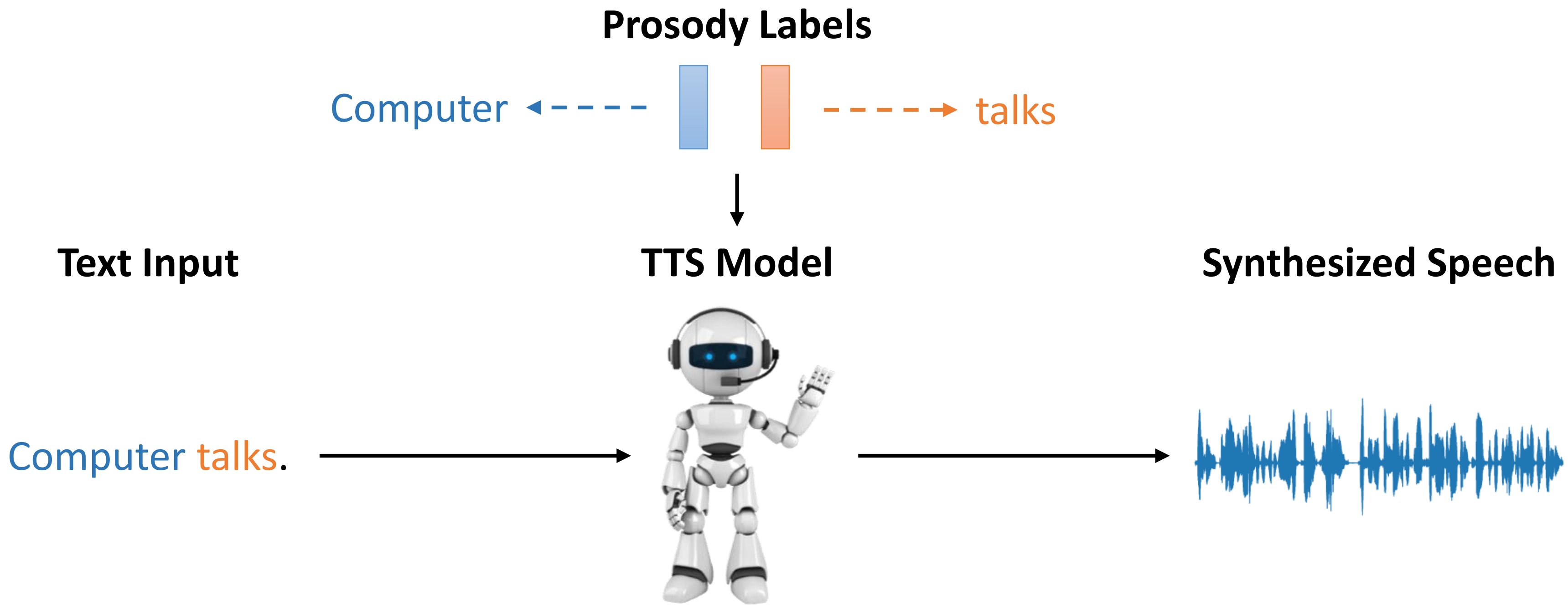

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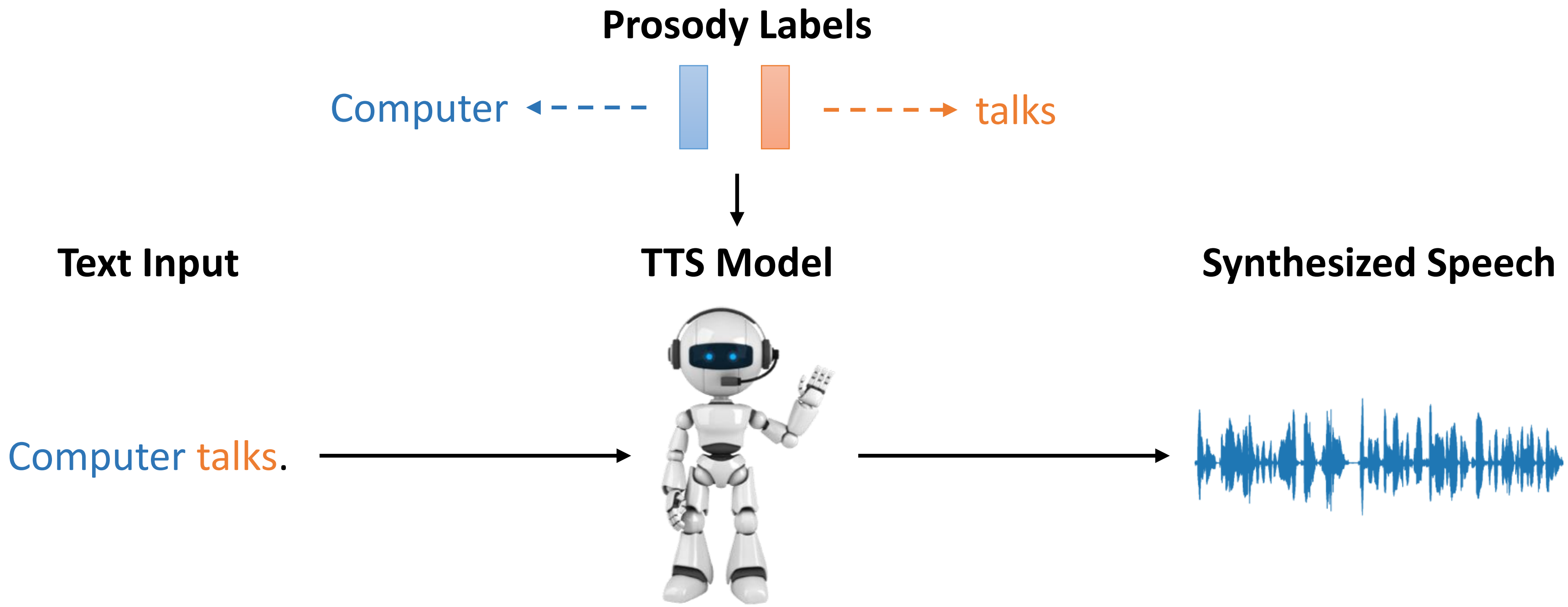
Fine-Grained Prosody Modeling [Lee, et al., ICASSP'19]

No teacher forcing for NATTS……



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Fine-Grained Prosody Modeling [Lee, et al., ICASSP’19]

No teacher forcing for NATTS……

Fine-grained prosody modeling can help!

[Ren, et al., 2020]

[Łańcucki, 2020]

Prosody Labels

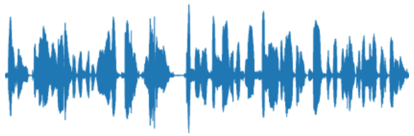
Computer ← - - - - - - - → talks

Text Input

Computer talks.

TTS Model

Synthesized Speech



Motivation

Granularity for Fine-Grained Prosody Modeling

Fine-Grained (e.g. phoneme-level)

Coarse-Grained (e.g. word-level)

Granularity for Fine-Grained Prosody Modeling

Fine-Grained (e.g. phoneme-level)

- Clear and specific prosody information
- Make training easier

Coarse-Grained (e.g. word-level)

Motivation

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Fine-Grained (e.g. phoneme-level)

- Clear and specific prosody information
- Make training easier

Coarse-Grained (e.g. word-level)

- Compatible with pretrained word-embeddings
- Accurate prosody prediction
- Contain high-level prosody information
  - Sentiment
  - Intention
  - …

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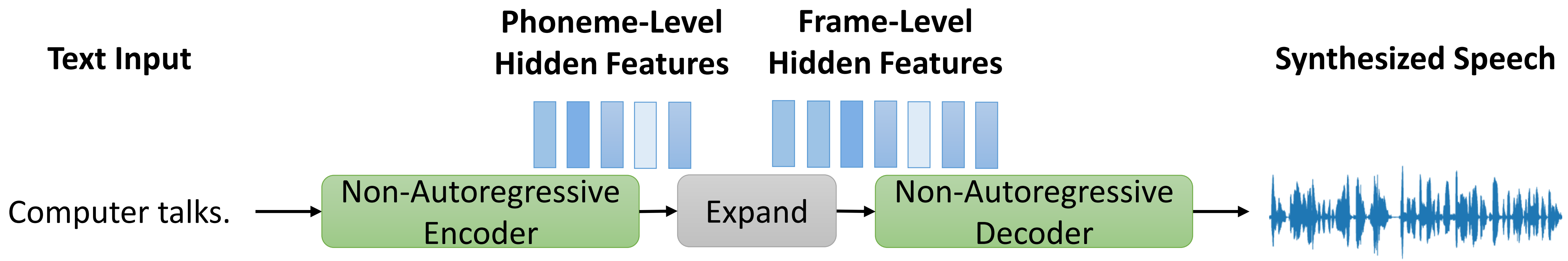
Combine the advantages by hierarchical prosody modeling!

Proposed Architecture

Baseline – FastSpeech2 [Ren, et al., 2020]



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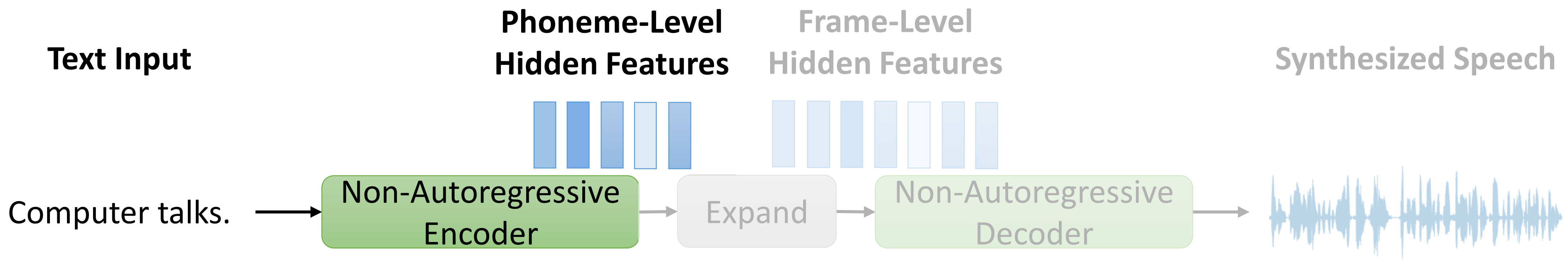

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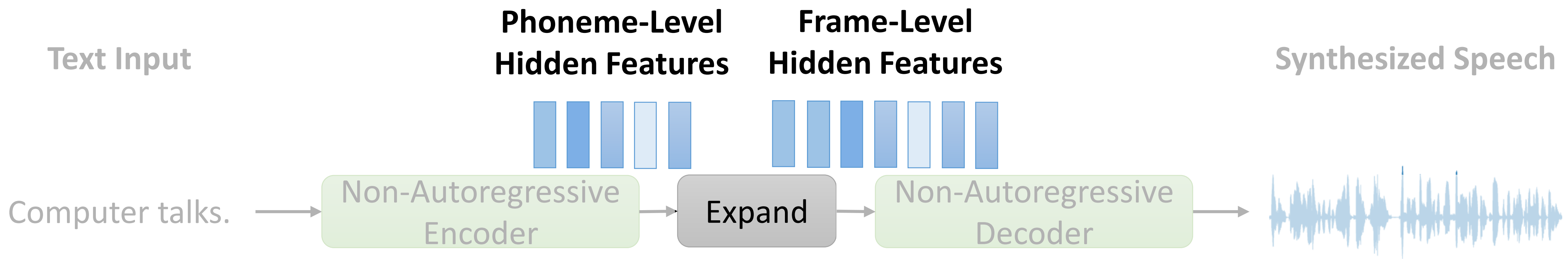

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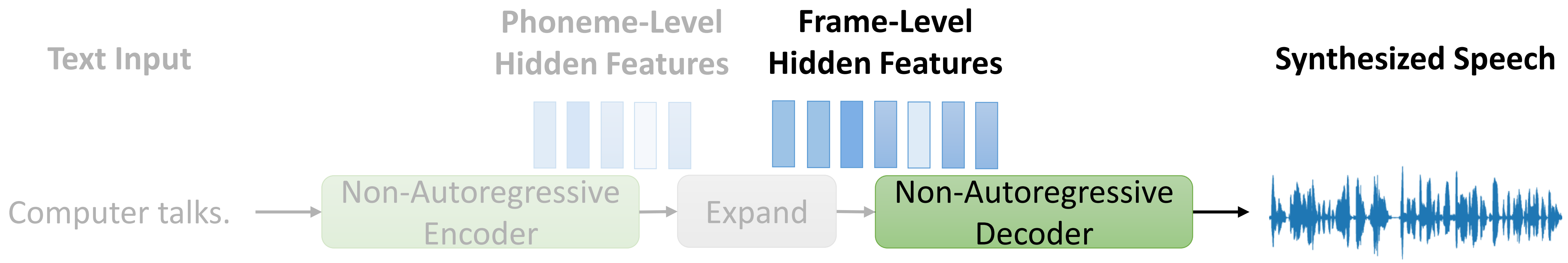
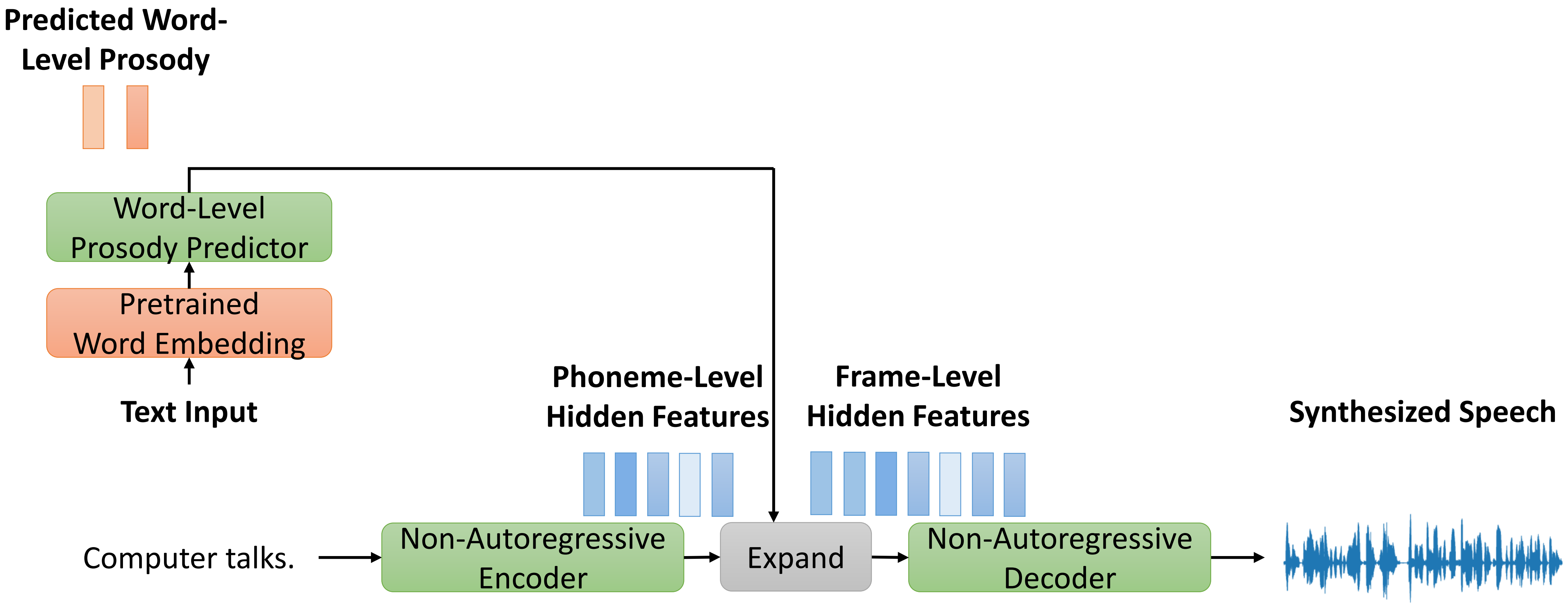


Hierarchical Prosody Modeling **Inference**



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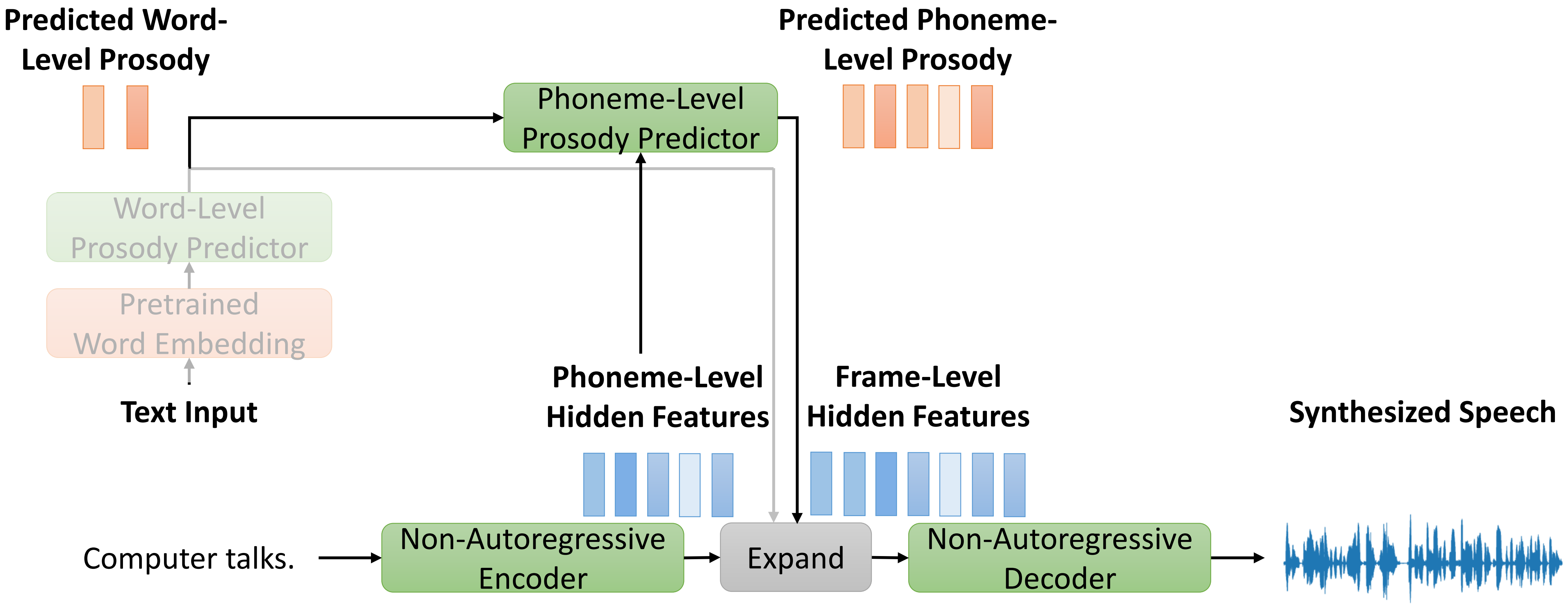

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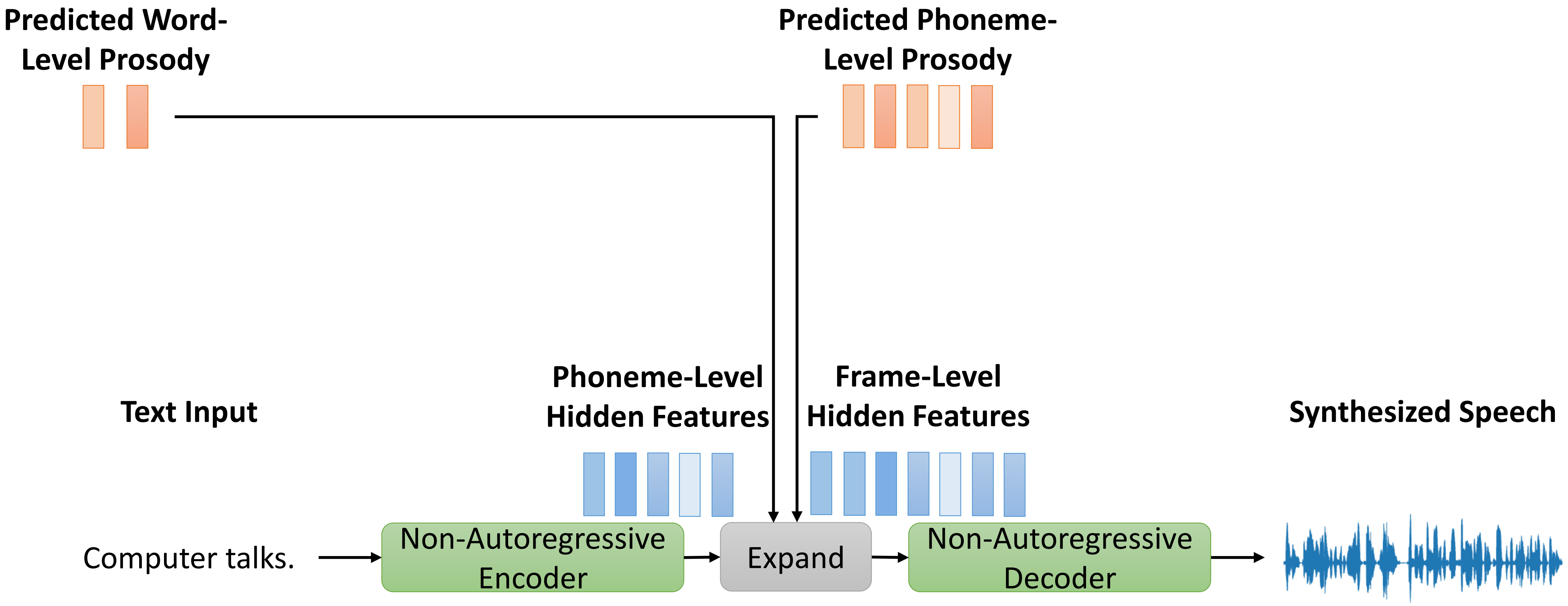

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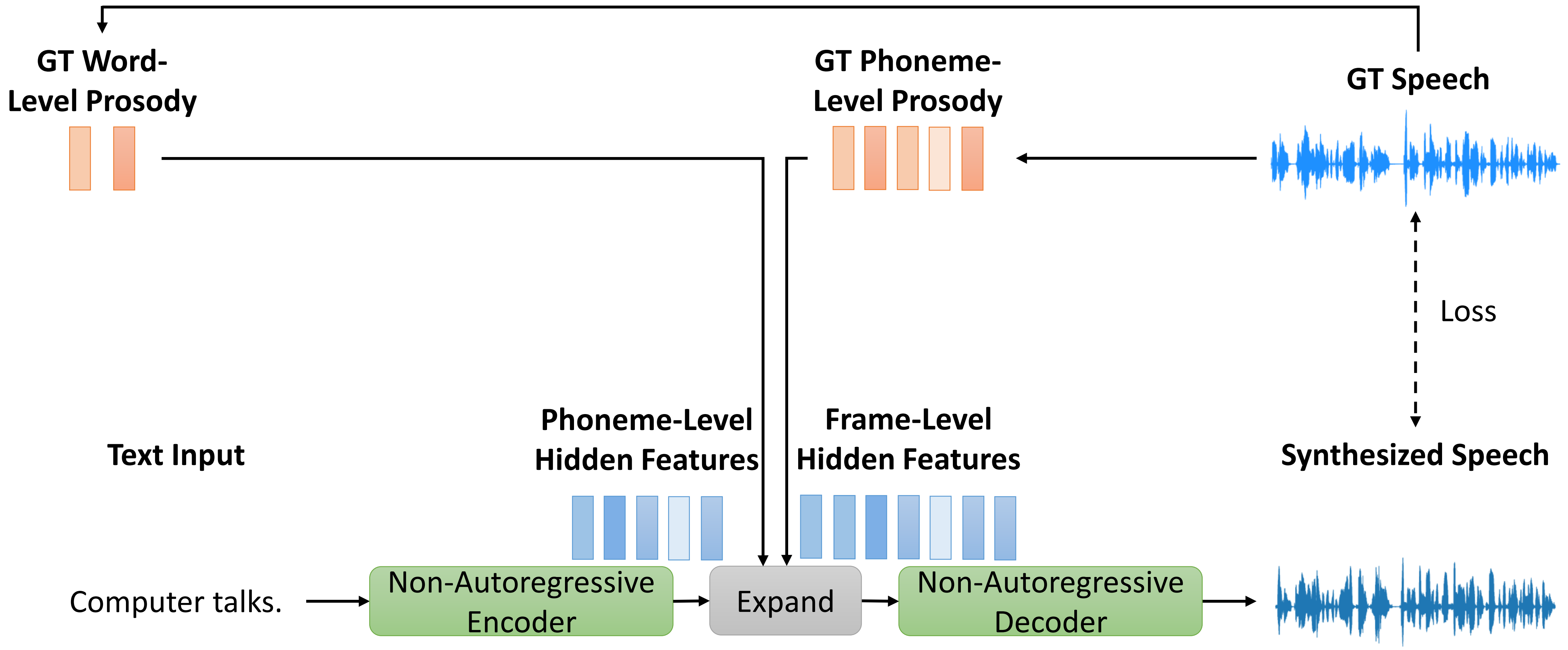
Hierarchical Prosody Modeling **Training**



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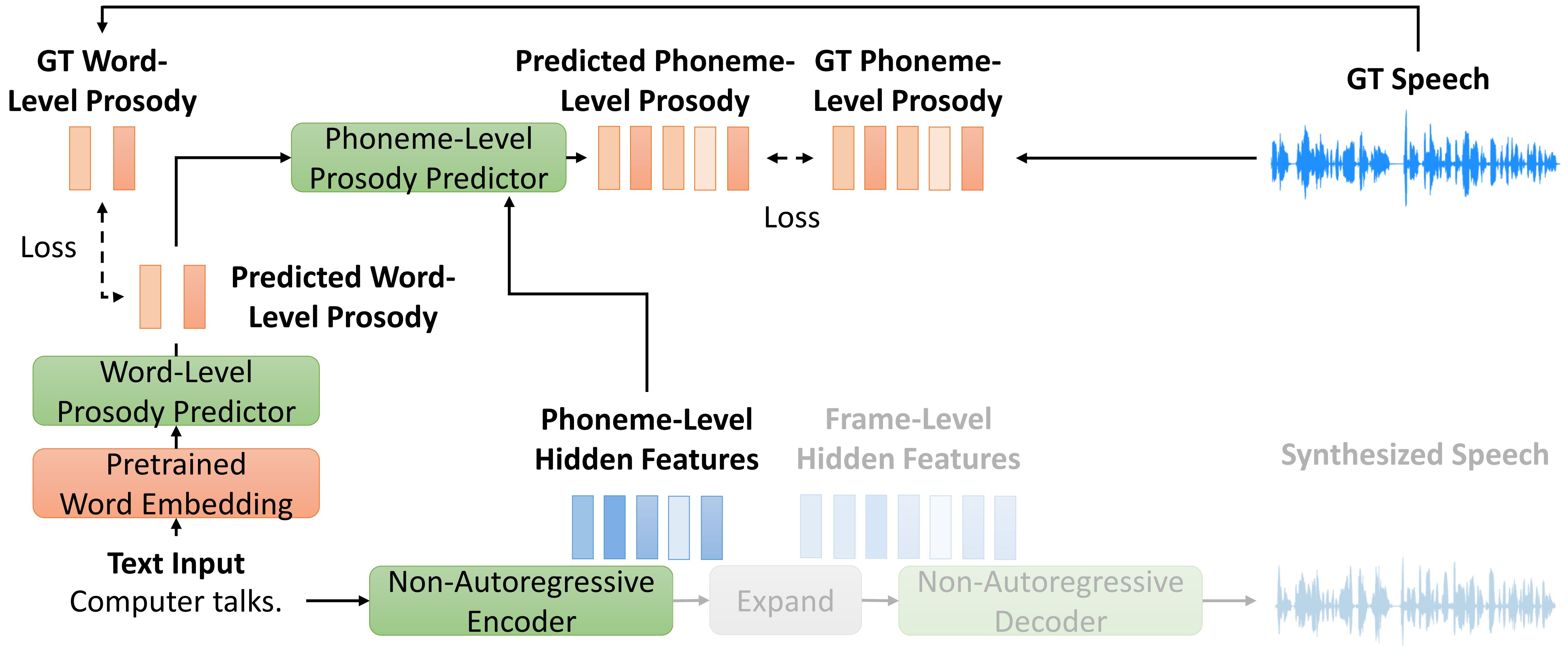

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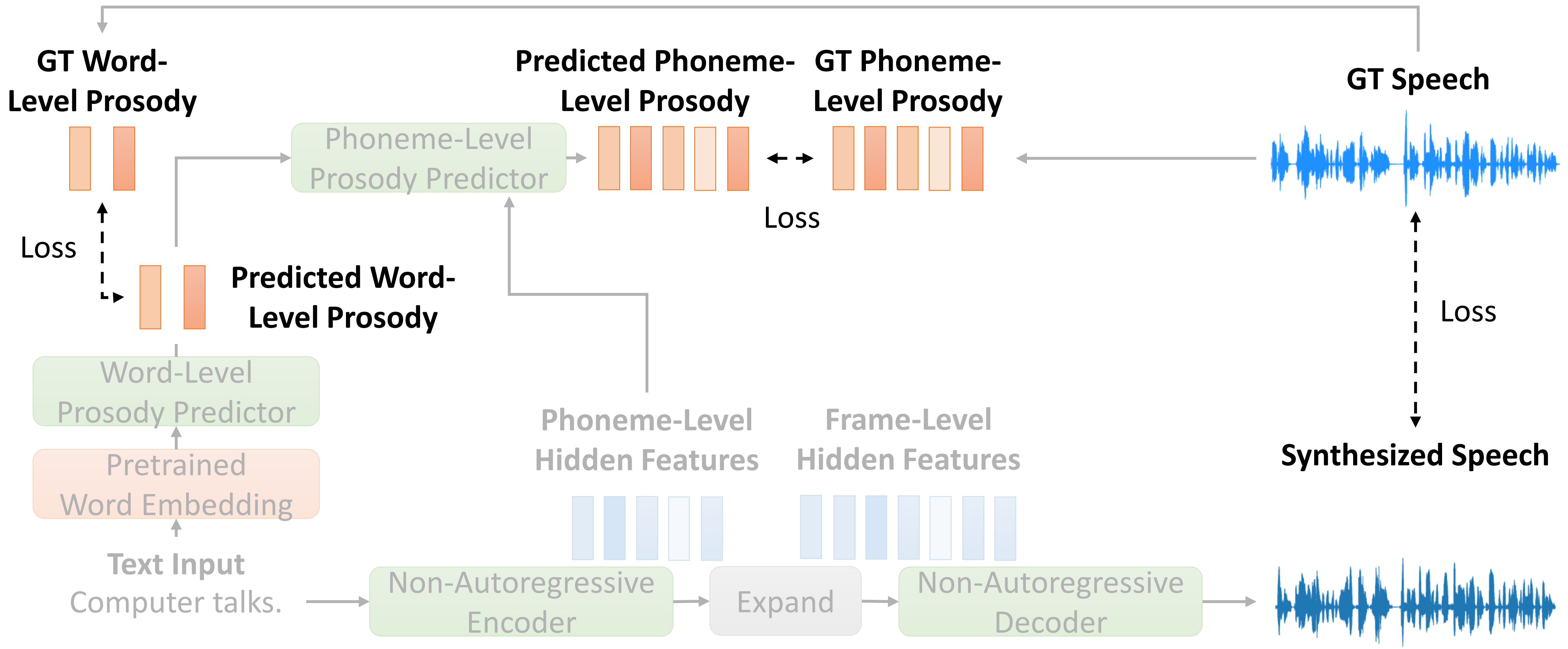
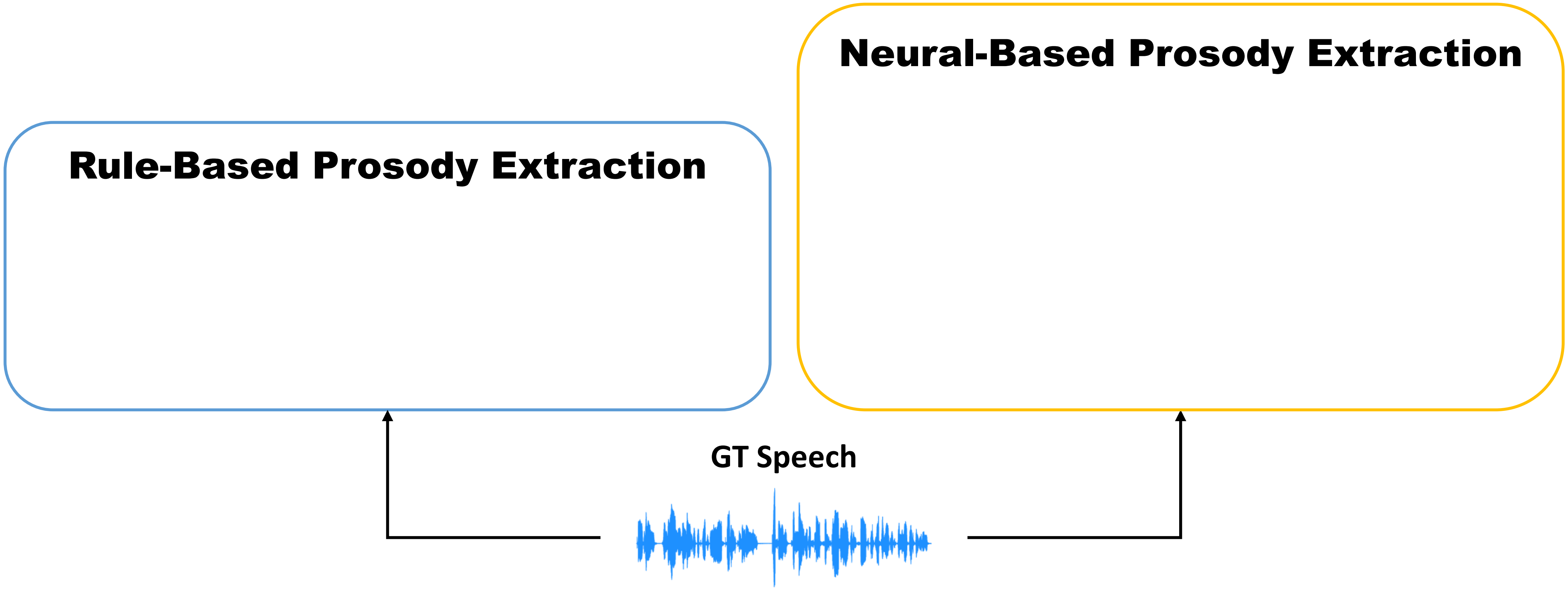


Different Prosody Labels



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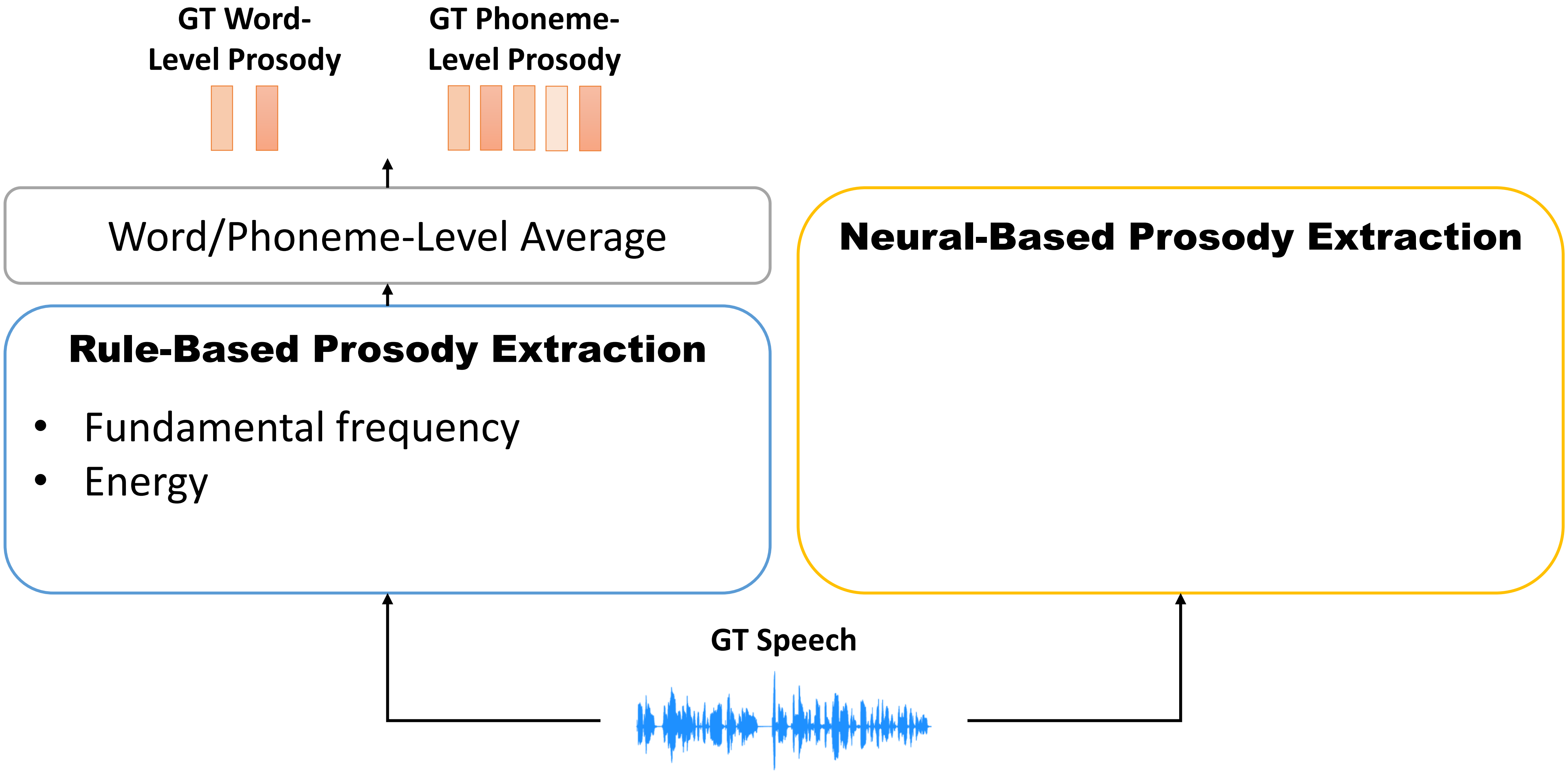

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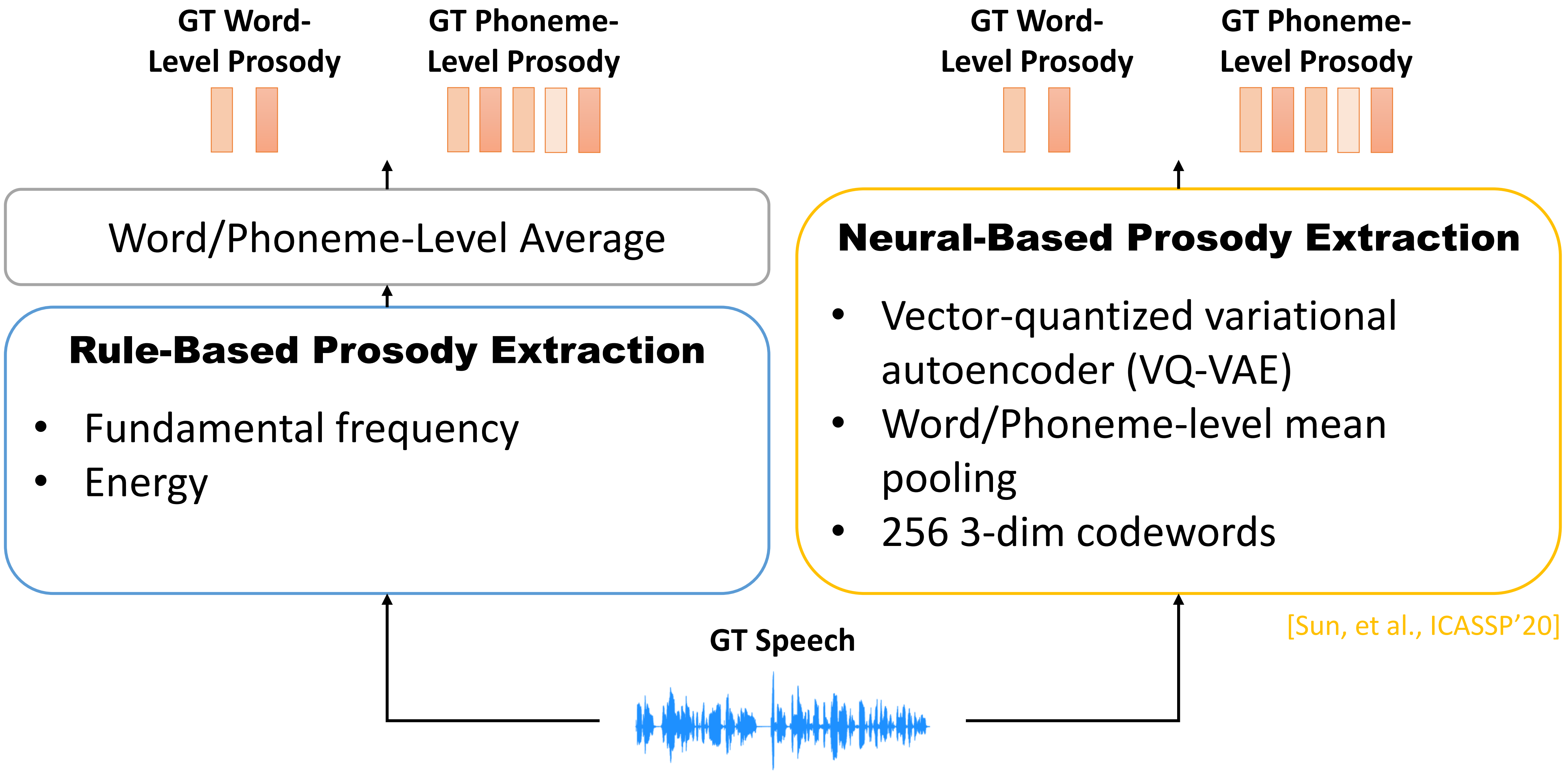

Experiments

Prosody Prediction Accuracy

Can Word Embedding Really Help?

Prosody Prediction Accuracy

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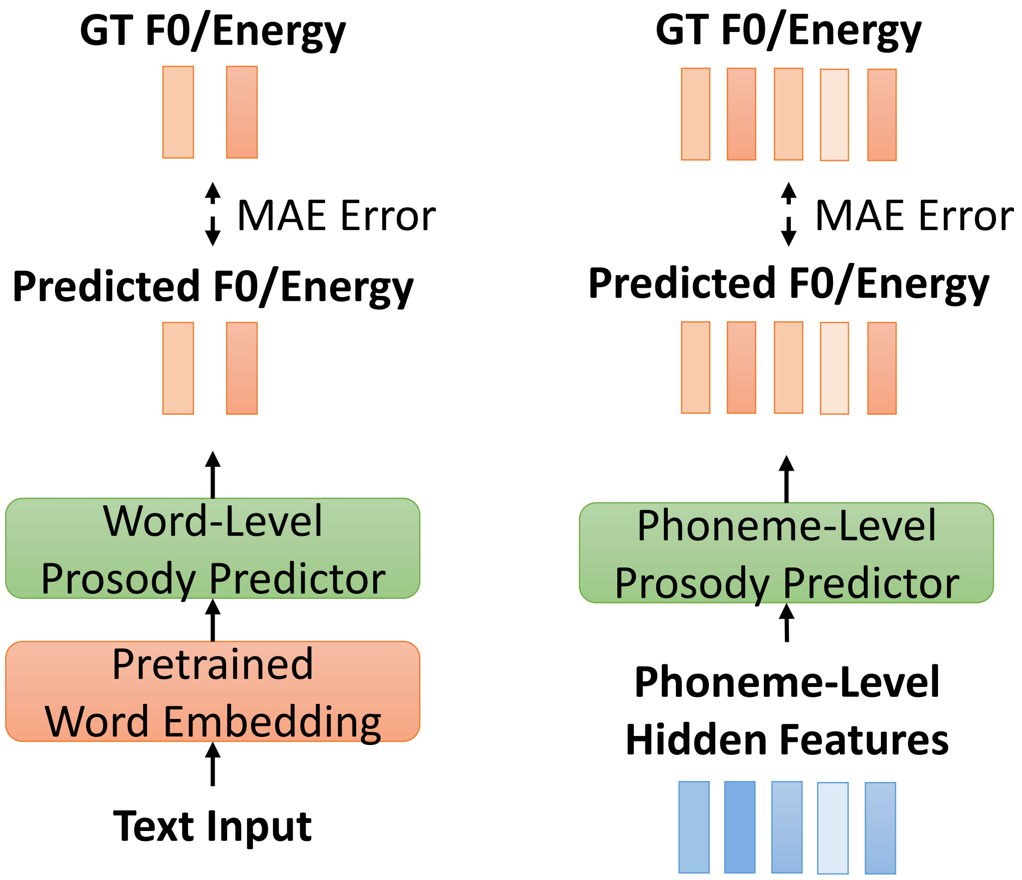

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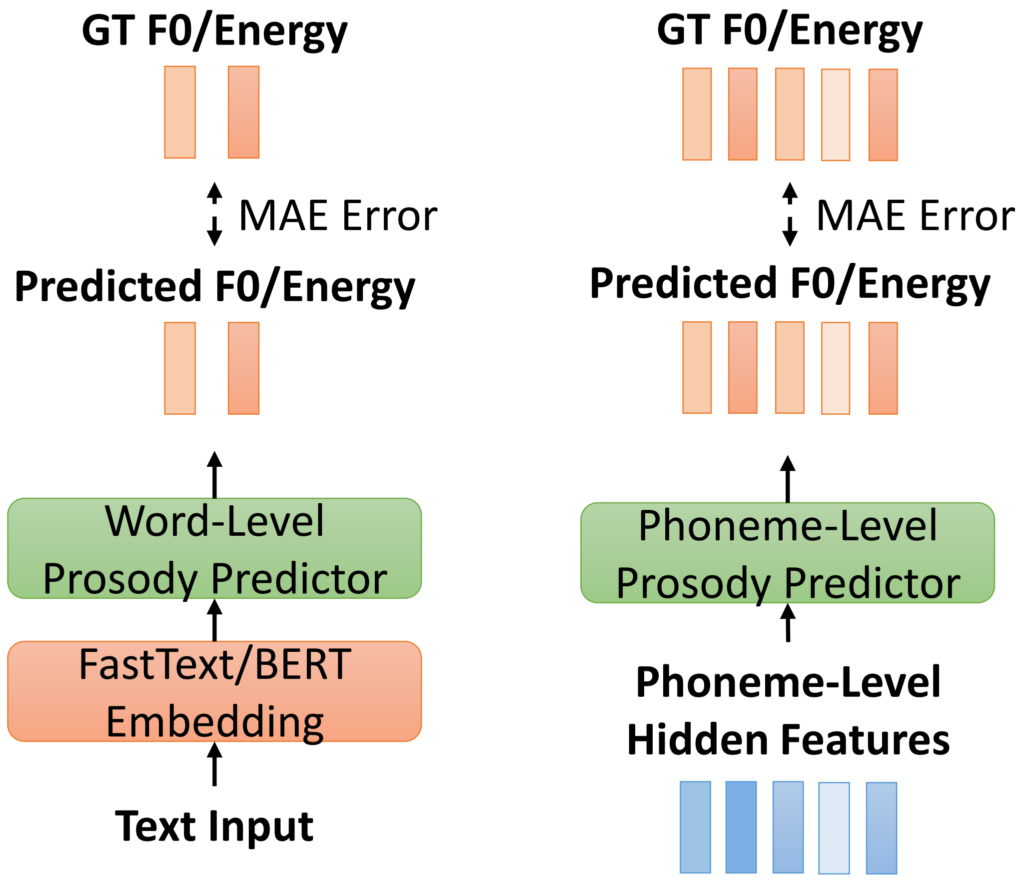

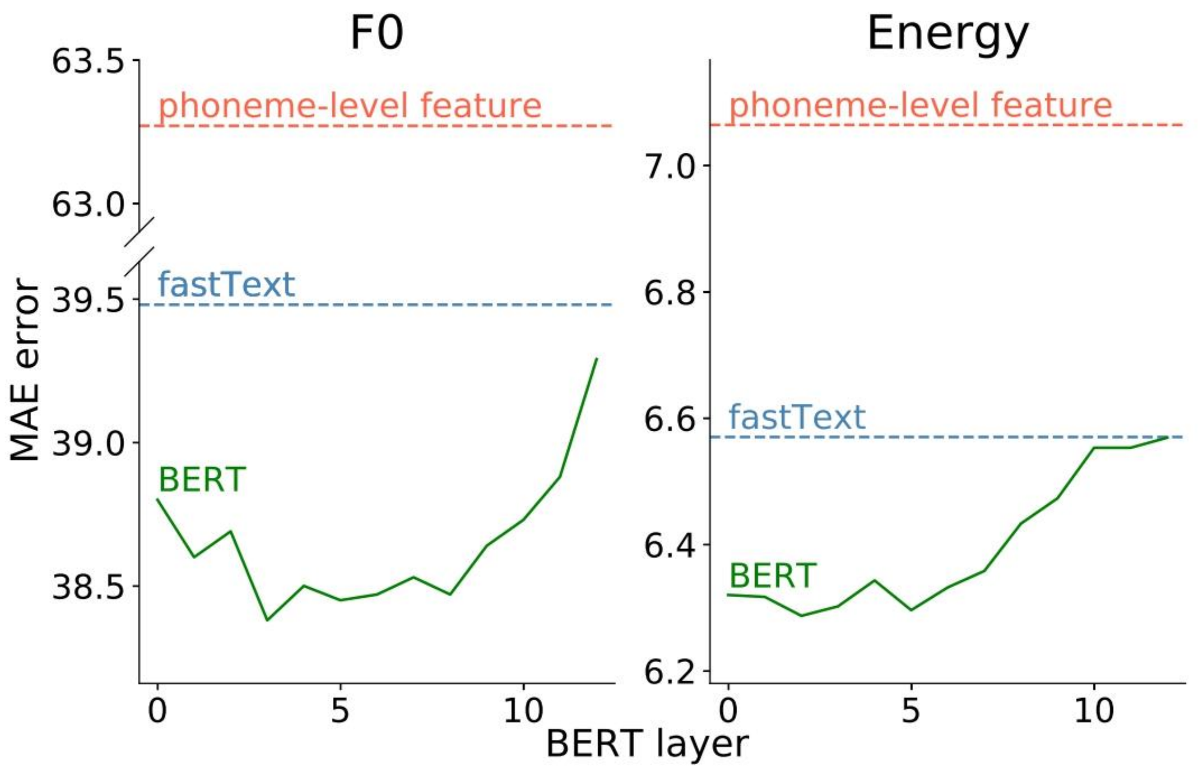

BERT > FastText > Phoneme-Level Feature

Different Prosody Labels

Objective Evaluation

Rule-Based Prosody Labels v.s. Neural-Based Prosody Labels

Different Prosody Labels

Objective Evaluation

Metrics

- GPE (gross pitch error)
- VDE (voice decision error)
- E-MAE (mean absolute error of energy)
- F0-MAE (mean absolute error of F0)

computed between synthesized utterances and the ground-truth utterances

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Rule-Based Prosody Labels v.s. Neural-Based Prosody Labels

	Prosody Label	GPE↓	VDE↓	F-MAE↓	E-MAE↓
Word-Level	Rule-Based	**0.3952**	**0.2800**	**40.202**	**7.264**
	Neural-Based	0.3977	0.2972	42.096	8.050
Phoneme-Level	Rule-Based	0.4084	0.2836	41.806	7.363
	Neural-Based	0.4113	0.2898	43.385	7.441
No Prosody Modeling		0.4063	0.2856	42.829	8.205

Different Prosody Labels

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Different Prosody Labels

Subjective Evaluation

Metrics

MOS (mean of opinion score)

Scale: 1 ~ 5

Different Prosody Labels

Subjective Evaluation

Metrics

MOS (mean of opinion score)

Scale: 1 ~ 5

	Prosody Label	MOS↑
Ground-Truth		4.318
Vocoder Reconstruction		3.722
Word-Level	Rule-Based	3.564
	Neural-Based	3.452
Phoneme-Level	Rule-Based	3.662
	Neural-Based	3.596
No Prosody Modeling		3.378

Different Prosody Labels

Subjective Evaluation

Metrics | MOS (mean of opinion score)

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Rule-Based > Neural-Based > No Prosody Modeling

Different Prosody Labels

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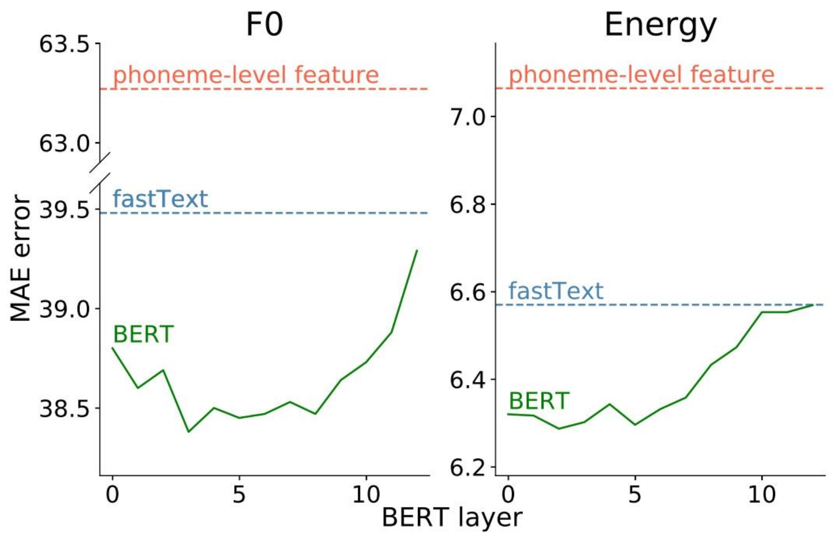

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Rule-Based > Neural-Based > No Prosody Modeling

Phoneme-Level > Word-Level

Contradiction?

Different Prosody Labels

Subjective Evaluation

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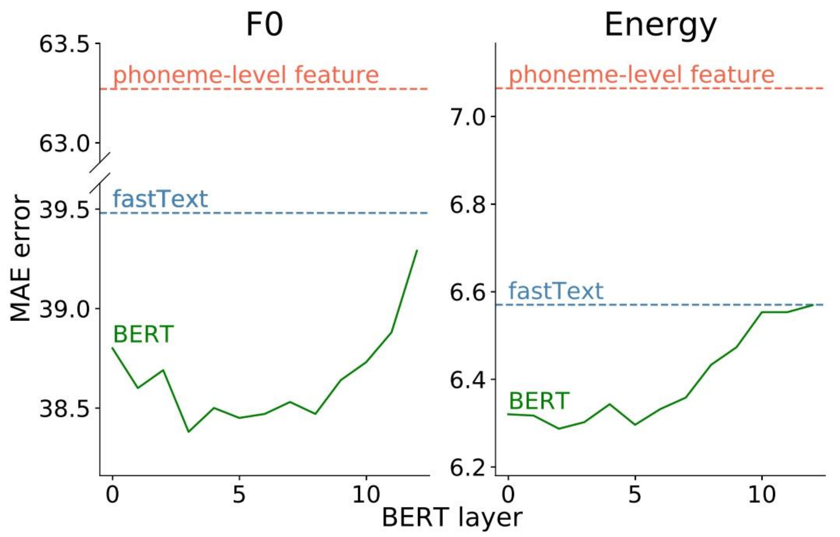

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Rule-Based > Neural-Based > No Prosody Modeling

Phoneme-Level > Word-Level

Contradiction?

Phoneme-Level

- Better quality

Word-Level

- Accurate prosody prediction

Different Prosody Labels

Subjective Evaluation

Metrics | MOS (mean of opinion score)

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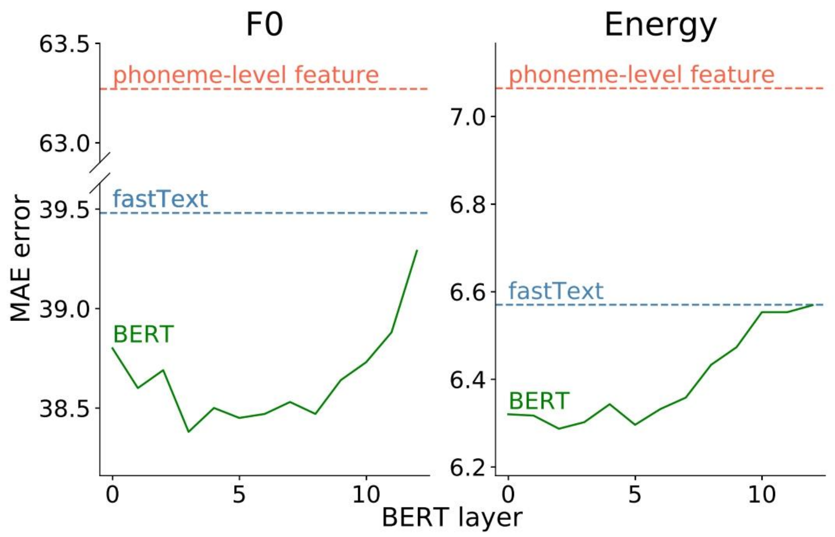

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Rule-Based > Neural-Based > No Prosody Modeling

Phoneme-Level > Word-Level *Contradiction?*

Phoneme-Level

- Better quality

Word-Level

- Accurate prosody prediction

That's why we need hierarchical prosody modeling!

Hierarchical Prosody Modeling

Objective Evaluation

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Hierarchical > Non-Hierarchical > No Prosody Modeling

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Hierarchical Prosody Modeling		**0.3886**	**0.2758**	**39.597**	**7.263**

For the hierarchical model, rule-based prosody labels are used at the word-level, and neural-based labels are used at the phoneme-level.

Hierarchical Prosody Modeling

Subjective Evaluation

Metrics

MOS (mean of opinion score)

Scale: 1 ~ 5

Hierarchical > Non-Hierarchical > No Prosody Modeling

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Hierarchical Prosody Modeling		**3.712**

For the hierarchical model, rule-based prosody labels are used at the word-level, and neural-based labels are used at the phoneme-level.

Hierarchical Prosody Modeling

Subjective Evaluation

Metrics

MOS (mean of opinion score)

Scale: 1 ~ 5

Hierarchical > Non-Hierarchical > No Prosody Modeling

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For the hierarchical model, rule-based prosody labels are used at the word-level, and neural-based labels are used at the phoneme-level.

Hierarchical Prosody Modeling

Pairwise Subjective Evaluation

Metrics

CMOS (comparative MOS)

Scale: -3 ~ 3

AXY score

Scale: -3 ~ 3

Hierarchical Prosody Modeling

Pairwise Subjective Evaluation

Metrics

- CMOS (comparative MOS) — *Scale: -3 ~ 3*
- AXY score — *Scale: -3 ~ 3*

How much the listener thinks the utterance generated by the hierarchical model is better than the utterance generated by the non-hierarchical model?

Hierarchical Prosody Modeling

Pairwise Subjective Evaluation

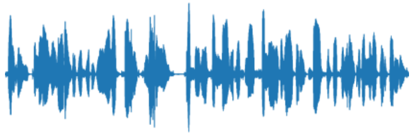
Ignore the audio quality and focus on the prosody

Metrics

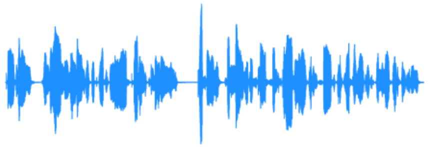
- CMOS (comparative MOS) — *Scale: -3 ~ 3*
- AXY score — *Scale: -3 ~ 3*

How much the listener thinks the utterance generated by the hierarchical model is better than the utterance generated by the non-hierarchical model?

Hierarchical



Non-Hierarchical



Hierarchical Prosody Modeling

Pairwise Subjective Evaluation

Ignore the audio quality and focus on the prosody

Metrics

CMOS (comparative MOS)

Scale: -3 ~ 3

AXY score

Scale: -3 ~ 3

Hierarchical > Non-Hierarchical

	Compared Model		CMOS↑ / p-value	AXY↑ / p-value
Hierarchical Prosody Modeling	Word-Level	Rule-Based	0.088 / 0.049	0.070 / 0.108
	Phoneme-Level	Rule-Based	0.00 / 0.500	0.114 / 0.027

For the hierarchical model, rule-based prosody labels are used at the word-level, and neural-based labels are used at the phoneme-level.

Conclusion

Contribution

- Compared different prosody modeling strategies for TTS

Contribution

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Coarse-Grained	Fine-Grained
Rule-Based Prosody Representation	Neural-Based Prosody Representation

Contribution

- Compared different prosody modeling strategies for TTS

Coarse-Grained	Fine-Grained
Rule-Based Prosody Representation	Neural-Based Prosody Representation

- Proposed a novel hierarchical prosody modeling architecture

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Objective Evaluation	Subjective Evaluation	Pairwise Subjective Evaluation

Future Work

- Extend to multi-level prosody modeling
- Apply to long-form TTS

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