

# CONCSS: Contrastive-based Context Comprehension for Dialogue-appropriate Prosody in Conversational Speech Synthesis



Yayue Deng<sup>1</sup>, Jinlong Xue<sup>1</sup>, Yukang Jia<sup>3</sup>, Qifei Li<sup>1</sup>, Yichen Han<sup>1</sup>, Fengping Wang<sup>1</sup>, Yingming Gao<sup>1</sup>, Dengfeng Ke<sup>2</sup>, Ya Li<sup>1</sup>

<sup>1</sup>Beijing University of Posts and Telecommunications, Beijing, China

<sup>2</sup>Beijing Language and Culture University, Beijing, China

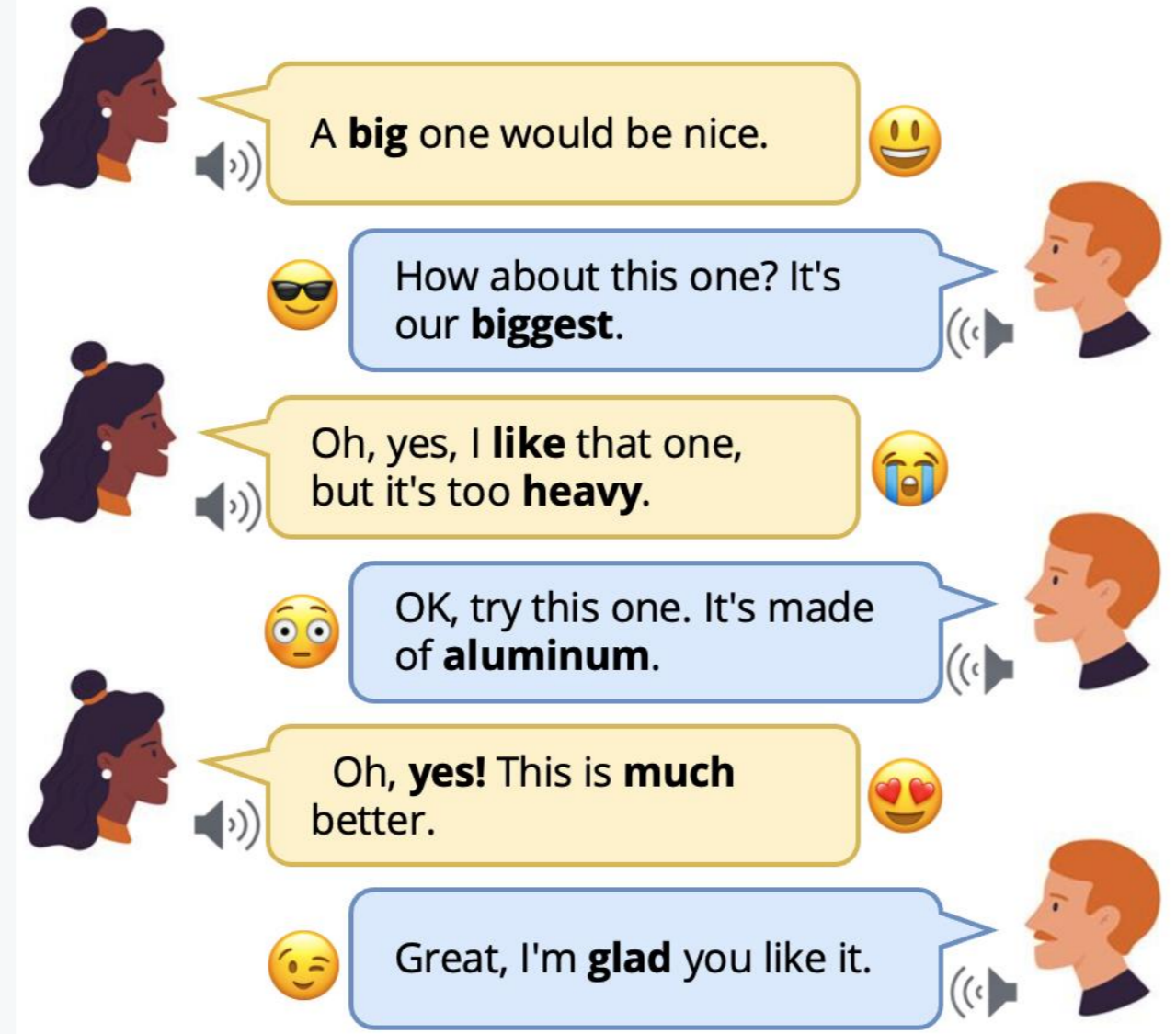
<sup>3</sup>Perfect World Co.,Ltd, Beijing, China



## Conversational Speech Synthesis (CSS)

### CSS Task Definition:

Given history dialogue, the CSS task focuses on improving the model's context understanding capability and generating audio with context-appropriate prosody.



## Motivation

### Limitation of Previous Works:

- Previous CSS approaches mostly rely on jointly training synthesis model and context encoder using the mel-reconstruction loss.
- Without explicit constraints, is this output vector of the context encoder sufficiently indicative of underlying context variations?

### Contribution:

- A novel conversational speech synthesis framework CONCSS
- A novel pretext task specific to CSS
- Comprehensively evaluate models on their ability to produce context-sensitive vectors and dialogue-appropriate prosody

## CONCSS Framework Overview

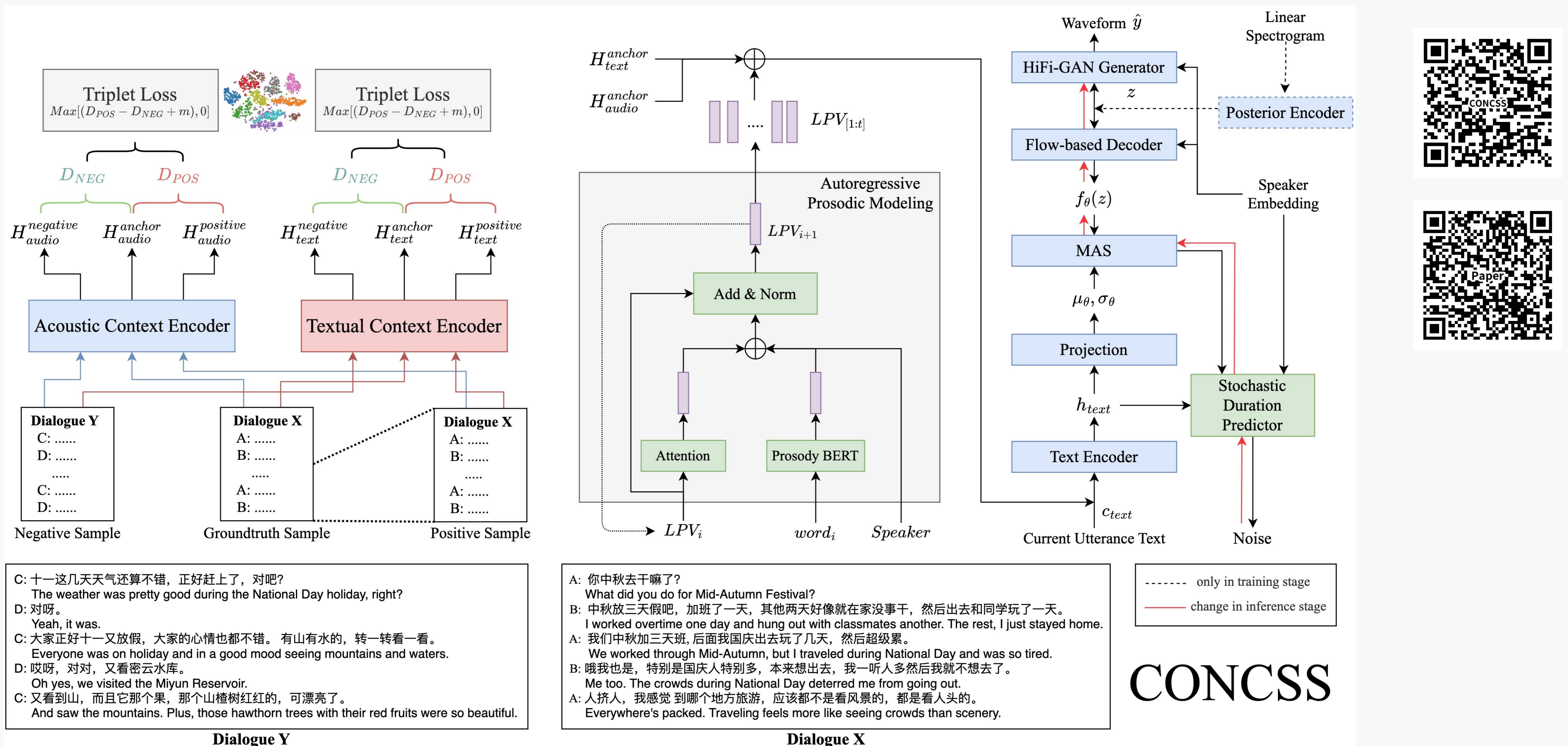


Fig.1. Illustration of our proposed CONtrastive-based Conversational Speech Synthesis (CONCSS).

## Method

### CONCSS = VITS+Four Enhancements :

- Leveraging an innovative pretext task to create context-dependent pseudo-labels

$$D(h_i + h_i^p) < D(h_i + h_i^n)$$

- Employ triplet loss with a hard negative sampling strategy

$$L(h_i^a, h_i^p, h_i^n) = \max \{D(h_i^a - h_i^p) - D(h_i^a - h_i^n) + m, 0\}$$

- An Acoustic and Textual Context Encoder

$$\begin{cases} L_{text}^k = L(H_{text}^a, H_{text}^p, H_{text}^n) \\ L_{audio}^k = L(H_{audio}^a, H_{audio}^p, H_{audio}^n) \end{cases}$$

$$L_{contra} = \frac{1}{N} \sum_{k=1}^N (L_{text}^k + L_{audio}^k)$$

- Utilize an autoregressive prosodic modeling (APM) module with a pre-trained prosodic language model

## Experiments and Conclusion

Table 1. Subjective evaluation (context-appropriate prosody and naturalness) for different models.

Model	GRU-based	M2CTTS	S1	S2	S3	S4
MOS (↑)	3.396 ± 0.107	3.438 ± 0.104	3.528 ± 0.097	3.708 ± 0.108	3.838 ± 0.110	<b>3.967 ± 0.120</b>

Models	GRU-based vs. M2CTTS	M2CTTS vs. S1	S1 vs. S2	S1 vs. S3	S2 vs. S3	S3 vs. S4	GRU-based vs. S4	M2CTTS vs. S4
CMOS (↑)	0.200	0.388	0.796	0.983	0.492	0.325	1.846	1.788

Table 2. Objective evaluation metrics primarily focus on the context-sensitive prosody. The Real context type uses the correct context for the current synthesized sentence, whereas the Fake type randomly selects from unrelated dialogues.

Method	Set	Type	Mel Loss (↓)	Log F0 RMSE (↓)	MCD (↓)
GRU-based		Real	3.599	0.2949 ± 0.1192	5.3590
		Fake	3.683	0.3001 ± 0.1164	5.3781
M2CTTS		Real	3.579	0.2936 ± 0.1014	5.3236
		Fake	3.596	0.3036 ± 0.1277	5.3882
CONCSS	S1	Real	3.609	0.2911 ± 0.1099	5.3382
		Fake	3.626	0.3203 ± 0.1093	5.4923
	S2	Real	3.556	0.2906 ± 0.1047	5.2883
		Fake	3.638	0.3311 ± 0.1417	5.5157
	S3	Real	3.530	0.2821 ± 0.0960	5.2748
		Fake	3.715	0.3272 ± 0.1455	5.6923
	S4	Real	<b>3.525</b>	<b>0.2803 ± 0.0961</b>	<b>5.2634</b>
		Fake	3.649	0.3252 ± 0.1097	5.6041

Table 3. Subjective evaluation between different context types.

Model	MOS (↑)		CMOS (↑)
	Real	Fake	Real vs Fake
GRU-based	3.442 ± 0.111	3.388 ± 0.102	0.325
M2CTTS	3.504 ± 0.100	3.312 ± 0.112	0.445
S1	3.638 ± 0.091	3.250 ± 0.116	0.492
S2	3.796 ± 0.076	3.229 ± 0.101	0.529
S3	<b>3.958 ± 0.074</b>	3.308 ± 0.100	<b>0.804</b>

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## References

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## Contact Information

Yayue Deng  
Email: yayue.deng@bupt.edu.cn  
Phone: +86 18810956816

