Wed-O-OS-7-1 INTERSPEECH2022 Presentation

Acoustic Modeling for End-to-End Empathetic Dialogue Speech Synthesis Using Linguistic and Prosodic Contexts of Dialogue History

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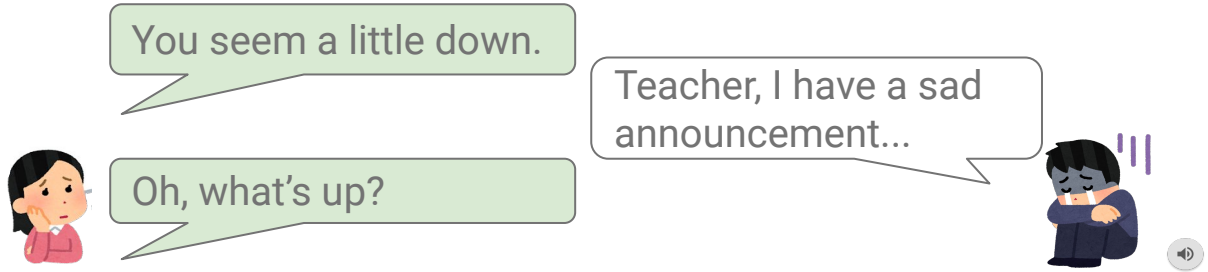
Main topic: dialogue system with empathy

- **Dialogue system:** interact w/ humans by text/speech
  - **Task-oriented**: satisfy user's requrest
    - e.g., Tourist information, restaurant reservation
  - **Non task-oriented**: communicate with user
    - e.g., Chit-Chat
- **Empathy:** active attempt to get inside other person [Davis+18]
  - c.f., Sympathy: synchronize self with other person in emotion

How can we develop dialogue system that can talk to users w/ empathetic speaking style?

Task definition

- **Empathetic Dialogue Speech Synthesis (DSS)** [Saito+22]
  - Reflect main elements of empathy (i.e., **emotion**) on synthetic speech
  - Estimate speech features that contribute to next response, considering **dialogue history** (interaction betw. system & user)



- **Challanging point**
  - Predicting **dialogue context** from linguistic & prosodic features (i.e., modeling **cross-modality** of text & speech)

Overview of our research

- **Conventional DSS method:** using text history only [Guo+20]
  - Learn dialogue context from text embeddings of dialogue history
  - **Limitation:** missing speech modality modeling
- **Proposed DSS method:** using both text & speech history
  - Extract prosody embedding from speech & aggregate two modality
  - Investigate 4 methods for better dialogue context modeling:
    1) pre-trained speech SSL* model, 2) style-guided training,
    3) cross-modal attention, 4) fine-grained embedding modeling
- **Result: more natural DSS than conventional method**

*SSL: Self-Supervised Learning

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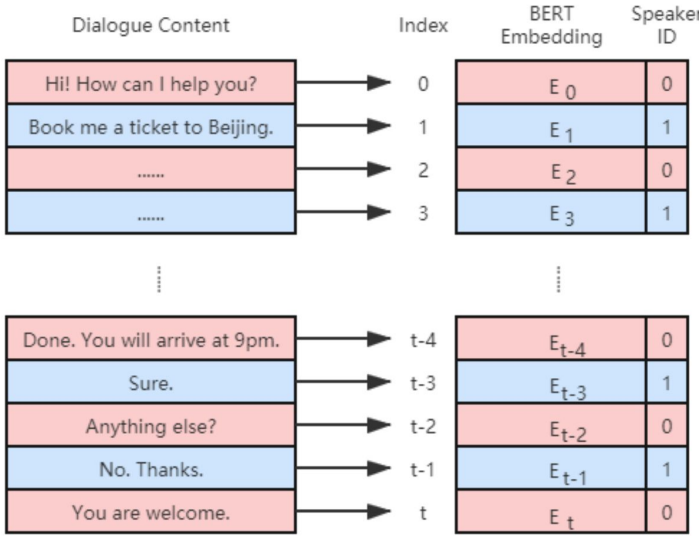
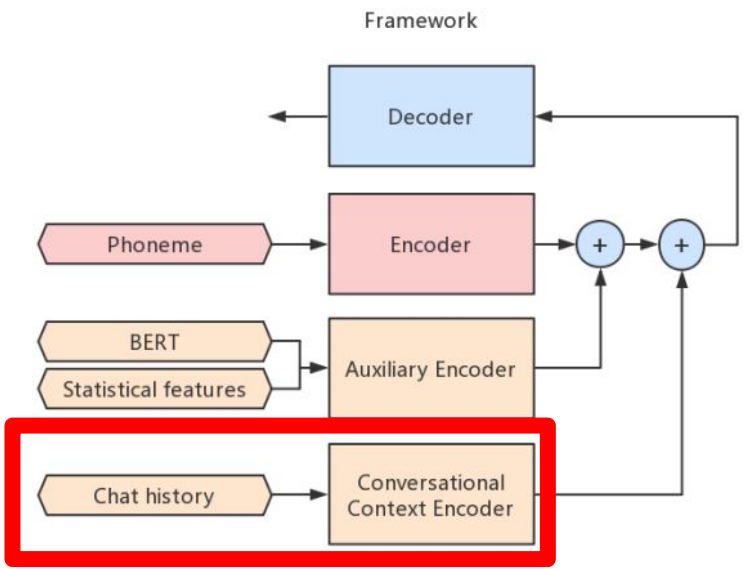
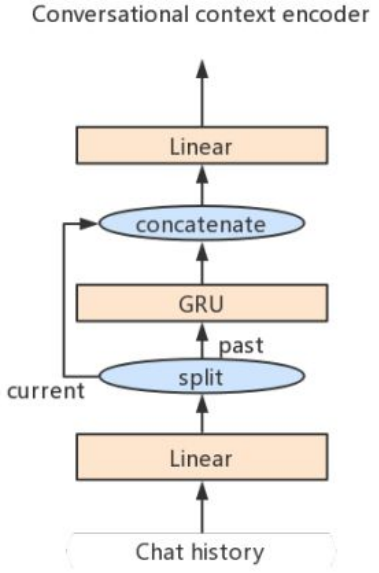
Conventional DSS method [Guo+20]

- **Overview:** E2E TTS w/ **Conversational Context Encoder (CCE)**
  - Step 1: obtain text embeddings using sentence BERT
  - Step 2: extract **context embedding** from chat history w/ CCE







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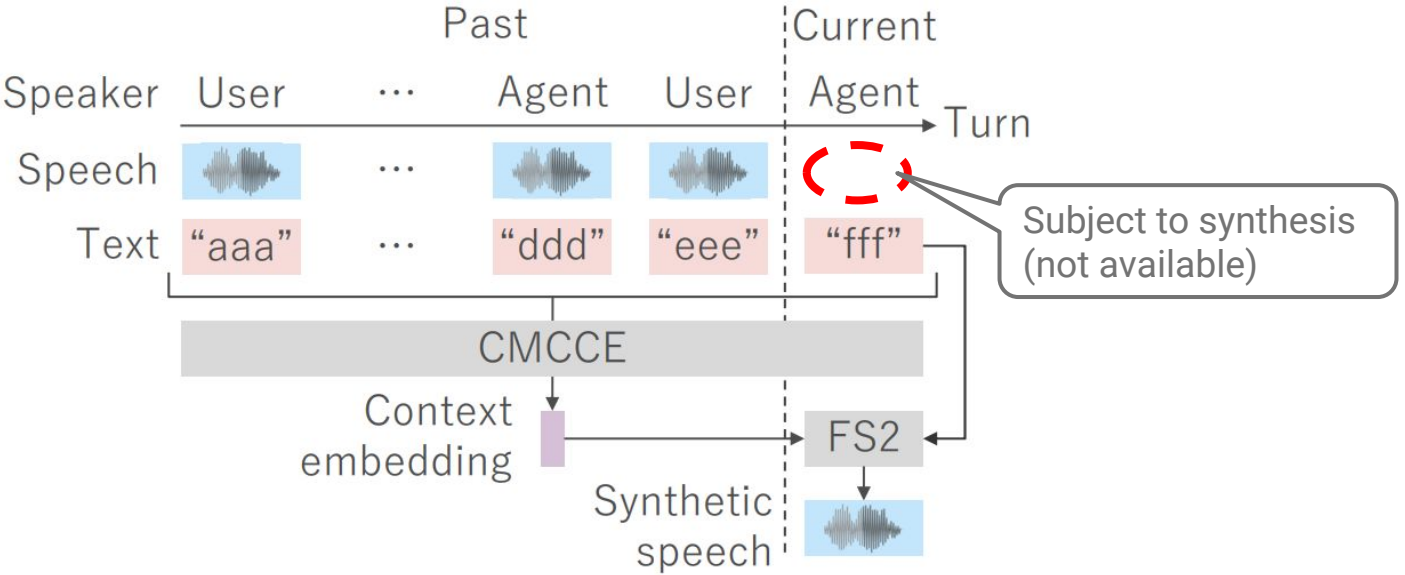
Motivation

- **One-to-many problem in TTS**
  - e.g., “What’s wrong?” w/ various speech prosody


- **Research questions**
  - RQ1: *Can we extract better dialogue context from chat history by considering BOTH text & speech?*
  - RQ2: *How can we learn the cross-modality of text & speech effectively, rather than processing them independently?*

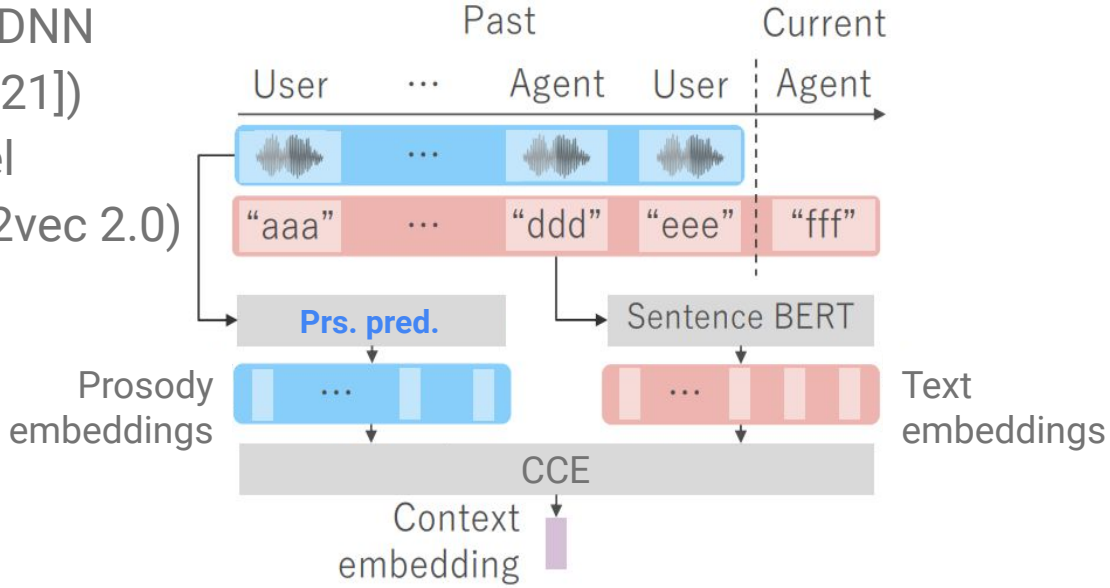
Overview of proposed method

- **Architecture:** FS2-based TTS model w/ **Cross-Modal (CM)CCE**
  - CMCCE: extracting context embedding from text/speech seqs.
  - 4 methods for better context embedding extraction



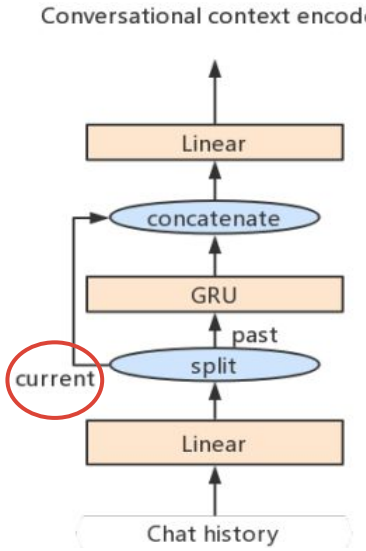
CMCCE w/ prosody predictor

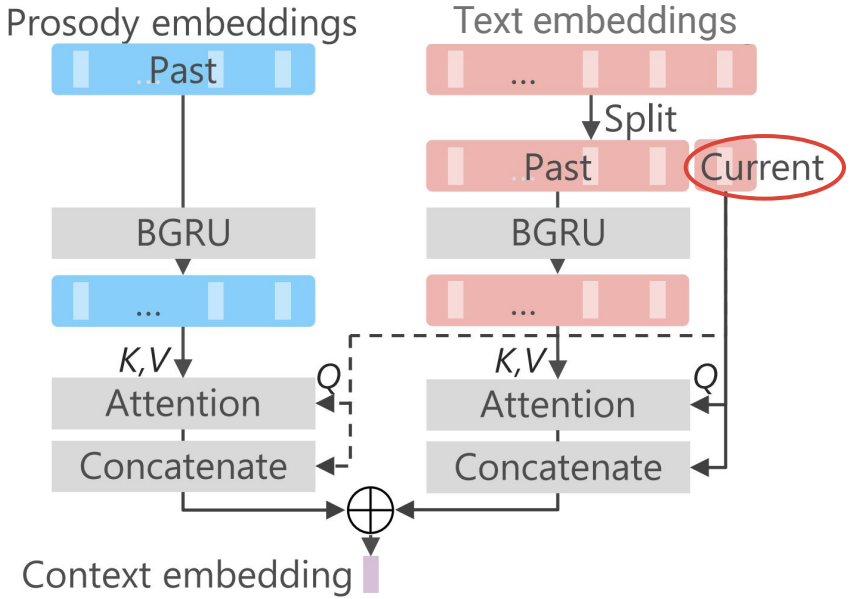
- **Main components**
  - Sentence BERT for text embedding extraction
  - **Prosody predictor** for prosody embedding extraction
    - Trainable DNN (e.g., [Du+21])
    - SSL model (e.g., wav2vec 2.0)



Cross-modal attention

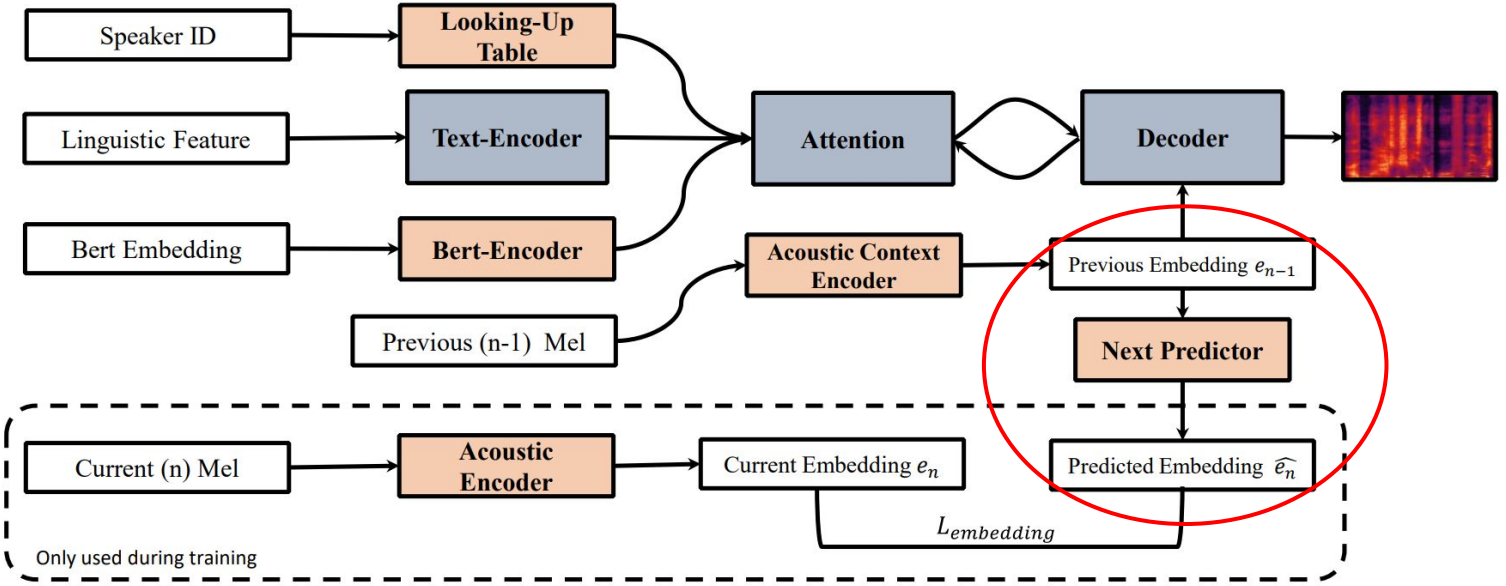
- **How to compress past information of dialogue history**
  - Guo et al.'s [Guo+20]: bi-directional Gated Recurrent Unit (GRU)
  - Ours: attention using embedding of current text as query





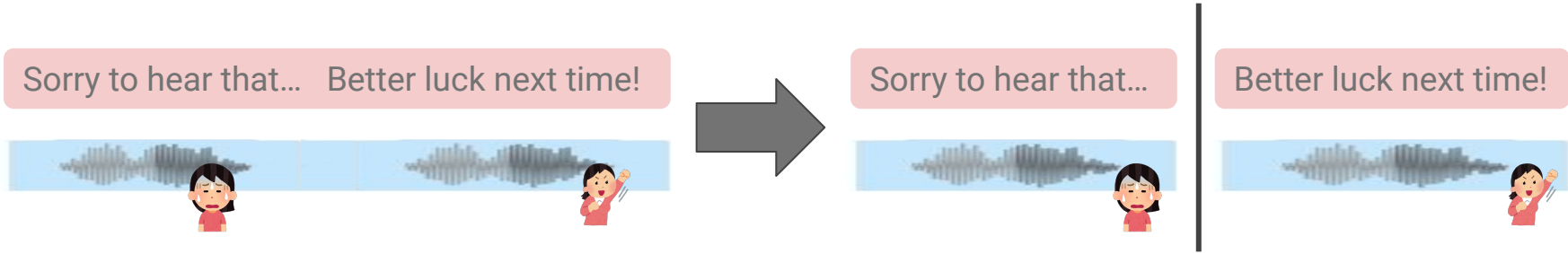
Style-guided context embedding learning

- **Core idea:** Cong et al's method [Cong+21]
  - Associating context embedding with current prosody embedding



Fine-grained context embedding modeling

- **Unit of embedding modeling**
  - Guo et al.'s [Guo+20]: utterance-wise
    - Cannot model change of prosodic variation within one utterance
  - Ours: **sentence**-wise
    - Divide current utterance into sentences by punctuation symbols
    - Extract text/prosody embedding for each sentence
    - Predict sentence-wise context embedding from extracted embeddings using CMCCE



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Experimental conditions

Corpus	STUDIES [Saito+22] (downsampled to 22,050 Hz)
Data splitting	{ Training, Validation, Test } = { 2,209, 221, 211 }
TTS model (w/o teacher forcing)	Text2Mel: FastSpeech 2 (FS2) [Ren+21] Vocoder: HiFi-GAN [Kong+20]
Dialogue history length	10 (same setting as [Guo+20])
Compared methods	**Baseline**: FS2 + CCE (Guo et al's method [Guo+20]) **Proposed**: FS2 + CMCCE ● SSL: pretrained SSL model as prosody extractor ● Attn: attention for cross-modal aggregation ● SG: style-guided embedding learning ● FG: fine-grained context modeling
Subjective evaluation	**Stage 1: Pairwise comparison (AB/XAB tests)** **Stage 2: MOS test**

Results of preference AB/XAB tests

- **w/o SSL**
  - Significant improvement by:
    - **+SG**
    - **+SG**+Attn and **+SG**+FG

    → **SG was effective in training for CMCCE w/ prosody predictor.**

Baseline	Naturalness	Similarity	Proposed (w/o SSL) SG	Attn	FG
	0.45 vs. 0.55	**0.54 vs. 0.46**			
	0.44 vs. 0.56	0.53 vs. 0.47	✓		
	0.50 vs. 0.50	0.54 vs. 0.46		✓	
	0.48 vs. 0.52	**0.54 vs. 0.46**			✓
	0.43 vs. 0.57	0.47 vs. 0.53	✓	✓	
	0.45 vs. 0.55	**0.45 vs. 0.55**	✓		✓

- **w/ SSL**
  - Significant improvement by:
    - **+Attn**
    - +SG+**Attn**

    → **Attn aggregated SSL-derived prosody & text embeddings.**
  - Fewer cases w/ improvement, compared with w/o SSL results

Baseline	Naturalness	Similarity	Proposed (w/ SSL) SG	Attn	FG
	0.50 vs. 0.50	**0.61 vs. 0.39**			
	0.53 vs. 0.47	0.46 vs. 0.54	✓		
	0.51 vs. 0.49	**0.44 vs. 0.56**		✓	
	0.52 vs. 0.48	0.50 vs. 0.50			✓
	0.43 vs. 0.57	0.50 vs. 0.50	✓	✓	
	0.46 vs. 0.54	**0.54 vs. 0.46**		✓	✓

Results of MOS test

- **Compared methods: Baseline vs. Proposed (w/o SSL)**
  - +SG+FG (best combination)
  - +SG, +FG (ablation)
  - +SG+Attn+FG (bonus)

Method			Naturalness MOS
Proposed (w/o SSL)			
SG	Attn	FG	
			3.59±0.10
✓			3.62±0.10
		✓	3.59±0.10
✓		✓	3.66±0.10
✓	✓	✓	3.55±0.10
Baseline			3.55±0.10

- **Summary of results**
  - **+SG+SG achieved the highest MOS.**
    - No significant difference betw. Baseline & Proposed…
  - +SG+Attn+FG did not improve the naturalness.
    - Richer model → more difficult training?

Speech samples (available online)

100 listeners (24 answers per listener)

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Conclusion

- **Purpose: development of more natural voice agent**
  - Control speaking style according to user's emotion w/ **empathy**
- **This talk: modeling dialogue context from text/speech history**
  - Extract prosody embedding from speech & aggregate two modality
  - Investigate 4 methods for better dialogue context modeling:
    1) pre-trained SSL* model, 2) style-guided training,
    3) cross-modal attention, 4) fine-grained embedding modeling
- **Result: more natural DSS than conventional method**
- **Future work: (semi-)supervised learning using emotion label**