Investigating on Incorporating Pretrained and Learnable Speaker Representations for Multi-Speaker Multi-Style Text-to-Speech

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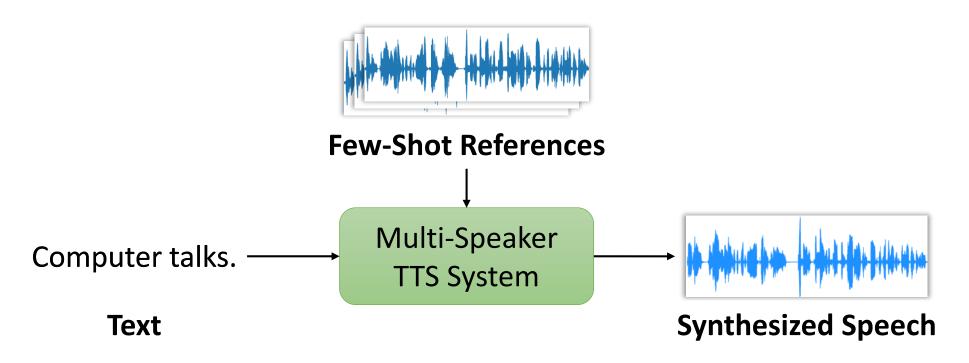


Outline

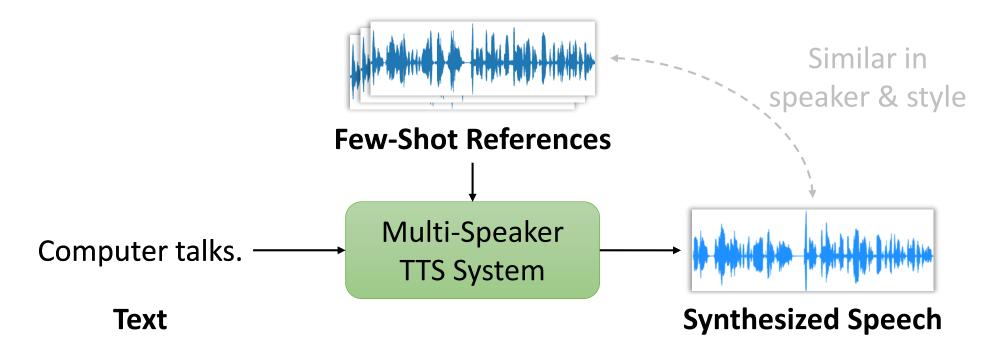
- Task Description
- Background & Motivation
- Methodology
- Experiments
- Conclusion

Task Description

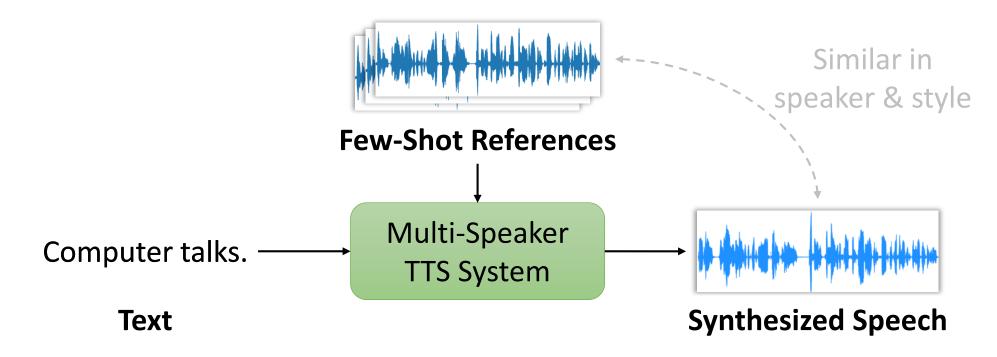
Multi-Speaker Multi-Style Voice Cloning



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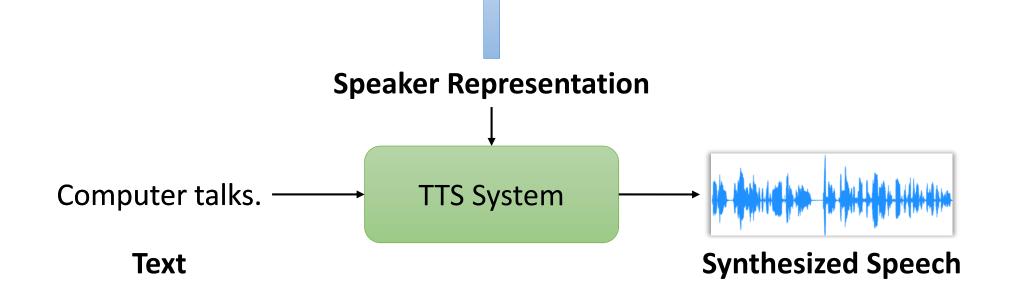


Challenge

- Extract speaker and style information from limited references
- Enable the TTS system to generalize to different speakers/styles

Background & Motivation

General Framework of Multi-Speaker TTS



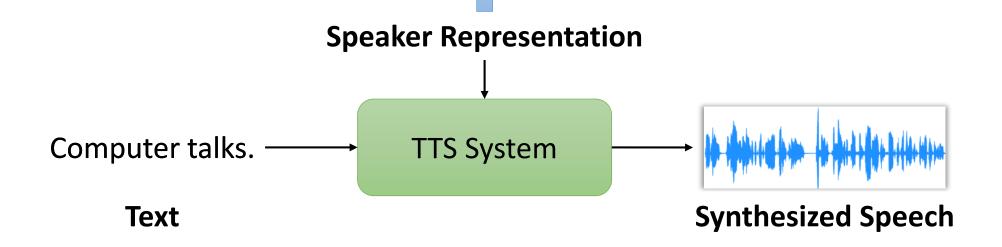
General Framework of Multi-Speaker TTS

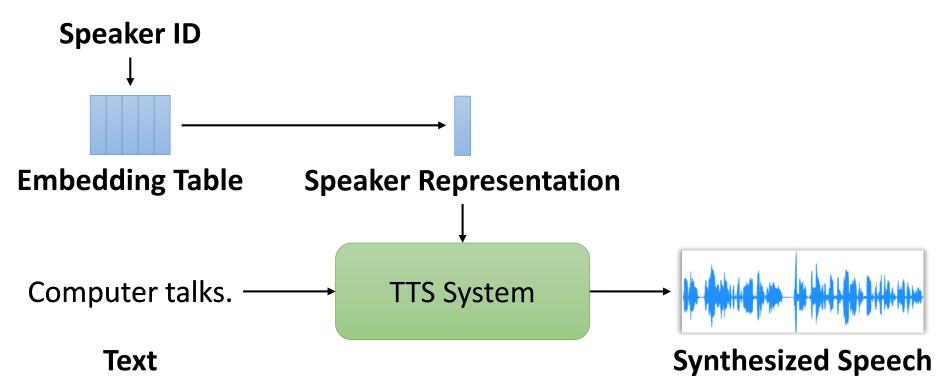
Learnable

- Embedding Table
- Trainable Speaker Encoder

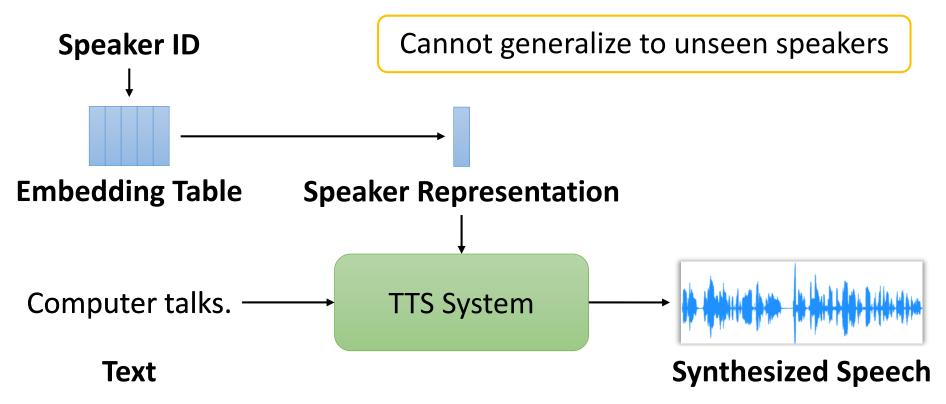
Pretrained

• Pretrained Speaker Encoder

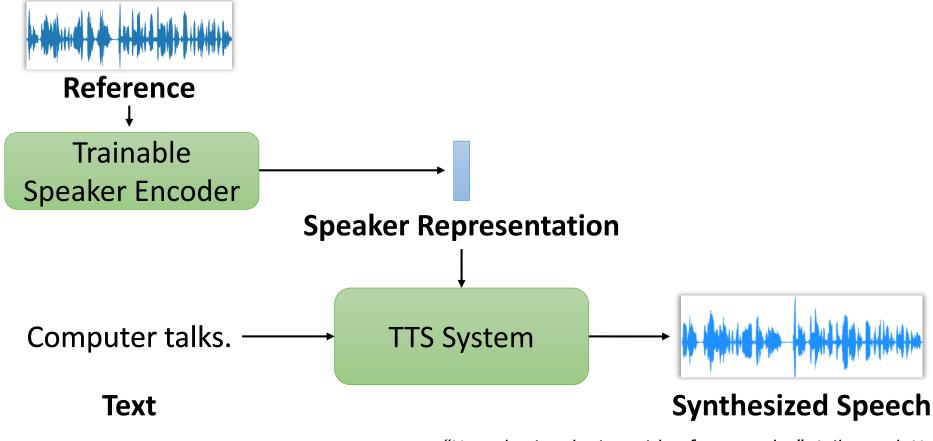




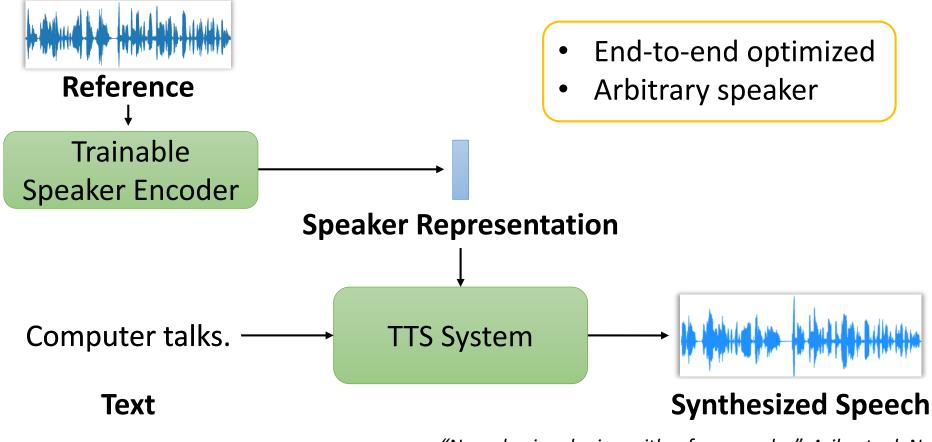
"Deep voice 3: Scaling text-to-speech with convolutional sequence learning", Ping, et. al, ICLR'18



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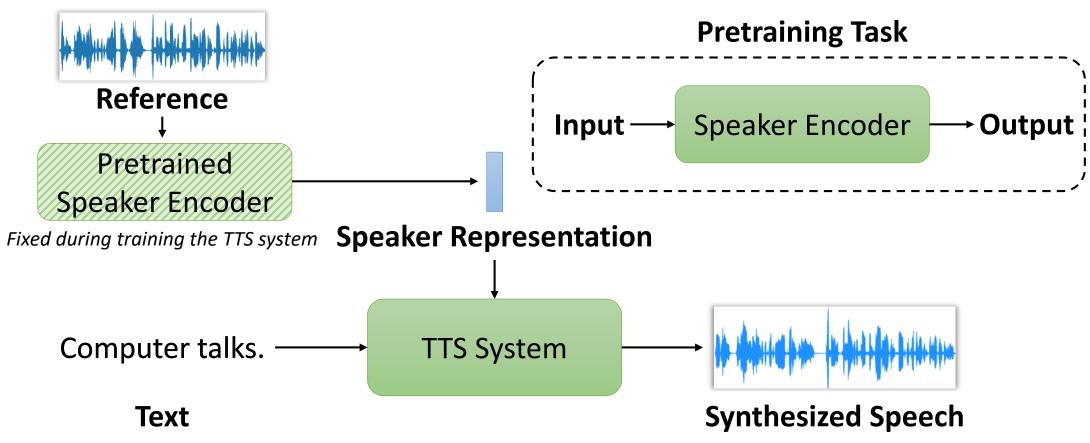


"Neural voice cloning with a few samples", Arik, et. al, NeurIPS'18 "Sample efficient adaptive text-to-speech", Chen, et. al, ICLR'19

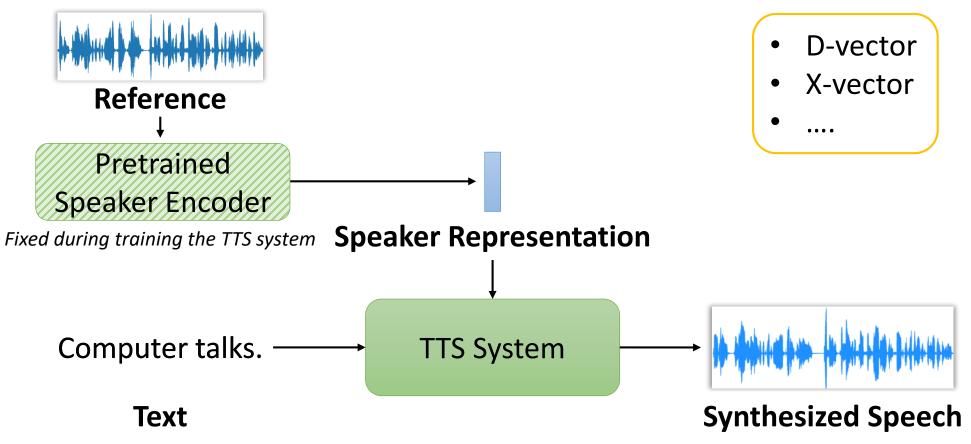


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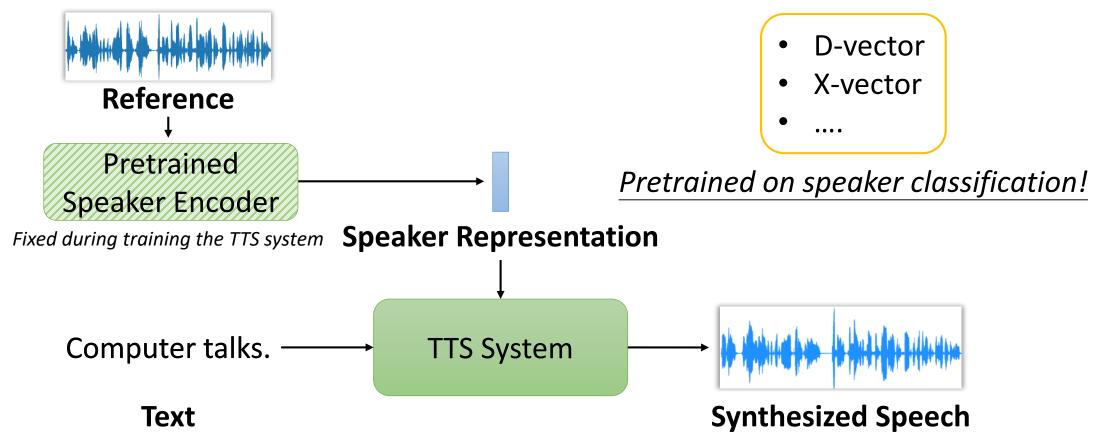
Pretraining Task Input \rightarrow Speaker Encoder \rightarrow Output



"Transfer learning from speaker verification to multi-speaker text-to-speech synthesis", Jia, et. al, NeurIPS'18 "Zero-shot multi-speaker text-to-speech with state-of-the-art neural speaker embeddings", Cooper, et. al, ICASSP'20



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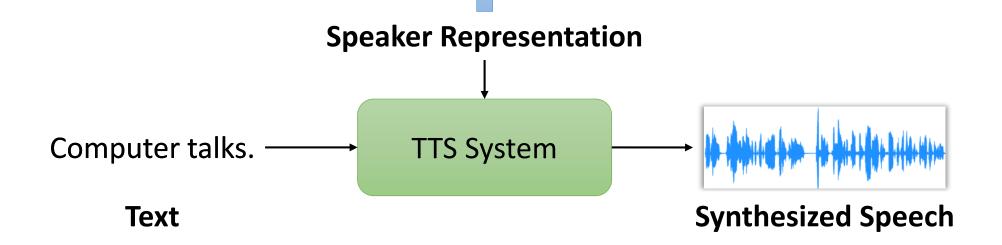
Motivation: Combining Different Representations

Learnable

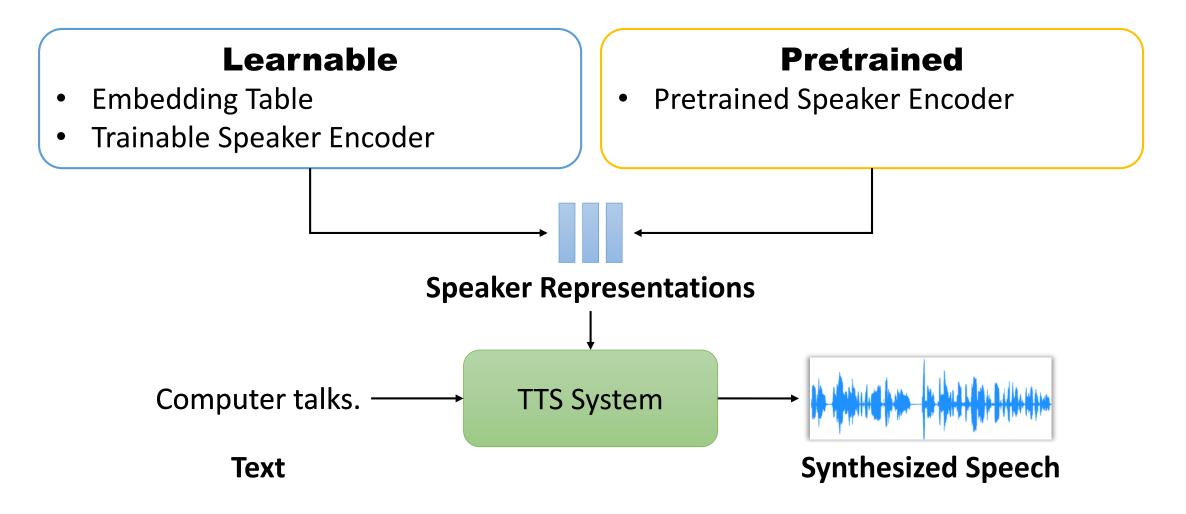
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Pretrained

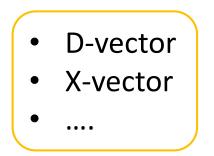
• Pretrained Speaker Encoder



Motivation: Combining Different Representations

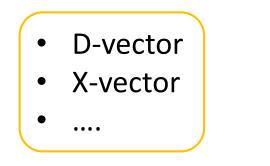


Motivation: Different Pretraining Tasks



Discriminative Pretraining Tasks e.g. speaker classification

Motivation: Different Pretraining Tasks



VS

Discriminative Pretraining Tasks e.g. speaker classification Generative Pretraining Tasks?

Methodology

Workflow

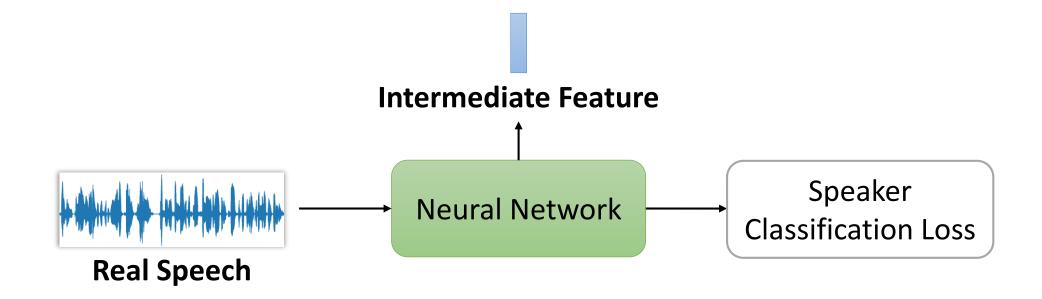


Speaker Representation Pretraining Discriminative Tasks: D-vec & X-vec



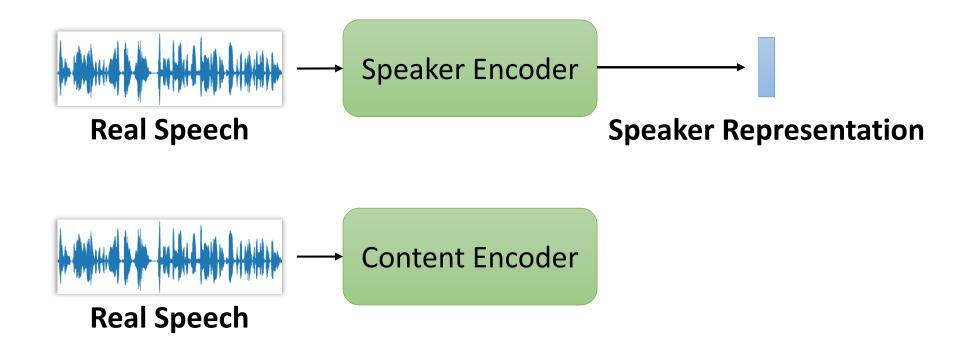
"Generalized end-to-end loss for speaker verification", Wan, et. al, ICASSP'18 "X-vectors: Robust dnn embeddings for speaker recognition", Snyder, et. al, ICASSP'18

Speaker Representation Pretraining Discriminative Tasks: D-vec & X-vec



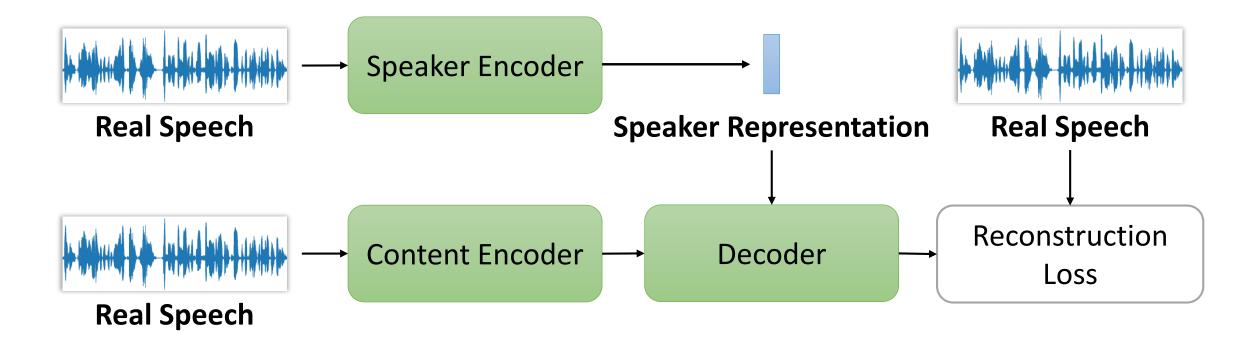
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Speaker Representation Pretraining Generative Tasks: AdaIN-VC (One-Shot)



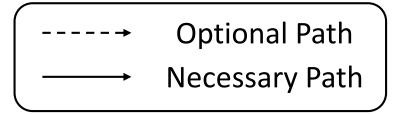
"One-Shot Voice Conversion by Separating Speaker and Content Representations with Instance Normalization", Chou, et. al, InterSpeech'19

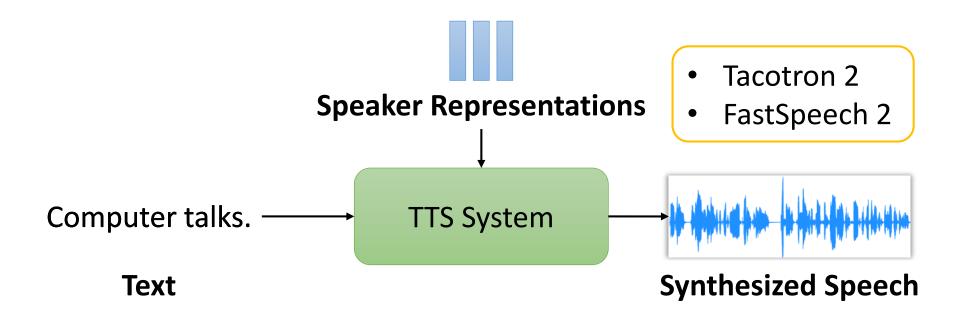
Speaker Representation Pretraining Generative Tasks: AdaIN-VC (One-Shot)

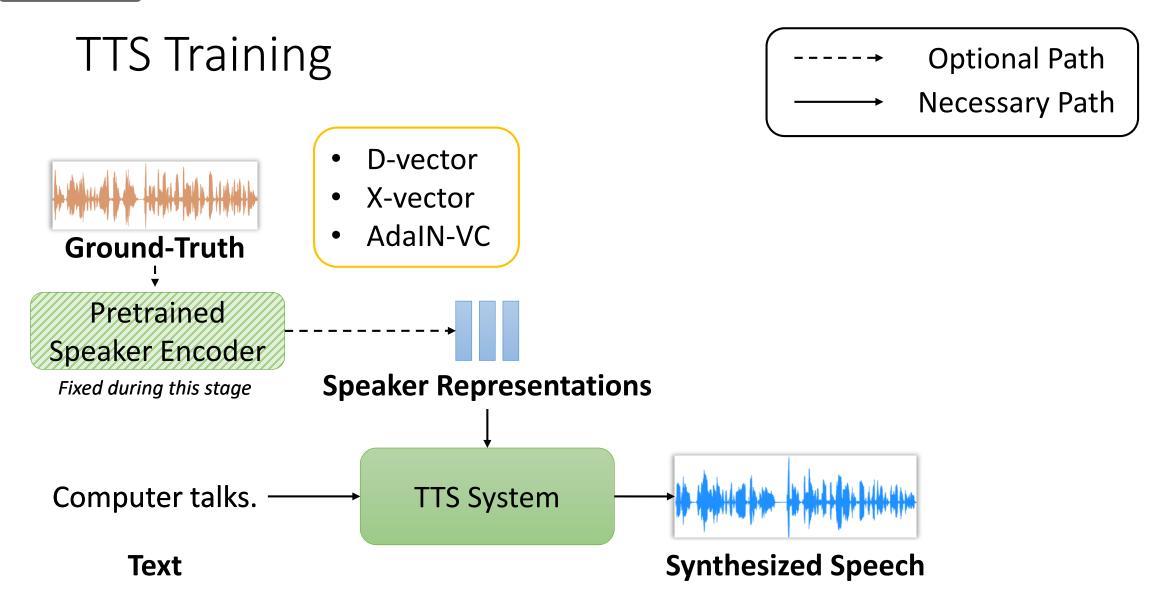


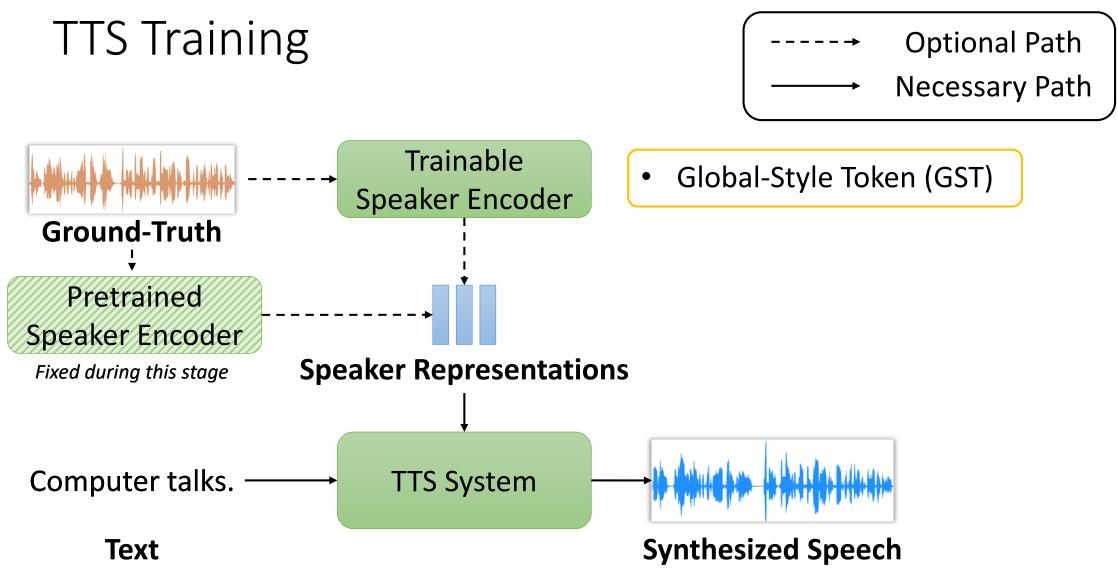
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TTS Training

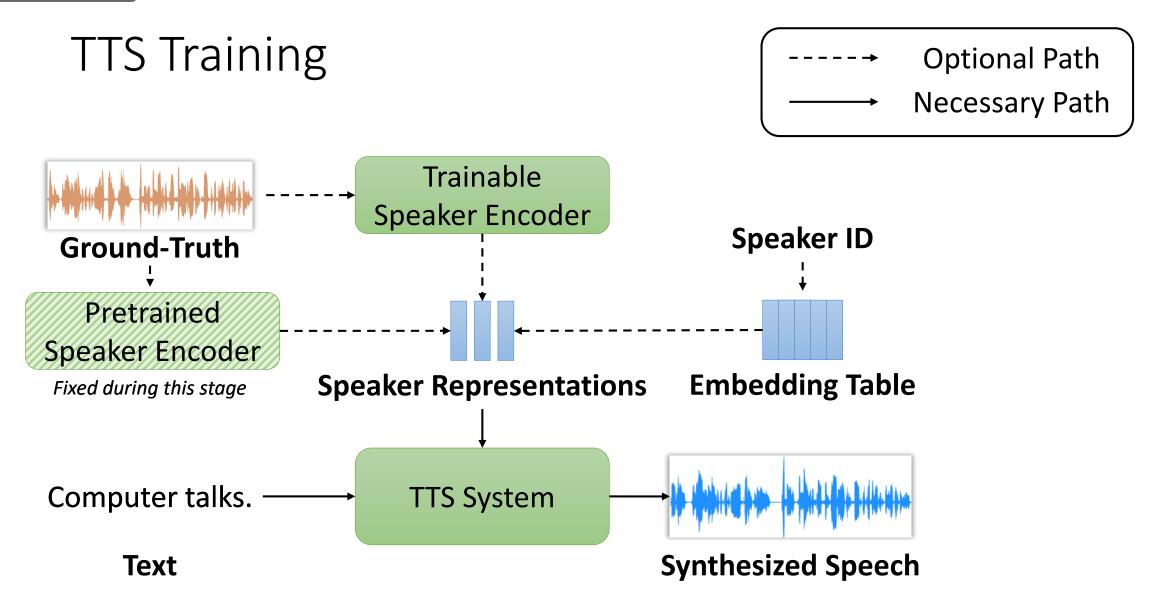


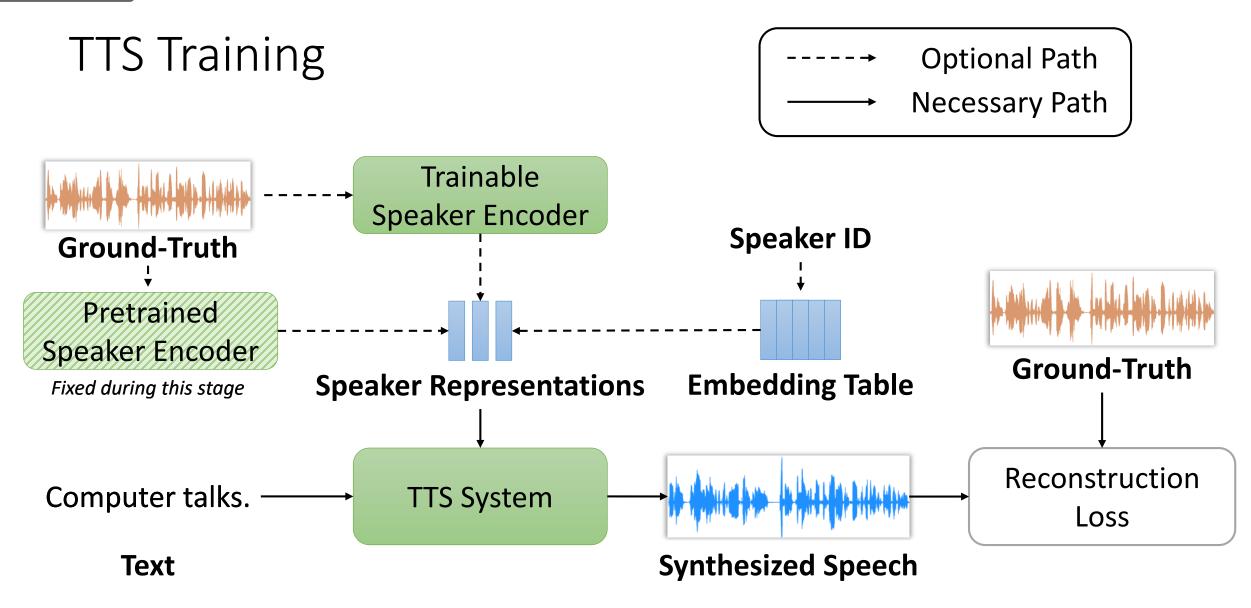


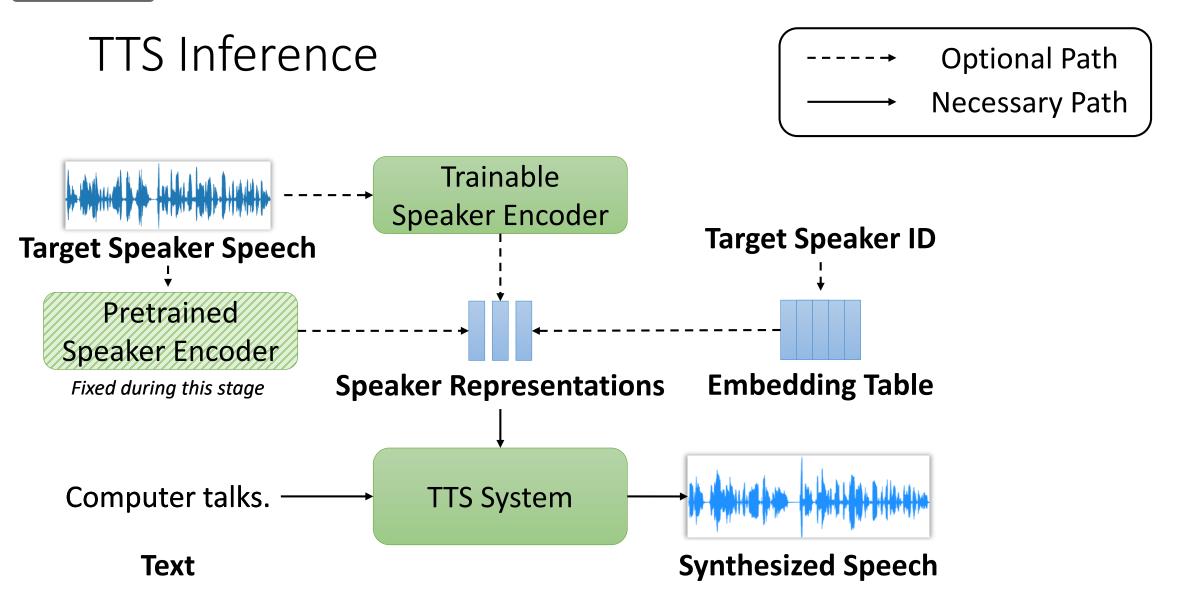




""Style tokens: Unsupervised style modeling, control and transfer in end-to-end speech synthesis", Wang, et. al, ICML'18







Experiments

Dataset

- Training: 96 hours of Mandarin speech by 230 speakers with transcriptions
 - AlShell-3
 - M2VoC dataset

Dataset

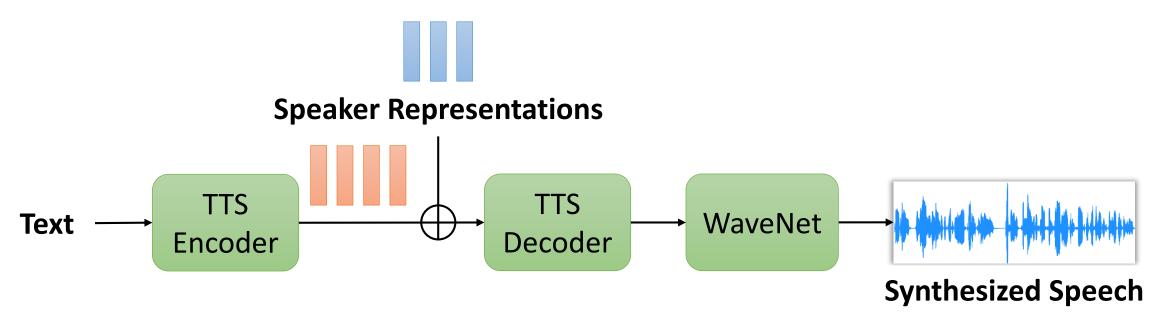
- Training: 96 hours of Mandarin speech by 230 speakers with transcriptions
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- 6 few-shot target speakers
 - Track 1: 3 speakers with 100 recordings
 - Track 2: 3 speakers with 5 recordings

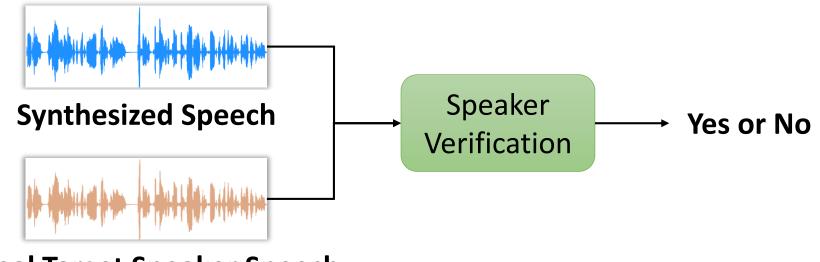
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- Training: 96 hours of Mandarin speech by 230 speakers with transcriptions
 - AlShell-3
 - M2VoC dataset
- 6 few-shot target speakers
 - Track 1: 3 speakers with 100 recordings
 - Track 2: 3 speakers with 5 recordings
- The few shot speakers are also used to train the speaker representation models and the TTS models

TTS Model Setup

- Tacotron 2 & FastSpeech 2
 - Speaker representations are added to encoder outputs
- WaveNet vocoder



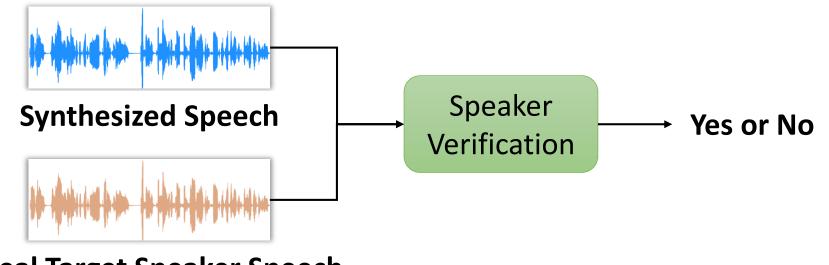


Real Target Speaker Speech

Metrics

Speaker Verification Accuracy

Scale: 0 ~ 1, the larger the better



Real Target Speaker Speech

Metrics

Speaker Verification Accuracy

Scale: 0 ~ 1, the larger the better

Model	Speaker Representation Pretrained			esentation Learnable		Results SV Accuracy	
	d-vec	x-vec	VC	embed	GST	Track 1	Track 2
	\checkmark					.772	.367
		\checkmark				.785	.377
(a) Tacotron 2			\checkmark			.942	.727
				\checkmark		.630	.703
					\checkmark	.102	.050
	\checkmark					.977	.323
		\checkmark				.973	.623
(b) FastSpeech2			\checkmark			.980	.837
				\checkmark		.988	.490
					\checkmark	.778	.340

Generative Pretraining > Others

Metrics

Speaker Verification Accuracy

Scale: 0 ~ 1, the larger the better

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					\checkmark	.778	.340

Audio samples (Track 2, 5 references)

Target Speaker d-vec x-vec VC embed GST

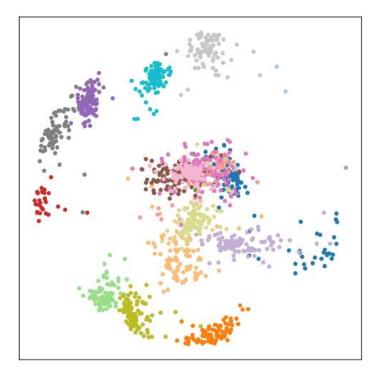
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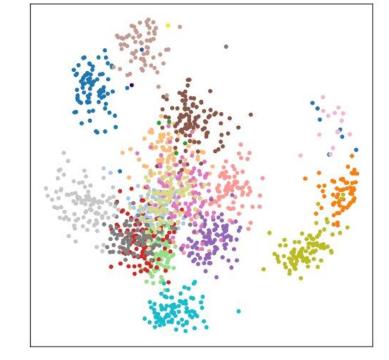
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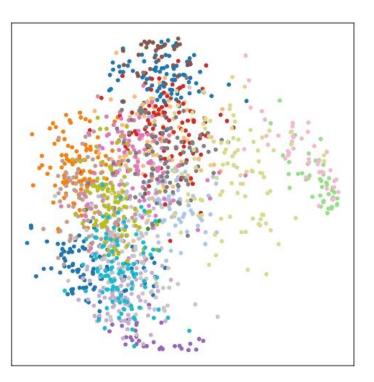
Metrics

Speaker Verification Accuracy

Scale: 0 ~ 1, the larger the better







(a) d-vector

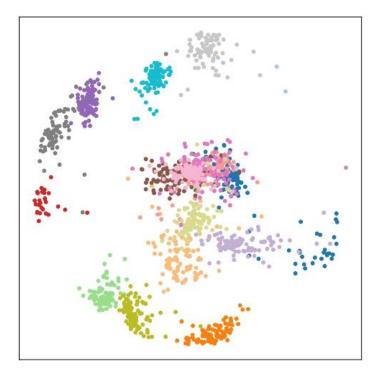
(b) x-vector

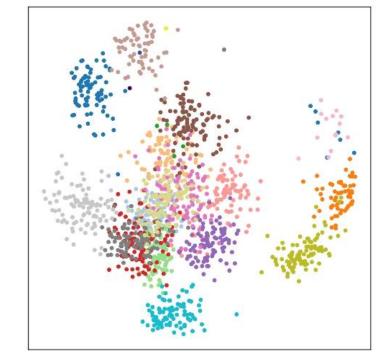
(c) VC

Metrics

Speaker Verification Accuracy

Scale: 0 ~ 1, the larger the better





More Continuous



(a) d-vector

(b) x-vector



Metrics

Speaker Verification Accuracy

Scale: 0 ~ 1, the larger the better

Model	Speaker Representation Pretrained			esentation Learnable		Results SV Accuracy	
	d-vec	x-vec	VC	embed	GST	Track 1	Track 2
(b) FastSpeech2	2		\checkmark			.980	.837
(c) FastSpeech2	\checkmark		\checkmark			.978	.747
		\checkmark	\checkmark			.992	.860
			\checkmark	\checkmark		.983	.937
			\checkmark		\checkmark	.982	.783
			\checkmark	\checkmark	\checkmark	.988	.897
	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	.990	.887

* The colored row is the model used for the final submission to the ICASSP 2021 M2VoC challenge. Due to the time limitation, we did not submit our best model.

Multiple speaker representations

Track 1 (100 references): No obvious difference

Metrics

Speaker Verification Accuracy

Scale: 0 ~ 1, the larger the better

Model	Speaker Representation Pretrained			esentation Learnable		Results SV Accuracy	
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		\checkmark	\checkmark			.992	.860
			\checkmark	\checkmark		.983	.937
			\checkmark		\checkmark	.982	.783
			\checkmark	\checkmark	\checkmark	.988	.897
	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	.990	.887

Multiple speaker representations

Track 1 (100 references): No obvious difference

Track 2 (5 references): Multiple Representations > Single Representation

* The colored row is the model used for the final submission to the ICASSP 2021 M2VoC challenge. Due to the time limitation, we did not submit our best model.

Subjective Evaluation (FastSpeech 2, Track 2)

Metrics

Quality MOS

Speaker Similarity MOS

Scale: 1 ~ 5, the larger the better

Subjective Evaluation (FastSpeech 2, Track 2)

Metrics

Quality MOS

Speaker Similarity MOS

Scale: 1 ~ 5, the larger the better

Model	Speaker Representation							
	x-vec	VC	Embed	VC+Embed				
MOSquality	3.47 ± .13	3.61 ± .13	3.65 ± .13	$3.55\pm.12$				
MOSsimilarity	$3.25\pm.13$	$3.19\pm.14$	$3.27\pm.13$	3.38 ± .14				

Speaker Similarity: Multiple Representations > Single Representation

Subjective Evaluation (FastSpeech 2, Track 2)

Metrics

Quality MOS

Speaker Similarity MOS

Scale: 1 ~ 5, the larger the better

Model	Speaker Representation							
ni outr	x-vec		Embed	VC+Embed				
	3.47 ± .13	3.61 ± .13	3.65 ± .13	$3.55\pm.12$				
MOSsimilarity	$3.25\pm.13$	$3.19\pm.14$	$3.27\pm.13$	3.38 ± .14				

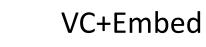
Audio samples (Track 2, 5 references)







10





Official Evaluation Results

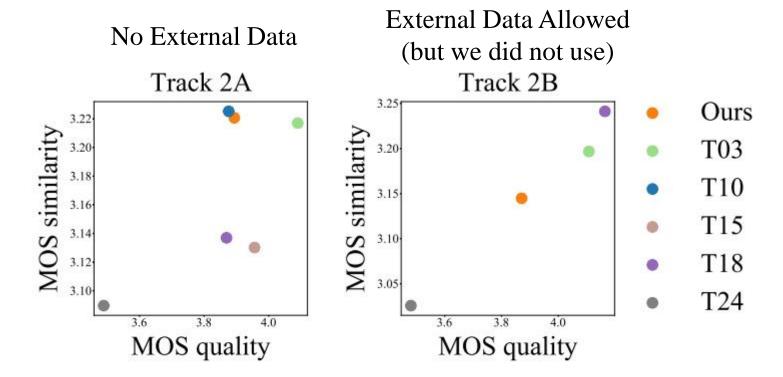


Fig. 3: The official subjective evaluation results of Track 2.

Conclusion

Conclusion

 Pretrained speaker representation + learnable speaker representations > single representation

Conclusion

- Pretrained speaker representation + learnable speaker representations > single representation
- Generative pretraining > discriminative pretraining

Resources

- Audio Samples: https://ming024.github.io/M2VoC/
- Code: https://github.com/ming024/FastSpeech2/tree/M2VoC
- Paper: https://arxiv.org/abs/2103.04088