2024 edition

Deep Learning for Music Analysis and Generation

Singing Voice Generation

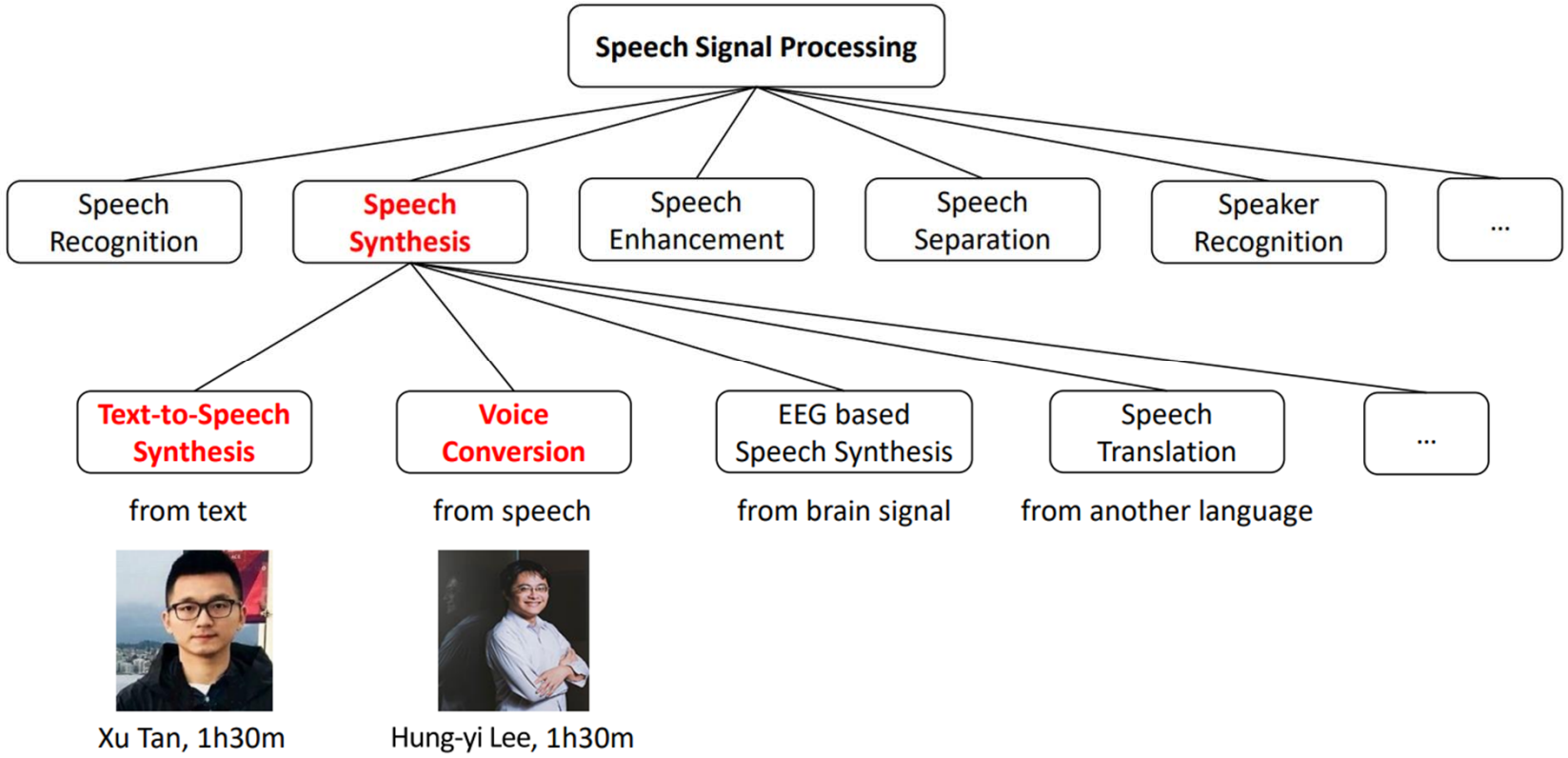
(text+MIDI → singing audio)

Yi-Hsuan Yang Ph.D.

yhyangtw@ntu.edu.tw

Reference 1: INTERSPEECH 2022 Tutorial

https://github.com/tts-tutorial/interspeech2022



Reference 2: ISMIR 2022 Tutorial

https://github.com/lukewys/ISMIR2022-tutorial

https://youtu.be/7U-zDL5con8?si=aKKAx6fB6ij44cko&t=4732

T3(M): Designing Controllable Synthesis System for Musical Signals

Outline

- **Singing voice processing: Historical review**
- Neural text-to-speech synthesis
- Neural singing voice synthesis
- Build your SVS model

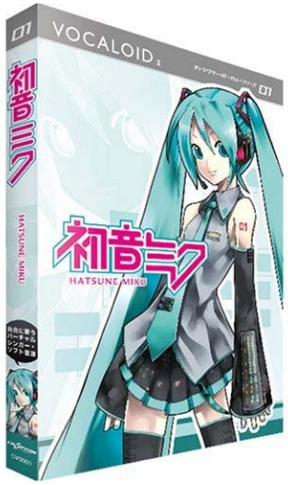
Reference: ISMIR 2015 Tutorial

http://ismir2015.uma.es/docs/ISMIR2015tutorial_Singing.pdf

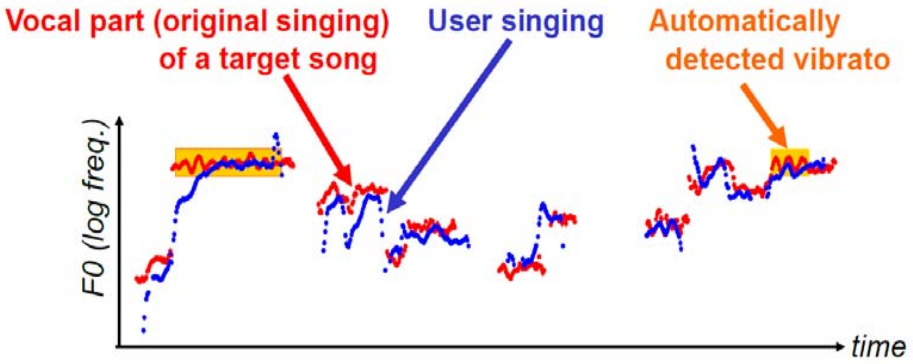
- All popular music cultures around the world use singing
- The singing voice is the most expressive of all musical instruments
- Singing voice produces both sound and words
- Various commercial applications

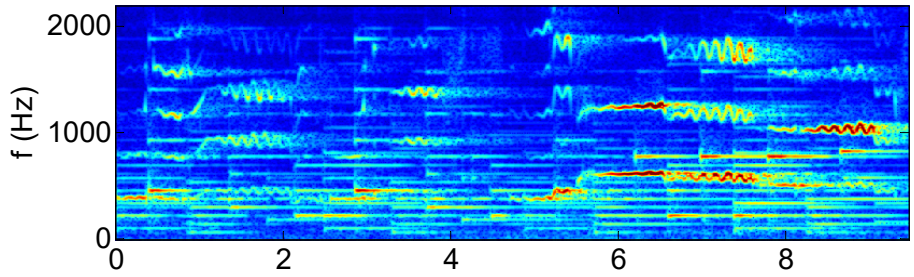
Commercial Applications

- Automatic pitch correction (e.g. auto-tune)
- Singing skill evaluation for Karaoke
- Query-by-humming (e.g. soundhound)
- Singing synthesis (e.g. vocaloid)



Singing Voice Analysis





Ref: Nakano et al, “MiruSinger: a singing skill visualization interface using real-time feedback and music CD recordings as referential data,” ISM 2007

https://songrium.jp/

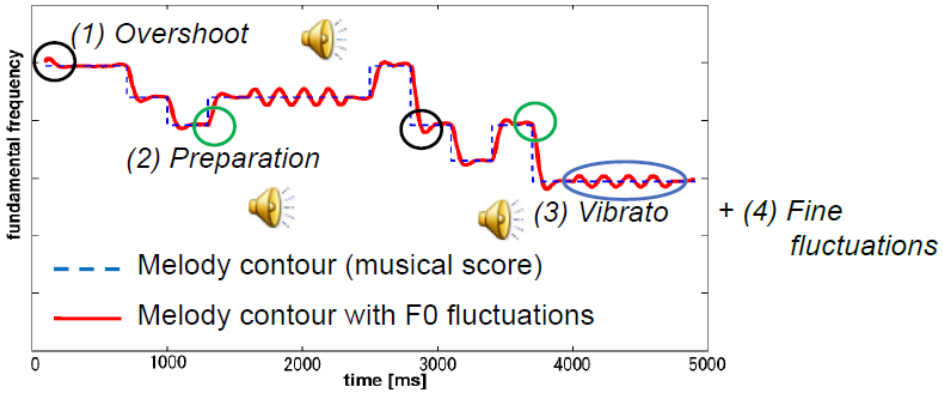
Ref: Kajita et al, “Songrium: Browsing and listening environment for music content creation community,” SMC 2015

Singing Voice Generation

- **Singing voice synthesis** (SVS)

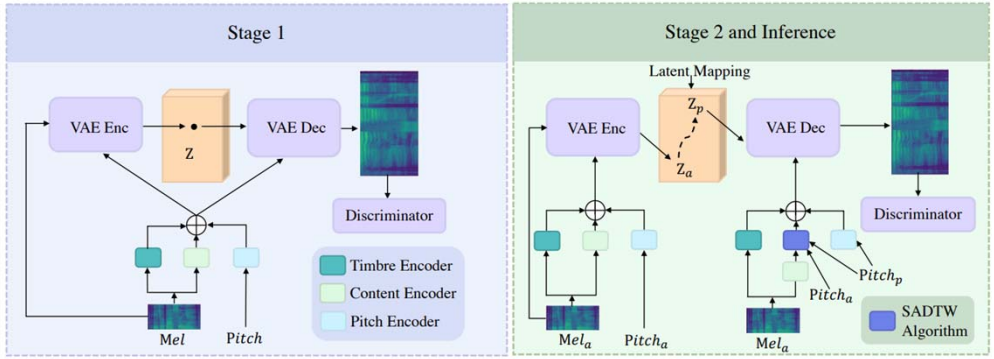
- **Singing voice conversion** (SVC)

- **Speech-to-singing synthesis**



Ref: Saitou et al, "Speech-to-singing synthesis: converting speaking voices to singing voices by controlling acoustic features unique to singing voices," WASPAA 2007

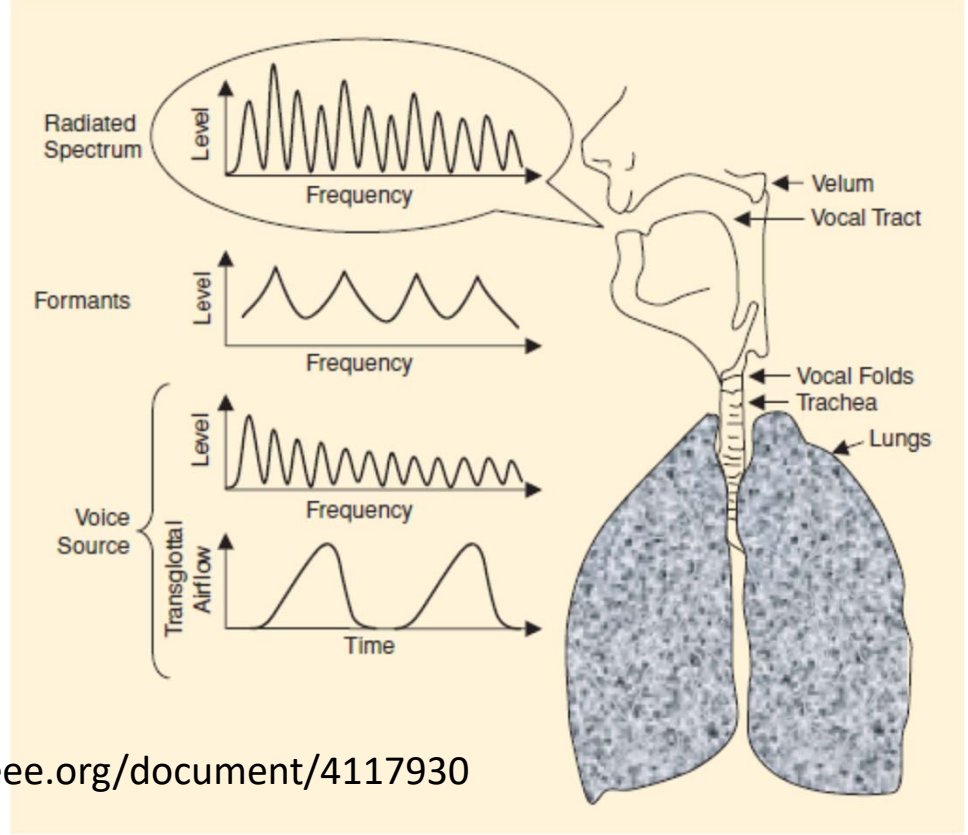
- **Singing voice beautification**



Ref: Liu et al, "Learning the beauty in songs: Neural singing voice beautifier," ACL 2022

Singing Generation Tasks: Singing Voice Synthesis

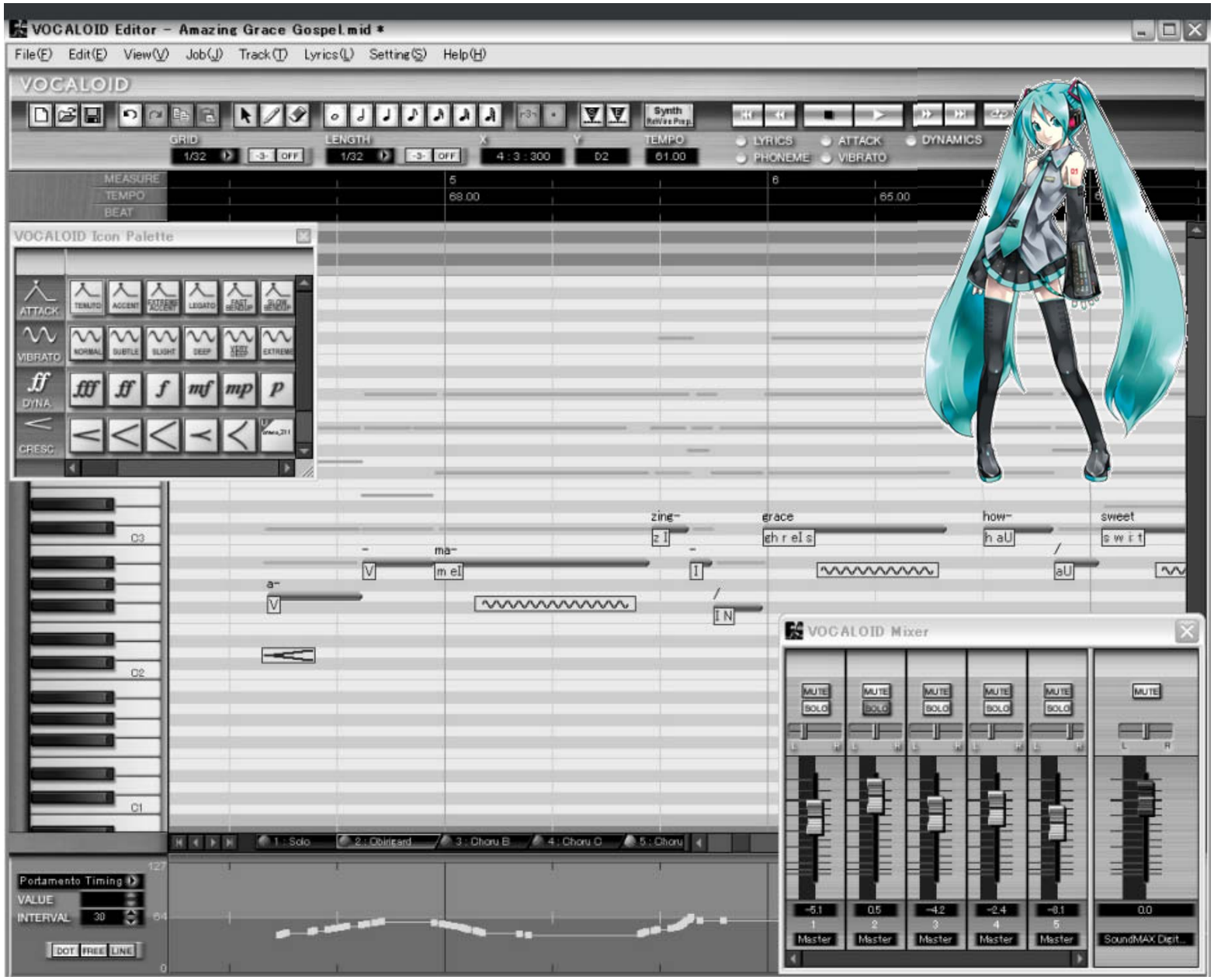
- **text+MIDI → singing audio**
- Cook, “Singing voice synthesis: History, current work, and future directions,” *CMJ 1996*
  https://www.jstor.org/stable/3680822?seq=6



https://ieeexplore.ieee.org/document/4117930

Vocaloid

- Vocal+android
  （歌唱）（人形機器人）
  - A singing voice synthesizer related product of Yamaha, first released in 2004
  - User types in lyrics and MIDI through an editor to create singing voice



Singing Voice Synthesis in the Past

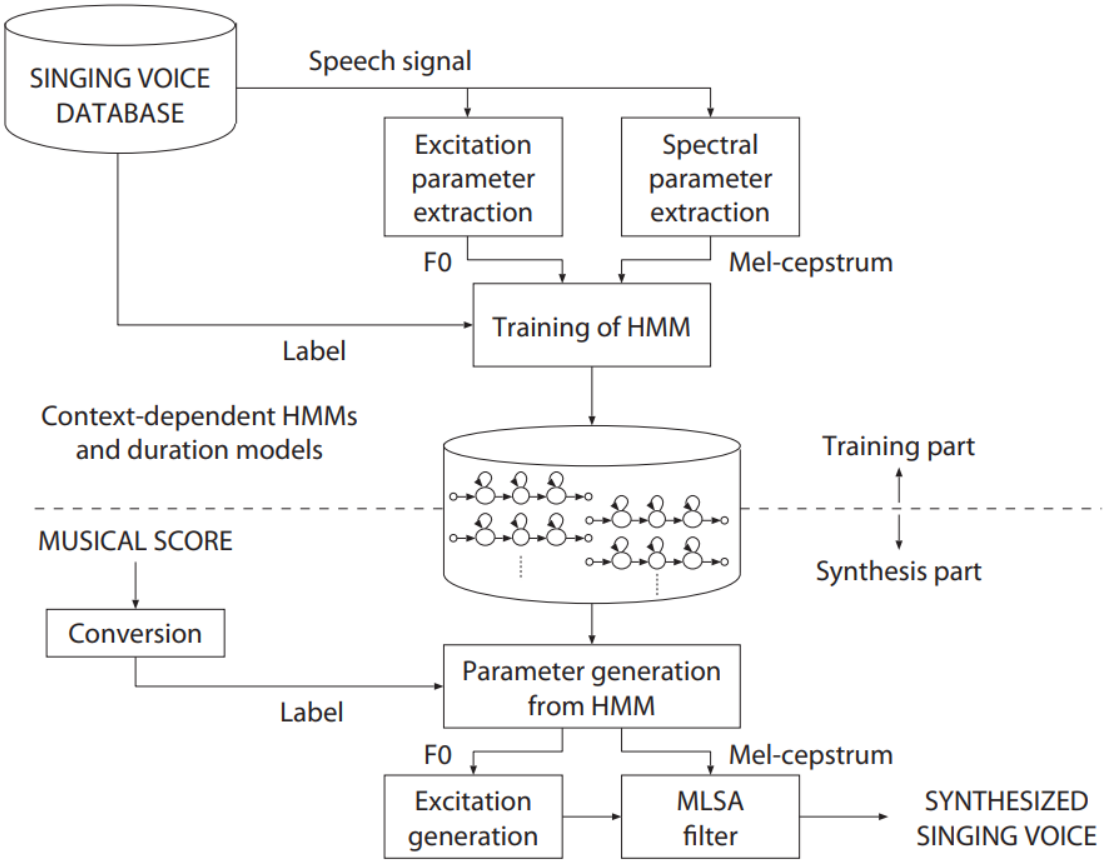
1. **Human knowledge**
2. **Lot's of signal processing**
3. **Few parameters**

- Great success, but characteristic ***robotic*** sound

Singing Voice Synthesis in 2010

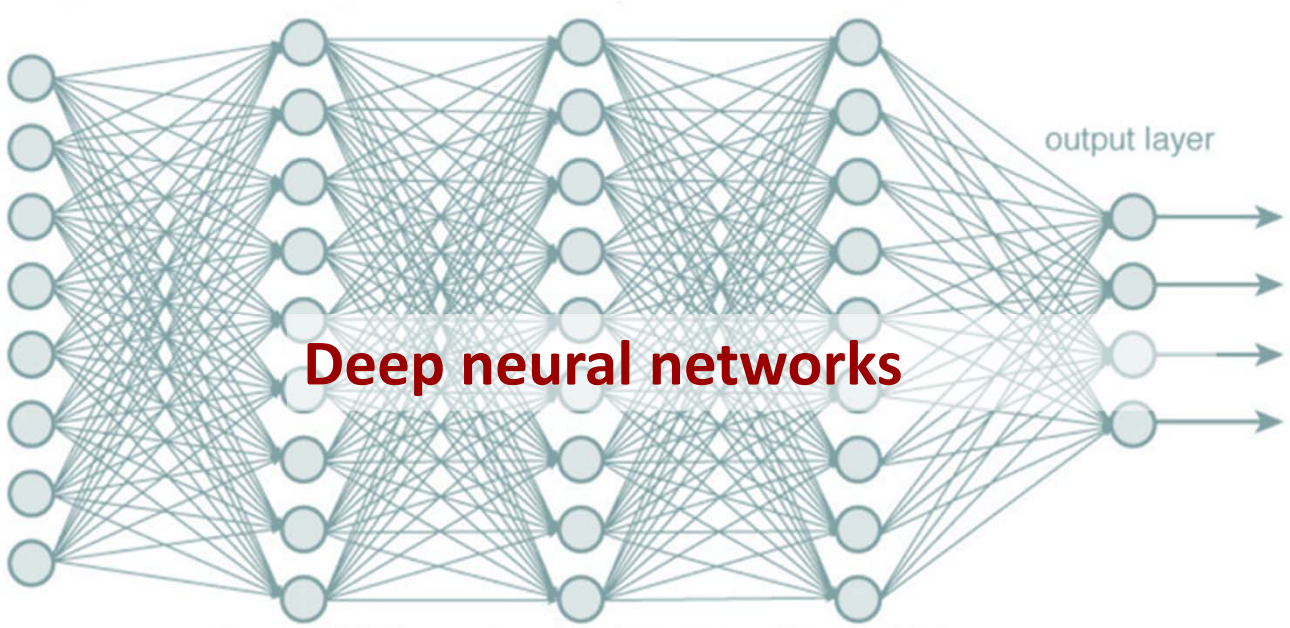
1. **Human knowledge**
2. **Lot's of signal processing**
3. **Few parameters**

- Oura et al., "Recent development of the **HMM-based** singing voice synthesis system—Sinsy," *Proc. ISCA Workshop on Speech Synthesis,* 2010



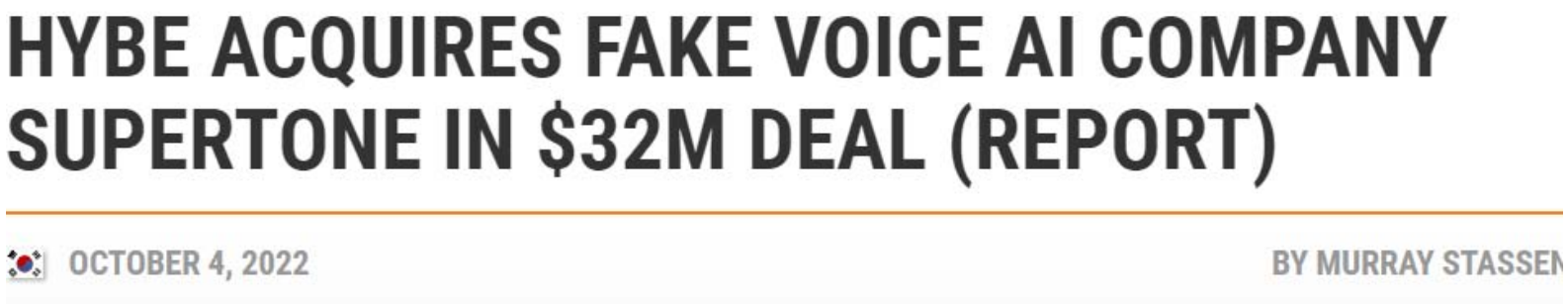
DL: It's about Learning Input/Output Relationships

- Input: **lyrics + melody notes** (per sentence)
- Output: corresponding **singing audio**



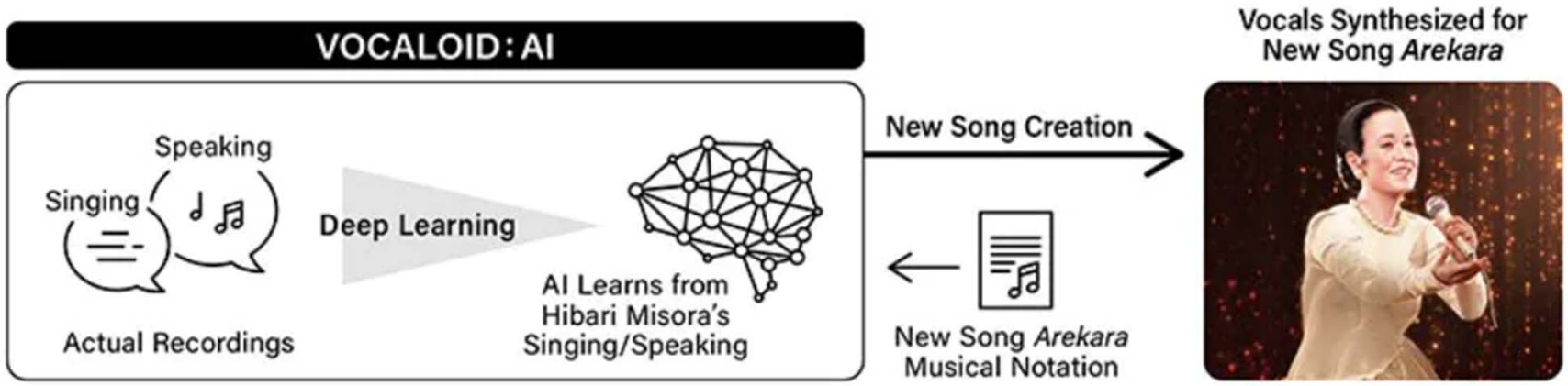
Research + Data

- **Supertone:** https://www.youtube.com/watch?v=MPG4_scT798
  - A startup co-founded by Prof. Kyogu Lee at Seoul National University
  - Tones of data ("We trained the backbone model on 10,571 hours (speech: 10,092 hours, singing: **479 hours**) of proprietary 44.1 kHz audio recordings composed of 6,176 speakers and **624 singers**")
  - Company acquired by HYBE (home to BTS) in Oct. 2022


HYBE ACQUIRES FAKE VOICE AI COMPANY SUPERTONE IN $32M DEAL (REPORT)

OCTOBER 4, 2022 BY MURRAY STASSEN

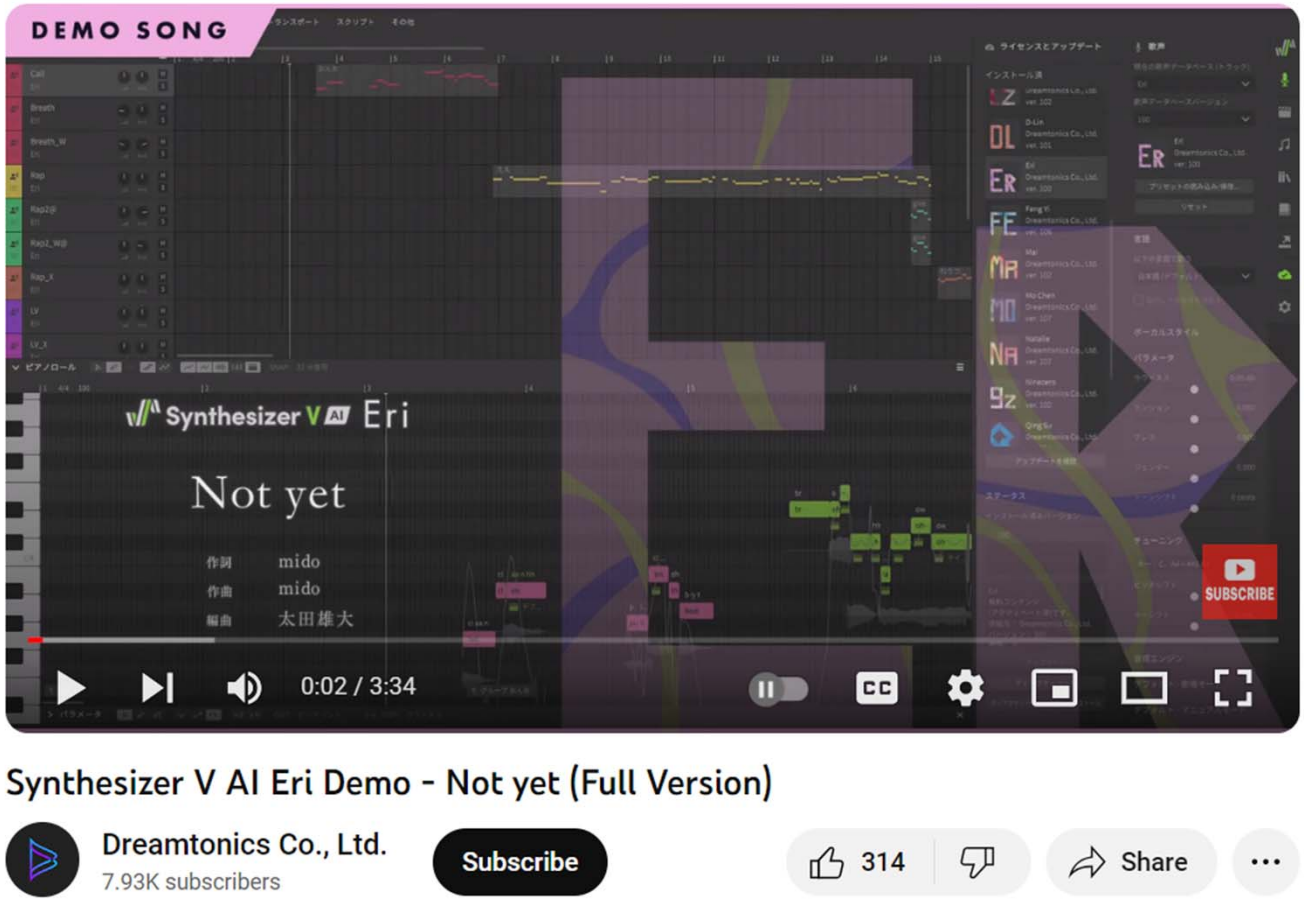
VOCALOID 6



VOCALOID6 uses VOCALOID:AI, an AI-based technology that makes it possible to generate even more natural-sounding and highly expressive singing voices.

SynthV

https://www.youtube.com/watch?v=Yrs4rF_V92s



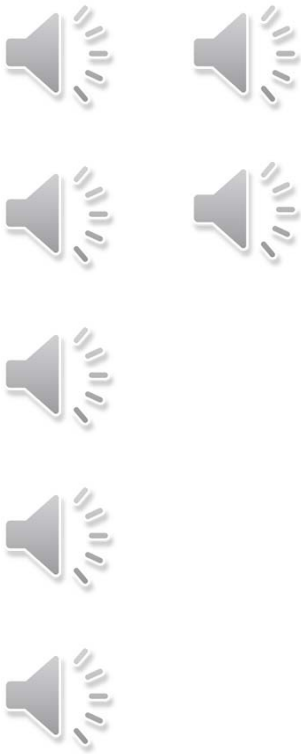
Our Own Experience

2019/08
AI phantom

2020/02
bad articulation

2021/06
intelligible

2021/10
AI Sandee v0



2022/06
better quality

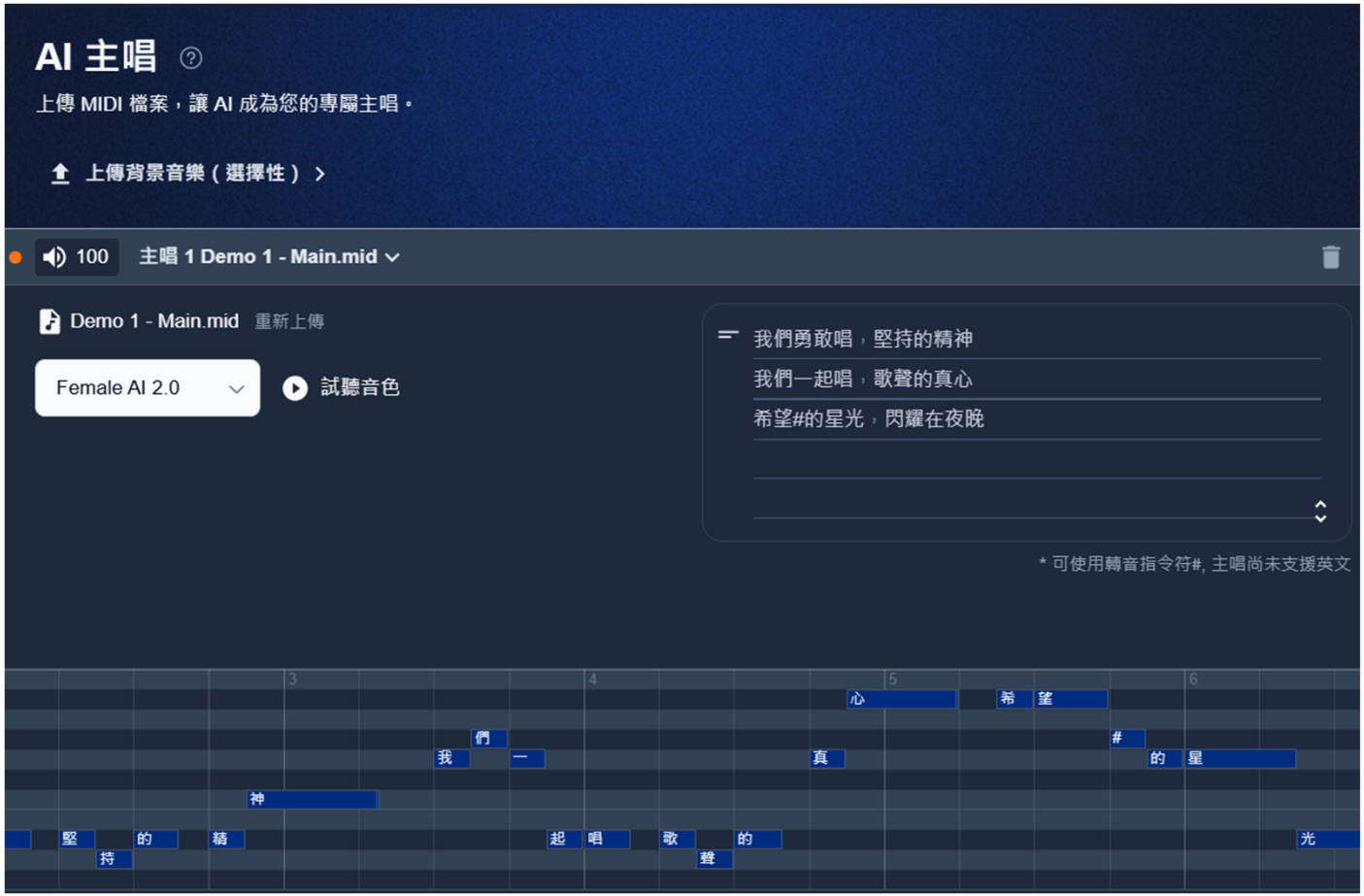
2022/12
close to ready

2023/03

Singing Synthesis at the Taiwan AI Labs

https://studio.yating.tw/music/ai-vocal

- For *pro* users
  - Given lyrics and melody notes (MIDI), generate singing audio



Singing Synthesis at the Taiwan AI Labs

https://studio.yating.tw/music/text-to-song

- For *common* users
  - Lyrics expansion
  - Given lyrics, generate melody
  - Singing synthesis
  - Backing track generation
  - Automatic mixing

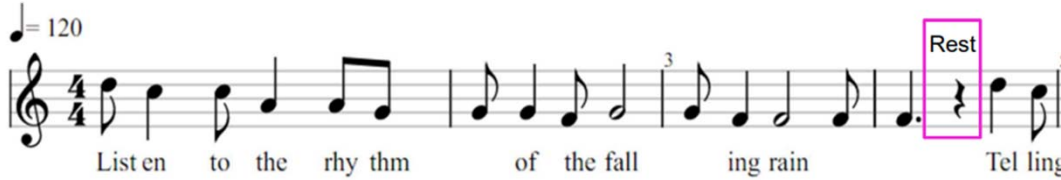
SVS vs SVC

- **Singing voice synthesis (SVS):**
  lyrics + MIDI notes → audio
  - input/output ***different domains***
    (**score → performance + sounds**)
  - **lots of details** to be determined
  - input/output ***different lengths***
  - need to consider **temporal dynamics**

- **Singing voice conversion (SVC):**
  ref audio → audio
  - ***same domains***
  - mainly about modeling **timbre**
  - can be of ***same length***
  - "**local" conversion** might be sufficient

SVS

- **text+MIDI → singing audio**
  (score → performance + sounds)

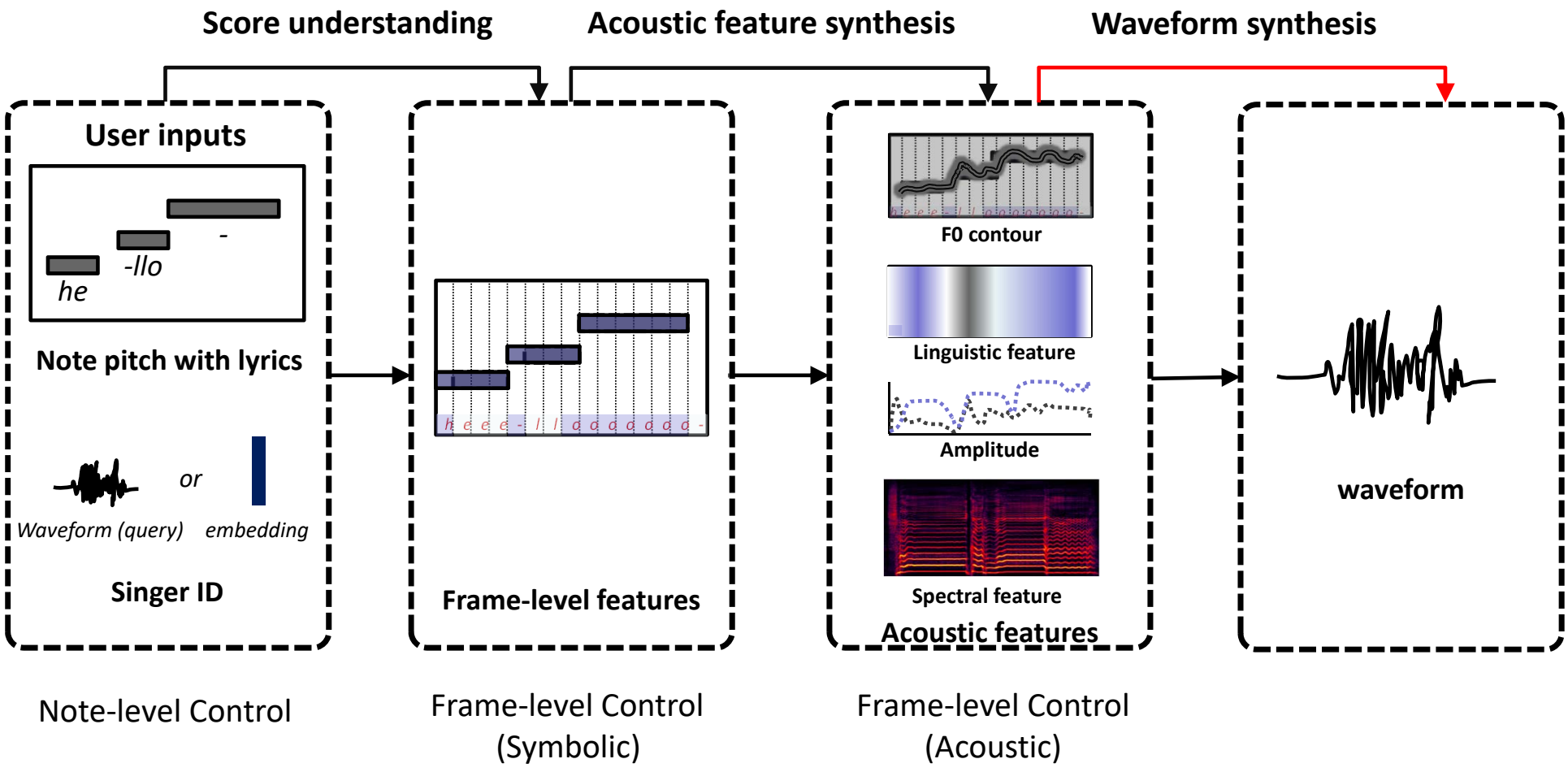


Lyrics	List	en	to	the	rhy	thm	of	the	fall	ing	rain	Tel	ing
Note	D5	C5	C5	A4	A4	G4	G4	F4	G4	F4	F4	D5	C5
Duration	0.5	1	0.5	1	0.5	1	1	0.5	2.5	1	4	1	0.5
Rest	0	0	0	0	0	0	0	0	0	0	0	1	0

Fig. 1: An example of alignment between lyrics and melody

- "Performance" attributes to predict from the score
  - **F0 [MIDI pitch → hz]**
  - **onset time** and **offset time** (in ms) **[musical time → physical time]**
  - singing techniques (optional)

SVS



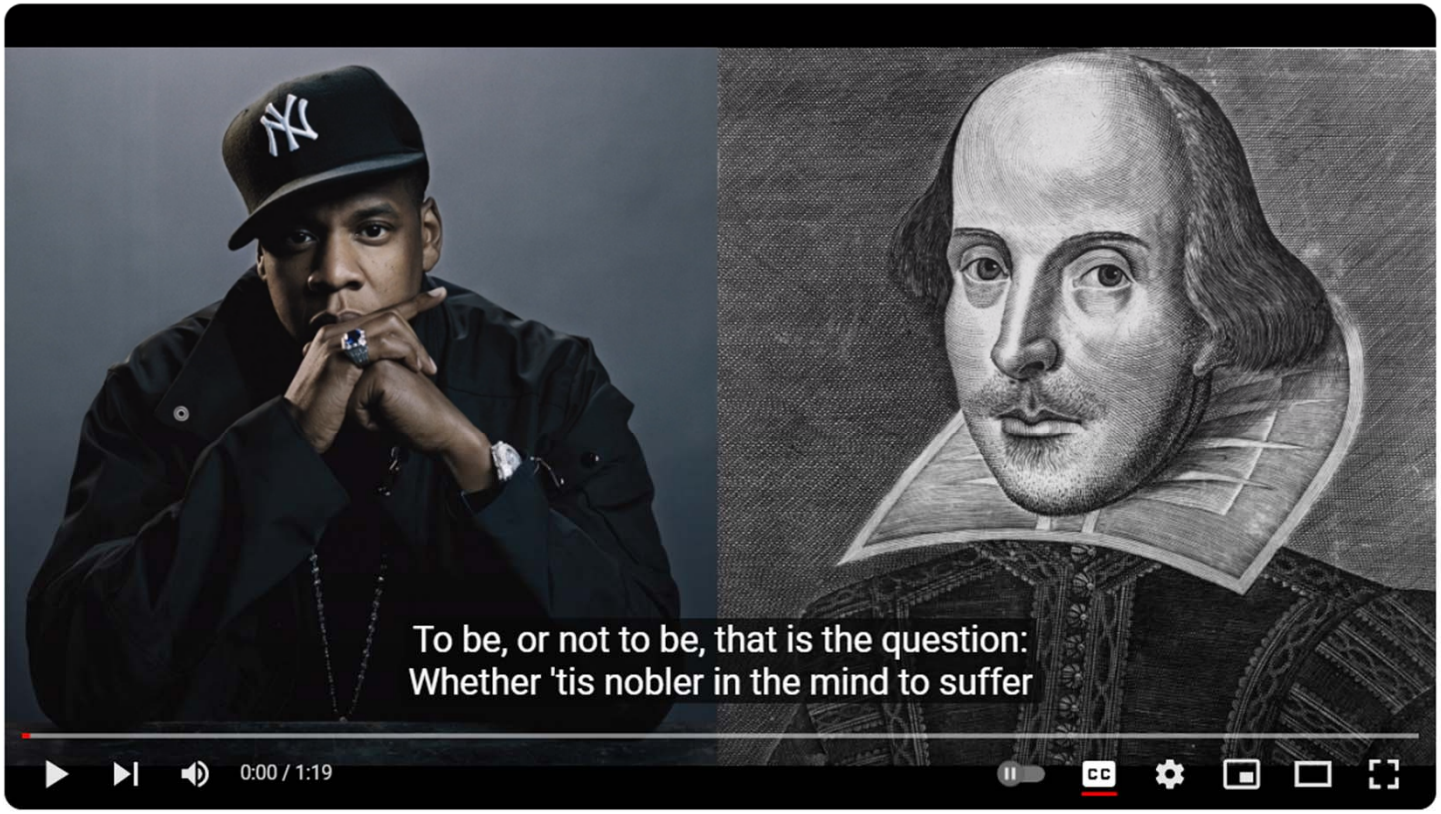
Adapted from the slides of the ISMIR 2022 tutorial presented by Hyeong-Seok Choi

Outline

- Singing voice processing: Historical review
- **Neural text-to-speech synthesis**
- Neural singing voice synthesis
- Build your SVS model

TTS

https://www.youtube.com/watch?v=m7u-y9oqUSw



Jay-Z raps the "To Be, Or Not To Be" soliloquy from Hamlet (Speech Synthesis)

Progress of SVS Benefits from that of TTS

- SVS and TTS are similar
  - **Text-to-speech** (TTS): given text (and speaker ID), generate audio
  - **Singing voice synthesis** (SVS): given text and **MIDI** (and singer ID), generate audio
  - Both can be viewed as conditional audio generation problem
  - Both need to predict the **onset** and **offset** of each word or syllable
- Differences
  - Musical expressivity (**f0**, dynamics, singing techniques)
  - Cost to collect data

TTS vs. SVS

- **TTS**:
  - text → speech audio
  - need to predict **onset time** and **offset time** of each word or syllable

- **SVS**:
  - text+MIDI → singing audio
  - need to predict **onset time**, **offset time, and f0** of each word or syllable

TTS

https://github.com/tts-tutorial/interspeech2022

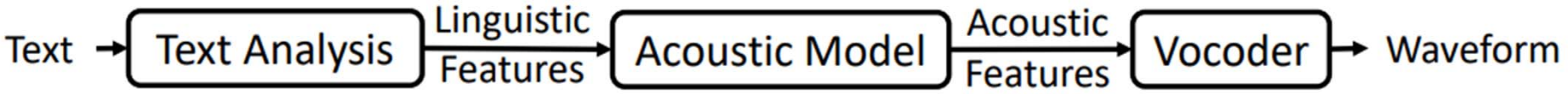


Figure 1: The three key components in neural TTS.

- Different linguistic features and acoustic features have been proposed
- SOTA neural TTS models
  - Simplify text analysis and directly take **character/phoneme sequences** as input
  - Simplify acoustic features with **Mel-spectrograms** (or directly generate waveform)

Ref: Tan et al, "A survey on neural speech synthesis," arXiv 2021

Character vs Phoneme

- **Character**/spelling (grapheme)
  - Used in LLM, ASR …
- Pronunciation (**phoneme**)
  - Used in TTS, SVS

User: Lyrics → Syllable ↔ Note

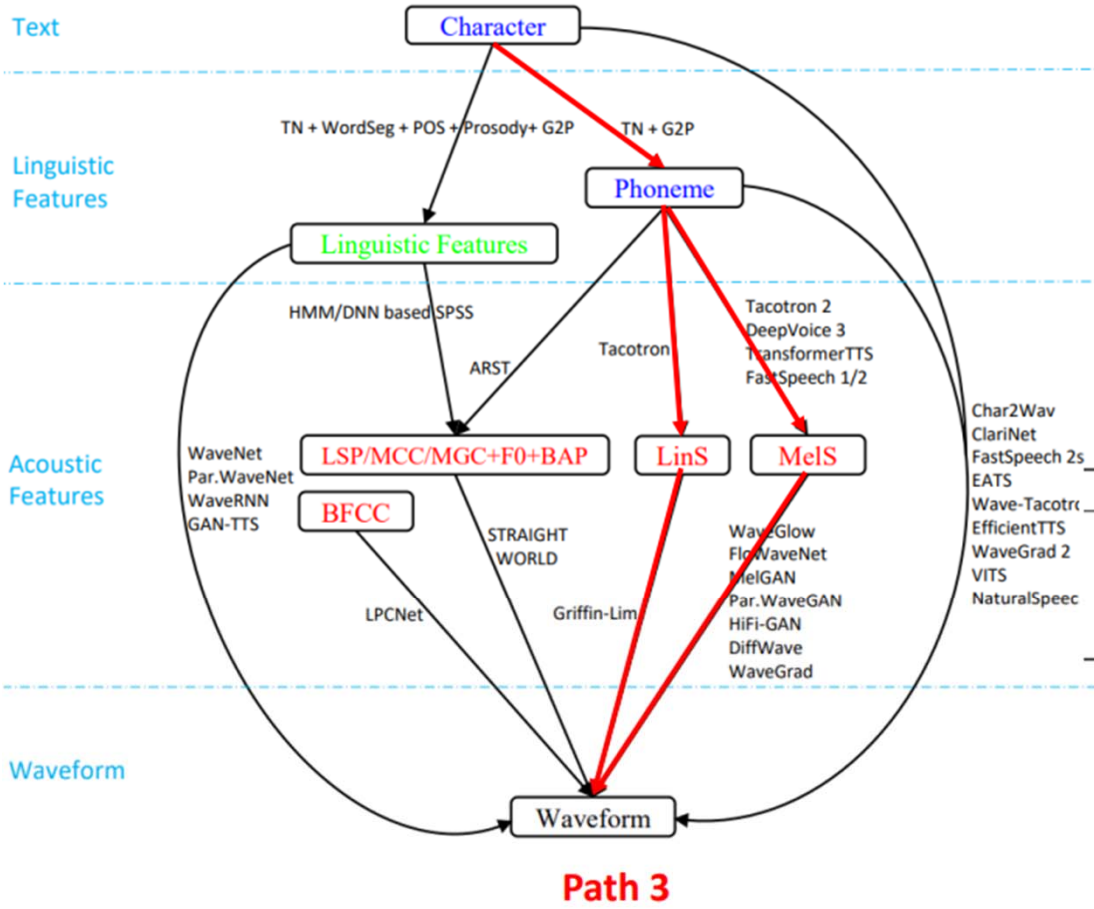
Example:
"to a place" → **User (syllabify)** → "to" "a" "place"
→ **Grapheme2Phoneme (G2P)** → "tʊ" "ə" "pleɪs"

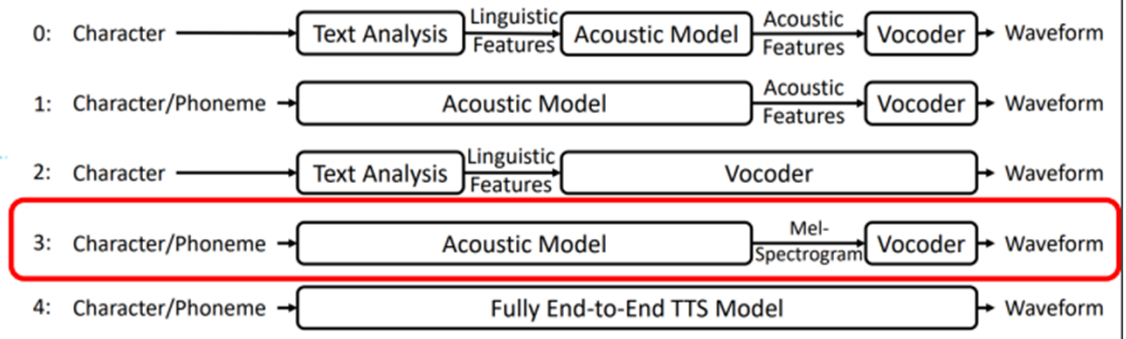
Snapshot of the ISMIR 2022 tutorial presented by Hyeong-Seok Choi

- Question: For 1) melody-to-lyrics generation, and 2) lyrics-to-melody generation, do we prefer the character- or the phoneme-based representation for the lyrics?

TTS

https://github.com/tts-tutorial/interspeech2022

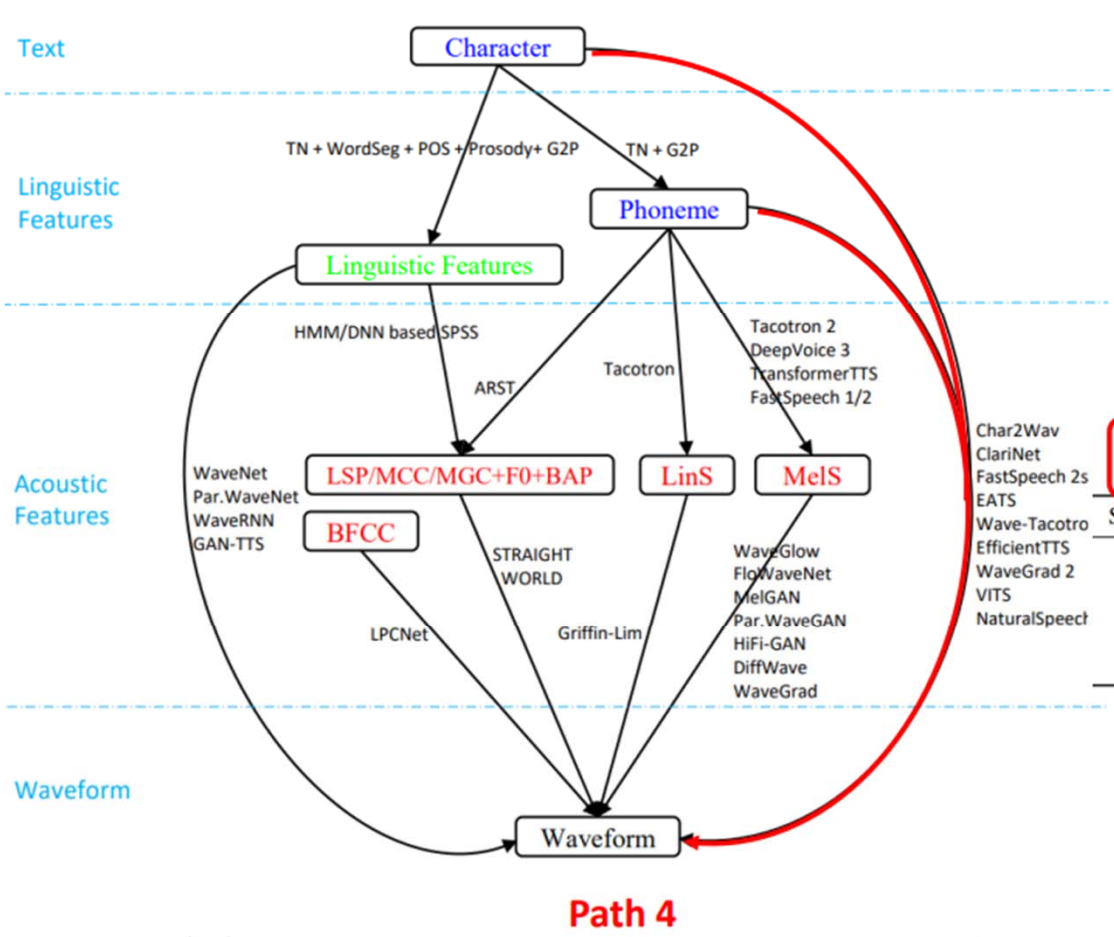


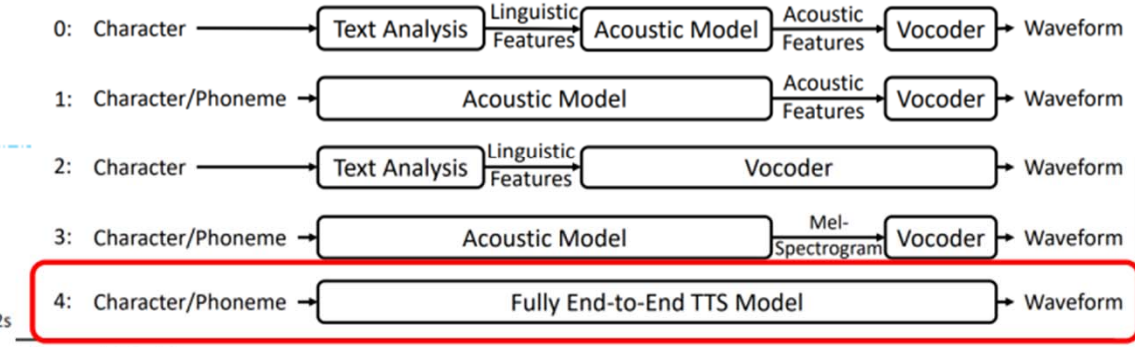


Stage	Models
0	SPSS [418, 358, 417, 427, 359]
1	ARST [377]
2	WaveNet [255], DeepVoice 1/2 [8, 88], Par. WaveNet [256], WaveRNN [151], HiFi-GAN [23]
3	DeepVoice 3 [271], Tacotron 2 [304], FastSpeech 1/2 [291, 293], WaveGlow [280], FloWaveNet [164]
4	Char2Wav [316], ClariNet [270], FastSpeech 2s [293], EATS [70], VITS [161], NaturalSpeech [346]

TTS

https://github.com/tts-tutorial/interspeech2022

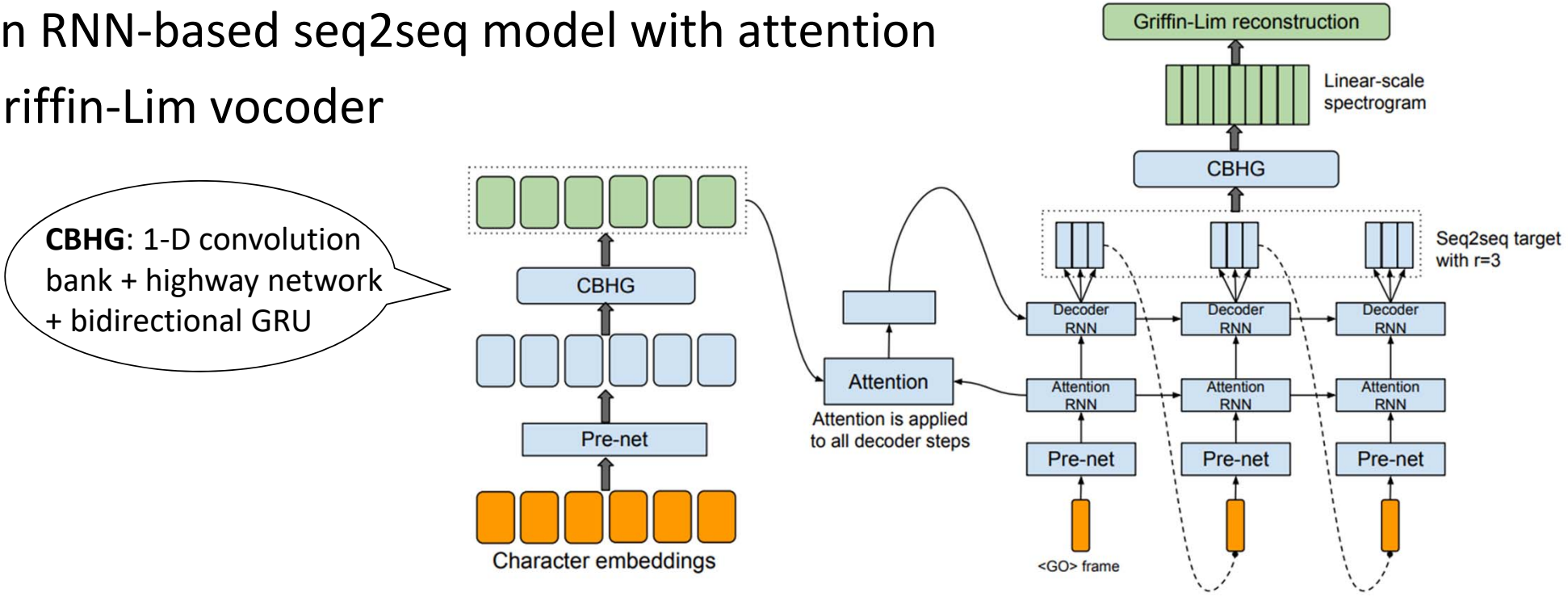




Stage	Models
0	SPSS [418, 358, 417, 427, 359]
1	ARST [377]
2	WaveNet [255], DeepVoice 1/2 [8, 88], Par. WaveNet [256], WaveRNN [151], HiFi-GAN [23]
3	DeepVoice 3 [271], Tacotron 2 [304], FastSpeech 1/2 [291, 293], WaveGlow [280], FloWaveNet [164]
4	Char2Wav [316], ClariNet [270], FastSpeech 2s [293], EATS [70], VITS [161], NaturalSpeech [346]

TacoTron

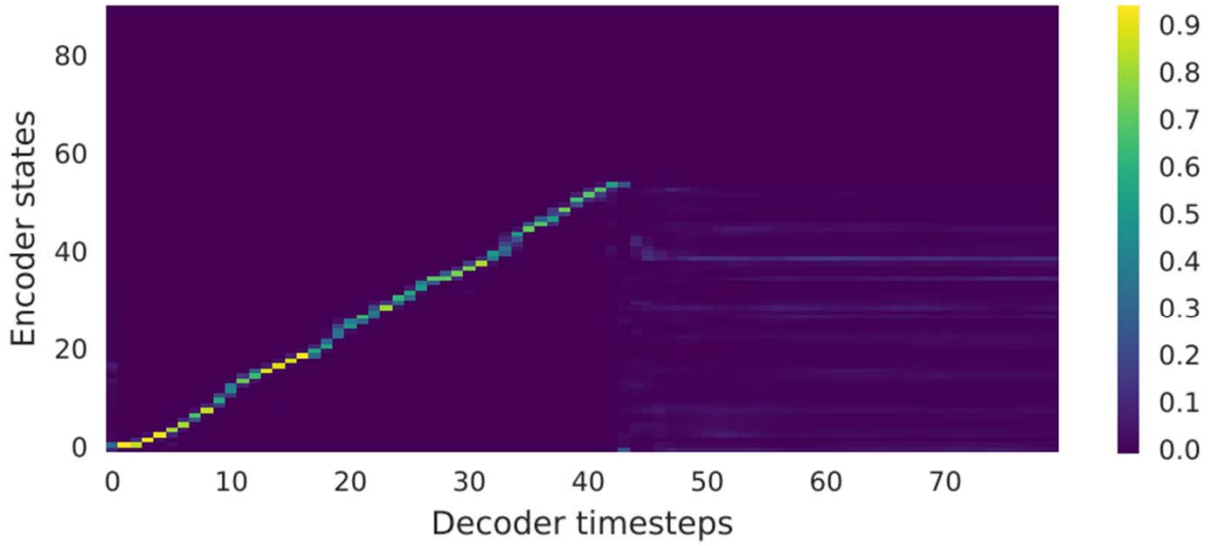
- Takes **characters** as input and **predict frames of (linear) spectrogram**
- **Autoregressive** (AR)
- An RNN-based seq2seq model with attention
- Griffin-Lim vocoder



Ref: Wang et al, "Tacotron: Towards end-to-end speech synthesis," INTERSPEECH 2017

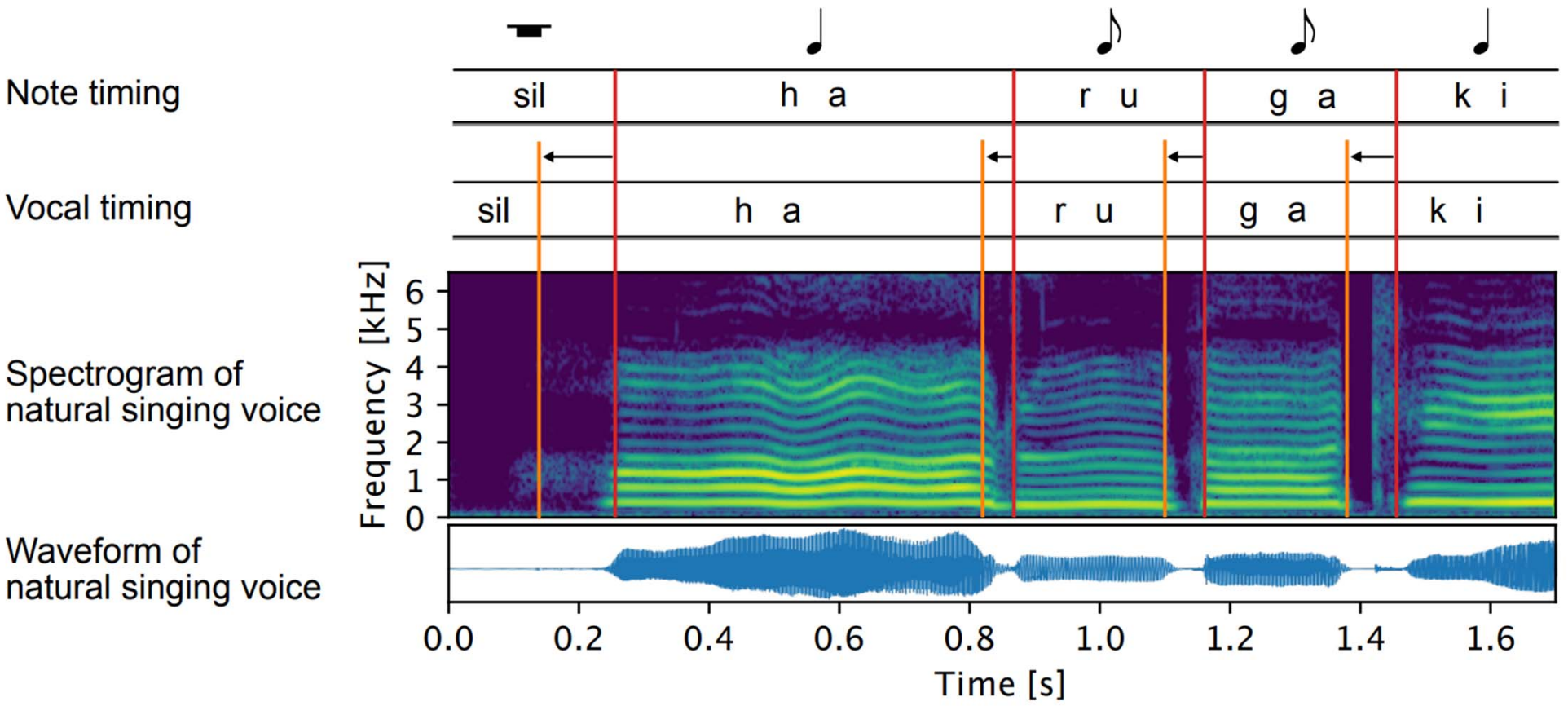
Why Attention?

- To learn the **alignment** between input text and output audio (i.e. to predict the onset/offset of each word or syllable)
- Unlike source separation and vocoder, for TTS & SVS, the input and output are of **different lengths**



(c) Tacotron (proposed)

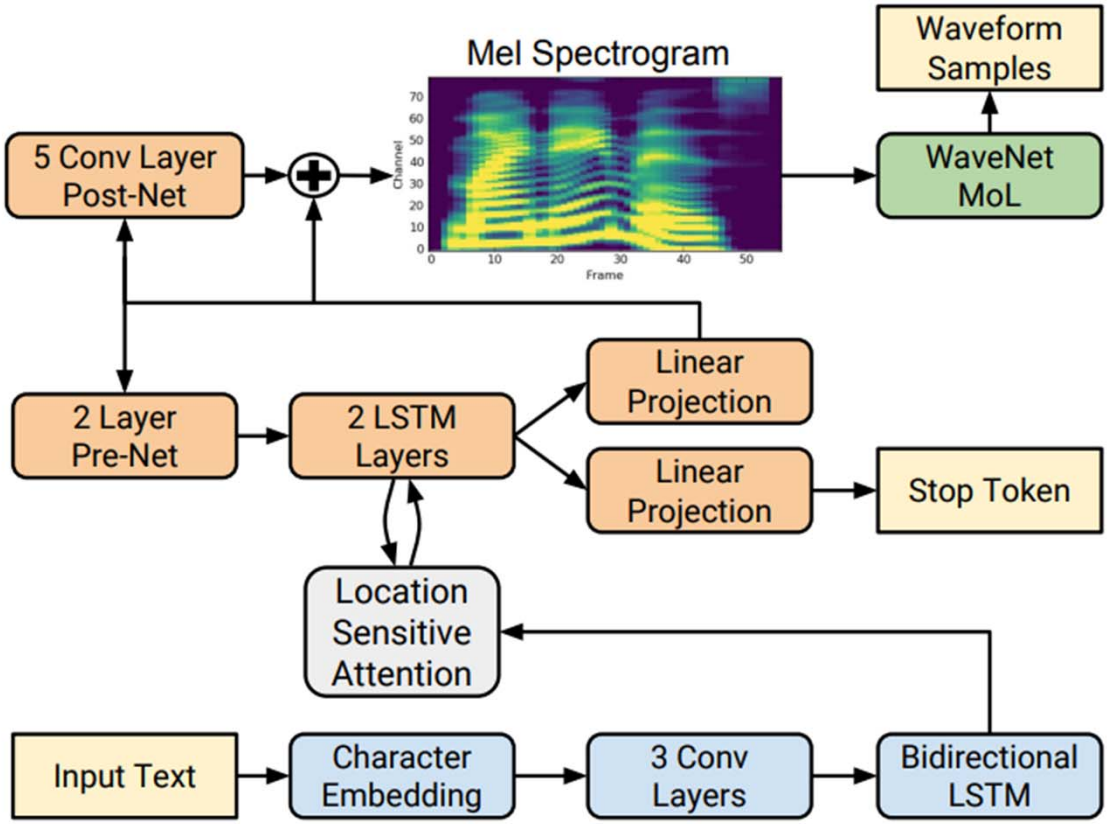
Text-Audio Alignment



TacoTron 2

- Modifications
  - Mel-spectrograms instead of linear spectrograms
  - WaveNet-like Mel-vocoder
  - Simpler architecture (no CBHG)
  - Location sensitive attention
  - “Stop token”

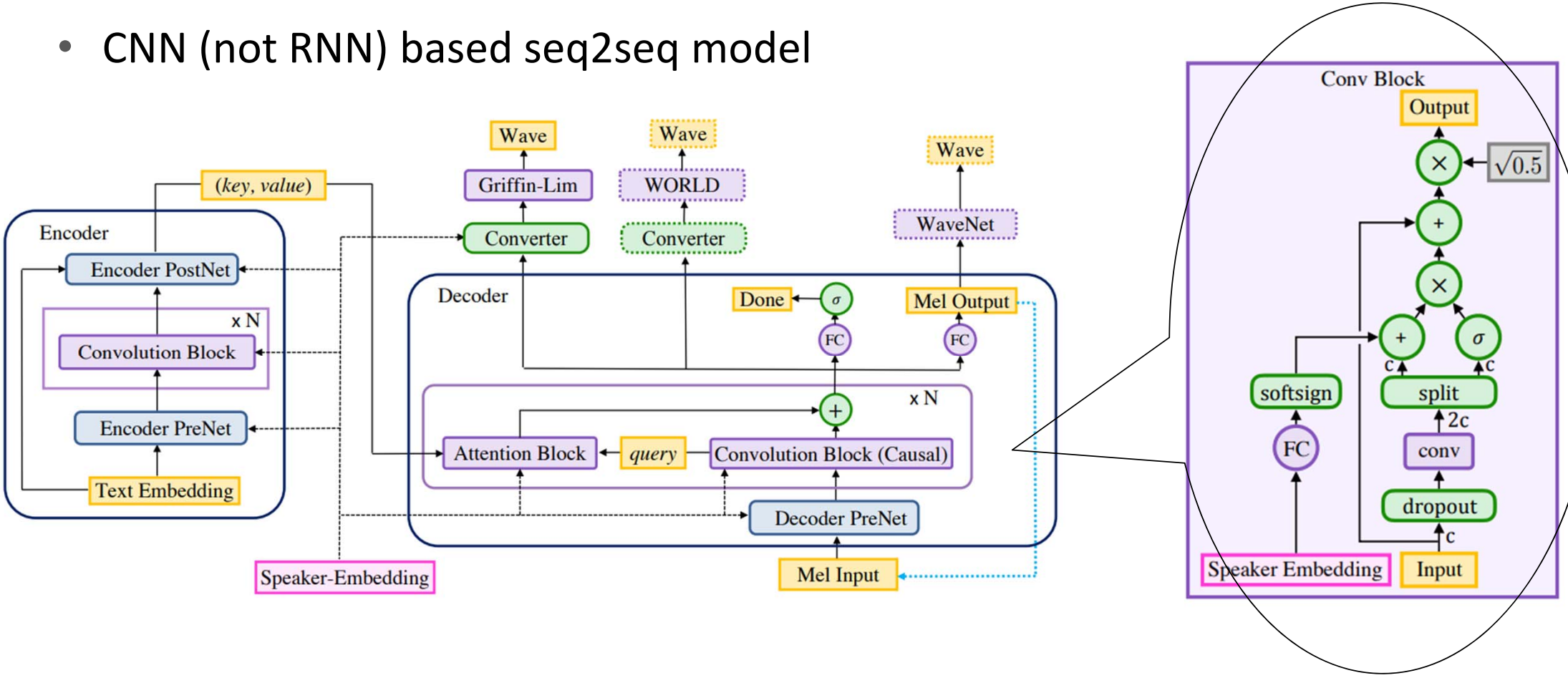
System	MOS
Parametric	3.492 ± 0.096
Tacotron (Griffin-Lim)	4.001 ± 0.087
Concatenative	4.166 ± 0.091
WaveNet (Linguistic)	4.341 ± 0.051
Ground truth	4.582 ± 0.053
Tacotron 2 (this paper)	$\mathbf{4.526 \pm 0.066}$



Ref: Shen et al, “Natural TTS synthesis by conditioning WaveNet on Mel spectrogram predictions,” ICASSP 2018

Deep Voice 3

- CNN (not RNN) based seq2seq model

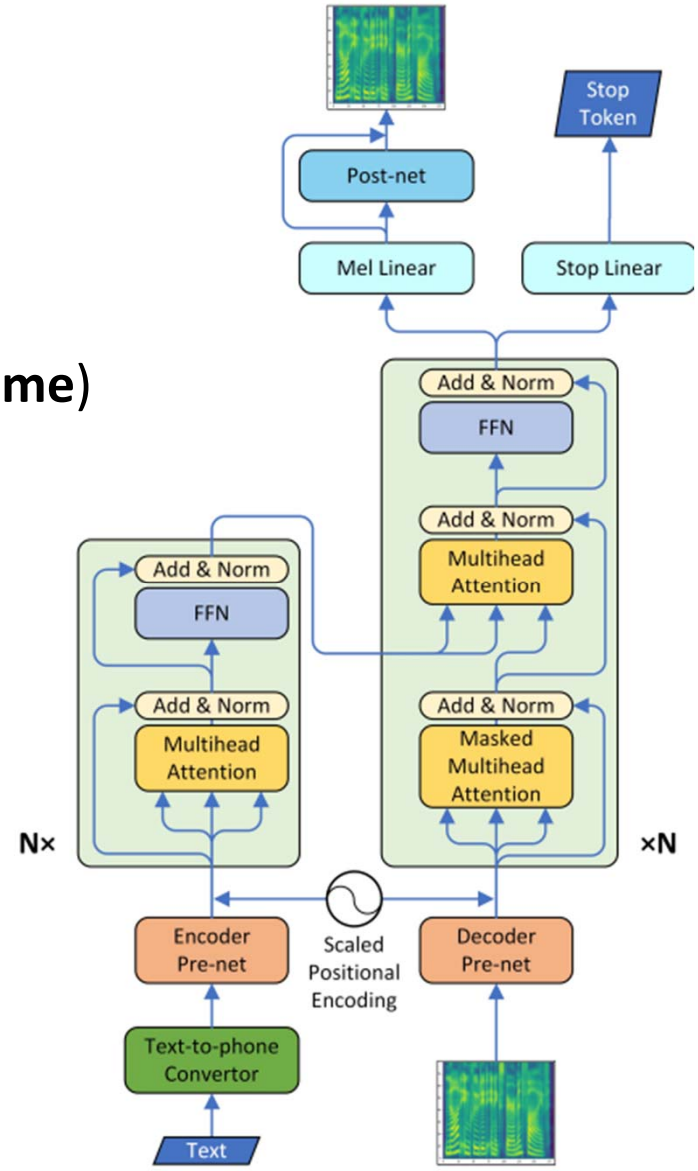


Ref: Ping et al, "Deep Voice 3: Scaling text-to-speech with convolutional sequence learning," ICLR 2018

Transformer-TTS

- Replace RNN by multi-head attention
- Using **phoneme** sequences as input
  - *Character/spelling* (**grapheme**) vs *pronunciation* (**phoneme**)

System	MOS	CMOS
Tacotron2	4.39 ± 0.05	0
Our Model	4.39 ± 0.05	**0.048**
Ground Truth	4.44 ± 0.05	-



Ref: Li et al, “Neural speech synthesis with Transformer network,” AAAI 2019

Drawbacks of AR-based Seq2seq models

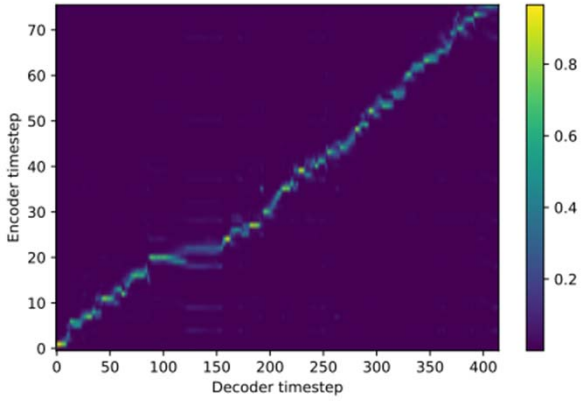
- **Slow inference speed**
- **Synthesized speech is usually not robust**
  - Due to *error propagation* and the *wrong attention alignments* between text and speech in the autoregressive generation, the generated mel-spectrogram is usually deficient with the problem of **words skipping** and **repeating**
- **Synthesized speech is lack of controllability**
  - Hard to directly control the *voice speed* and *prosody* in autoregressive generation

Ref: Ren et al, "Fastspeech: Fast, robust and controllable text to speech," NeurIPS 2019

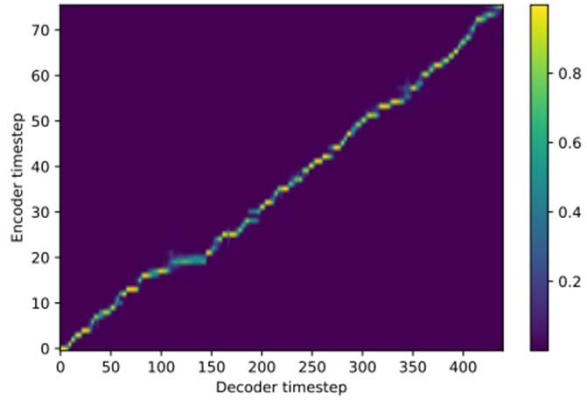
Robustness Problem About Alignment

- Properties of good alignment [1]
  - **Monotonicity**
  - **Continuity**
  - **Completeness**: cover all input tokens

- However, unless specifically enforcing related constraints (e.g., [2]), the alignment learned by attention modules may not have the aforementioned properties



(c) *Tacotron 2*



(d) *Tacotron 2 with* $\mathcal{L}_{align}$

Ref 1: “EfficientTTS: An efficient and high-quality text-to-speech architecture,” ICML 2021

Ref 2: “One TTS alignment to rule them all,” arXiv 2021

Drawbacks of Autoregressive models

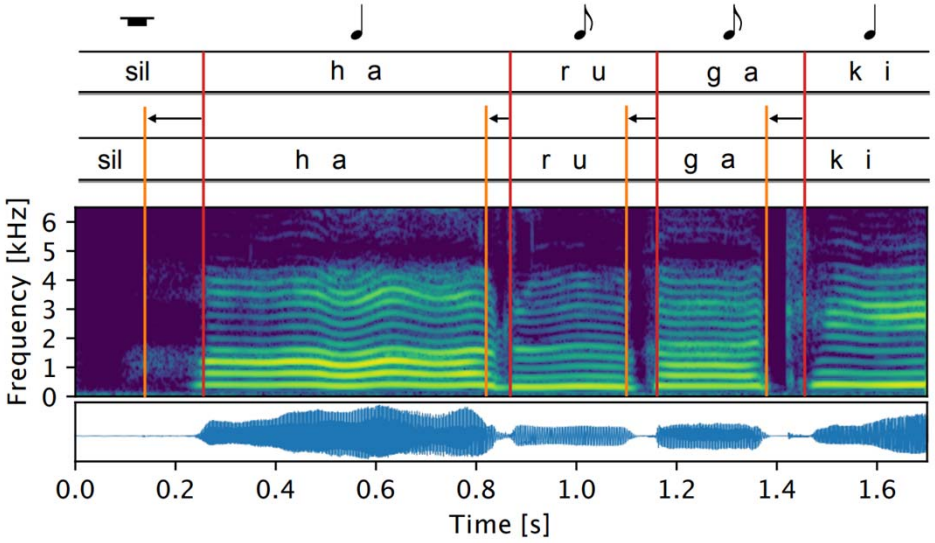
- **Slow inference speed → Use non-autogressive models!**
- **Synthesized speech is usually not robust → Predict phoneme duration!** (i.e. predict onset and offset times)
  - Due to *error propagation* and the *wrong attention alignments* between text and speech in the autoregressive generation, the generated mel-spectrogram is usually deficient with the problem of words skipping and repeating"
- **Synthesized speech is lack of controllability → Add conditioning**
  - Hard to directly control the voice speed and prosody in autoregressive generation

Ref: Ren et al, "FastSpeech: Fast, robust and controllable text to speech," NeurIPS 2019

Predict Phoneme Duration?

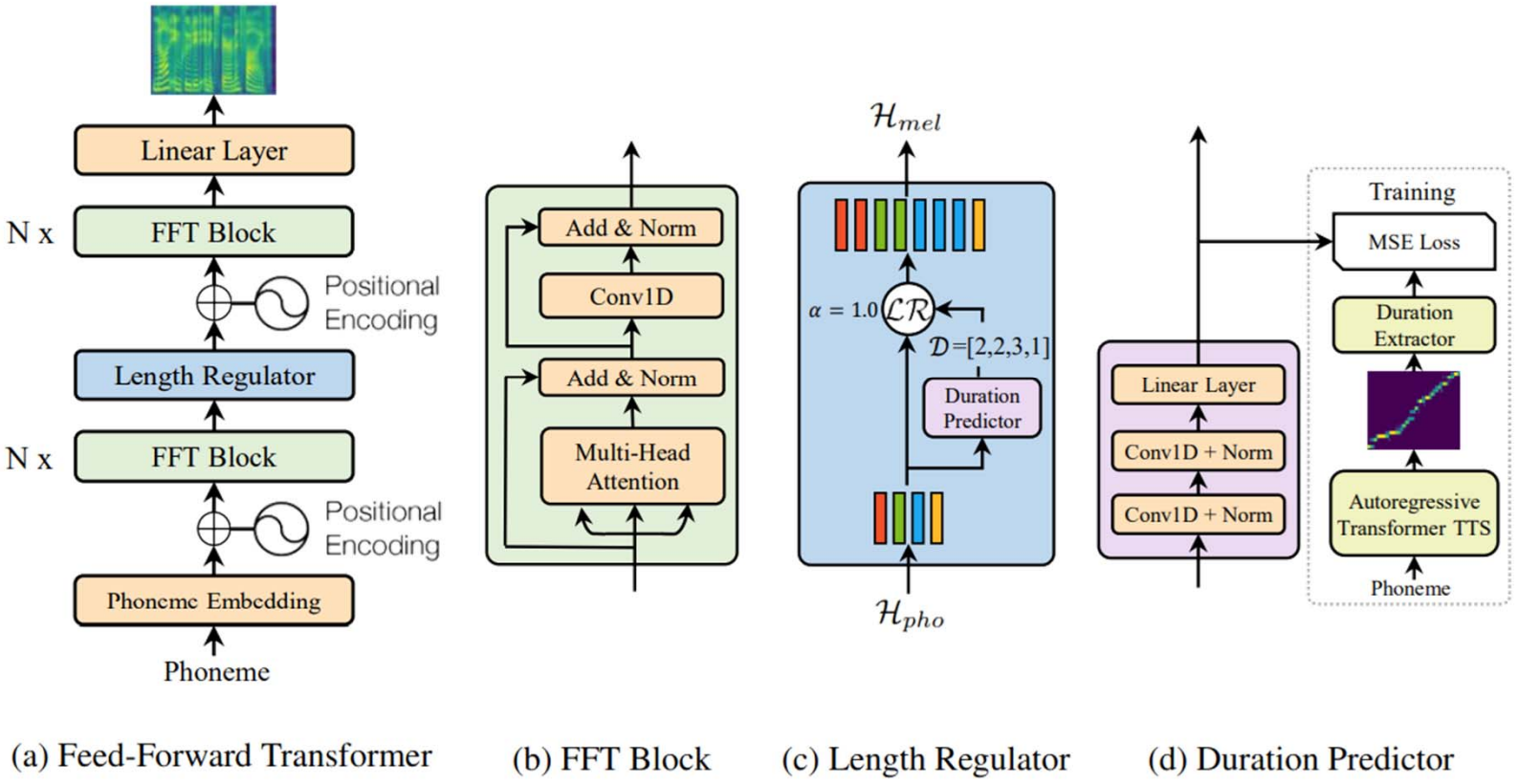
- Cross-attention based alignment is too much because for TTS the alignment between input sequence and output sequence must be monotonic
  - For other tasks such as machine translation (MT), the alignment may not be monotonic, making cross-attention a good choice; but this is not the case here

- It's actually good enough to know the **duration** of each character or phoneme (e.g., how many frames, or how many time samples)



FastSpeech

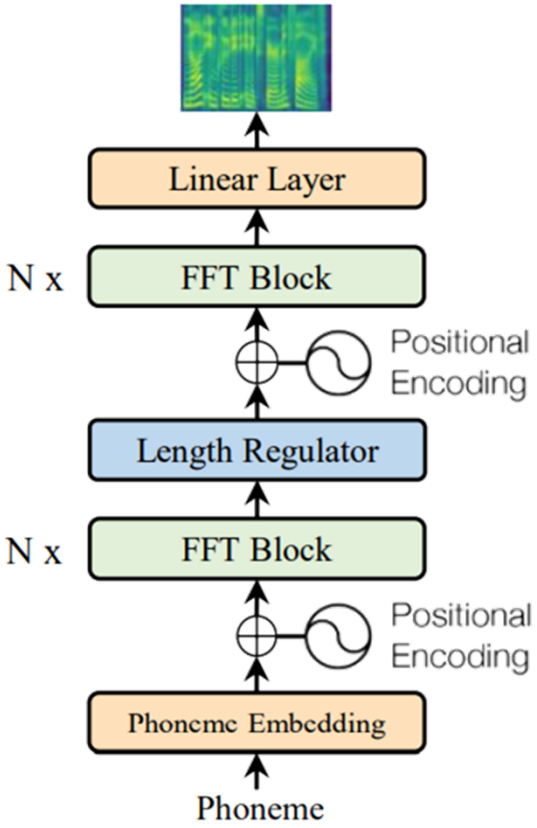
https://speechresearch.github.io/fastspeech/



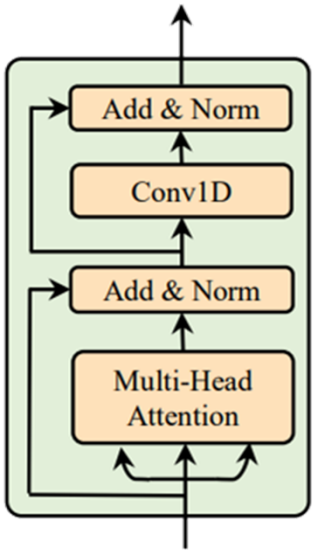
(a) Feed-Forward Transformer (b) FFT Block (c) Length Regulator (d) Duration Predictor

Ref: Ren et al, "Fastspeech: Fast, robust and controllable text to speech," NeurIPS 2019

FastSpeech



(a) Feed-Forward Transformer



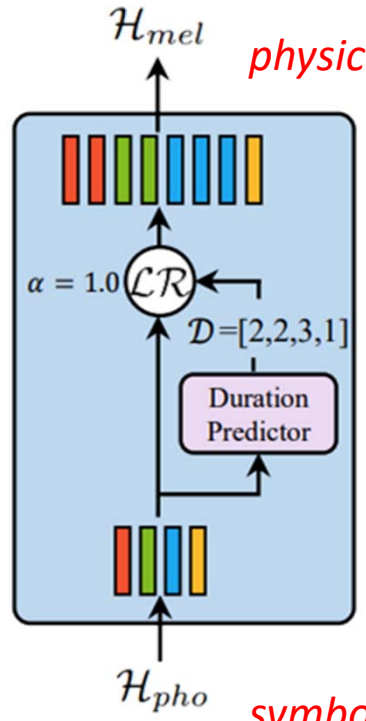
(b) FFT Block

- **Feed-forward Transformer** (FFT)
  → Non-autogressive & *fast inference*
  - No causal masking
  - Parallel generation
  - Conv1D instead of dense layers inside an FFT block

Ref: Ren et al, "Fastspeech: Fast, robust and controllable text to speech," NeurIPS 2019

FastSpeech

- **Length regulator** → *Robustness*
  - Up-samples the phoneme sequence according to the **phoneme duration** (i.e., the number of frames that each phoneme corresponds to) to match the length of the mel-spectrogram sequence
- The phoneme duration is from a **duration predictor**
  - Explicitly determine the correspondence between the phoneme sequence and the mel-spectrogram sequence
  - **Hard alignment**
- We can also *manually* adjust the phoneme duration → *Controllability*

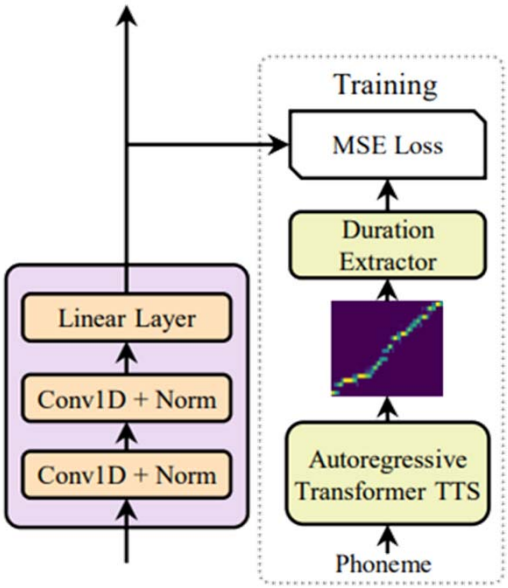


(c) Length Regulator

Ref: Ren et al, "Fastspeech: Fast, robust and controllable text to speech," NeurIPS 2019

FastSpeech

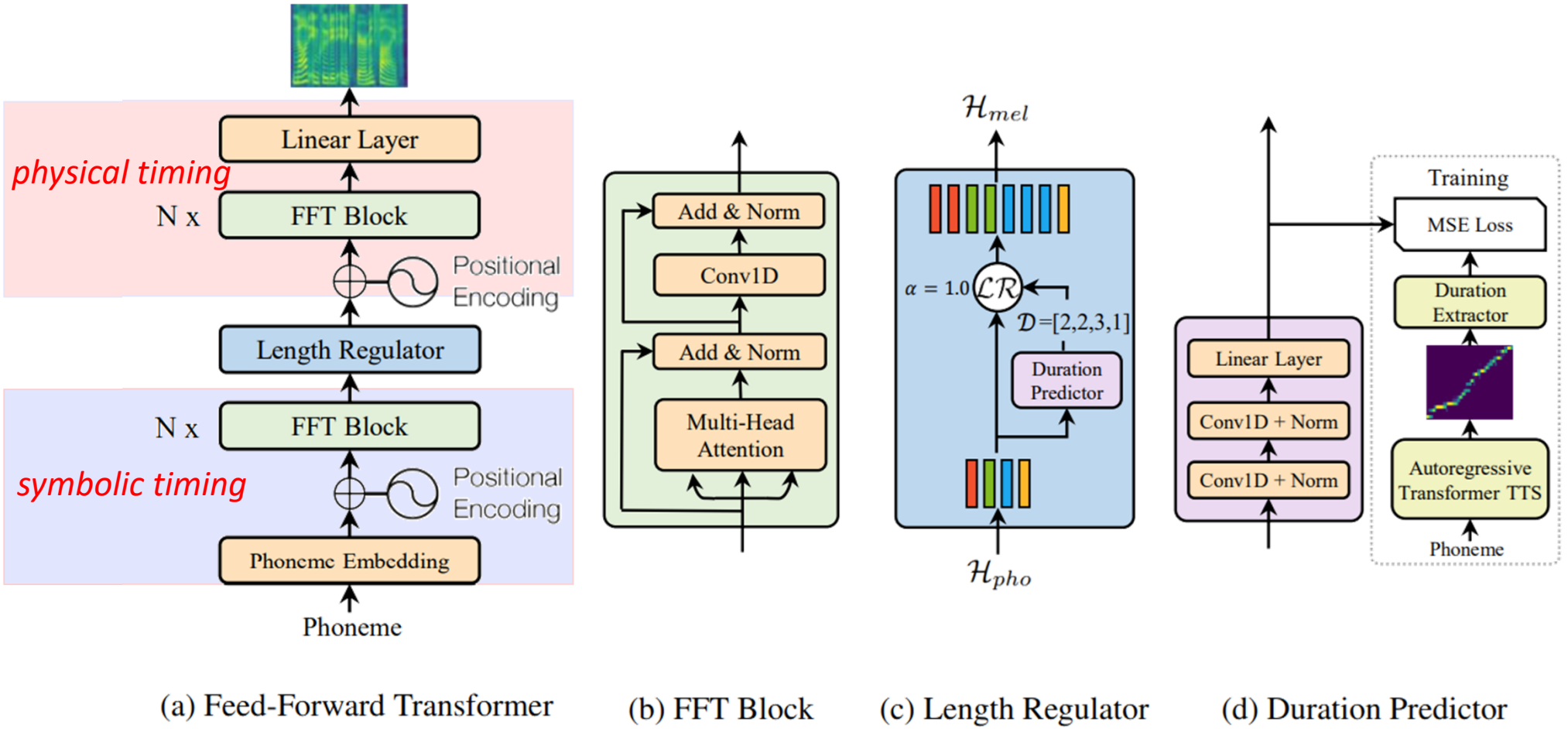
- **Phoneme duration predictor**
  - Produces *hard alignments*, which is very different from soft and automatic attention alignments in the autoregressive models
  - Predict the length in the **logarithmic** domain and use **MSE loss**
  - **Jointly trained** with FFT layers
- Ground truth phoneme duration for training?
  - From an autoregressive *teacher* model
  - Via Montreal forced alignment (MFA)
  - Or by **manually labeling**



(d) Duration Predictor

Ref: Ren et al, "Fastspeech: Fast, robust and controllable text to speech," NeurIPS 2019

FastSpeech



(a) Feed-Forward Transformer (b) FFT Block (c) Length Regulator (d) Duration Predictor

Ref: Ren et al, "Fastspeech: Fast, robust and controllable text to speech," NeurIPS 2019

FastSpeech: Evaluation Result

Method	MOS
GT	4.41 ± 0.08
GT (Mel + WaveGlow)	4.00 ± 0.09
Tacotron 2 [22] (Mel + WaveGlow)	3.86 ± 0.09
Merlin [28] (WORLD)	2.40 ± 0.13
Transformer TTS [14] (Mel + WaveGlow)	3.88 ± 0.09
FastSpeech (Mel + WaveGlow)	3.84 ± 0.08

Table 1: The MOS with 95% confidence intervals.

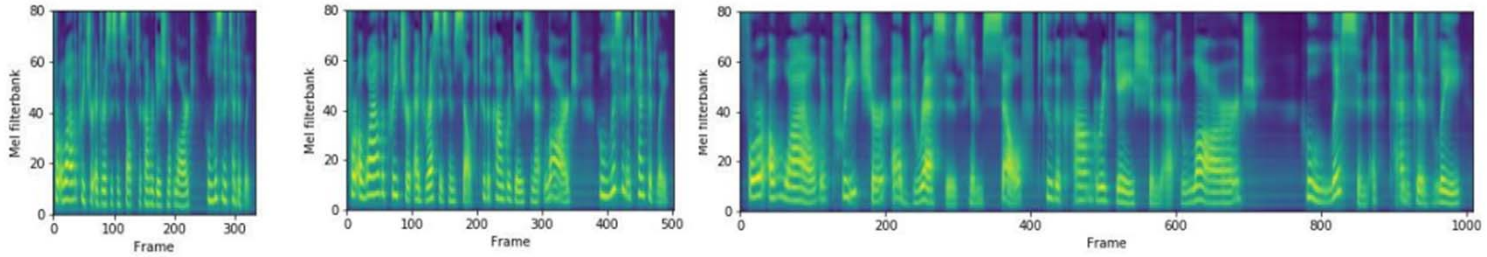
Method	Latency (s)	Speedup
Transformer TTS [14] (Mel)	6.735 ± 3.969	/
FastSpeech (Mel)	0.025 ± 0.005	269.40×
Transformer TTS [14] (Mel + WaveGlow)	6.895 ± 3.969	/
FastSpeech (Mel + WaveGlow)	0.180 ± 0.078	38.30×

Table 2: The comparison of inference latency with 95% confidence intervals. The evaluation is conducted on a server with 12 Intel Xeon CPU, 256GB memory, 1 NVIDIA V100 GPU and batch size of 1. The average length of the generated mel-spectrograms for the two systems are both about 560.

Method	Repeats	Skips	Error Sentences	Error Rate
Tacotron 2	4	11	12	24%
Transformer TTS	7	15	17	34%
FastSpeech	0	0	0	0%

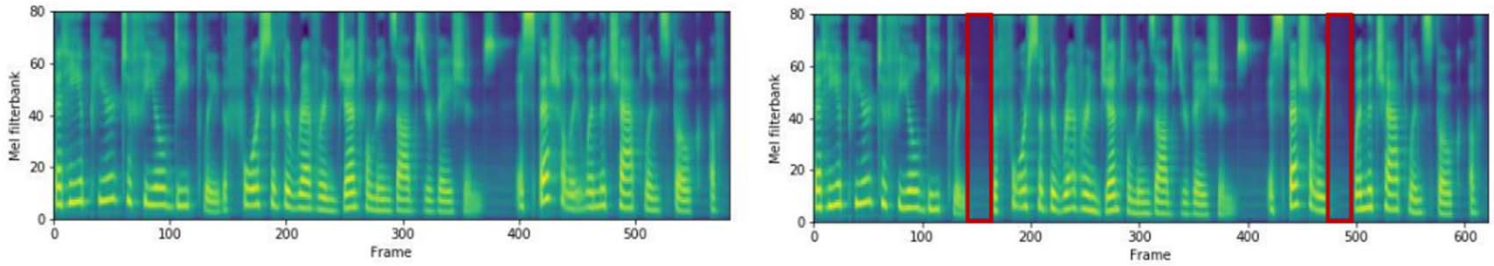
Table 3: The comparison of robustness between FastSpeech and other systems on the 50 particularly hard sentences. Each kind of word error is counted at most once per sentence.

FastSpeech: Controllability



(a) 1.5x Voice Speed (b) 1.0x Voice Speed (c) 0.5x Voice Speed

Figure 3: The mel-spectrograms of the voice with 1.5x, 1.0x and 0.5x speed respectively. The input text is "*For a while the preacher addresses himself to the congregation at large, who listen attentively*".

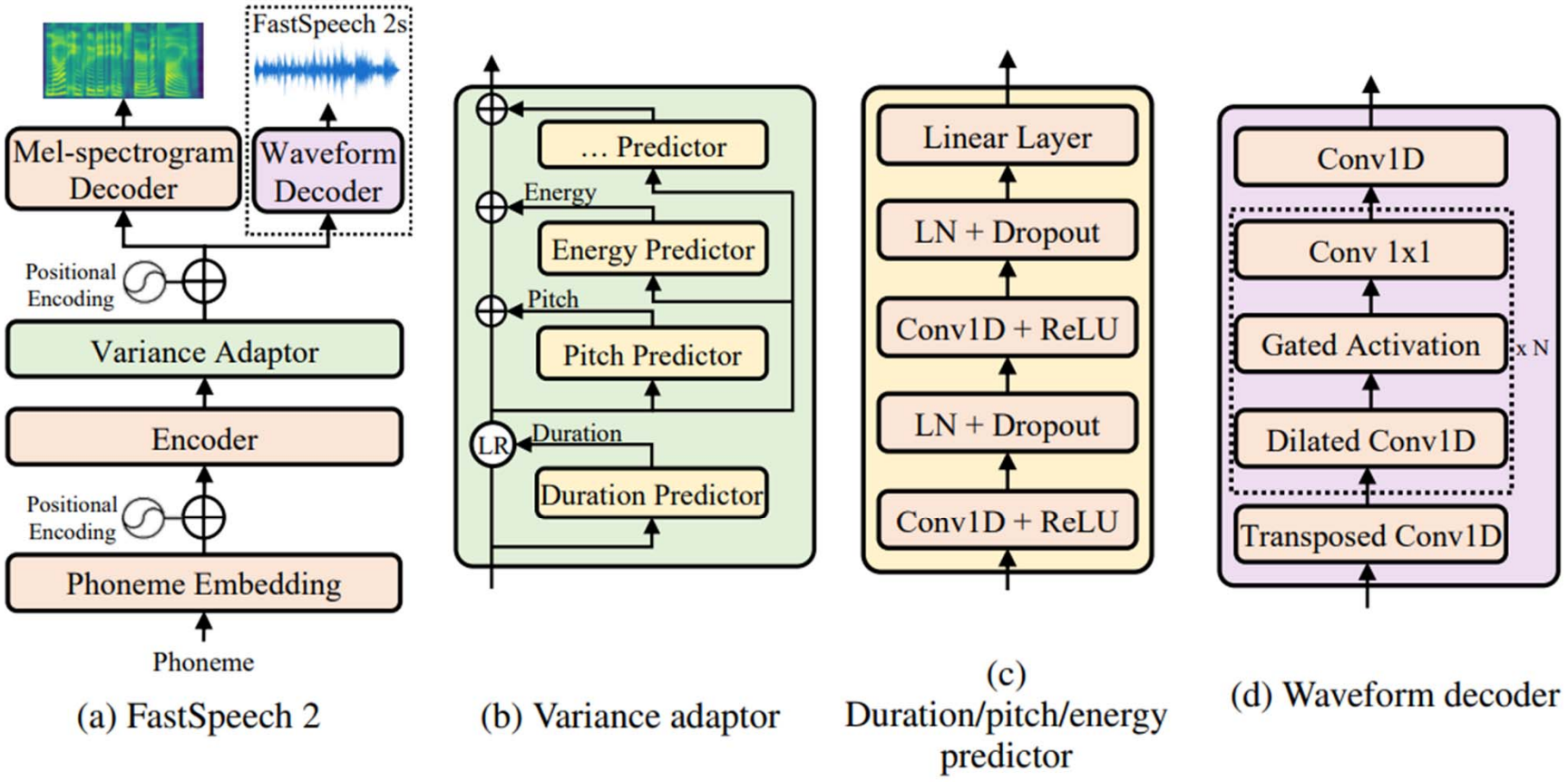


(a) Original Mel-spectrograms (b) Mel-spectrograms after adding breaks

Figure 4: The mel-spectrograms before and after adding breaks between words. The corresponding text is "*that he appeared to feel **deeply** the force of the reverend gentleman's observations, **especially** when the chaplain spoke of*". We add breaks after the words "*deeply*" and "*especially*" to improve the prosody. The red boxes in Figure 4b correspond to the added breaks.

FastSpeech 2 & FastSpeech 2s

https://speechresearch.github.io/fastspeech2/



Ref: Ren et al, "Fastspeech 2: Fast and high-quality end-to-end text to speech," ICLR 2021

FastSpeech 2 vs FastSpeech

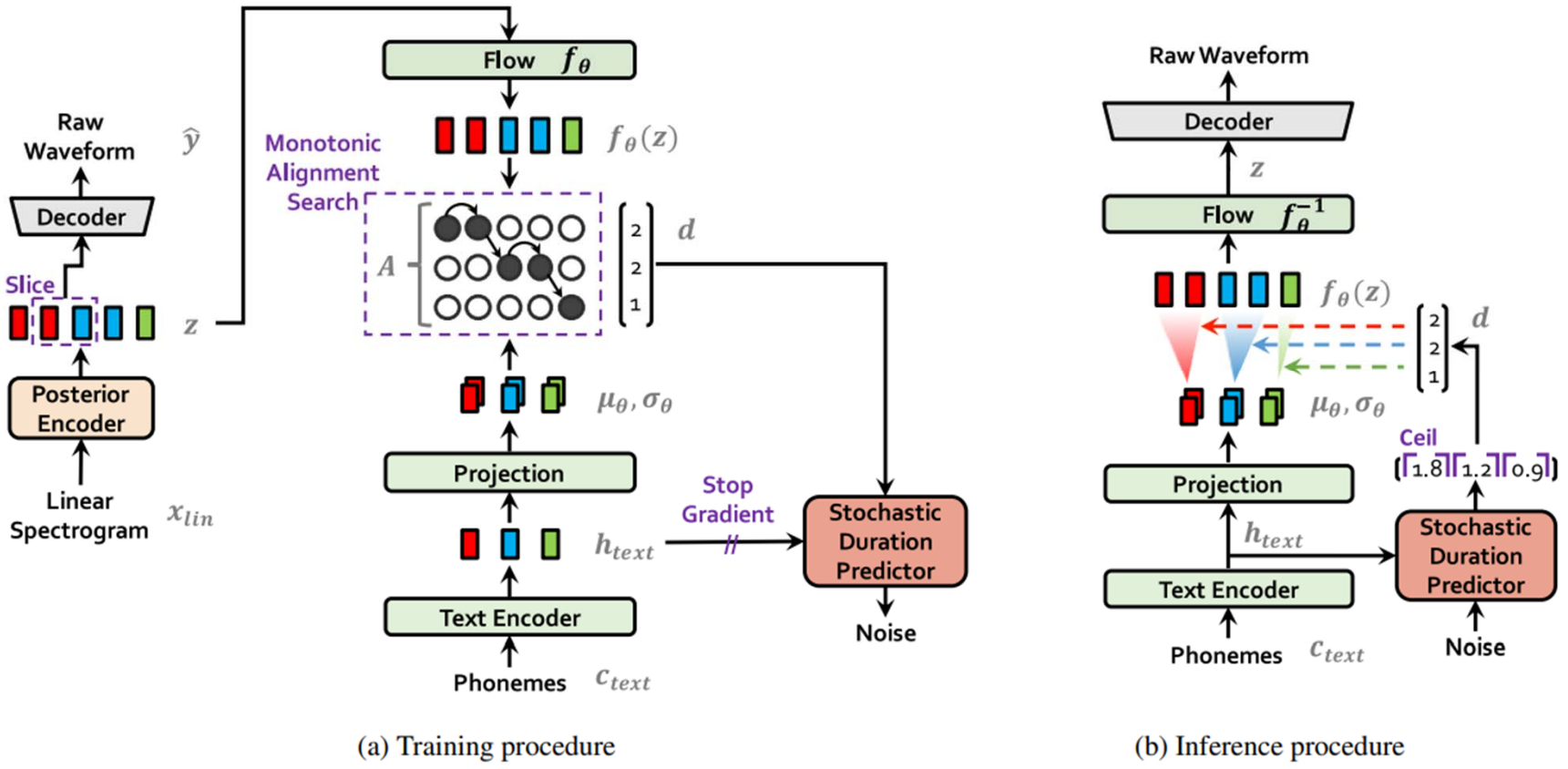
- 3x training speed-up
- More controllable

Method	MOS
GT	4.30 ± 0.07
GT (Mel + PWG)	3.92 ± 0.08
Tacotron 2 (Shen et al., 2018) (Mel + PWG)	3.70 ± 0.08
Transformer TTS (Li et al., 2019) (Mel + PWG)	3.72 ± 0.07
FastSpeech (Ren et al., 2019) (Mel + PWG)	3.68 ± 0.09
FastSpeech 2 (Mel + PWG)	3.83 ± 0.08
FastSpeech 2s	3.71 ± 0.09

Method	Training Time (h)	Inference Speed (RTF)	Inference Speedup
Transformer TTS (Li et al., 2019)	38.64	9.32×10^{-1}	/
FastSpeech (Ren et al., 2019)	53.12	1.92×10^{-2}	48.5×
FastSpeech 2	**17.02**	1.95×10^{-2}	47.8×
FastSpeech 2s	92.18	$\mathbf{1.80 \times 10^{-2}}$	**51.8**×

VITS

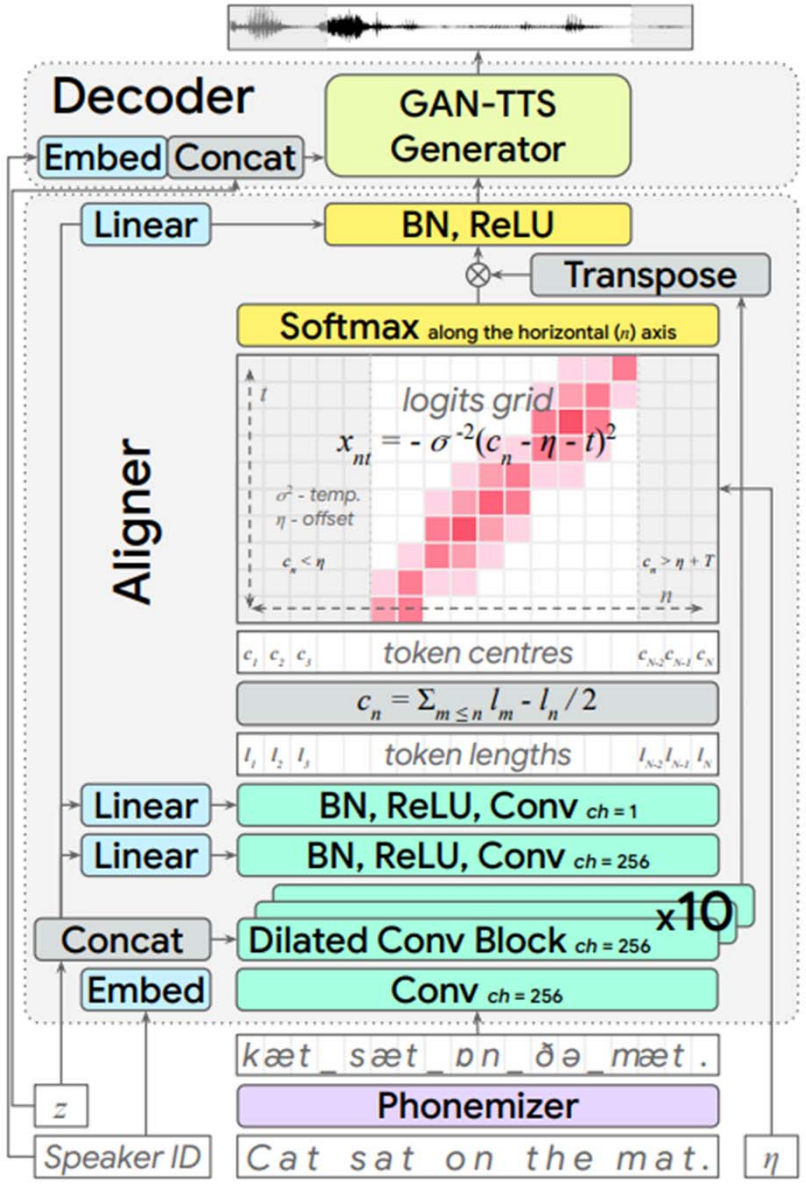
https://jaywalnut310.github.io/vits-demo/



Ref: Kim et al, “Conditional variational autoencoder with adversarial learning for end-to-end text-to-speech,” ICML 2021

EATS

- Feedforward, not autoregressive
- Directly generate waveforms; no vocoders
- **“Soft DTW”** for **differentiable alignment**



Ref: Donahue et al, “End-to-end adversarial text-to-speech,” ICLR 2021

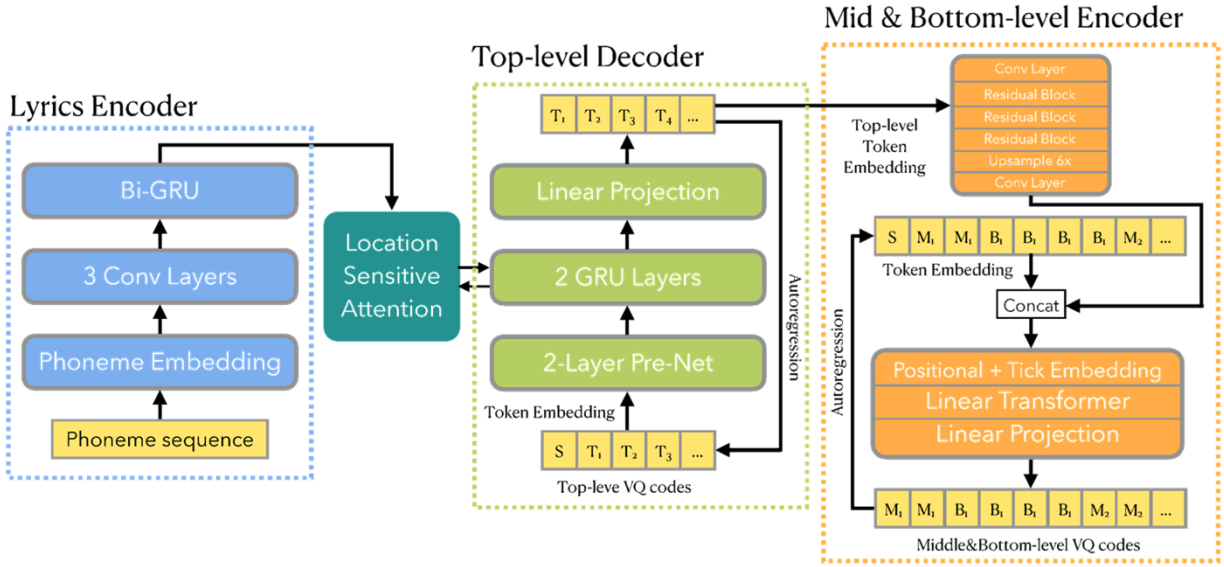
Drawbacks of Non-autoregressive models

- It's kind of deterministic; **lack randomness**
- Result of autoregressive models can sometimes sound more natural possibly due to the autoregressive prediction

Ref: Ren et al, "FastSpeech: Fast, robust and controllable text to speech," NeurIPS 2019

KaraSinger (from our lab)

- Autoregressive
  - Based on TacoTron 2
- Two modes
  - **MIDI-free** (https://jerrygood0703.github.io/KaraSinger/)
  - **MIDI-free & lyrics-free** (unpublished)



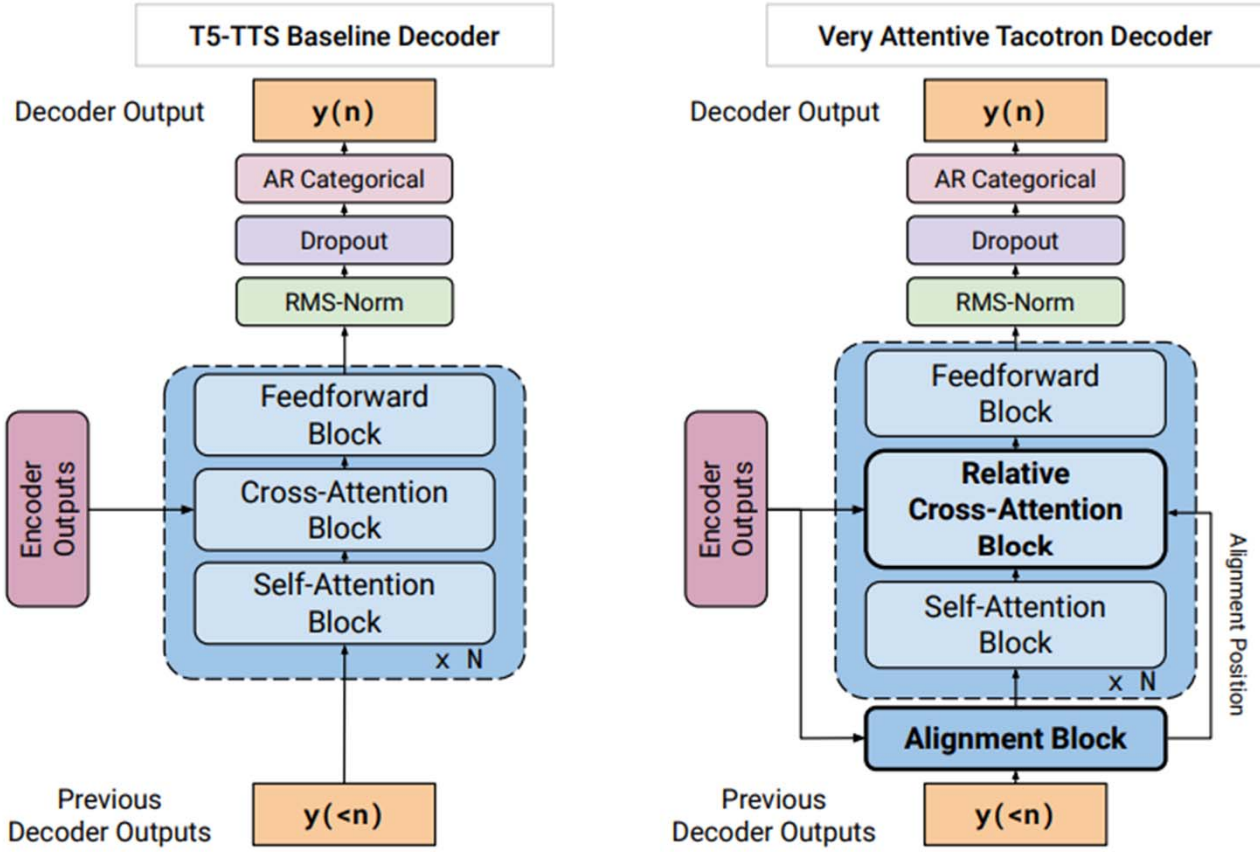
Ref 1: Liao et al, “KaraSinger: Score-free singing voice synthesis with VQ-VAE using Mel-spectrograms,” ICASSP 2022

Ref 2: Liu et al, “Score and lyrics-free singing voice generation,” ICCC 2020

Very Attentive Tacotron

Robust and unbounded length generalization in autoregressive Transformer-based TTS

https://google.github.io/tacotron/publications/very_attentive_tacotron/index.html



Ref: Battenberg et al, "Very Attentive Tacotron: Robust and unbounded length generalization in autoregressive Transformer-based text-to-speech," arXiv 2024

Recap: TTS

- **TacoTron 2** (ICASSP'18)
  - Use a recurrent seq2seq architecture
  - Autoregressive
  - Let attention learns the alignment between the input phoneme sequence and the output Mel-spectrogram sequence

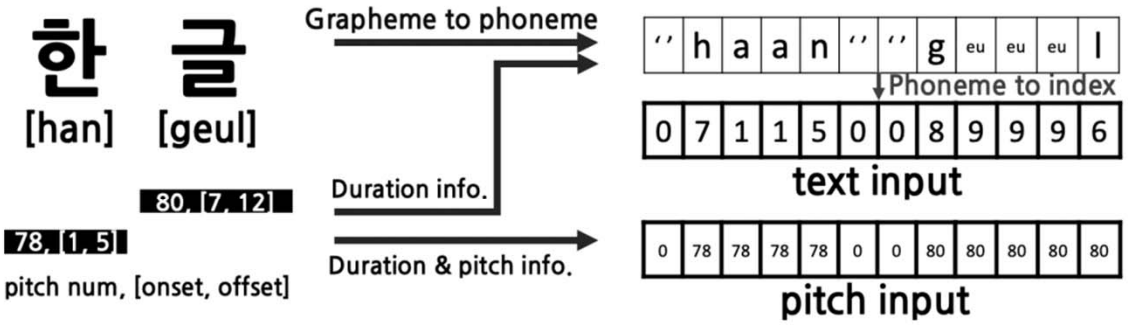
- **FastSpeech 2** (ICLR'21)
  - Use a feed-forward Transformer architecture
  - Non-autoregressive
  - Use duration predictor (among many other variance adaptors)

Outline

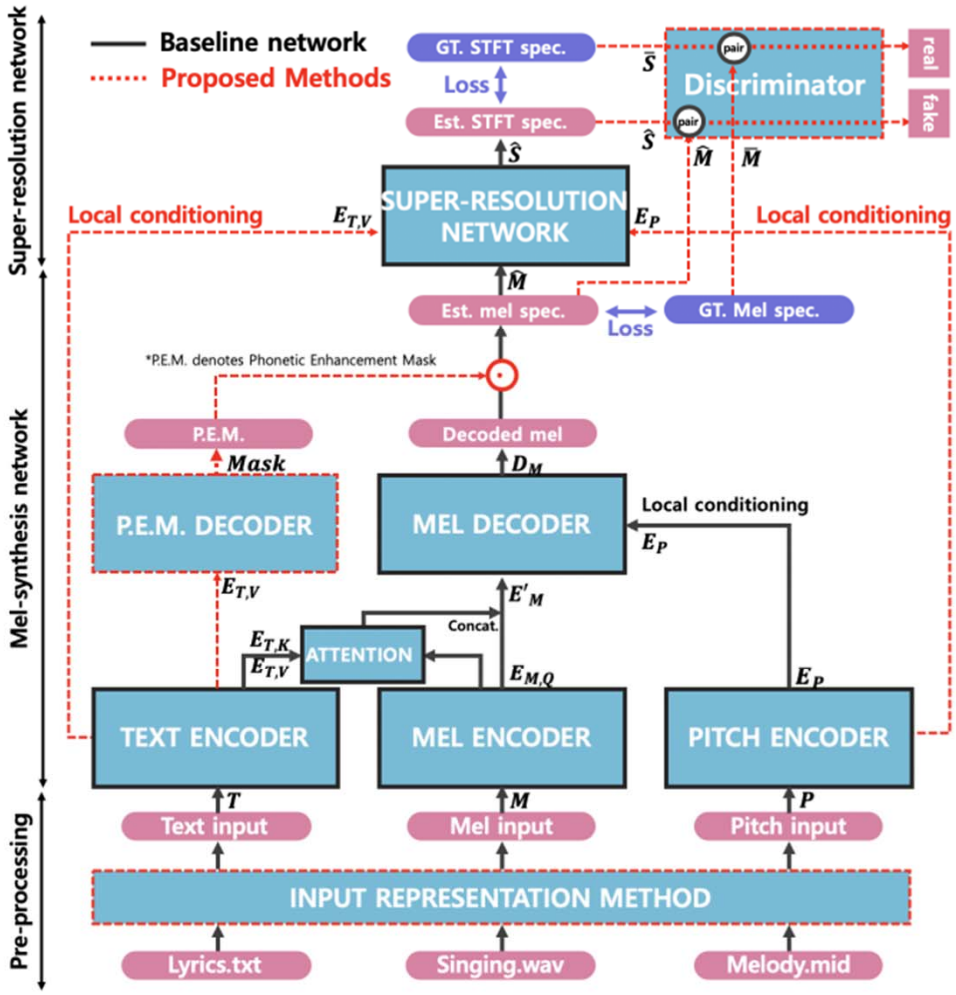
- Singing voice processing: Historical review
- Neural text-to-speech synthesis
- **Neural singing voice synthesis**
- Build your SVS model

SNU'2019 Model

- Autoregressive
- Use GAN
- **Pitch embedding**



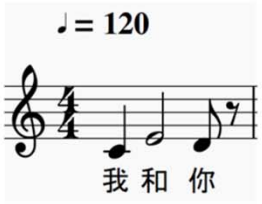
- **DB**: 60 songs from 1 female singer (~2hrs), manual annotation

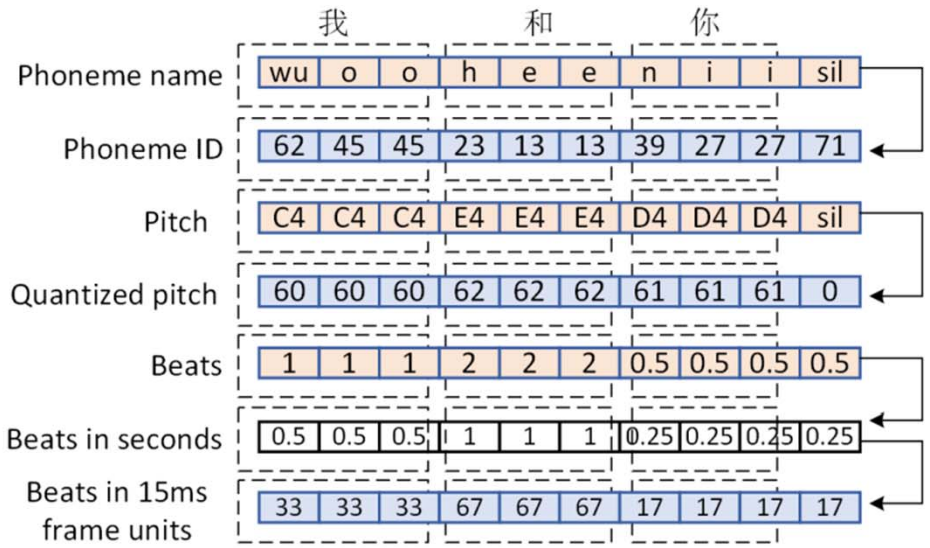


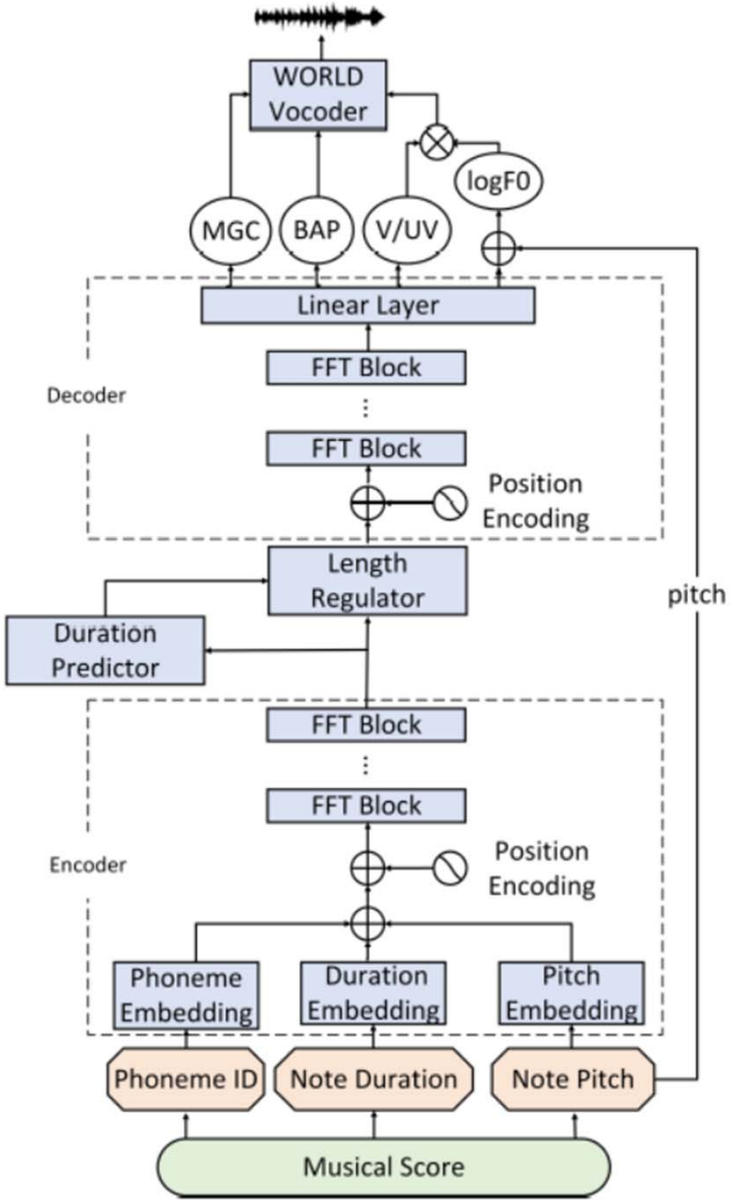
Ref: Lee et al, "Adversarially trained end-to-end Korean singing voice synthesis system," INTERSPEECH 2019

XiaoiceSing

- FastSpeech + WORLD vocoder
- **DB**: 2297 Mandarin pop songs from a female singer (~74hrs), manual annotation





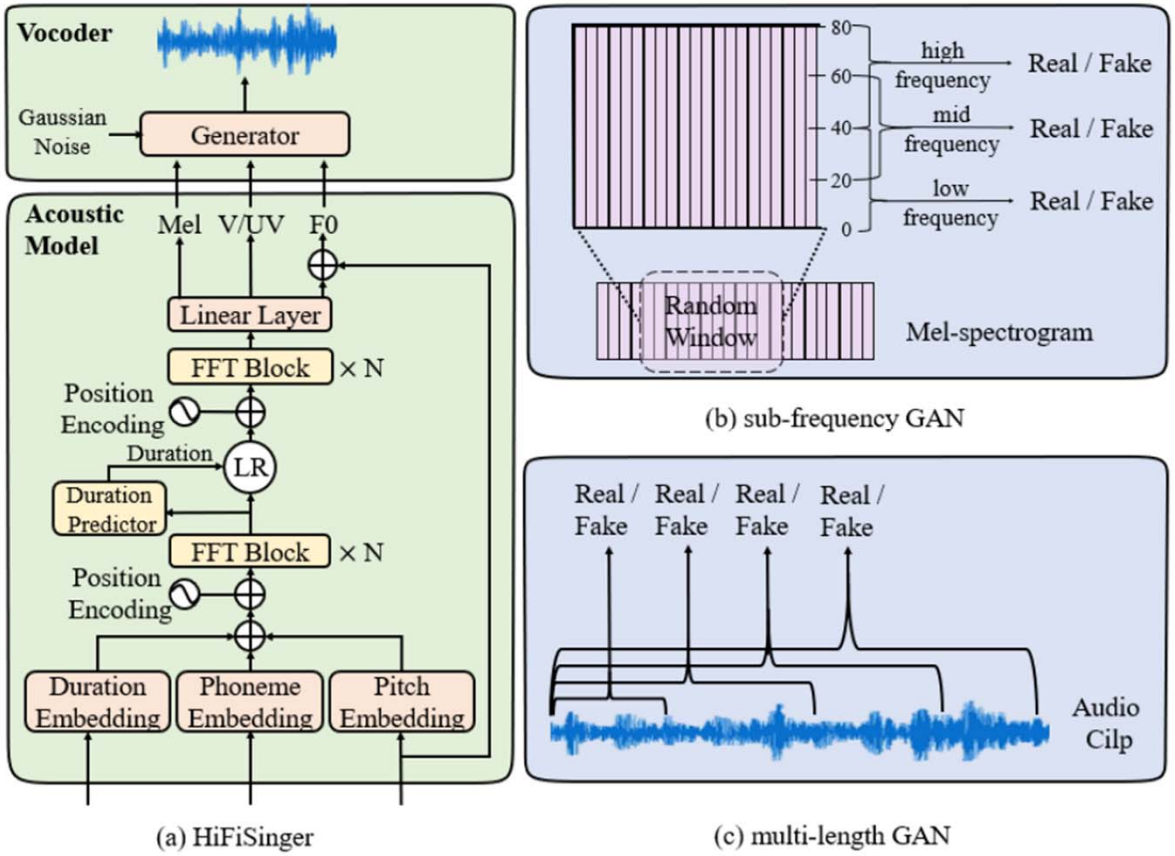


Ref: Lu et al, "XiaoiceSing: A high-quality and integrated singing voice synthesis system," INTERSPEECH 2020

HiFiSinger

https://speechresearch.github.io/hifisinger/

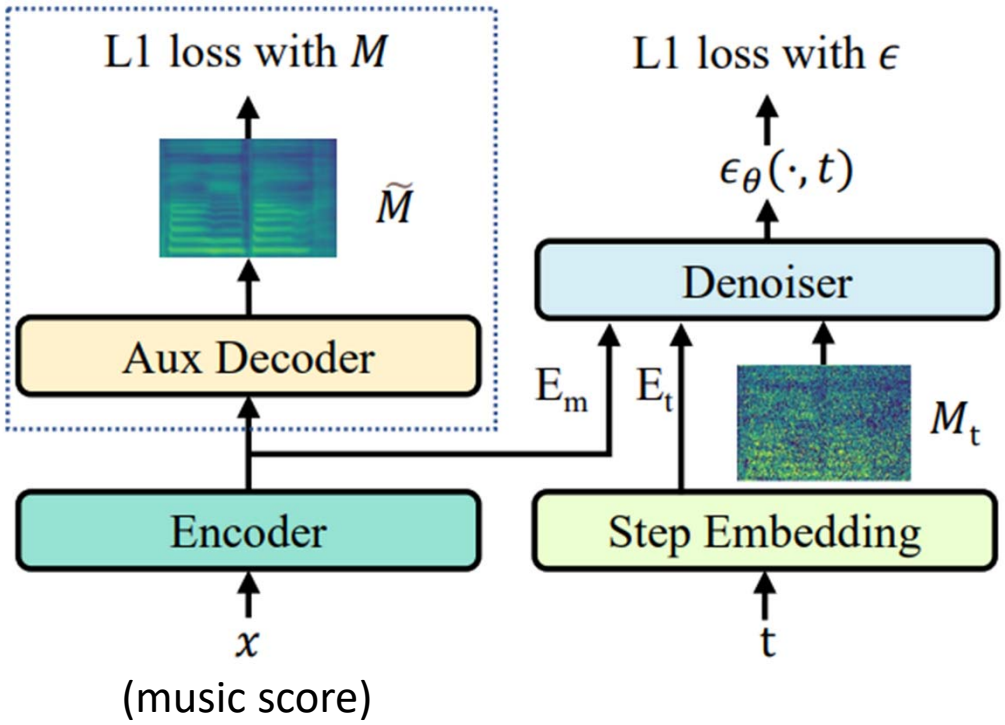
- Use Parallel WaveGAN based neural vocoder
- Use sub-frequency GAN to improve Mel-spectrogram generation
- Use multi-length GAN to improve waveform generation
- **DB**: 11 hrs songs from a female singer, manual annotation

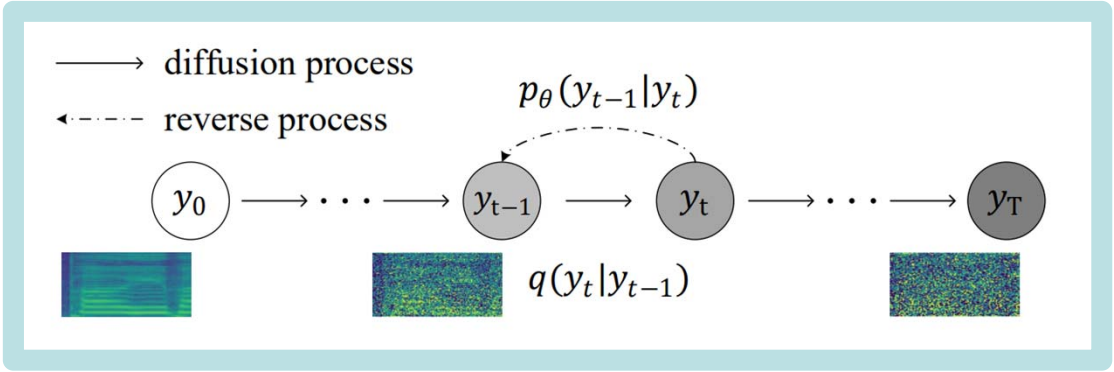


Ref: Chen et al, "HiFiSinger: Towards high-fidelity neural singing voice synthesis," arXiv 2020

DiffSinger

https://jisang93.github.io/hidden singer-demo/





- **FastSpeech-like encoder** to provide condition for the reverse diffusion process
- **Non-causal WaveNet-based denoiser** to convert noise into Mel-specrogram

Ref: Ren et al, "DiffSinger: Singing voice synthesis via shallow diffusion mechanism," AAAI 2022

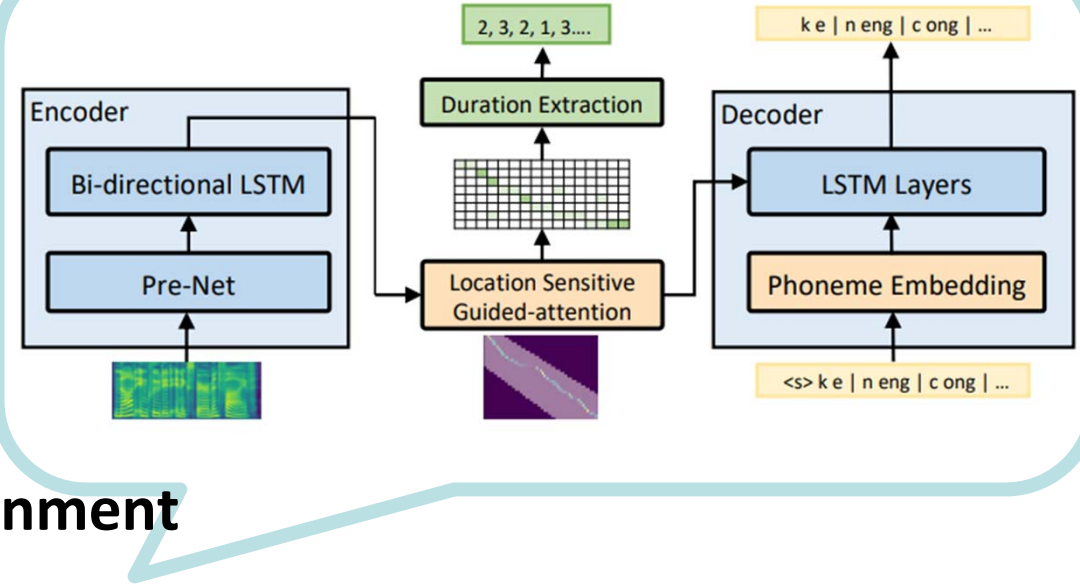
Progress of SVS Benefits from that of TTS

- SVS and TTS are similar
  - **Text-to-speech** (TTS): given text (and speaker ID), generate audio
  - **Singing voice synthesis** (SVS): given text and **MIDI** (and singer ID), generate audio
  - Both can be viewed as conditional audio generation problem
  - Both need to predict the **onset** and **offset** of each word or syllable
- Differences
  - Musical expressivity (**f0**, dynamics, singing techniques)
  - Cost to collect data

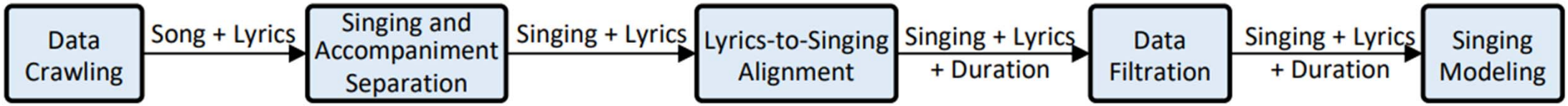
DeepSinger

https://speechresearch.github.io/deepsinger/

- Huge effort in building an SVS dataset
  - **Record singing** in professional studio
  - **Manual annotation** to get paired data
    - Usually first manually split a whole song into aligned lyrics and audio in sentence level, and then extract the duration of each phoneme either by manual alignment or a phonetic timing model

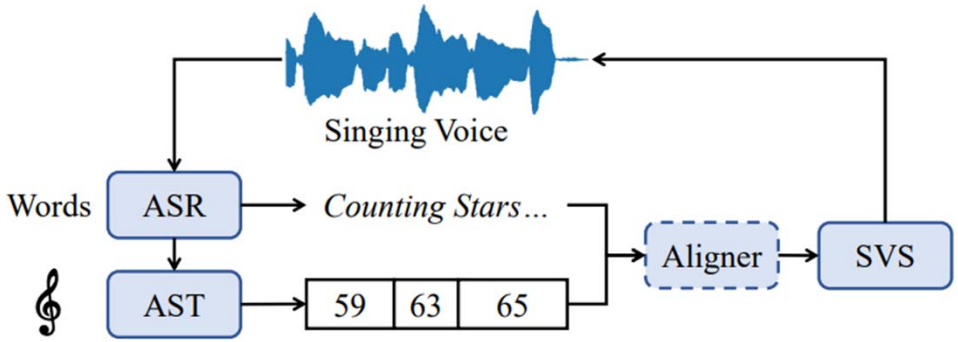


- Data **from the web** + a**utomatic alignment**



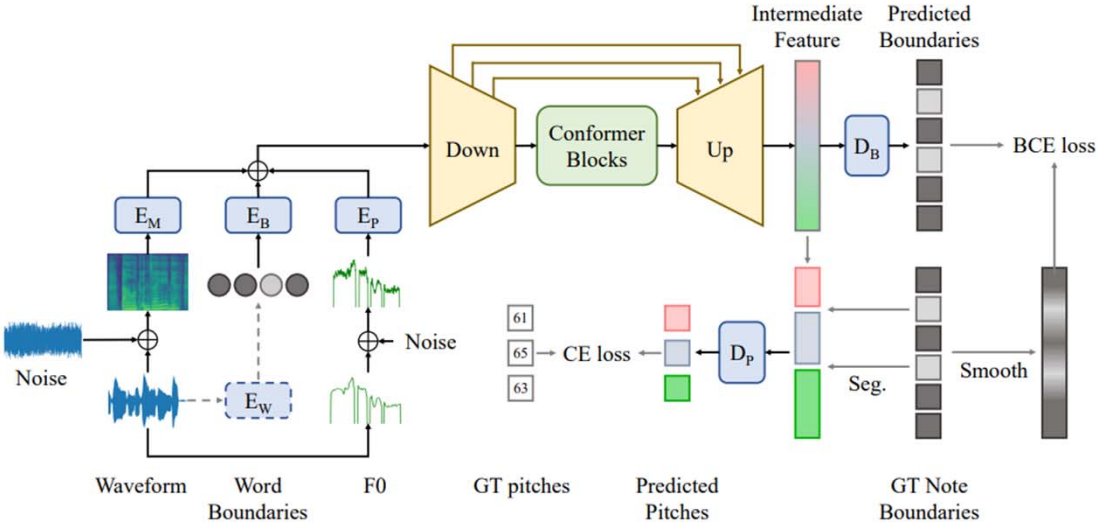
Ref: Ren et al, "DeepSinger: Singing voice synthesis with data mined from the web," KDD 2020

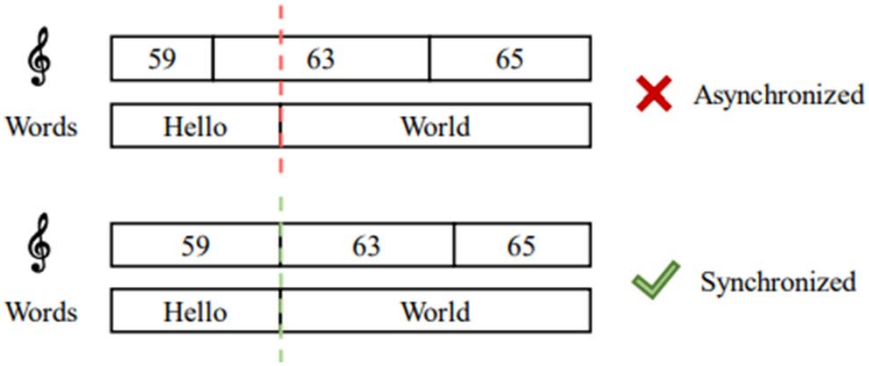
Automatic Alignment



AST: automatic singing voice transcription

ASR: automatic speech recognition





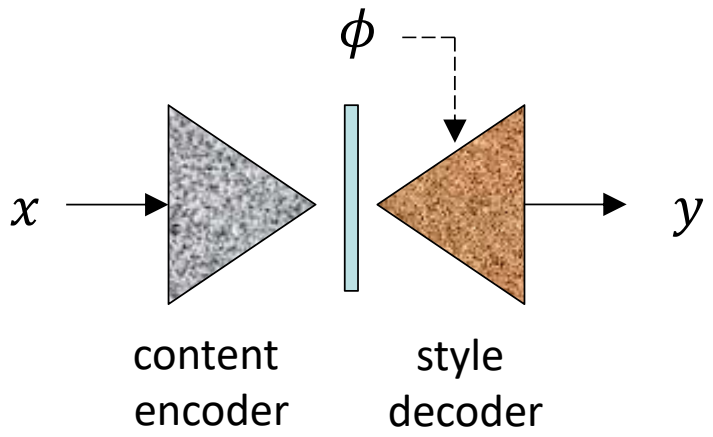
Model	RPA	MOS-P	MOS-Q
GT	96.1	4.02 ± 0.05	4.04 ± 0.06
S(large)	45.2	3.36 ± 0.12	3.45 ± 0.09

-P: pitch correction; -Q: overall quality

Ref: Li et al, "Robust singing voice transcription serves synthesis," ACL 2024

Singing Voice Conversion

- One-to-one (only a target singer) vs one-to-many
- In-domain vs cross-domain



Ref: Huang et al, "The singing voice conversion challenge 2023," ASRU 2023

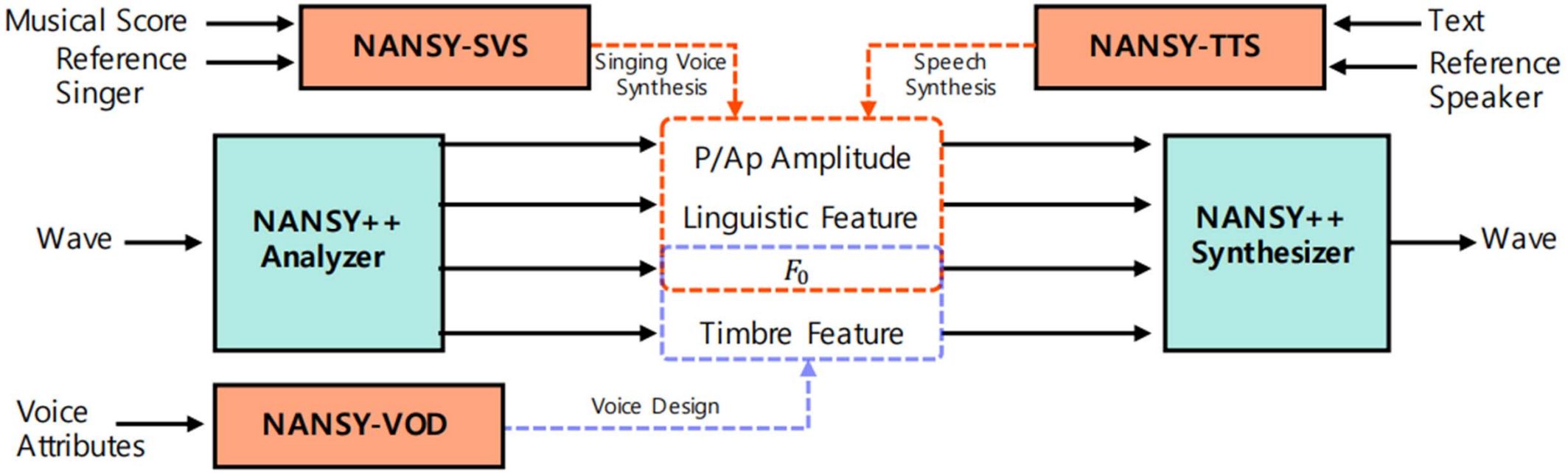
Table 3: Details of participating systems in SVCC 2023.

ID	Content Feature	VAE	Vocoder
B01	PPG	N	HiFi-GAN
B02	HuBERT	N	HN-uSFGAN
T01	PPG	N	HiFi-GAN + BigVGAN∗
T02	HuBERT	Y	DSPGAN
T03	HuBERT	Y	HiFi-GAN
T04	Unknown		
T05	PPG	N	HiFi-GAN
T06	ContentVec	Y	N/A (nsf-HiFi-GAN)‡
T07	HuBERT	Y	N/A (HiFi-GAN)‡
T08	Unknown		
T09	Uncertain	Y	nsf-HiFi-GAN
T10	WavLM	N	BigVGAN
T11	PPG	N	HiFi-GAN
T12	HuBERT	N	HiFi-GAN
T13	ContentVec	N	SiFi-GAN
T14	Unknown		
T15	None (Melspec)†	N	nsf-HiFi-GAN
T16	PPG	N	BigVGAN
T17	HuBERT	N	nsf-HiFi-GAN
T18	Unknown		
T19	None (Melspec)†	N	HiFi-GAN
T20	HuBERT	Y	nsf-HiFi-GAN
T21	ContentVec	Y	nsf-HiFi-GAN
T22	PPG+ContentVec	N	BigVGAN
T23	PPG	Y	DSPGAN

Nansy++

https://bald-lifeboat-9af.notion.site/Demo-Page-For-NANSY-67d92406f62b4630906282117c7f0c39

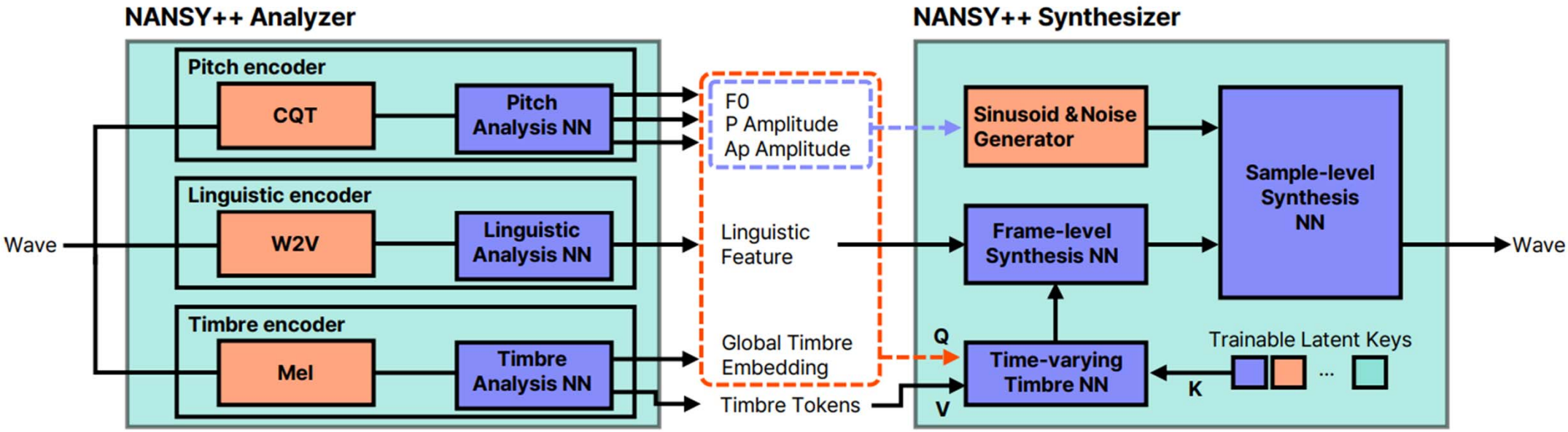
- A single model that do 1) VC/SVC, 2) TTS, 3) SVS, and 4) voice designing



Ref: Choi et al, "NANSY++: Unified voice synthesis with neural analysis and synthesis," ICLR 2023

Nansy++

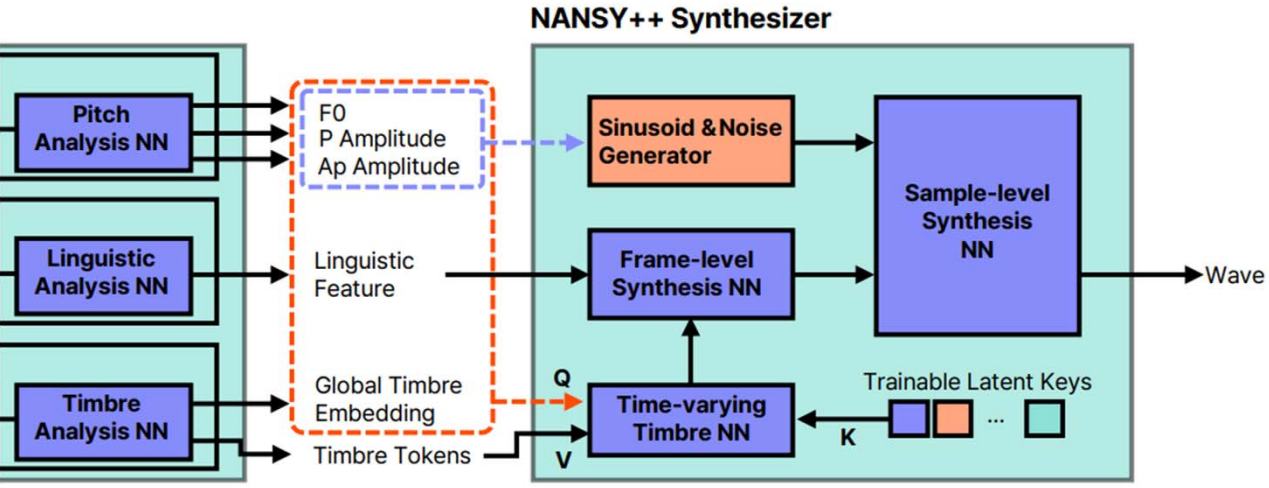
- "We trained the backbone model on 10,571 hours (speech: 10,092 hours, singing: 479 hours) of proprietary 44.1 kHz audio recordings composed of 6,176 speakers and 624 singers"

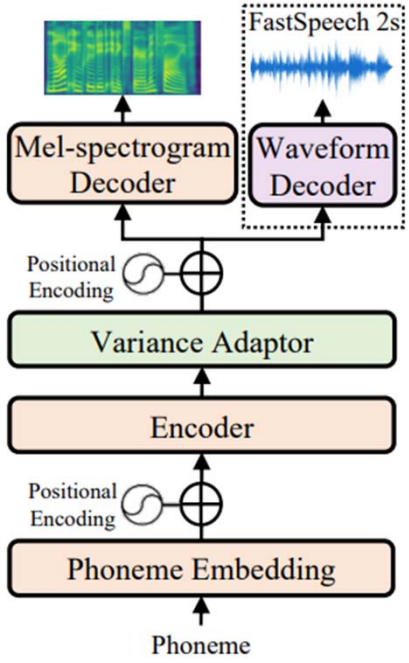


Ref: Choi et al, "NANSY++: Unified voice synthesis with neural analysis and synthesis," ICLR 2023

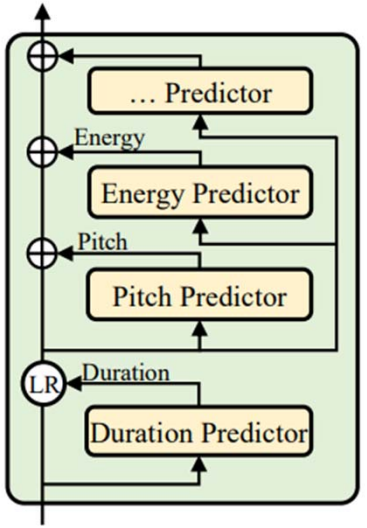
Nansy++ vs FastSpeech 2

- Nansy++ may provide more explicit disentanglement of various attributes and therefore allows for more flexible control





(a) FastSpeech 2



(b) Variance adaptor

Recap: SVS

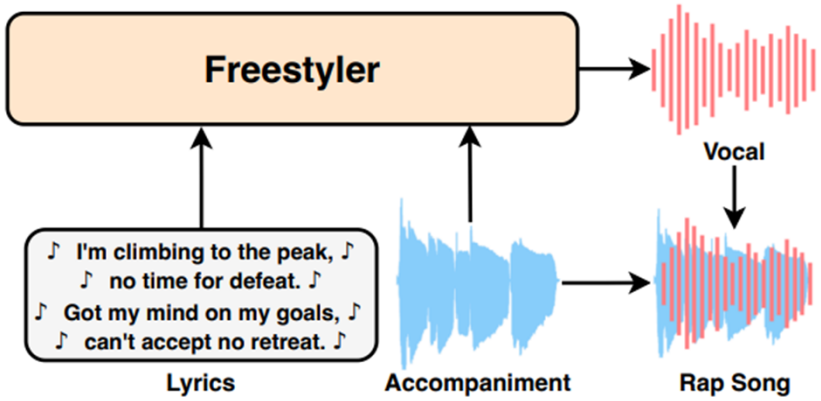
- Many SVS papers do not open source code…
  - For example: HiFiSinger, Nansy++

- One exception:
  DiffSinger
  - https://github.com/MoonInTheRiver/DiffSinger

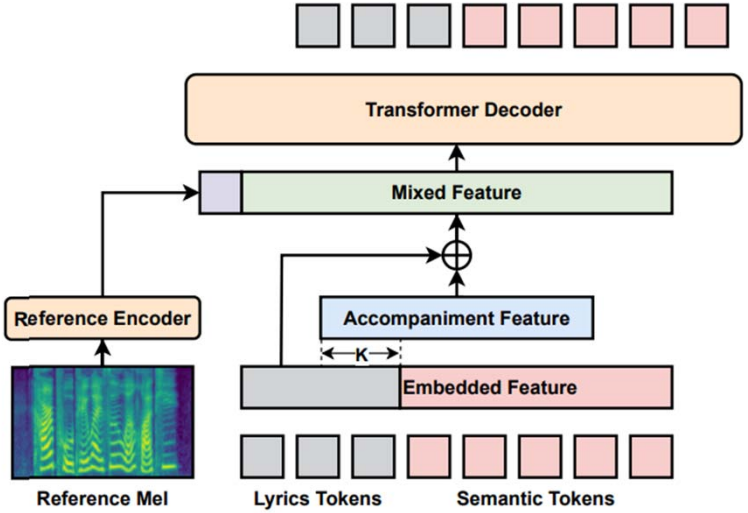
Mel Pipeline	Dataset	Pitch Input	F0 Prediction	Acceleration Method	Vocoder
DiffSpeech (Text->F0, Text+F0->Mel, Mel->Wav)	Ljspeech	None	Explicit	Shallow Diffusion	HiFiGAN
DiffSinger (Lyric+F0->Mel, Mel->Wav)	PopCS	Ground-Truth F0	None	Shallow Diffusion	NSF-HiFiGAN
DiffSinger (Lyric+MIDI->F0, Lyric+F0->Mel, Mel->Wav)	OpenCpop	MIDI	Explicit	Shallow Diffusion	NSF-HiFiGAN
FFT-Singer (Lyric+MIDI->F0, Lyric+F0->Mel, Mel->Wav)	OpenCpop	MIDI	Explicit	Invalid	NSF-HiFiGAN
DiffSinger (Lyric+MIDI->Mel, Mel->Wav)	OpenCpop	MIDI	Implicit	None	Pitch-Extractor + NSF-HiFiGAN
DiffSinger+PNDM (Lyric+MIDI->Mel, Mel->Wav)	OpenCpop	MIDI	Implicit	PLMS	Pitch-Extractor + NSF-HiFiGAN
DiffSpeech+PNDM (Text->Mel, Mel->Wav)	Ljspeech	None	Implicit	PLMS	HiFiGAN

Freestyler

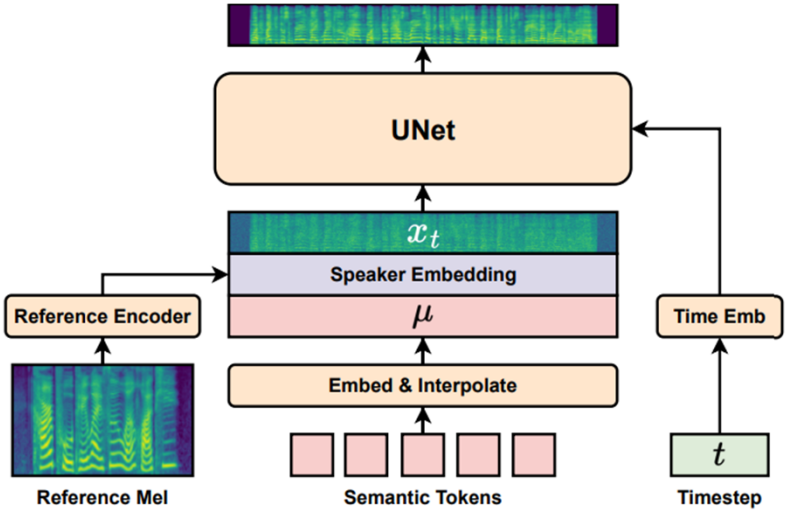
https://nzqian.github.io/Freestyler/



First off, I want to thank the pioneers for making this possible. Fake, humbleness, snake, dummy shit is intolerable. Living by principle. Staring out over women in swimming suits by the pool. I'm a slide with a few. Every chance was spoiled. No enhancement pill. No dear antler oil. And they panties be soiled. I know some niggas that'll damage your squad. You



(a) Lyrics-to-Semantic



(b) Semantic-to-Spectrogram

Ref: Ning et al, “Drop the beat! Freestyler for accompaniment conditioned rapping voice generation, arXiv 2024

Outline

- Singing voice processing: Historical review
- Neural text-to-speech synthesis
- Neural singing voice synthesis
- **Build your SVS model**

Datasets

https://gtsinger.github.io/

Corpus	Language	Singer	Hours		Manual Annotations				Controlled Comparison
			Singing	Speech	Align	RMS	Tech	Style	
VocalSet [25]	1	20	10.1	0	✗	✗	✗	✗	✓
CSD [4]	2	1	4.86	0	✗	✗	✗	✗	✗
KVT [10]	1	114	18.85	0	✗	✗	✗	✓	✗
PopBuTFy [16]	2	34	50.8	0	✗	✗	✗	✗	✗
OpenSinger [8]	1	66	50	0	✗	✗	✗	✗	✗
NHSS [20]	1	10	4.75	2.25	✗	✗	✗	✗	✗
Tohoku Kiritan [18]	1	1	1	0	✓	✗	✗	✗	✗
OpenCpop [23]	1	1	5.25	0	✓	✗	✗	✗	✗
M4Singer [26]	1	20	29.77	0	✓	✗	✗	✗	✗
GTSinger (Ours)	**9**	**20**	**80.59**	**16.16**	✓	✓	✓	✓	✓

Ref: Zhang et al, “GTSinger: A global multi-technique singing corpus with realistic music scores for all singing tasks, 2024

Datasets: SingStyle111

https://dsqvival.github.io/singstyle111/

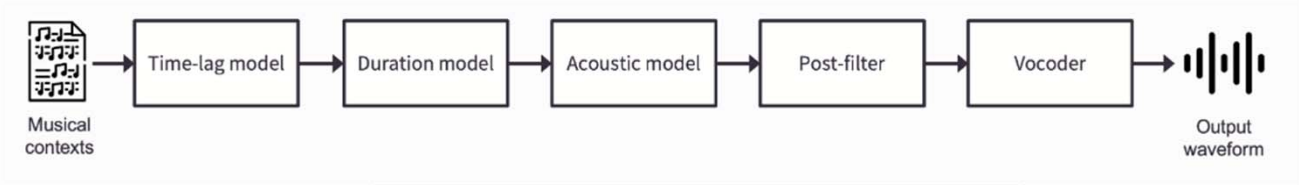
Dataset	Language	Style	#Hour	#Singer	Quality	Musicality	Score	Align-ment	Style Transfer
Opencpop [41]	Chinese	Pop	5.25	1	Studio	Ama.	Perform. MIDI	✓	✗
M4Singer [42]	Chinese	Pop	29.77	20	Studio	50% Ama. 50% Prof.	Perform. MIDI	✓	✗
Children Song [43]	Korean English	Children	4.86	1	Studio	Prof. but plain	Perform. MIDI	word	✗
Tohoku Kiritan [44]	Japanese	Pop	0.95	1	Studio	Prof.	Score	✓	✗
PopCS [28]	Chinese	Pop	5.89	6	Not Clean	Ama.	✗	✗	✗
Open-Singer [35]	Chinese	Pop	50	66	Studio	Ama.	✗	✗	✗
VocalSet [45] Annotated [46]	Five Vowels	Opera	10.1	20	Studio	Prof.	Score	✓	technique transfer
NHSS [47]	English	Pop	3.5	10	Studio	Ama.	✗	✓	✗
NUS-48E [48]	English	Pop Children	1.41	12	Studio	Ama.	✗	✓	✗
RWC [49]	Japanese English	Pop	4	27	Not Solo	Prof.	Both	✗	✗
TONAS [50]	Spanish	Flamenco	0.34	> 40	Not Clean	Prof.	✗	✗	✗
Vocadito [51]	Seven Languages	Pop Children	0.23	29	Not Clean	Ama.	✗	✗	✗
MIR-1K [52]	Chinese	Pop	2.22	19	Not Solo	Ama.	✗	✗	✗
StyleSing111 (Ours)	English Chinese Italian	Opera Pop Folk Jazz etc.	12.8	8	Studio	Prof.	Both	✓	✓

- Children
  ▶ 0:03 / 0:15
- Chinese Folk
  ▶ 0:02 / 0:16
- Jazz
  ▶ 0:03 / 0:12
- Musical
  ▶ 0:02 / 0:13
- Opera
  ▶ 0:08 / 0:14
- Pop
  ▶ 0:00 / 0:00
- Rock
  ▶ 0:00 / 0:00

Ref: Dai et al, “SingStyle111: A multilingual singing dataset with style transfer, ISMIR 2023

Library for SVS: NNSVS

https://github.com/nnsvs/nnsvs
https://nnsvs.github.io/
https://r9y9.github.io/projects/nnsvs/



Stage 0: Data preparation

Stage 1: Feature generation

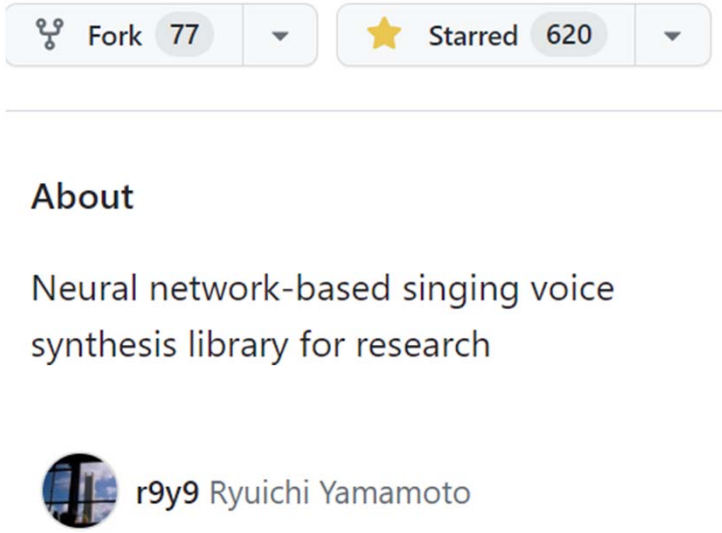
Stage 2: Train time-lag model

Stage 3: Train duration model

Stage 4: Train acoustic model

Stage 5: Generate features

Stage 6: Synthesis waveforms



Ref: Yamamoto et al, "NNSVS: A neural network-based singing voice synthesis toolkit," ICASSP 2023

Library for SVS: Muskits

https://github.com/SJTMusicTeam/Muskits

- **Various network architecutres** for end-to-end SVS
  - RNN-based non-autoregressive model
  - Xiaoice
  - Sequence-to-sequence Transformer (with GLU-based encoder)
  - MLP singer
  - Tacotron-singing (in progress)
  - DiffSinger (to be published)
- Multi-speaker & Multilingual extention
  - Speaker ID embedding
  - Language ID embedding
  - Global sytle token (GST) embedding
- Various language support
  - Jp / En / Kr / Zh

About

An opensource music processing toolkit

Table 1: *Details of experimental data: N_{src}, N_{lang}, N_{singer} stands for number of databases, languages, and singers, respectively.*

Task	N_{src}, N_{lang}, N_{singer}	Duration(h)		
		Train	Dev	Test
Single-singer	1,1,1	0.63	0.08	0.07
Multi-singer	4,1,4	3.01	0.34	0.38
Multilingual	6,4,6	11.72	0.49	1.01
Transfer	1,1,1	0.71	0.02	0.05

Ref: Shi et al, “Muskits: an end-to-end music processing toolkit for singing voice synthesis,” INTERSPEECH 2022

Useful Tools

- Grapheme-to-phoneme conversion
  - **phonemizer**: https://github.com/bootphon/phonemizer
  - **g2p**: https://github.com/Kyubyong/g2p

- Forced alignment
  - **Montreal Forced Aligner**: https://github.com/MontrealCorpusTools/Montreal-Forced-Aligner

Library for SVC: so-vits-svc

https://github.com/svc-develop-team/so-vits-svc