

2023 September 29

Deep Learning for Music Analysis and Generation

# Vocoders

(mel → audio)



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# Objectives

- Traditional DSP-based **source-filter** model for audio
- **Upsampling** layers in DL models for audio
- The design of **GANs** for audio
- It's a type of *conditional* audio **generation** task (with *strong condition*)
  - “mel → audio”

# Reference 1: ICASSP 2022 Short Course

<https://www.slideshare.net/jyamagis/advancements-in-neural-vocoders>

<https://colab.research.google.com/drive/1EO-ggi1U9f2zXwTiqg7AEIjVx11JKta7>

Tutorial on neural vocoder.

By Xin Wang, National Institute of Informatics, 2022. See more in LICENSE Section.

This was used for ICASSP 2022 short course **Inclusive Neural Speech Synthesis, LECTURE 1, vocoder**.

Full Table of contents:

- Introduction & basics:
  - [chapter\\_1\\_introduction.ipynb](#): entry point, and Python/Pytorch conventions used in this hands-on session;
  - [chapter\\_2\\_DSP\\_tools\\_Python.ipynb](#): selected DSP tools for speech processing;
  - [chapter\\_3\\_DSP\\_tools\\_in\\_DNN\\_Pytorch.ipynb](#): selected DSP tools implemented as layers in neural networks;
- DSP-based Vocoder:
  - [chapter\\_4\\_DSP-based\\_Vocoder](#): traditional DSP-based vocoder included in [SPTK toolkit](#);
- Neural vocoders:
  - [chapter\\_5\\_DSP+DNN\\_NSF.ipynb](#): a simple neural vocoder without autoregressive, GAN, or flow;
  - [chapter\\_6\\_AR\\_WaveNet.ipynb](#): the autoregressive WaveNet;
  - [chapter\\_7\\_AR\\_iLPCNet.ipynb](#): the autoregressive iLPCNet;
  - [chapter\\_8\\_Flow\\_WaveGlow.ipynb](#): the flow-based WaveGlow model;
  - [chapter\\_9\\_GAN\\_HiFiGAN\\_NSFW/GAN.ipynb](#): the simple but high-quality HiFiGAN vocoder. We also show the NSF combi

## Advancements in Neural Vocoder

Junichi Yamagishi and Xin Wang  
National Institute of Informatics, Japan

2021 Speech Processing Courses in Crete  
Inclusive Neural Speech Synthesis  
July 27, 2021

# Reference 2: Aalto University Course

<https://speechprocessingbook.aalto.fi/Modelling/Vocoder.html>

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## Introduction to Speech Processing

1. Preface
2. Introduction
3. Basic Representations
4. Pre-processing
5. Modelling tools in speech processing
6. Evaluation of speech processing methods
7. Speech analysis
8. Recognition tasks in speech processing
9. Speech Synthesis
10. Transmission, storage and telecommunication
11. Speech enhancement
12. Computational models of human language processing
13. Speech data and experiment design

# Reference 3: ISMIR 2019 Tutorial

<https://salu133445.github.io/ismir2019tutorial/>

## Generating Music with GANs

Hao-Wen Dong, Yi-Hsuan Yang

UC San Diego & Academia Sinica  
Taiwan AI Labs & Academia Sinica

- [!\[\]\(8c4dca64662d21542001ca0ed7eeb688\_img.jpg\) Home](#)
- [!\[\]\(3de35c640e7147a3fb61ee393128d2ae\_img.jpg\) Abstract](#)
- [!\[\]\(d1438aeefda19c86ae7477bf1fb30796\_img.jpg\) Presenters](#)
- [!\[\]\(dc4d2c544087998b6f093f485f5119d7\_img.jpg\) Materials](#)
- [!\[\]\(f26ab61dd00ea7e5f19553908ec3fa6b\_img.jpg\) Links](#)
- [!\[\]\(ecf85e064bcd351a8999f71bf3f405e7\_img.jpg\) Contact](#)
- [!\[\]\(b7205a03f3dd3fe6f731085a326bb0d6\_img.jpg\) GitHub](#)
- [!\[\]\(fea63d7e313047478d89177e38e2c72d\_img.jpg\) Music AI Lab](#)

Welcome to the website for the tutorial “Generating Music with GANs—An Overview and Case Studies” at ISMIR 2019 (November 4th at Delft, The Netherlands).

### Slides

- [ismir2019-tutorial-slides.pdf](#)

### Notebooks

- GAN for images (MNIST Database): [gan.ipynb](#) 
- GAN for piano rolls (Lakh Pianoroll Dataset): [musegan.ipynb](#) 

### Related projects

- [MuseGAN](#)
- [LeadSheetGAN](#)

# Outline

- **General idea**
- DL components: upsampling layers and GAN
- GAN-based Mel-vocoders
- Advanced topics

# What is a Vocoder?

<https://speechprocessingbook.aalto.fi/Modelling/Vocoder.html>

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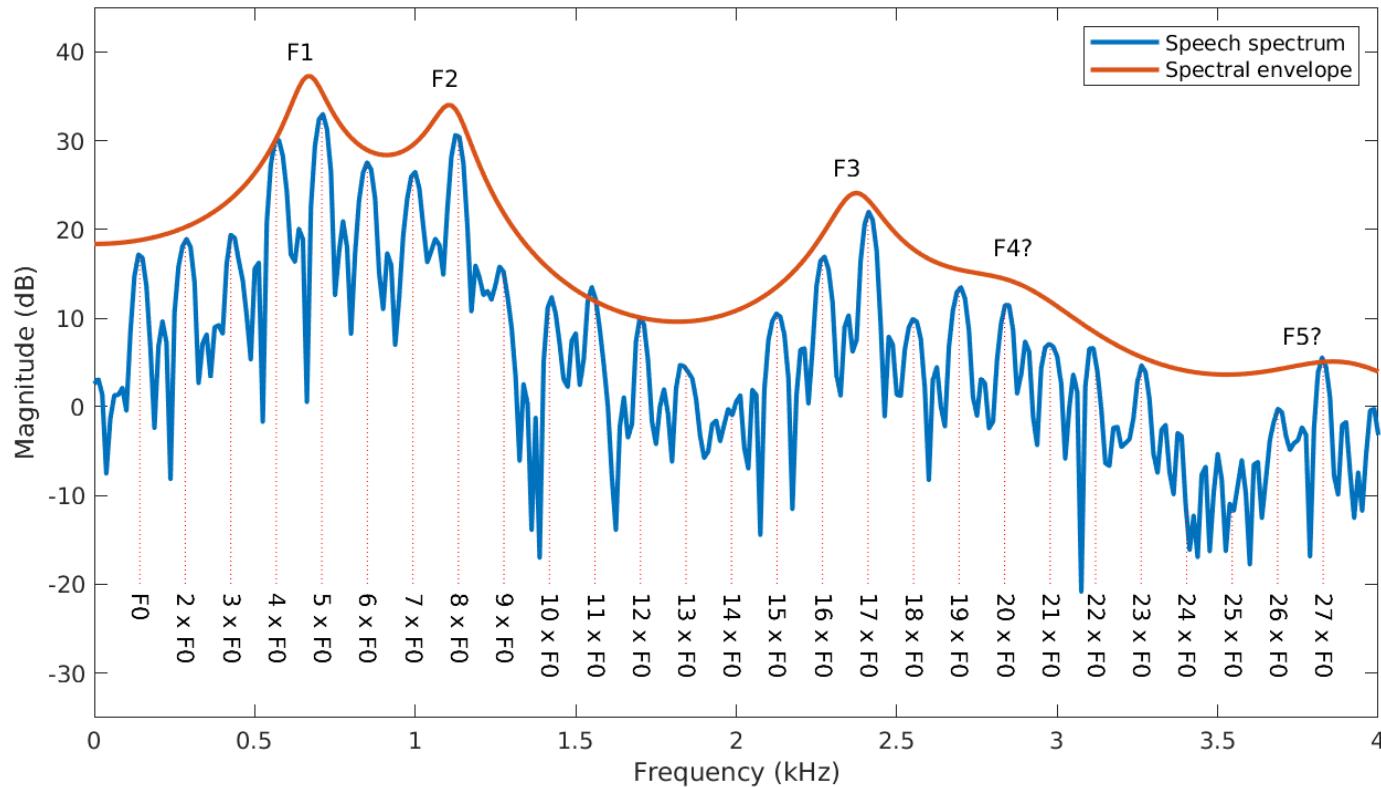
- **Vocoder** = voice and encoder
  - “Refers to a process of applying a **speech-like** characteristic to a sound”
  - “The basic idea of the vocoder is that any sound which has a **formant** structure [i.e., **peaks in the spectrum**], will be perceived as a **speech sound**.”
  - “Thus if we modify a sound such that it has peaks in the spectrum similar to a speech sound, then it will be perceived as a speech sound. Many of the original features of the sound will be preserved, but it will then have the added interpretation as a speech sound. It is as if the original sound would become the carrier tone of the speech signal.”

Ref: Figure from

[https://speechprocessingbook.aalto.fi/Introduction/Speech\\_production\\_and\\_acoustic\\_properties.html#content-acoustic-properties](https://speechprocessingbook.aalto.fi/Introduction/Speech_production_and_acoustic_properties.html#content-acoustic-properties)

# What is a Vocoder?

[https://speechprocessingbook.aalto.fi/Introduction/Speech\\_production\\_and\\_acoustic\\_properties.html#content-acoustic-properties](https://speechprocessingbook.aalto.fi/Introduction/Speech_production_and_acoustic_properties.html#content-acoustic-properties)



# What is a Vocoder?

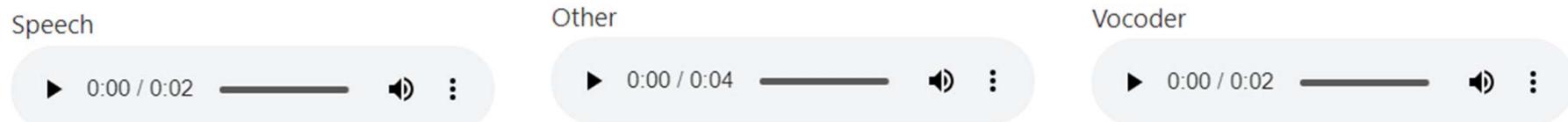
<https://speechprocessingbook.aalto.fi/Modelling/Vocoder.html>

- Formant analysis via Mel-spectral envelope
- Applying the envelope (“*vocoded*”)

We can then extract the mel-envelopes of the speech and other signals, remove the envelope shape from the other by division, and apply the speech envelope by multiplication as

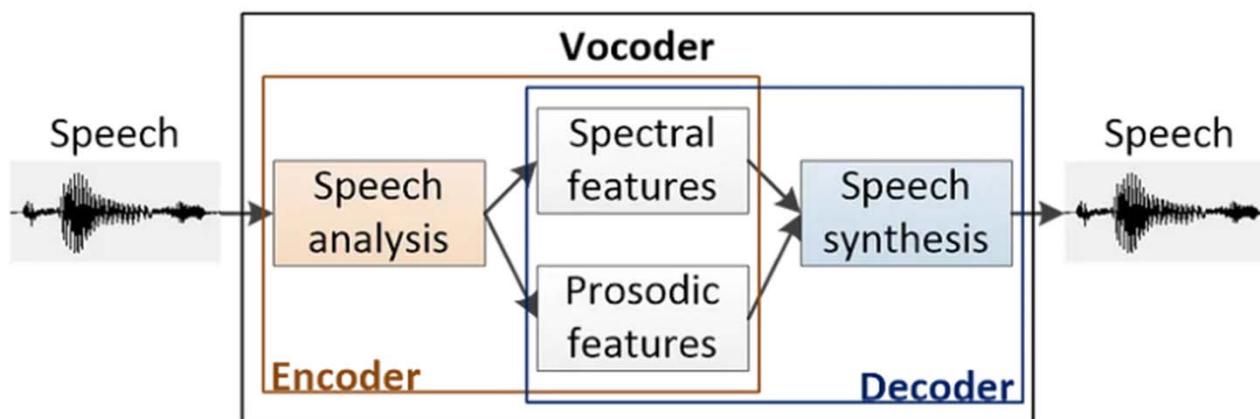
$$\text{Spectrum}[\text{Vocoder}] = \text{Spectrum}[\text{Other}] \times \frac{\text{Envelope}[\text{Speech}]}{\text{Envelope}[\text{Other}]}$$

where  $\text{Spectrum}[X]$  and  $\text{Envelope}[X]$  refer to the spectrum and magnitude envelope of  $X$ , respectively.



# What is a Vocoder?

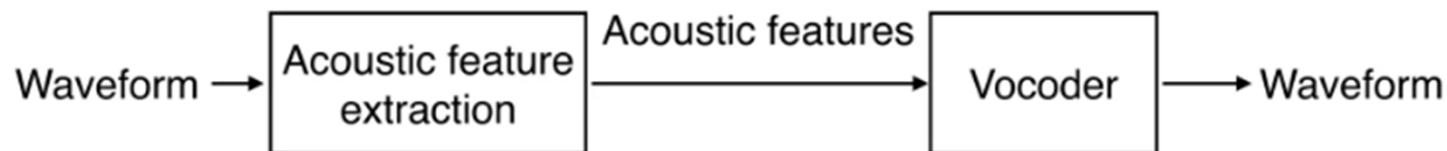
- **Vocoder:** acoustic features → audio waveforms
  - Mostly for **speech** audio initially
  - Early approaches mainly rely on **DSP**
  - SOTA approaches use **DL**
  - The term is now used more broadly to refer to such a conversion for **any sounds**



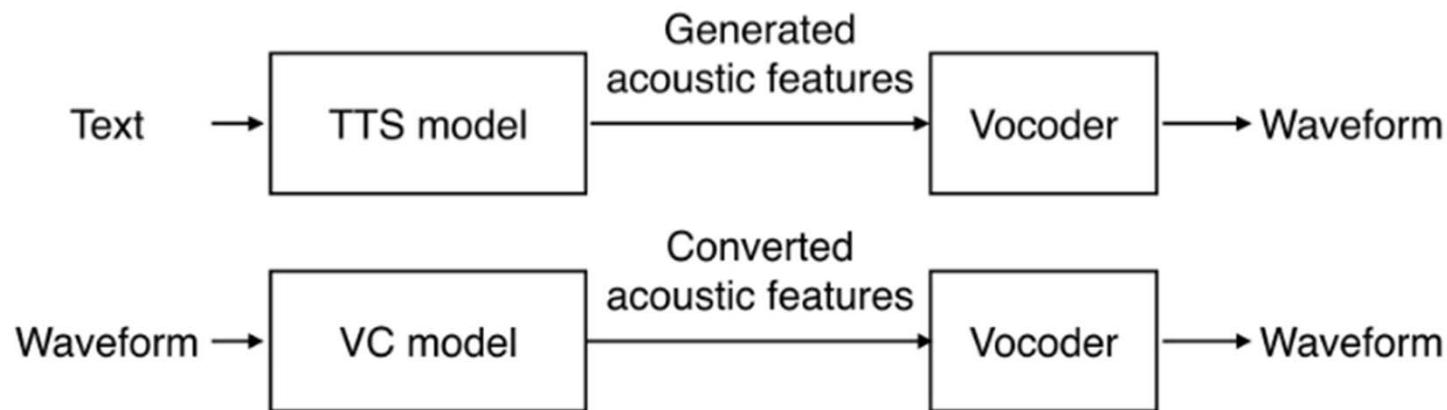
Ref: Figure from <https://medium.com/@bigpon517/2020-speech-generation-0-vocoder-and-rnn-and-cnn-based-speech-waveform-generative-models-c324c88e789a>

# Copy-Synthesis, TTS, and VC

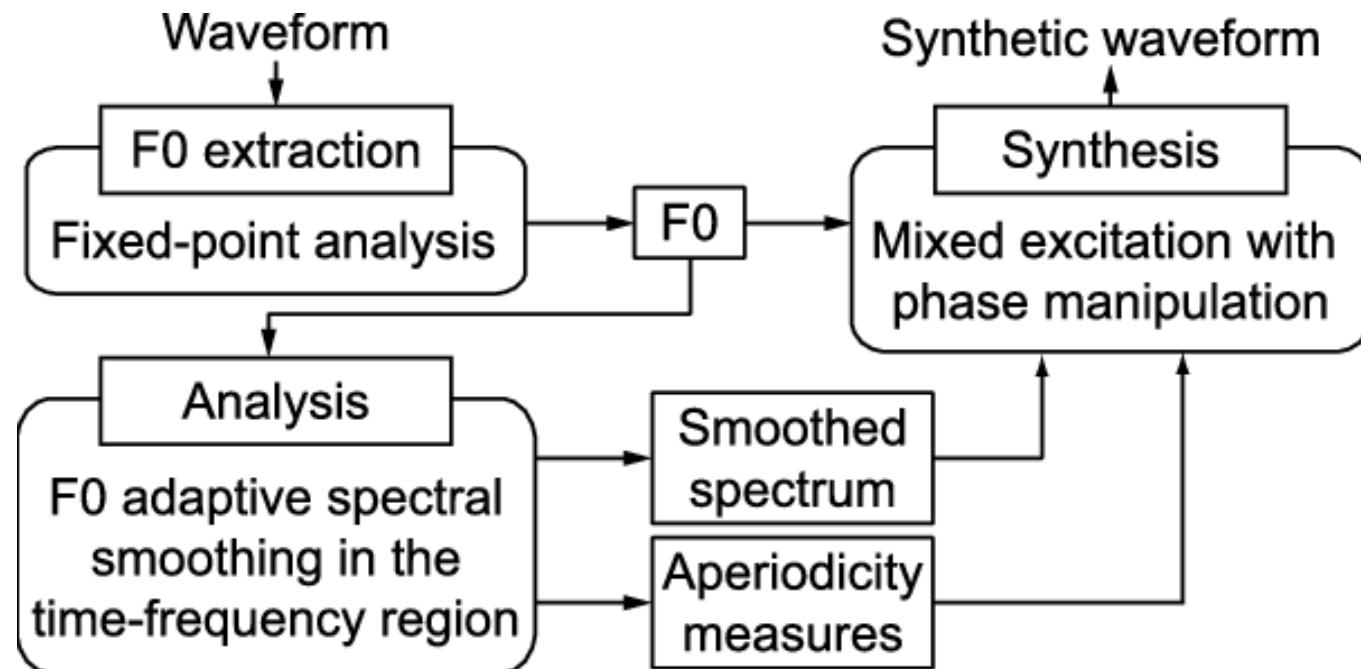
- Copy-synthesis



- TTS and VC (in the general form)



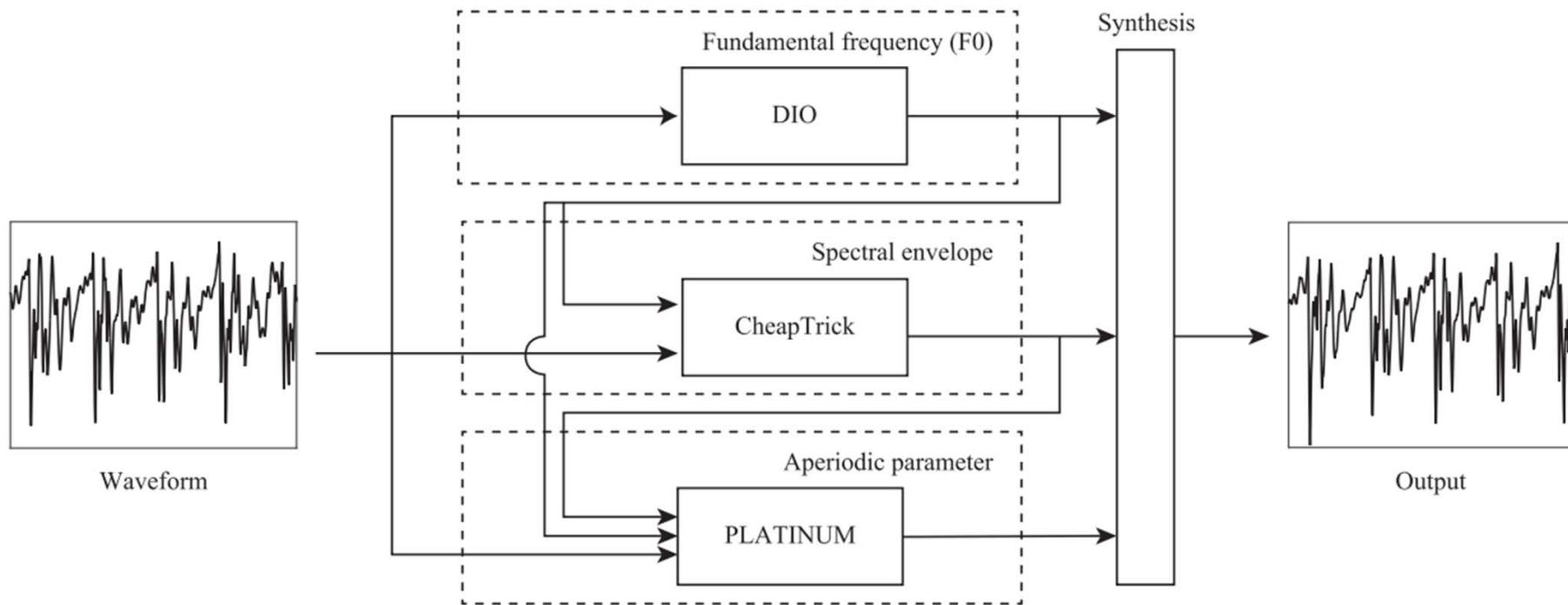
# STRAIGHT Vocoder: F0 + Spectral Envelop + Aperiodicity



Ref 1: Kawahara et al, "Restructuring speech representations using a pitch-adaptive time–frequency smoothing and an instantaneous-frequency-based F0 extraction: Possible role of a repetitive structure in sounds," Speech Communication 1999.

Ref 2: Figure from [https://www.researchgate.net/figure/A-block-diagram-of-STRAIGHT-vocoding-method\\_fig6\\_220239312](https://www.researchgate.net/figure/A-block-diagram-of-STRAIGHT-vocoding-method_fig6_220239312)

# WORLD Vocoder : F0 + Spectral Envelop + Aperiodicity

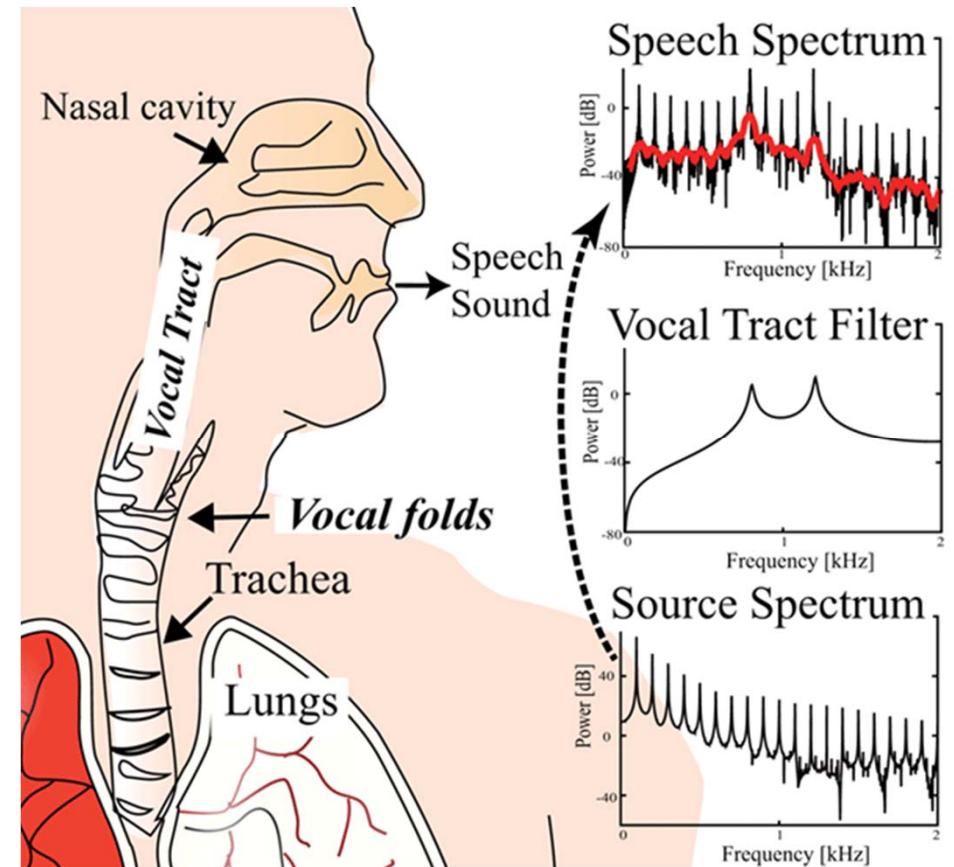


**Fig. 1** Overview of the developed system. WORLD consists of three analysis algorithms for determining the F0, spectral envelope, and aperiodic parameters and a synthesis algorithm incorporating these parameters.

Ref: Morise et al, "World: A vocoder-based high-quality speech synthesis system for real-time applications," IEICE Transactions on Information and Systems, 2016.

# Source-Filter Model

- Assumes that speech is a convolution between a **source signal** (*periodic or noise-like*) and an LTI filter
- Excitation source signals
  - Periodic* sound: vowels; nasal consonants
  - Aperiodic* sound: fricative consonants
  - A mixture of periodic and aperiodic sound (example: [z])

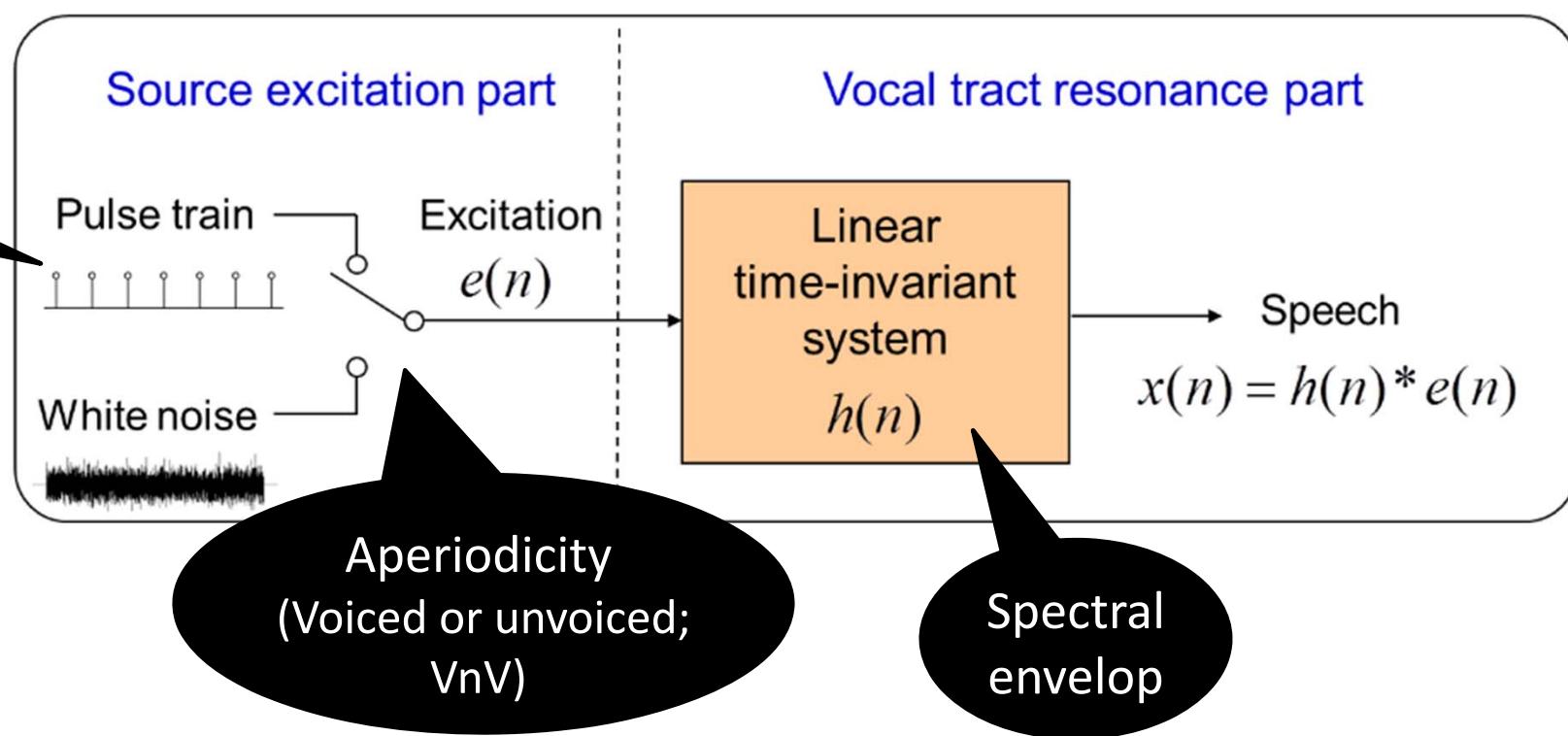


Ref: Figure from

<https://oxfordre.com/linguistics/display/10.1093/acrefore/9780199384655.001.0001/acrefore-9780199384655-e-894>

# Source-Filter Model

- Assumes that speech is a convolution between an **excitation signal** (*periodic or noise-like*) and an LTI **filter**

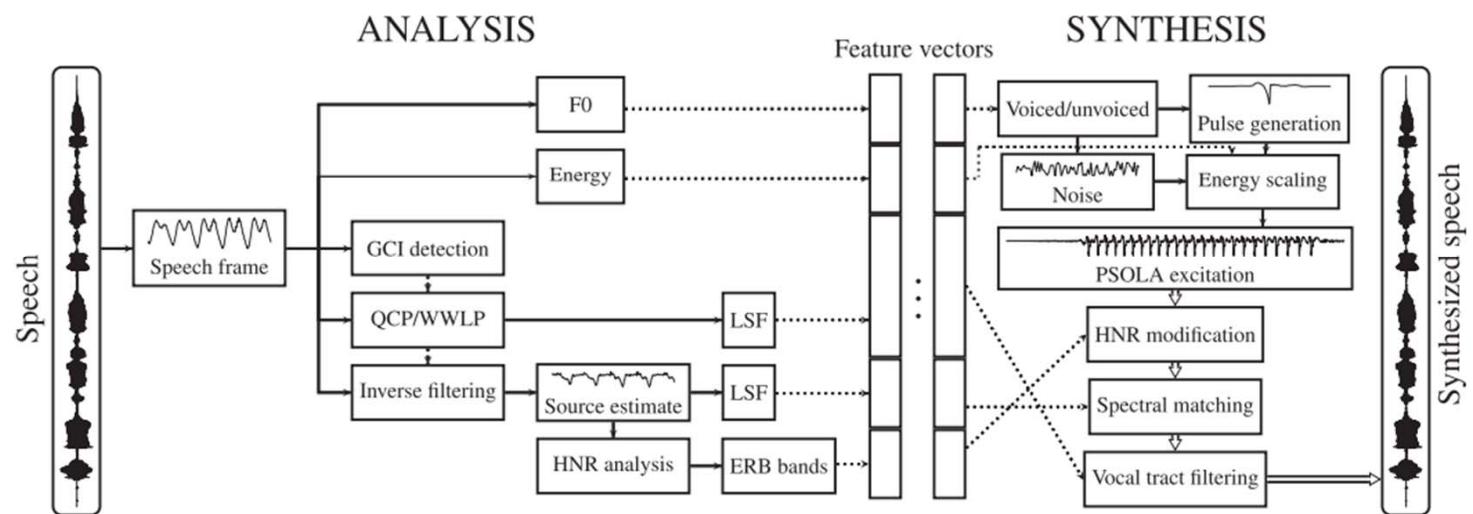


Ref: Figure from <https://blog.csdn.net/xmdxcsj/article/details/72419803>

# Many Other Vocoder

<https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8357921>

- “The vocoders developed can be categorized roughly into three groups”
  - Mixed excitation with a spectral envelope (e.g., STRAIGHT, WORLD)
  - Sinusoidal vocoders
  - Glottal vocoders



Ref: Airaksinen et al, “A Comparison Between STRAIGHT, glottal, and sinusoidal vocoding in statistical parametric speech synthesis”, TASLP 2018

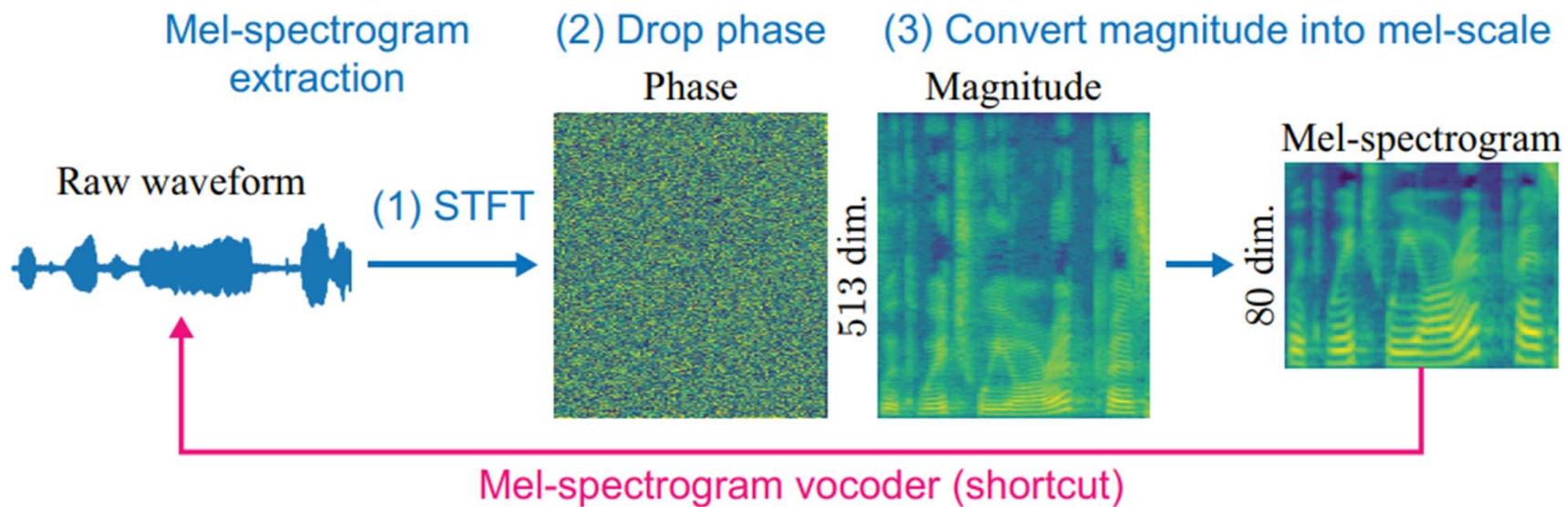
# Library: SPTK

<https://github.com/sp-nitech/SPTK>

- Aperiodicity extraction ( `ap` )
- Conversion from/to log area ratio ( `lar2par` and `par2lar` )
- Dynamic range compression ( `drc` )
- Entropy calculation ( `entropy` )
- Huffman coding ( `huffman` , `huffman_encode` , and `huffman_decode` )
- Magic number interpolation ( `magic_intpl` )
- Median filter ( `medfilt` )
- Mel-cepstrum postfilter ( `mcpf` )
- Mel-filter-bank extraction ( `fbank` )
- Nonrecursive MLPG ( `mlpg -R 1` )
- Pitch adaptive spectrum estimation ( `pitch_spec` )
- Pitch extraction by DIO used in WORLD ( `pitch -a 3` )
- Pole-zero plot ( `gpolezero` )
- Scalar quantization ( `quantize` and `dequantize` )
- Spectrogram plot ( `gspecgram` )
- Stability check of LPC coefficients ( `lpccheck` )
- Subband decomposition ( `pqmf` and `ipqmf` )
- WORLD synthesis ( `world_synth` )
- Windows build support

# Mel-Vocoder

- **Mel-vocoder:** Mel-spectrogram → audio waveforms



# Mel-Vocoder

- **Mel-vocoder:** Mel-spectrogram → audio waveforms
- For not only speech but **any sounds**
- We can divide an audio synthesis model into two steps:
  - The **generator** generates acoustic features, or the Mel-spectrogram
  - The **vocoder** converts Mel-spectrogram into waveforms
- Why Mel-vocoder becomes popular in the DL era
  - More information than F0 + spectral envelop + aperiodicity
  - Modern computing devices can deal with acoustic features with a larger dimension

# Mel-Vocoder: Approaches

- Pure **signal processing** techniques
  - Griffin & Lim algorithm
- **Autoregressive** neural networks
  - WaveNet, SampleRNN, WaveRNN
  - “Inference with these models is inherently **slow** and inefficient because audio samples must be **generated sequentially**”
- **Non-autoregressive** neural networks
  - “Orders of magnitudes faster than their auto-regressive counterparts because they are highly parallelizable and can fully exploit modern deep learning hardware”

# Griffin & Lim Algorithm

- Initially for magnitude spectrogram → audio waveforms
- Iterative optimization
- No training is needed
- Robotic artifacts

算法步骤：

- 随机初始化一个相位谱
- 用这个相位谱与已知的幅度谱（来自MEL谱）经过ISTFT（逆傅里叶变换）合成新的语音波形
- 用合成语音做STFT，得到新的幅度谱和新的相位谱
- 丢弃新的幅度谱，用已知幅度谱与新的相位谱合成新的语音
- 重复2,3,4多次，直至合成的语音达到满意的效果或者迭代次数达到设定的上限

[https://blog.csdn.net/CSDN\\_71560364126/article/details/103968034](https://blog.csdn.net/CSDN_71560364126/article/details/103968034)

# Griffin & Lim Algorithm

[https://speechprocessingbook.aalto.fi/  
Modelling/griffinlim.html](https://speechprocessingbook.aalto.fi/Modelling/griffinlim.html)

```
# example signal
original_waveform = np.sin(np.linspace(0,221,400))
_,_,original_spectrogram = scipy.signal.stft(original_waveform,nperseg=100, return_onesided=True)
frames = original_spectrogram.shape[1]

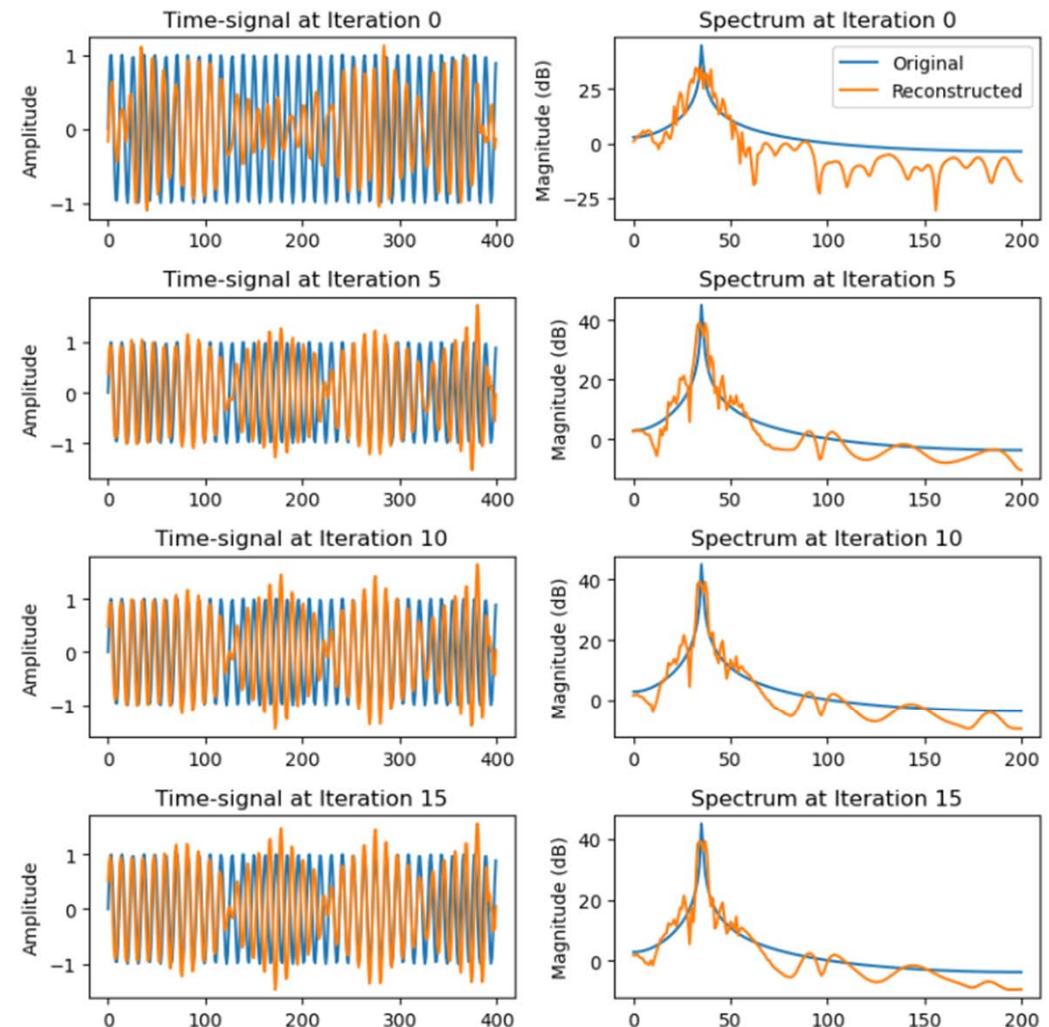
# initialize target magnitude spectrogram
magnitude_spectrogram = np.abs(original_spectrogram)

# initial guess of complex spectrogram = random phase
spectrogram = magnitude_spectrogram*np.exp(1j*2*np.pi*np.random.rand(51,frames))
```

```
plt.figure(figsize=(8,8))
N = 4
K = 5
for h in range(N*K - K+1):
    waveform = scipy.signal.istft(spectrogram, nperseg=100, input_onesided = True, boundary=True)
    waveform = np.real(waveform)
    _,_,spectrogram = scipy.signal.stft(waveform,      nperseg=100, return_onesided=True)
    spectrogram = np.exp(1j*np.angle(spectrogram))*magnitude_spectrogram

    if h % K == 0:
        k = h//K
        plt.subplot(N,2,2*k+1)
        plt.plot(original_waveform)
        plt.plot(waveform)
        plt.title(f"Time-signal at Iteration {h}")
        plt.ylabel('Amplitude')

        plt.subplot(N,2,2*k+2)
        plt.plot(20*np.log10(np.abs(scipy.fft.rfft(original_waveform))),label='Original')
        plt.plot(20*np.log10(np.abs(scipy.fft.rfft(waveform))),label='Reconstructed')
        plt.title(f"Spectrum at Iteration {h}")
        plt.ylabel('Magnitude (dB)')
        if h==0: plt.legend()
```



# Griffin & Lim-based Mel-Vocoder via LibROSA

[https://librosa.org/doc/main/generated/librosa.feature.inverse.mel\\_to\\_audio.html](https://librosa.org/doc/main/generated/librosa.feature.inverse.mel_to_audio.html)  
[#librosa.feature.inverse.mel\\_to\\_audio](#)

```
librosa.feature.inverse.mel_to_audio(M, *, sr=22050,  
n_fft=2048, hop_length=None, win_length=None, window='hann',  
center=True, pad_mode='constant', power=2.0, n_iter=32, length=None,  
dtype=<class 'numpy.float32'>, **kwargs) [source]
```

Invert a mel power spectrogram to audio using Griffin-Lim.

This is primarily a convenience wrapper for:

```
>>> S = librosa.feature.inverse.mel_to_stft(M)  
>>> y = librosa.griffinlim(S)
```

- **mel-to-stft**: approximate STFT magnitude from a Mel power spectrogram

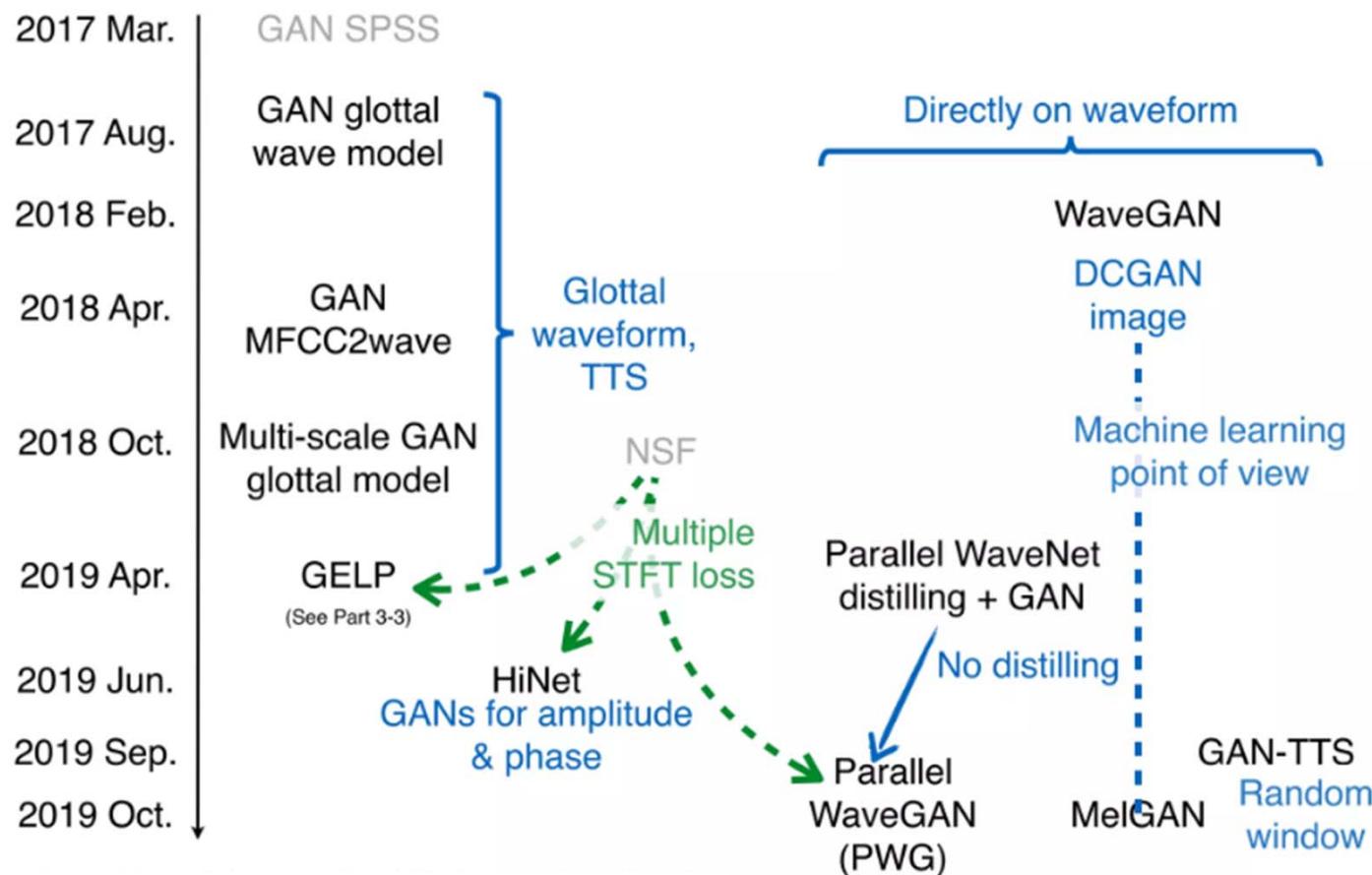
# Autoregressive vs Non-autoregressive Generation

- **Autoregressive**
  - Causal (no information about the future)
  - One sample at a time
  - Good for *online* application
  - Too slow for offline application
  - And good for *unconditional audio generation*
  - Examples: WaveNet, Transformer
- **Non-autoregressive**
  - Non-causal
  - Good for Mel-vocoding because we have seen the entire input

# Non-autoregressive Neural Vocoder

- Via **knowledge-distillation** of autoregressive models
  - Parallel WaveNet (Oord et al., 2017) and Clarinet (Ping et al., 2018)
- Via **flow-based** models
  - WaveGlow (Prenger et al., 2019)
- Via **GAN-based** models
  - Reconstruction loss + adversarial loss
  - SOTA

# GAN-based Models



Ref: Figure from <https://www.slideshare.net/jyamagis/advancements-in-neural-vocoders> (page 111)

# Why GAN? (Or, Why Reconstruction Loss Alone is Not Enough)

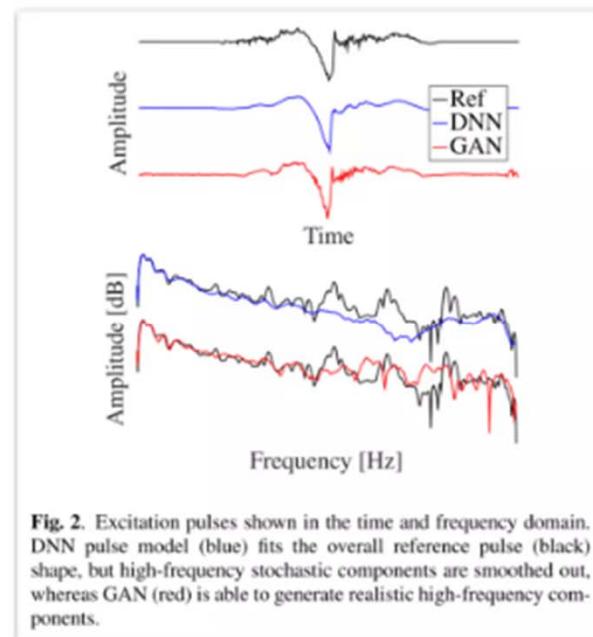
*This new methodology ... has allowed for waveforms to be generated ... at ... a higher real-time speed than in models with autoregressive constraints*

*MelGAN is substantially faster than other mel-spectrogram inversion alternatives*

*Multi-band MelGAN runs at more than 10x faster than real-time on CPU.*

- Not only about fast inference speed
- Also on combating with the over-smoothing

*(Conventional) models are limited due to the point-wise regression in the time domain, which results in **smoothing and loss of high frequencies**.*

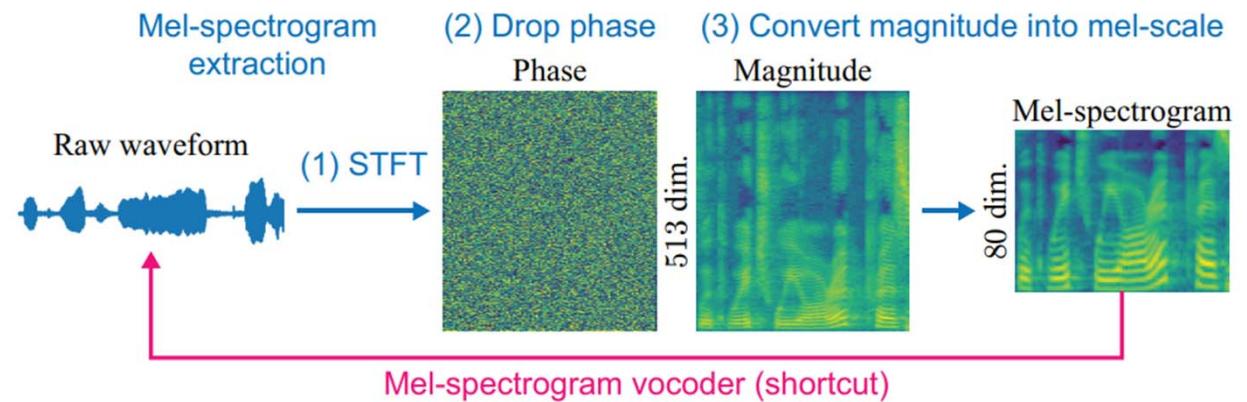


**Fig. 2.** Excitation pulses shown in the time and frequency domain. DNN pulse model (blue) fits the overall reference pulse (black) shape, but high-frequency stochastic components are smoothed out, whereas GAN (red) is able to generate realistic high-frequency components.

# Mel-Vocoder

- **Mel-vocoder:** Mel-spectrogram → audio waveforms

- Upsampling
  - Time-frequency conversion
    - Inverse the Mel-scale
    - Predict the phase



- There is a “ground truth” output
  - The input (“Mel-spectrogram”) is temporally aligned with the expected output
  - Paired data for training such a model can be easily obtained

# Source Separation vs Mel-Vocoder

Task	Input/Output	Conditioning type	Data availability
<b>Source separation</b>	audio (mixture) → audio (stem)	<i>strong &amp; time-aligned</i> conditioning (perfect alignment)	Harder to get paired data
<b>Mel-vocoder</b>	mel → audio	<i>strong &amp; time-aligned</i> conditioning (output sequence length is a factor of the input sequence length)	Extremely use to get paired data

- *Strong* condition: it can be said that there is a “ground-truth” output
- *Time-aligned*: the condition is time-varying and is temporally aligned with the input
- From encoder/decoder perspective
  - Timbre classifier: encoder (downsampling)
  - Source separation : encoder/decoder
  - Mel-vocoder: decoder (upsampling)

# Other Types of Audio Generation Problems

Task	Input/Output	Conditioning type	Data availability
Source separation	audio (mixture) → audio (stem)	<i>strong &amp; time-aligned</i> conditioning	Harder to get paired data
Mel-vocoder	mel → audio	<i>strong &amp; time-aligned</i> conditioning	Extremely hard to get paired data
Voice conversion	audio (source) → audio (target)		
Accomp. generation	audio (singing) → audio (accomp.)		
Audio synthesis	MIDI → audio		
Audio generation	x → audio		

# Recap: Approaches to Deal with Phase for STFT-based Models

<https://source-separation.github.io/tutorial/basics/phase.html>

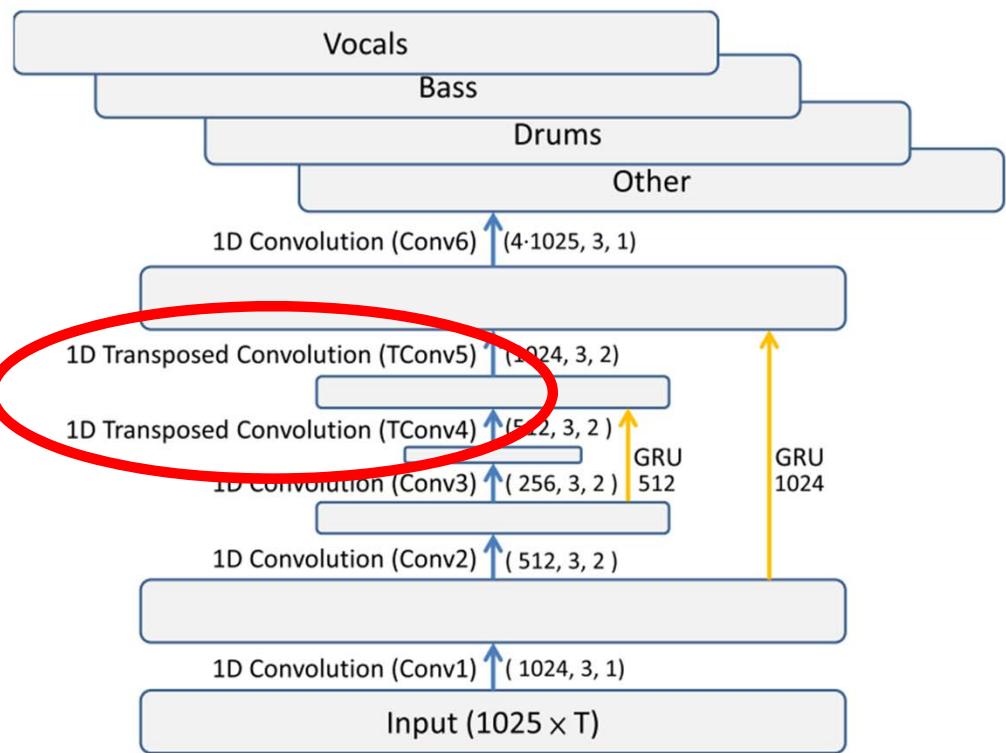
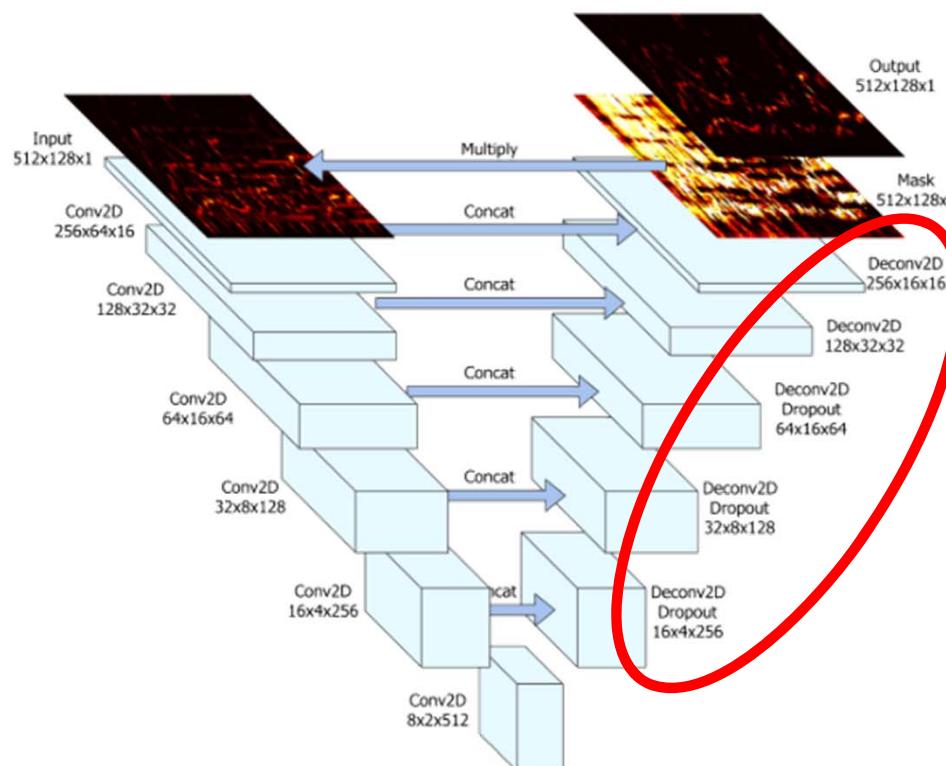
- **Copy the phase (from the input)**
  - Work fine for source separation (but **NOT** for Mel-vocoders)
- **Given the magnitude, estimate the phase**
  - Griffin & Lim
  - DL-based Mel-vocoders
- **Work on audio waveforms, not spectrograms**
  - See the next lecture

# Outline

- General idea
- **DL components: upsampling layers and GAN**
- GAN-based Mel-vocoders
- Advanced topics

# Upsampling Layers: Transposed Convolution

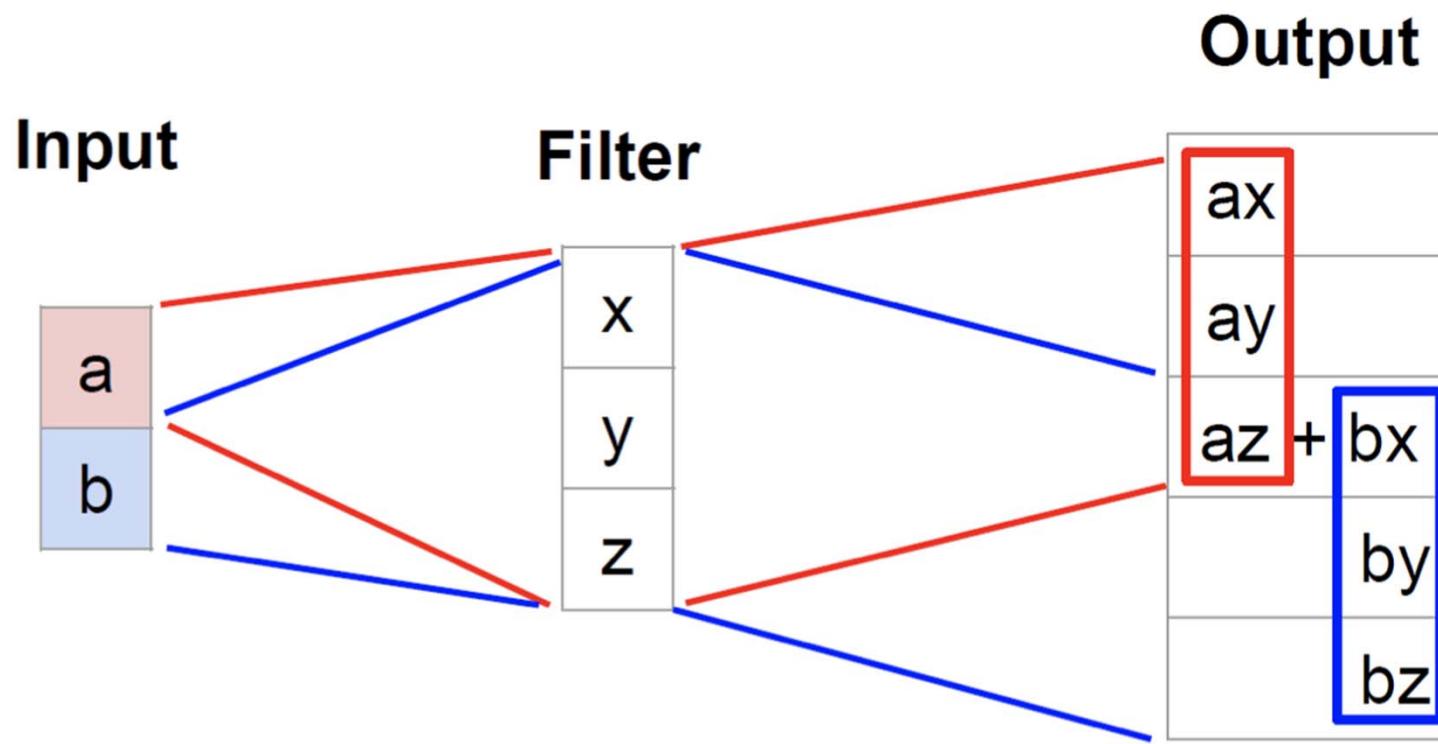
- Also known as “deconvolution layers”



U-Net-based source separation model [jansson17ismir]

ARC [liu18icmla]

# Convolution and Transposed Convolution



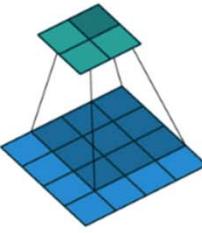
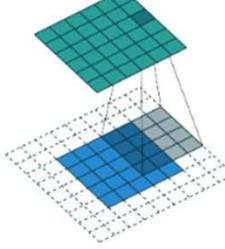
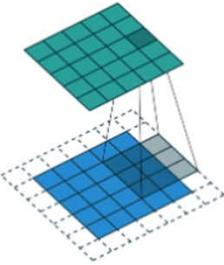
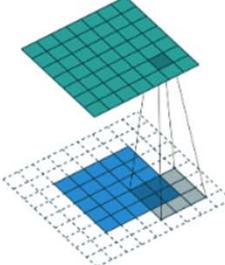
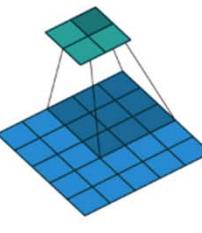
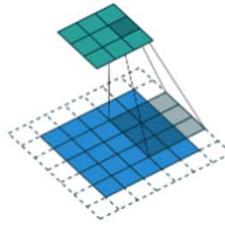
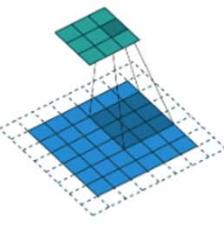
Ref: Figure from <https://medium.com/jun94-devpblog/dl-12-unsampling-unpooling-and-transpose-convolution-831dc53687ce>

# Downsampling Layers: Convolution

[https://github.com/vdumoulin/conv\\_arithmetic](https://github.com/vdumoulin/conv_arithmetic)

## Convolution animations

*N.B.: Blue maps are inputs, and cyan maps are outputs.*

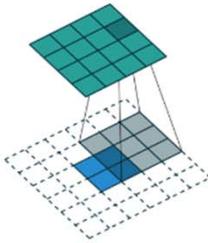
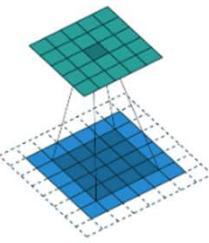
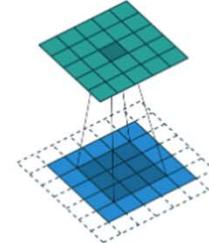
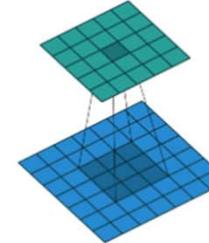
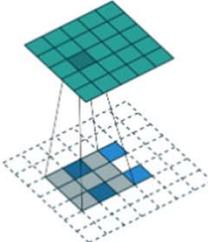
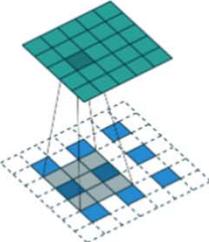
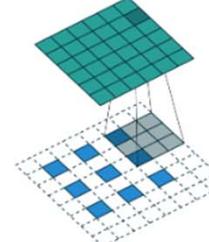
			
No padding, no strides	Arbitrary padding, no strides	Half padding, no strides	Full padding, no strides
			
No padding, strides	Padding, strides	Padding, strides (odd)	

# Upsampling Layers: Transposed Convolution

[https://github.com/vdumoulin/conv\\_arithmetic](https://github.com/vdumoulin/conv_arithmetic)

Transposed convolution animations

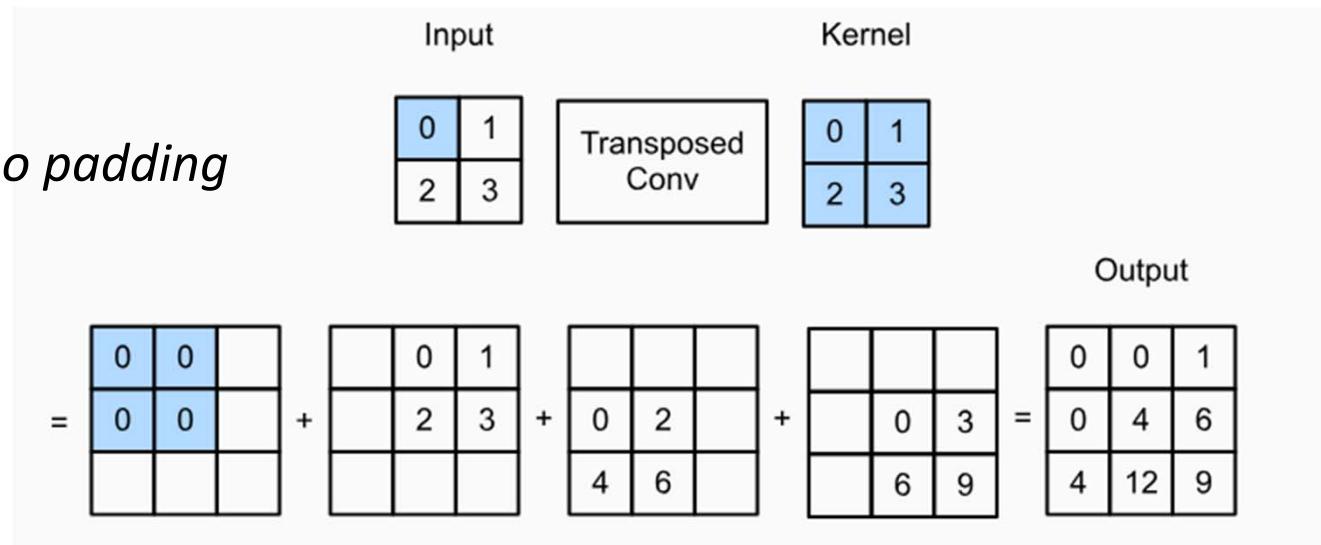
N.B.: Blue maps are inputs, and cyan maps are outputs.

			
No padding, no strides, transposed	Arbitrary padding, no strides, transposed	Half padding, no strides, transposed	Full padding, no strides, transposed
			
No padding, strides, transposed	Padding, strides, transposed	Padding, strides, transposed (odd)	

# Upsampling Layers: Transposed Convolution

[https://d2l.ai/chapter\\_computer-vision/transposed-conv.html](https://d2l.ai/chapter_computer-vision/transposed-conv.html)

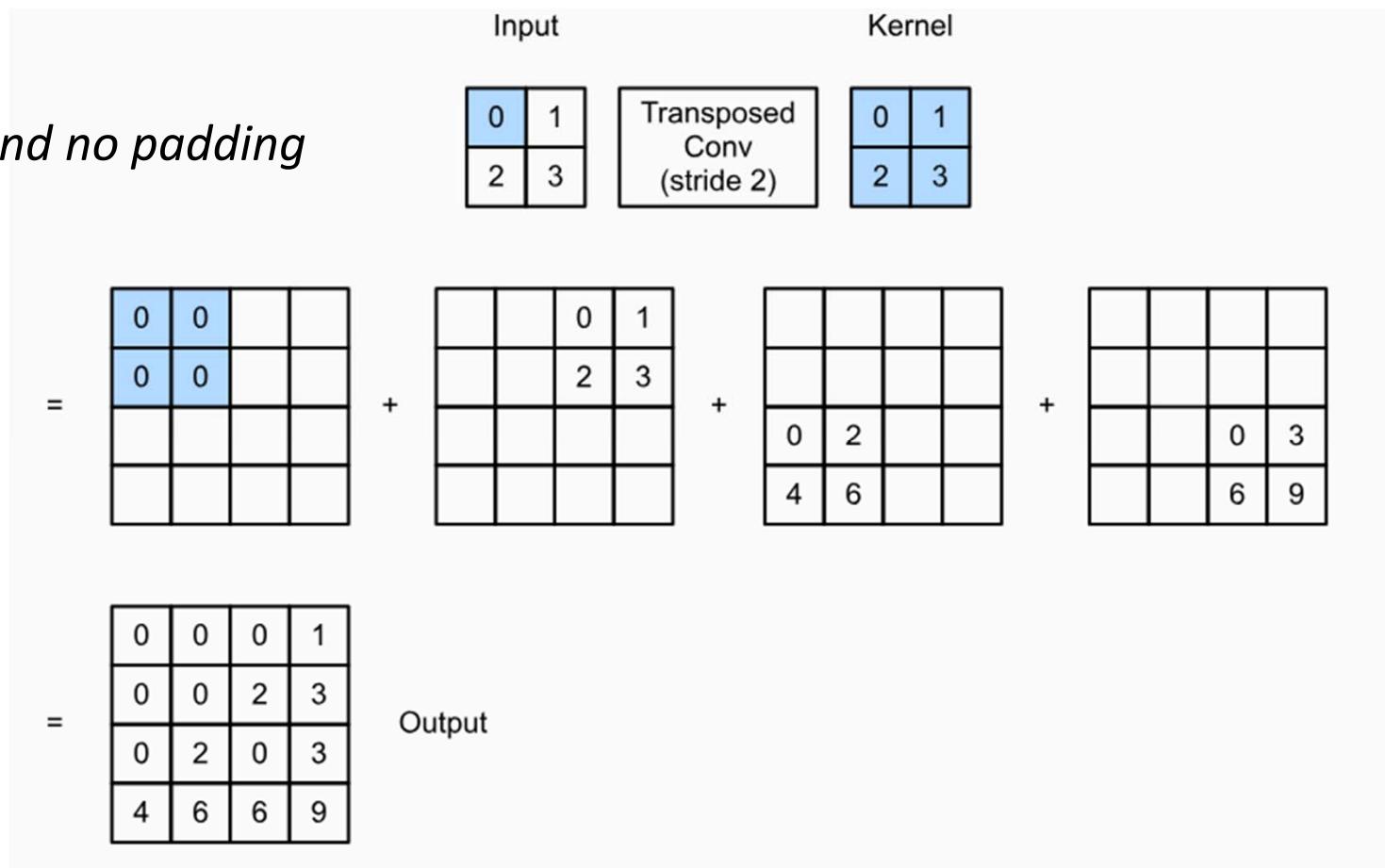
*stride of 1 and no padding*



# Upsampling Layers: Transposed Convolution

[https://d2l.ai/chapter\\_computer-vision/transposed-conv.html](https://d2l.ai/chapter_computer-vision/transposed-conv.html)

*stride of 2 and no padding*



# Upsampling Layers: The Checkerboard Artifacts in Images

<https://distill.pub/2016/deconv-checkerboard/>

- Due to uneven overlaps when the kernel size (the output window size) is not divisible by the stride (the spacing between points on the top)
- Solution: Use a kernel size that is divided by your stride

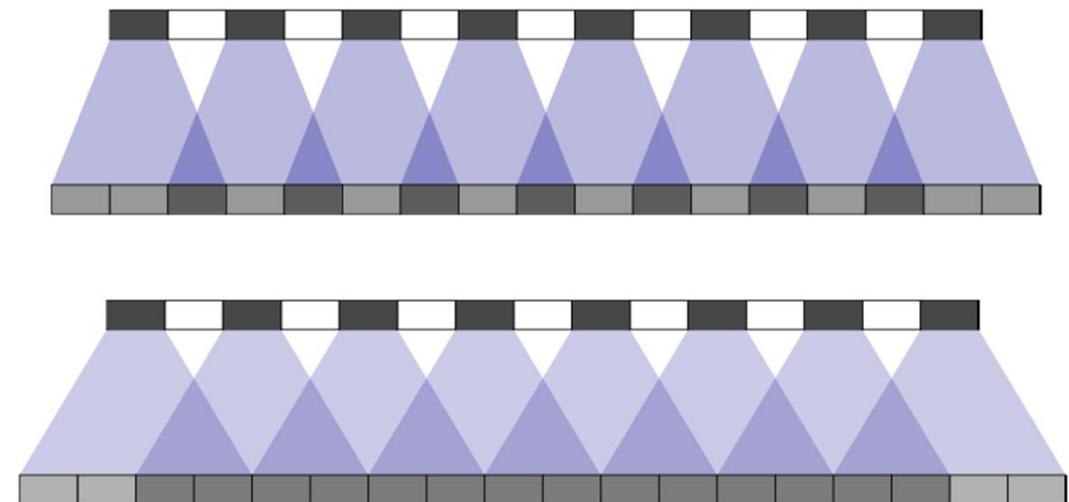


Radford, et al., 2015 [1]

Salimans et al., 2016 [2]

Donahue, et al., 2016 [3]

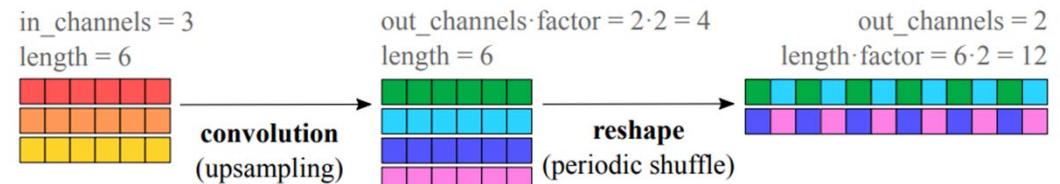
Dumoulin, et al., 2016 [4]



# Upsampling Layers: The Checkerboard Artifacts in Audio

<http://www.jordipons.me/apps/upsamplers/>

- Explore other neural upsampler approaches
  - **Transposed convolution:** no overlap (length=stride) or full overlap (length is multiple of the stride), not partial overlap
    - “Even under no overlap and full overlap setups, the loss function and the weights’ initialization issues remain”
  - **Interpolation upsamplers**
    - Nearest neighbor interpolation
    - Linear interpolation
    - Stretch interpolation
    - Sinc interpolation
  - **Subpixel convolution**



# Upsampling Layers: The Checkerboard Artifacts in Audio

<http://www.jordipons.me/apps/upsamplers/>

- Explore other neural upsampler approaches
- In the context of **source separation**

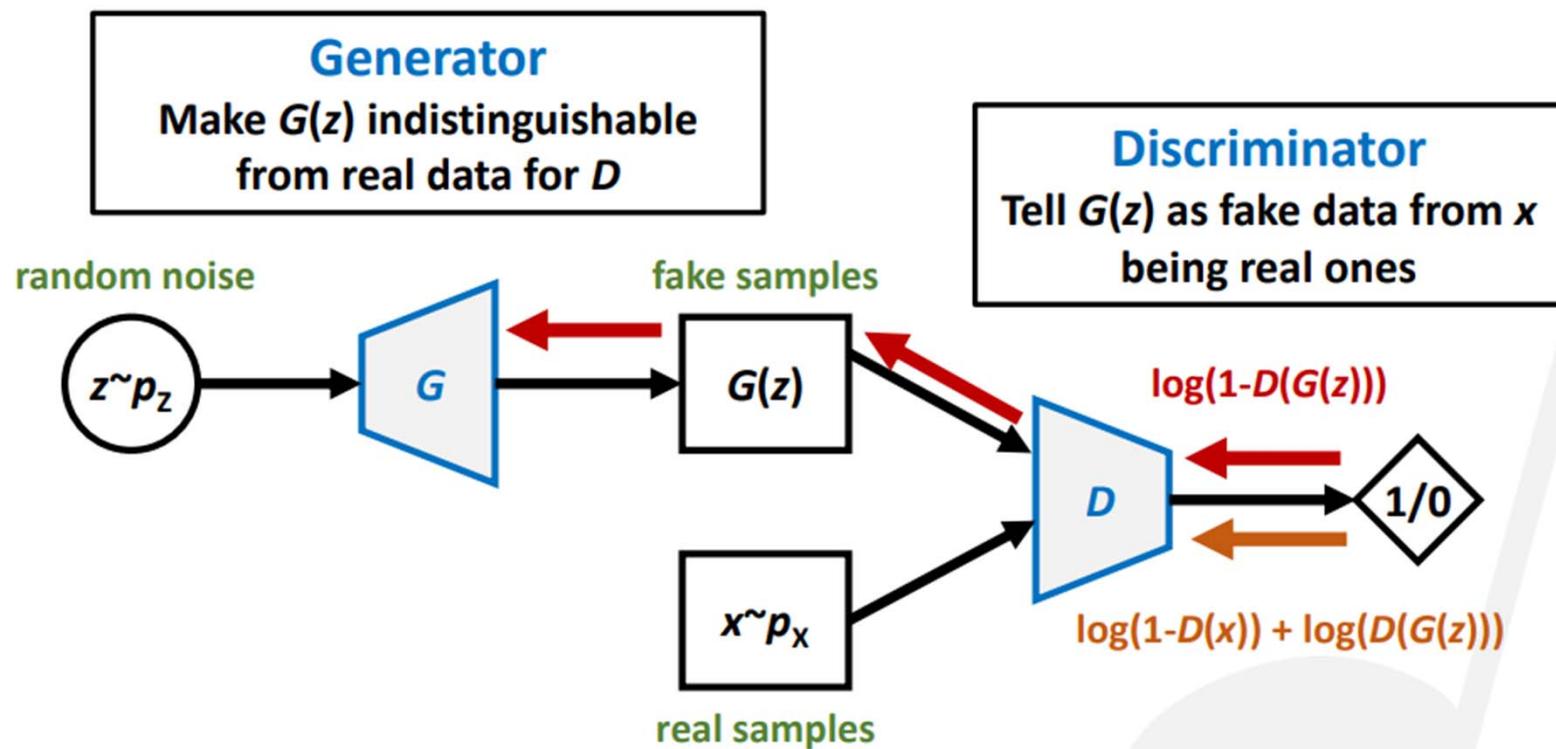
Music source separation (MUSDB [27] benchmark)	SDR ↑	epoch	#parm
Demucs-like (Fig. 1, b): transposed CNN (full-overlap)	5.35	319 s	703M
Demucs-like (Fig. 1, c): nearest neighbor interpolation	5.17	423 s	716M
Demucs-like: linear interpolation	4.62	430 s	716M
Demucs-like (Fig. 1, d): subpixel CNN	5.38	311 s	729M
Modified (Fig. 9, a): transposed CNN (full-overlap)	5.37	326 s	703M
Modified (Fig. 9, b): subpixel CNN	5.38	315 s	729M
WaveUnet [2]: linear interpolation	3.23	-	10M
Demucs [3]: transposed convolution (full-overlap)	5.34 <sup>4</sup>	-	648M
OpenUnmix [30]: spectrogram-based	5.36	-	8.9M
Sams-net [31]: spectrogram-based	5.65	-	3.7M

“Informal listening, however, reveals that **tonal artifacts** can emerge even after training, **especially in silent parts and with out-of-distribution data** (e.g., with sounds and conditions not seen during training)”

“We find that **nearest neighbor** and **linear interpolation models** do not have this disadvantage, although they achieve worse SDR scores.”

# GAN: Generative Adversarial Network

<https://salu133445.github.io/ismir2019tutorial/>



# GANs vs VAEs

<https://salu133445.github.io/ismir2019tutorial/>

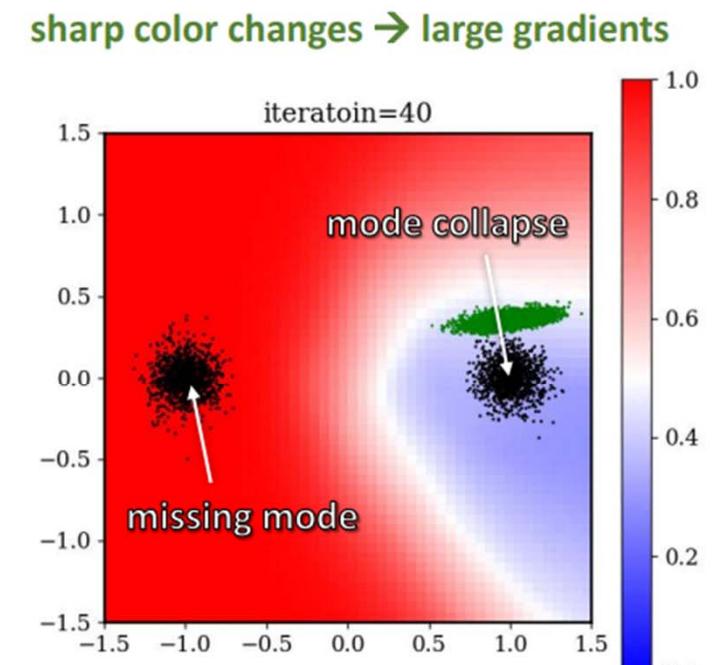
	<b>GAN</b>	<b>VAE</b>
<b>Objective</b>	(generator) fool the discriminator (discriminator) tell real data from fake ones	reconstruct real data using pixel-wise loss
	tend to be sharper	tend to be more blurred
<b>Results</b>		
<b>Diversity</b>	Higher	Lower
<b>Stability</b>	Lower	Higher

# GAN: Mode Collapse and Missing Mode

<https://salu133445.github.io/ismir2019tutorial/>

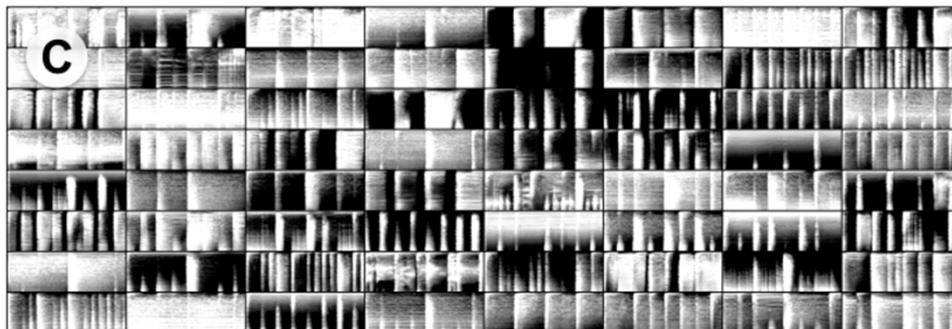
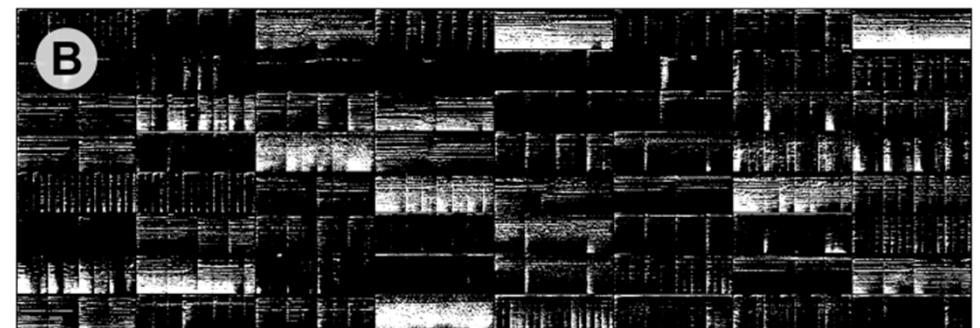
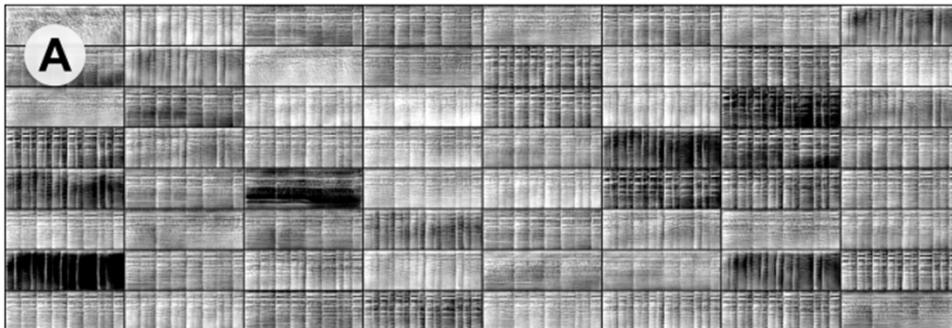
- **Key**—discriminator provides generator with gradients as a guidance for improvement
  - Discrimination is easier than generation
  - Discriminator tends to provide large gradients
  - Result in unstable training of the generator
- Common failure cases
  - Mode collapse
  - Missing modes
- Also see:

<https://github.com/soumith/ganhacks>



# GAN: Gradient Vanishing

- Gradient *vanishes* when the discriminator is too strong



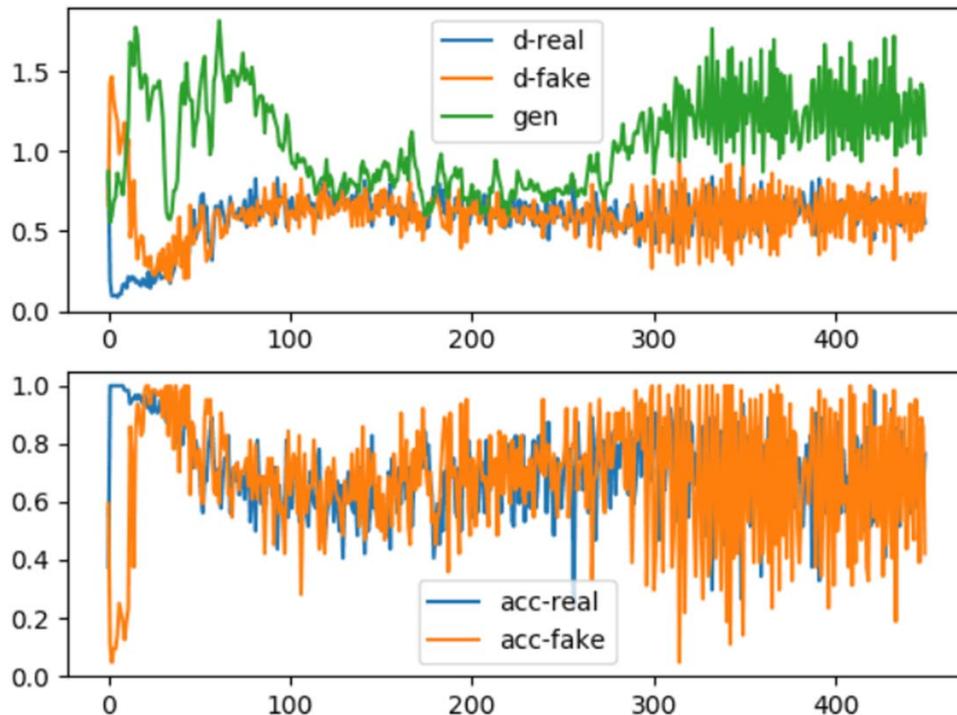
- Examples from Mel-spectrogram generation (not Mel-vocoder)
  - (A) Mode collapse
  - (B) Gradient vanishing
  - (C) Successful training

Ref: Yeh et al, “Exploiting pre-trained feature networks for generative adversarial networks in audio-domain loop generation,”  
ISMIR 2022

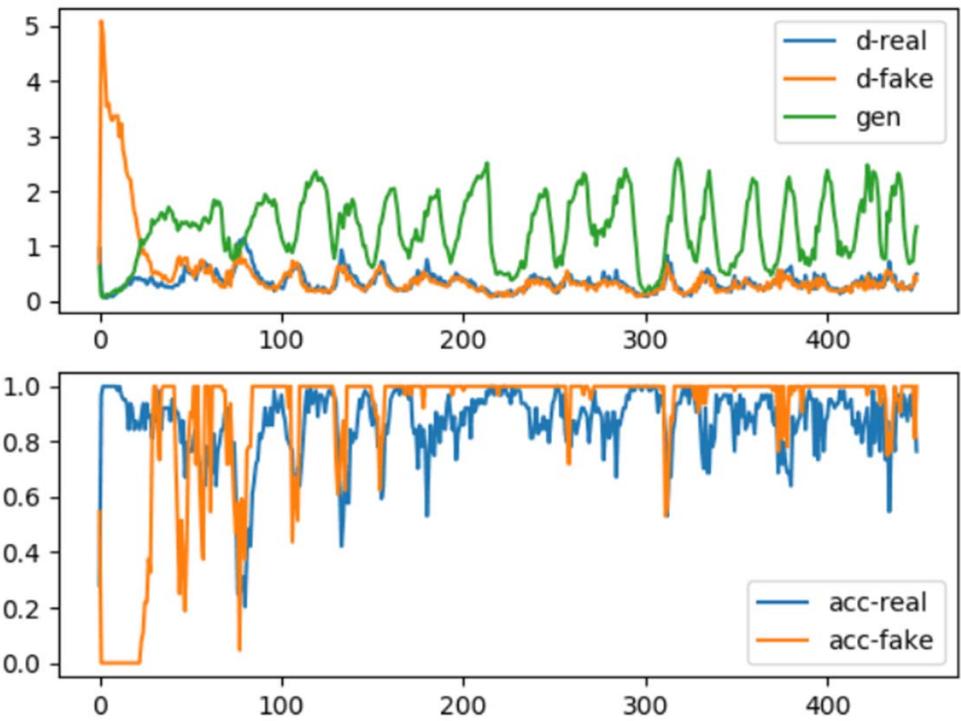
# GAN: Training Dynamics

<https://machinelearningmastery.com/practical-guide-to-gan-failure-modes/>

Line plots of Loss and Accuracy for a **stable GAN**



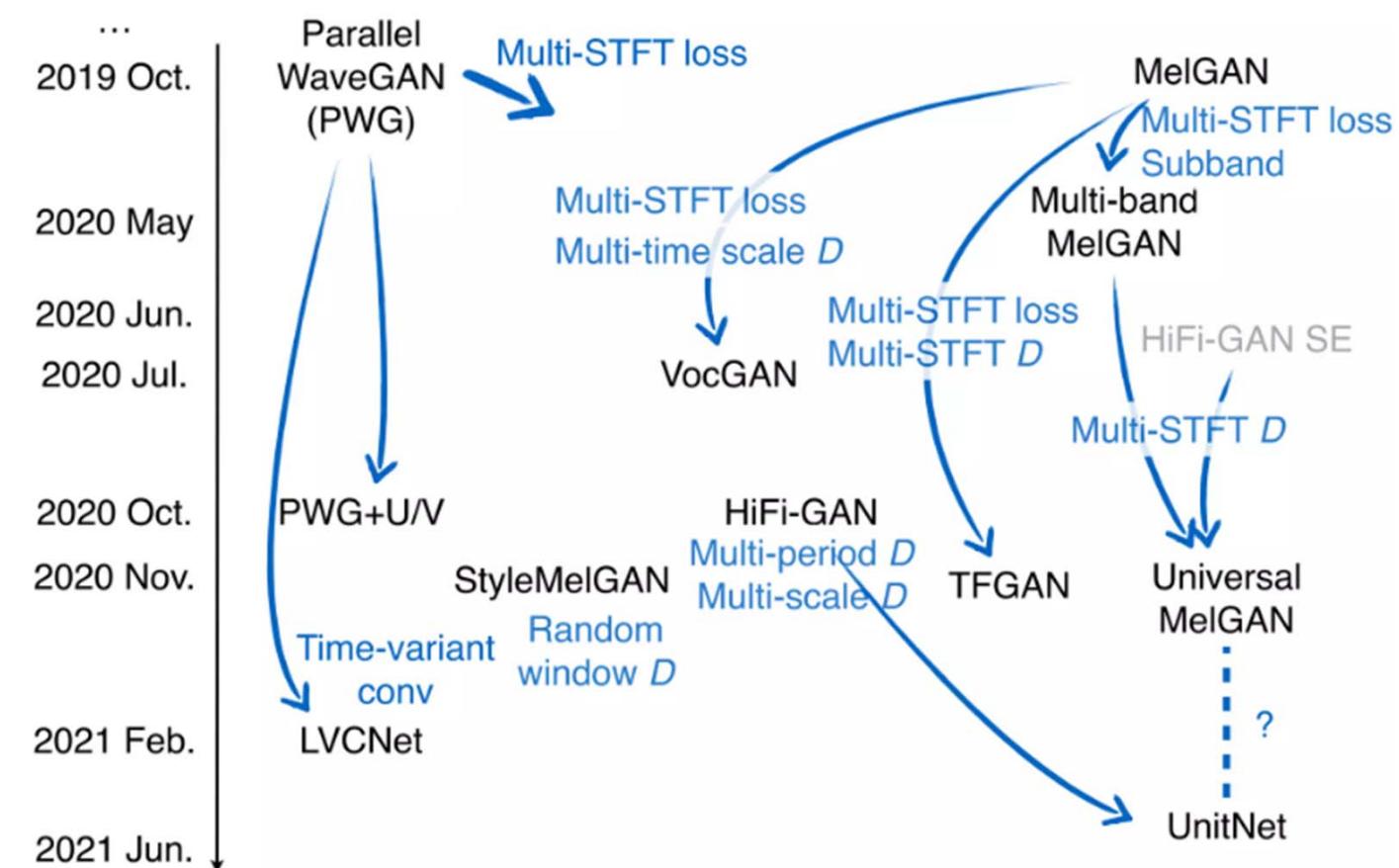
Line plots of for a GAN with **mode collapse**



# Outline

- General idea
- DL components: upsampling layers and GAN
- **GAN-based Mel-vocoders**
- Advanced topics

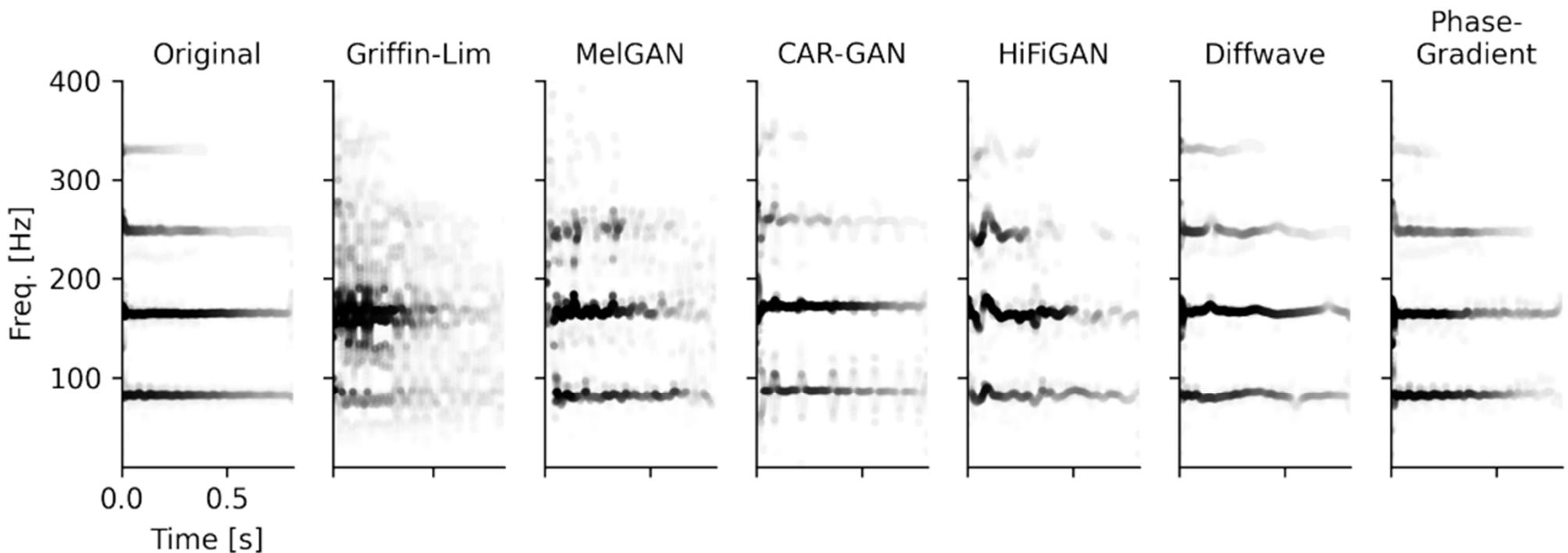
# GAN-based Models



Ref: Figure from <https://www.slideshare.net/jyamagis/advancements-in-neural-vocoders> (page 112)

# GAN-based Models

- Great improvement over the years



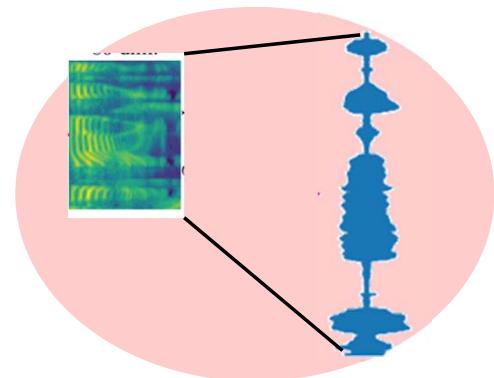
## GAN-based Models

- Let's talk about the following models
  - MelGAN (arXiv:1910.06711; NeurIPS'19)
  - MB-MelGAN (arXiv:2005.05106; INTERSPEECH'20)
  - HiFiGAN (arXiv:2010.05646; NeurIPS'20)
  - iSTFTNet (arXiv:2203.02395; ICASSP'22)

# MelGAN (NeurIPS'19)

[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)

- First GAN-based, non-autoregressive Mel-Vocoder
  - **Feedforward**: upsamples the input to create the output
- Smaller and **much faster**



Model	Number of parameters (in millions)	Speed on CPU (in kHz)	Speed on GPU (in kHz)
Wavenet (Shen et al., 2018)	24.7	0.0627	0.0787
Clarinet (Ping et al., 2018)	10.0	1.96	221
WaveGlow (Prenger et al., 2019)	87.9	1.58	223
<b>MelGAN (ours)</b>	<b>4.26</b>	<b>51.9</b>	<b>2500</b>

# MelGAN

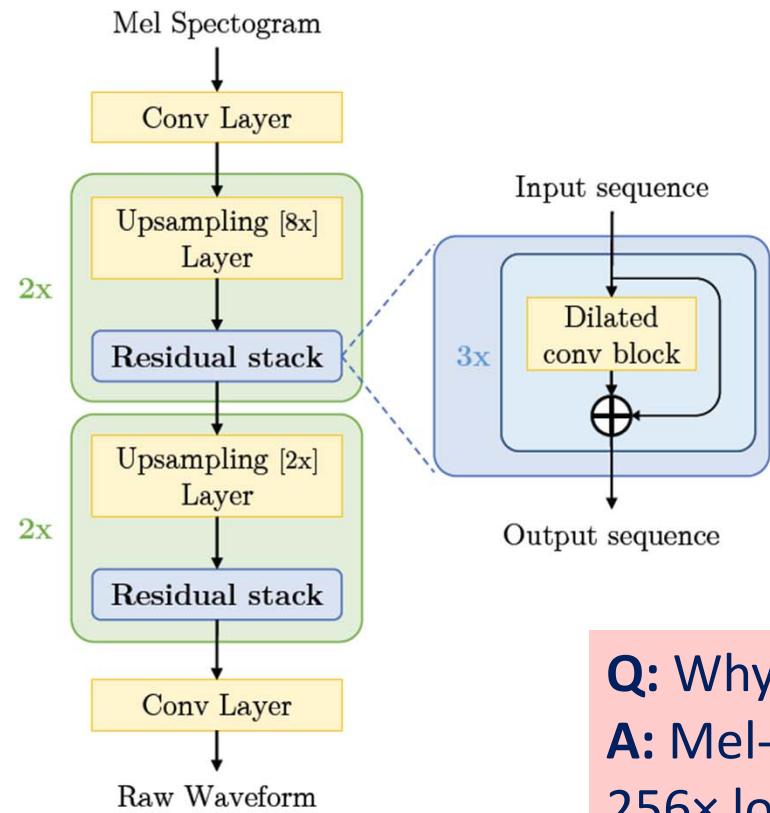
[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)

- First GAN-based, non-autoregressive Mel-Vocoder
- Smaller and much faster than competing methods at the time
- But a bit less accurate  
than WaveNet and  
Flow-based models  
such as WaveGlow

Model	MOS	95% CI
Griffin Lim	1.57	±0.04
WaveGlow	4.11	±0.05
WaveNet	4.05	±0.05
MelGAN	3.61	±0.06
Original	<b>4.52</b>	<b>± 0.04</b>

# MelGAN: Generator

[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)



## Architecture

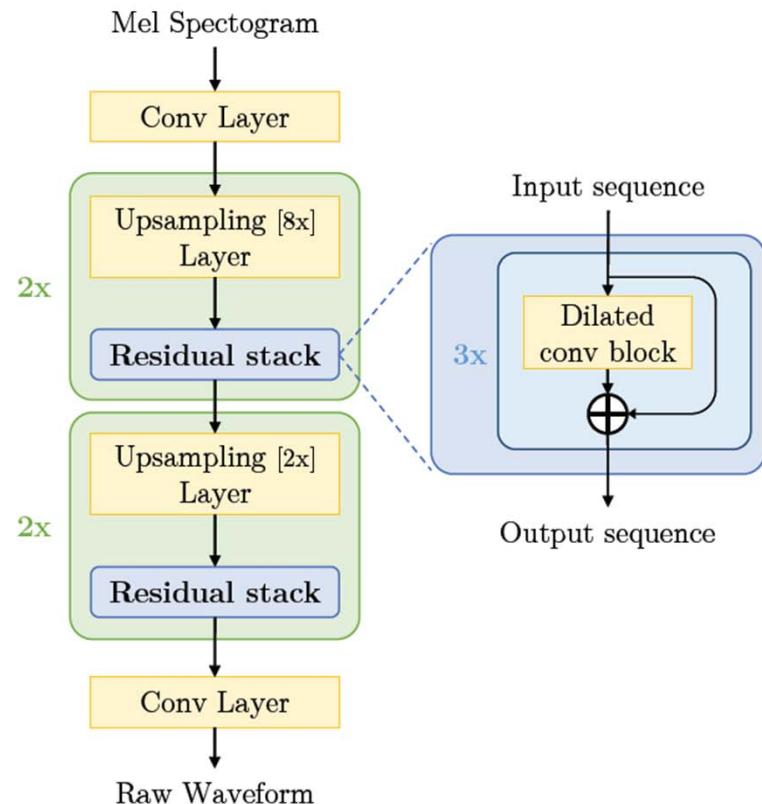
- Stack of transposed convolutional layers to upsample the input sequence.
- Each transposed convolutional layer followed by a stack of residual blocks.

**Q:** Why [8x8x2x2]?

**A:** Mel-spectrogram (used for all experiments) is at a 256x lower temporal resolution

# MelGAN: Generator

[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)

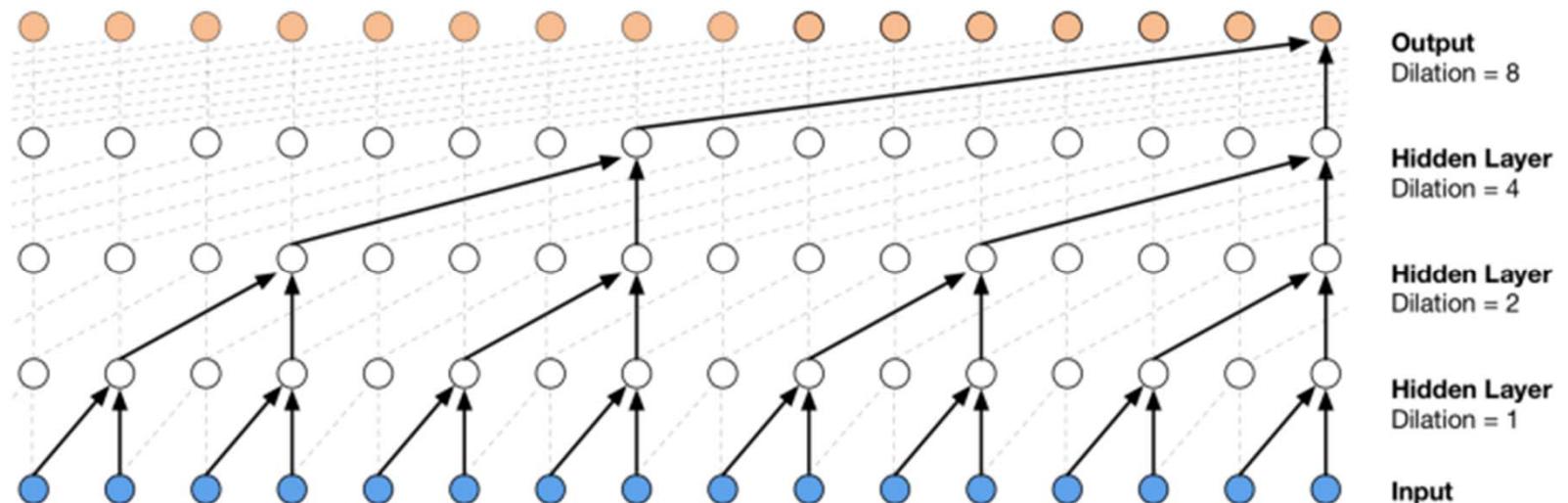


## Induced Receptive Field

- **Residual blocks with dilations** so temporally far output activations of each layer has significant overlapping inputs.
- Receptive field of a stack of dilated convolution layers **increases exponentially** with the number of layers.

# Dilation?

- **Dilated convolution** ( $\neq$  transposed convolution)
  - Increase reception field exponentially with linearly increasing number of parameters
  - See the WaveNet paper
- Stride  $\neq$  dilation



Ref: van den Oord et al, "Wavenet: A generative model for raw audio," ISCA 2016

# MelGAN: Generator

[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)

---

## Checkerboard Artifacts

- Kernel-size as a **multiple** of stride
- Dilation grows as a **power** of the kernel-size
- Receptive field of the stack looks like a fully balanced (seeing input uniformly) and symmetric tree

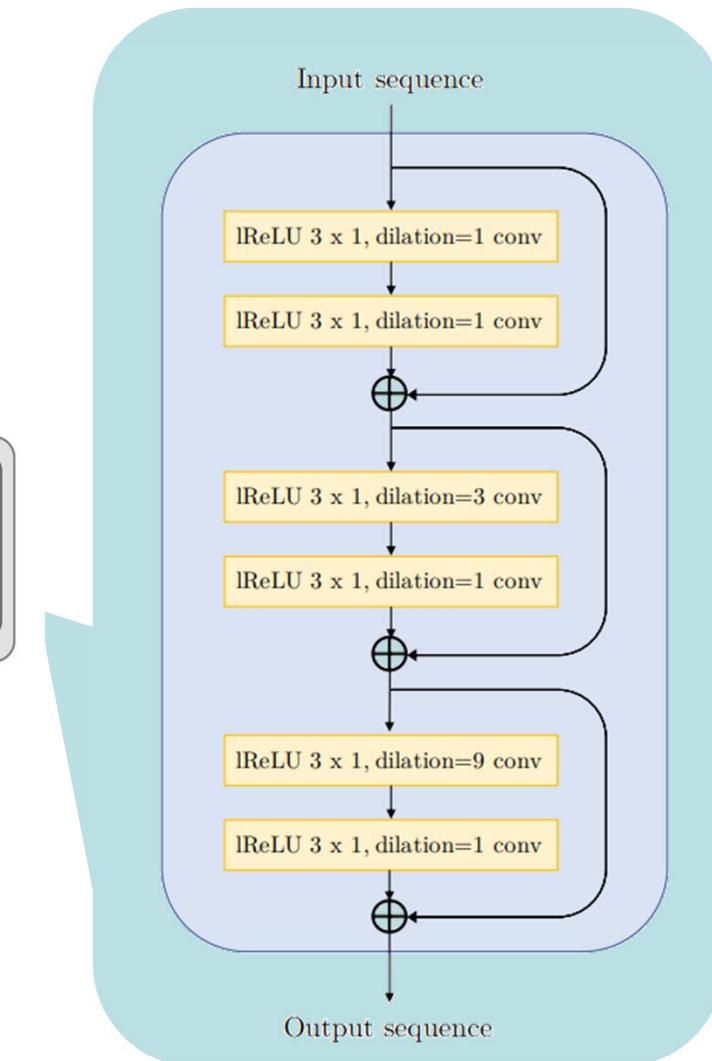
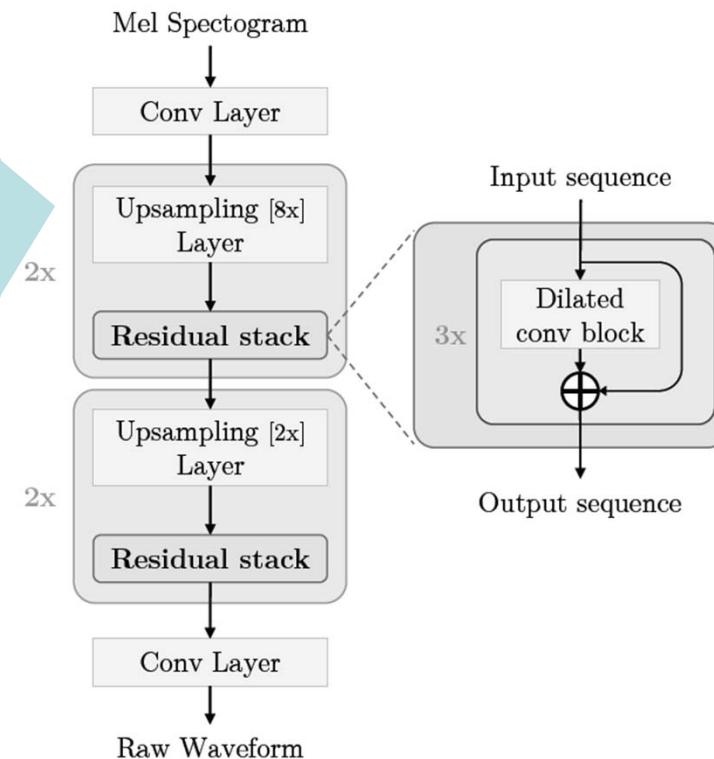
## Normalization

- Instance-norm washes away pitch information, making audio sound metallic
- Spectral-norm's strong Lipschitz constraint badly impacts feature matching objective
- **Weight-norm** works best

# MelGAN: Generator

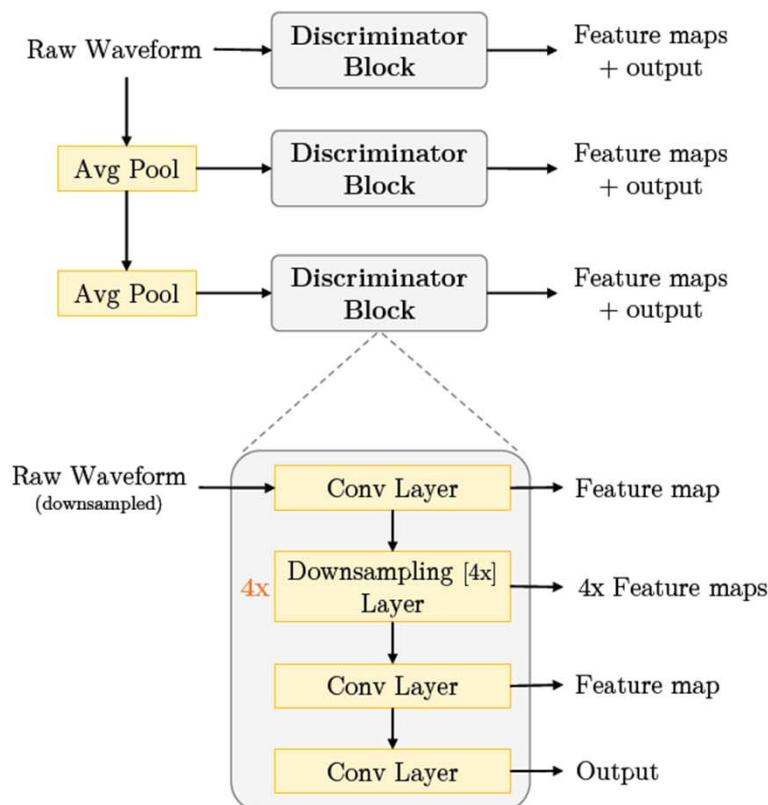
$7 \times 1$ , stride=1 conv 512
lReLU $16 \times 1$ , stride=8 conv transpose 256
Residual Stack 256
lReLU $16 \times 1$ , stride=8 conv transpose 128
Residual Stack 128
lReLU $4 \times 1$ , stride=2 conv transpose 64
Residual Stack 64
lReLU $4 \times 1$ , stride=2 conv transpose 32
Residual Stack 32
lReLU $7 \times 1$ , stride=1 conv 1 Tanh

(a) Generator Architecture



# MelGAN: Discriminator

[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)



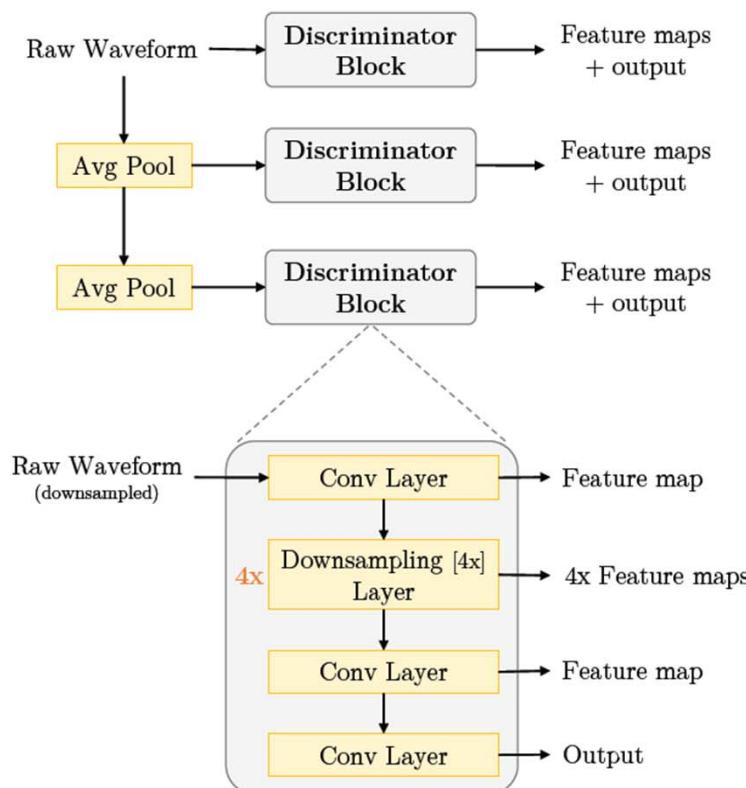
## Multiscale Architecture

- 3 discriminators (identical structure) operate on different audio scales -- original scale, 2x and 4x downsampled.
- Each discriminator biased to learn features for **different frequency range** of the audio.

“For example, the discriminator operating on downsampled audio does not have access to high frequency component, hence, it is biased to learn discriminative features based on low frequency components only.”

# MelGAN: Discriminator

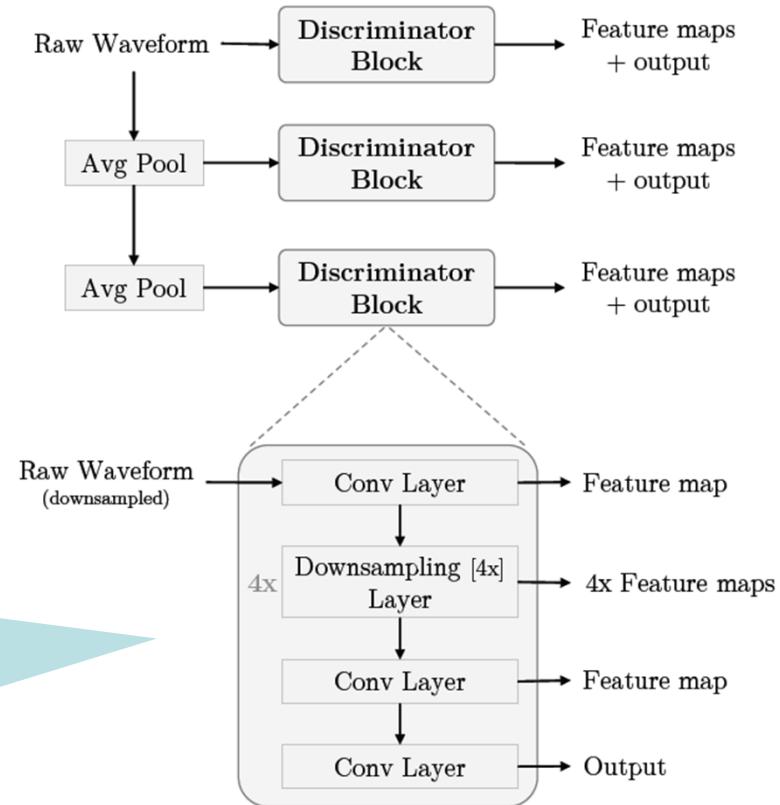
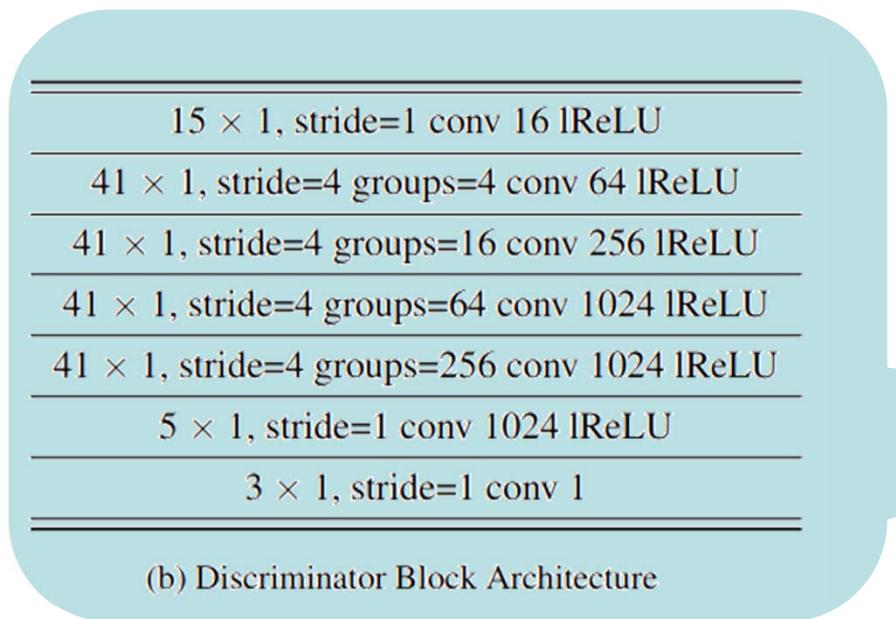
[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)



## Window-based objective

- Each individual discriminator is a Markovian window-based discriminator (analogues to image patches, Isola et al. (2017))
- Discriminator learns to classify between distributions of **small audio chunks**.
- Overlapping large windows maintain coherence across patches

# MelGAN: Discriminator



# MelGAN: Loss Functions

[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)

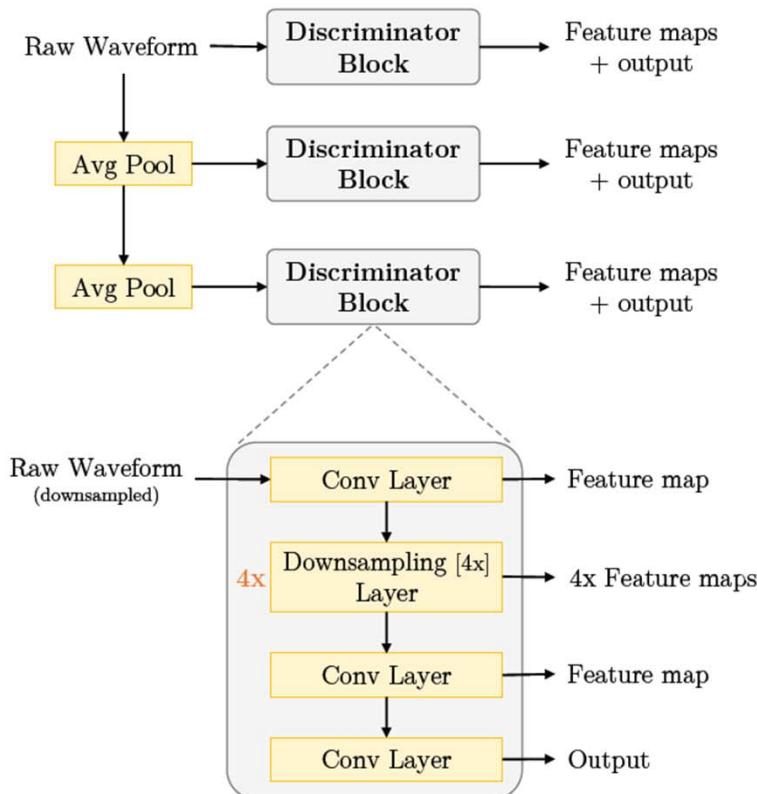
We use the hinge loss formulation (Lim & Ye, 2017; Miyato et al., 2018):

$$\min_{D_k} \mathbb{E}_x \left[ \min(0, 1 - D_k(x)) \right] + \mathbb{E}_{s,z} \left[ \min(0, 1 + D_k(G(s, z))) \right], \forall k = 1, 2, 3$$

$$\min_G \mathbb{E}_{s,z} \left[ \sum_{k=1,2,3} -D_k(G(s, z)) \right]$$

# MelGAN: Loss Functions

[https://github.com/descriptinc/melgan-neurips/blob/master/melgan\\_slides.pdf](https://github.com/descriptinc/melgan-neurips/blob/master/melgan_slides.pdf)



We additionally use a feature matching objective (Larsen et al., 2015) to train the generator:

$$\mathcal{L}_{\text{FM}}(G, D_k) = \mathbb{E}_{x, s \sim p_{\text{data}}} \left[ \sum_{i=1}^T \frac{1}{N_i} \|D_k^{(i)}(x) - D_k^{(i)}(G(s))\|_1 \right]$$

Overall Generator Objective:

$$\min_G \left( \mathbb{E}_{s, z} \left[ \sum_{k=1,2,3} -D_k(G(s, z)) \right] + \lambda \sum_{k=1}^3 \mathcal{L}_{\text{FM}}(G, D_k) \right)$$

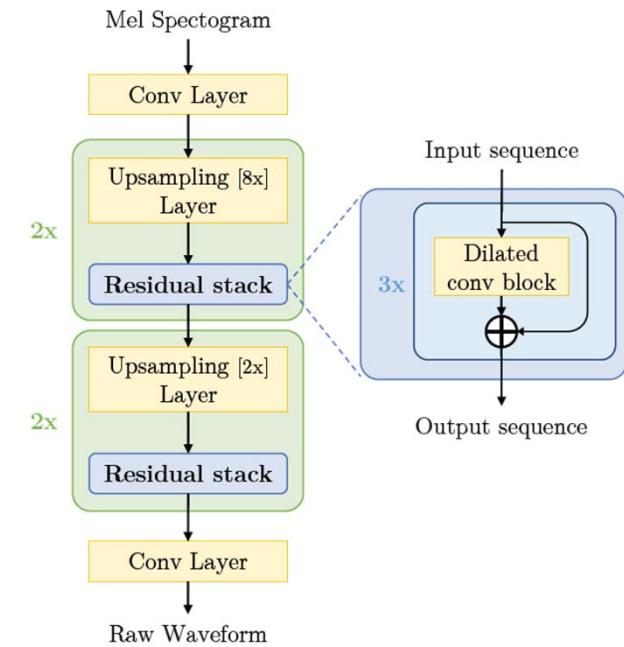
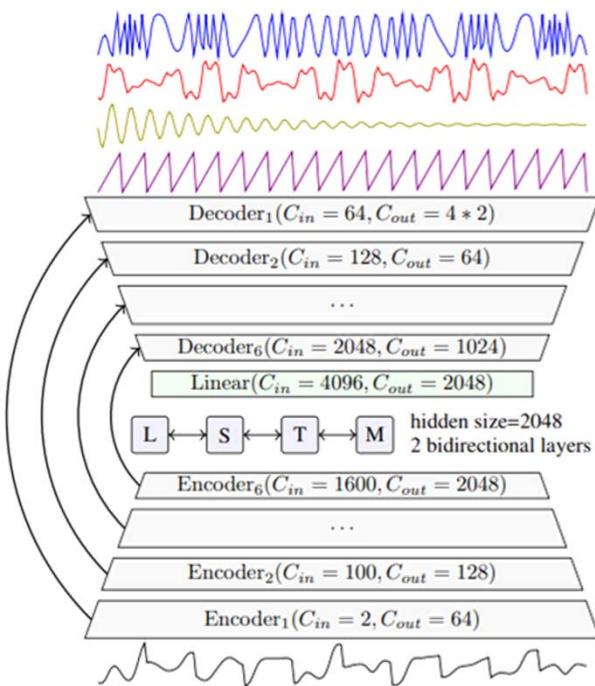
# Question: Why Not Waveform-domain Loss Functions?

<https://www.soundsandwords.io/audio-loss-functions/>

- **Not shift invariant**
  - “If your models comes up with the exact correct output, but it’s shifted just 1 millisecond too early or late, a human would consider it a perfect match but error would likely spike. This can especially manifest as phase shift invariance, where two waves have similar frequencies but out-of-sync phases, leading to a large gap in waveform distance.”
- **Not reflect our perception of audio**
  - “If training a model for human ears, with L1/L2 you risk overweighting the importance of low frequency sounds”

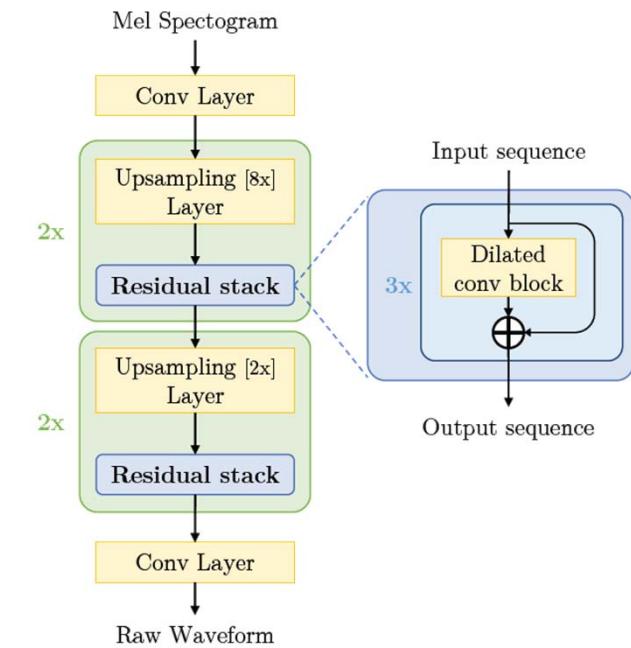
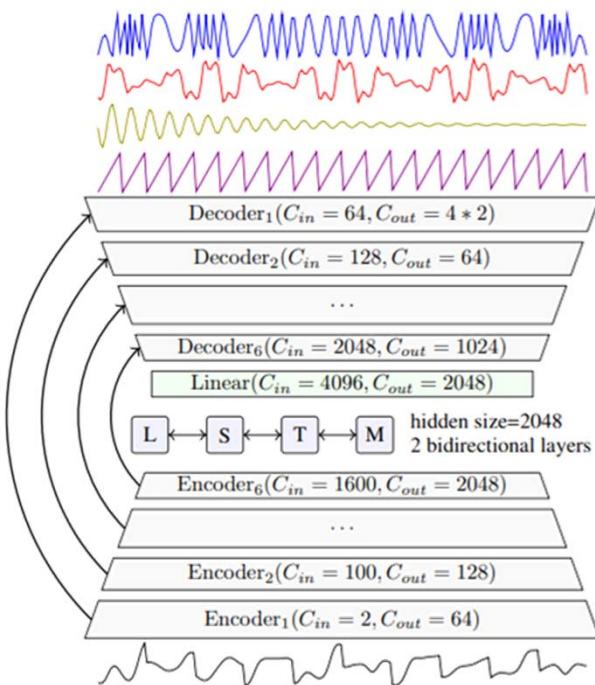
# Question: Why not U-Net?

- **Source separation**
  - Use U-Net
  - Use waveform domain loss
- **Mel-vocoder**
  - Do not use U-Net
  - Dot not use waveform domain loss



# Question: Why Not GAN for Source Separation?

- **Source separation**
  - Do not use GAN
- **Mel-vocoder**
  - Use GAN a lot



# MelGAN: Ablation Study

Model	MOS	95% CI
w/ Spectral Normalization	1.33	±0.07
w/ L1 loss (audio space)	2.59	±0.11
w/o Window-based Discriminator	2.29	±0.10
w/o Dilated Convolutions	2.60	±0.10
w/o Multi-scale Discriminator	2.93	±0.11
w/o Weight Normalization	3.03	±0.10
<b>Baseline (MelGAN)</b>	<b>3.09</b>	<b>± 0.11</b>

- “Instance normalization washes away important pitch information, making the audio sound metallic. We also obtained poor results when applying spectral normalization”
- “Adding L1 loss in audio space introduces audible noise that hurts audio quality”

# MB-MelGAN

- Improved version of MelGAN
1. Increase the receptive field of the generator (F3)
  2. Substitute the feature matching loss with the **multi-resolution STFT loss** (F1, F2)
    - Avoid the problems of **time-domain loss**
    - **Pre-train** the generator using STFT loss, then adversarial loss
  3. Extend MelGAN with **multiband processing**
    - The generator takes mel-spectrograms as input and produces sub-band signals which are subsequently summed back to full-band signals as discriminator input.

Index	Model	MOS
F0	MelGAN [20]	$3.98 \pm 0.04$
F1	+ Pretrain $G$	$4.04 \pm 0.03$
F2	+ $L_{mr-stft}(G)$	$4.06 \pm 0.04$
F3	+ Deepen ResStack	<b><math>4.35 \pm 0.05</math></b>

Ref: Yang et al, “Multi-band MelGAN: Faster Waveform Generation for High-Quality Text-to-Speech,” INTERSPEECH 2020

# Multi-resolution STFT Loss

- Firstly explored elsewhere (e.g., in Parallel WaveGAN)
- Avoid the problems of time-domain loss
- **Multiple resolutions:** different window sizes and hop sizes

$$L_{sc}(x, \tilde{x}) = \frac{\| |STFT(x)| - |STFT(\tilde{x})| \|_F}{\| |STFT(x)| \|_F}$$

$$L_{mag}(x, \tilde{x}) = \frac{1}{N} \| \log |STFT(x)| - \log |STFT(\tilde{x})| \|_1$$

$$L_{mr\_stft}(G) = \mathbb{E}_{x, \tilde{x}} \left[ \frac{1}{M} \sum_{m=1}^M (L_{sc}^m(x, \tilde{x}) + L_{mag}^m(x, \tilde{x})) \right]$$

- **Pre-train** the generator using STFT loss, then adversarial loss

# HiFiGAN (NeurIPS'20)

<https://github.com/jik876/hifi-gan>

- A great improved version of MelGAN that outperforms WaveNet, WaveGlow
- Very widely-used

Model	MOS (CI)	Speed on CPU (kHz)	Speed on GPU (kHz)	# Param (M)
Ground Truth	4.45 ( $\pm 0.06$ )	—	—	—
WaveNet (MoL)	4.02 ( $\pm 0.08$ )	—	0.07 ( $\times 0.003$ )	24.73
WaveGlow	3.81 ( $\pm 0.08$ )	4.72 ( $\times 0.21$ )	501 ( $\times 22.75$ )	87.73
MelGAN	3.79 ( $\pm 0.09$ )	145.52 ( $\times 6.59$ )	14,238 ( $\times 645.73$ )	4.26
Highest MOS →	HiFi-GAN V1	<b>4.36</b> ( $\pm 0.07$ )	31.74 ( $\times 1.43$ )	3,701 ( $\times 167.86$ )
Most light-weight →	HiFi-GAN V2	4.23 ( $\pm 0.07$ )	214.97 ( $\times 9.74$ )	16,863 ( $\times 764.80$ )
Fastest →	HiFi-GAN V3	4.05 ( $\pm 0.08$ )	<b>296.38</b> ( $\times 13.44$ )	<b>26,169</b> ( $\times 1,186.80$ )

Ref: Kong et al., “HiFi-GAN: Generative adversarial networks for efficient and high fidelity speech synthesis,” NeurIPS 2020

# HiFiGAN: Generator

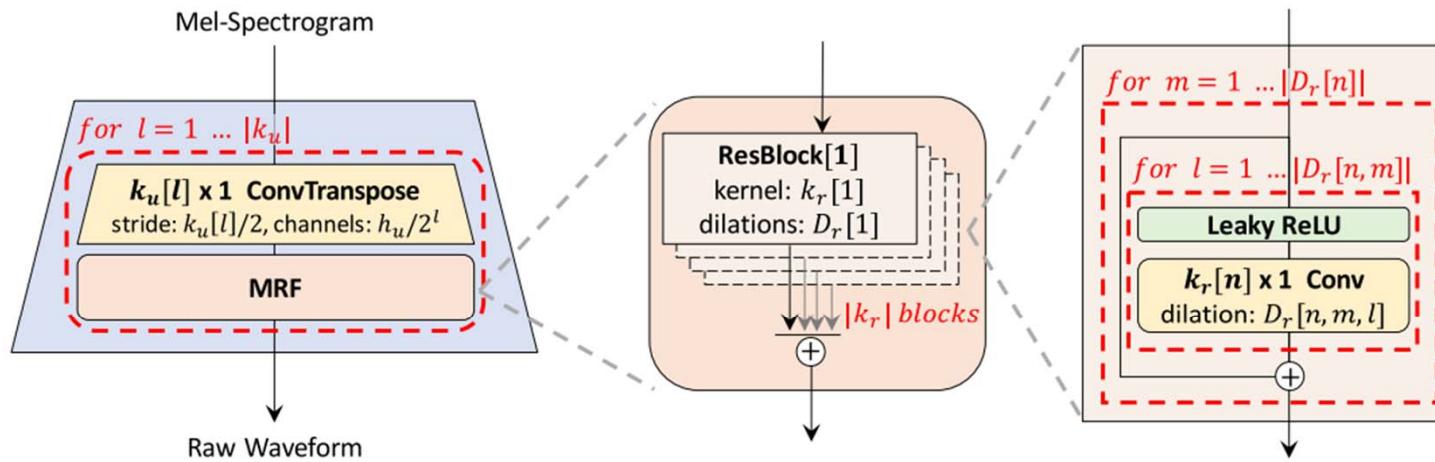


Figure 1: The generator upsamples mel-spectrograms up to  $|k_u|$  times to match the temporal resolution of raw waveforms. A MRF module adds features from  $|k_r|$  residual blocks of different kernel sizes and dilation rates. Lastly, the  $n$ -th residual block with kernel size  $k_r[n]$  and dilation rates  $D_r[n]$  in a MRF module is depicted.

- Multi-receptive field fusion (MRF)
- Different **kernel sizes** and **dilation rates** are selected for each **residual block** to form diverse receptive field patterns

# HiFiGAN: Generator

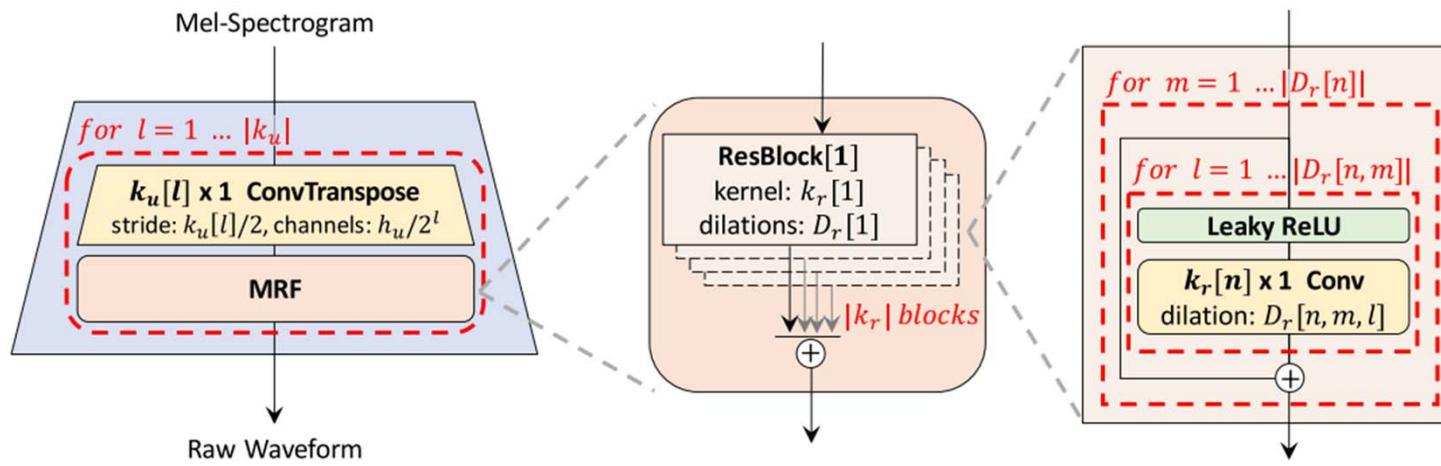
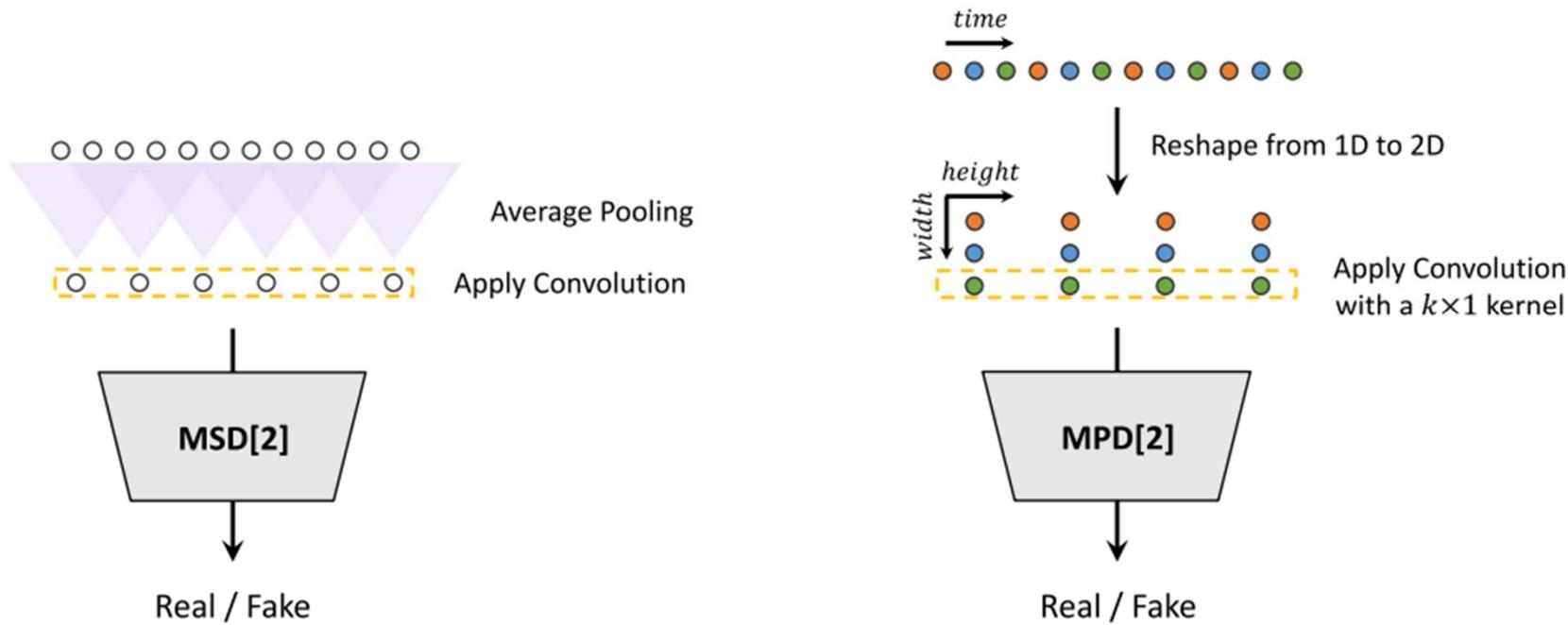


Table 5: Hyper-parameters of three generator  $V1$ ,  $V2$ , and  $V3$ .

Model	Hyper-Parameters			
	$h_u$	$k_u$	$k_r$	$D_r$
$V1$	512	[16, 16, 4, 4]	[3, 7, 11]	$[[1, 1], [3, 1], [5, 1]] \times 3$
$V2$	128	[16, 16, 4, 4]	[3, 7, 11]	$[[1, 1], [3, 1], [5, 1]] \times 3$
$V3$	256	[16, 16, 8]	[3, 5, 7]	$[[1], [2]], [[2], [6]], [[3], [12]]$

# HiFiGAN: Discriminator



- Multi-scale discriminator (MSD) + a new **multi-period discriminator (MPD)**
  - “MPD is a mixture of sub-discriminators, each of which only accepts equally spaced samples of an input audio [and therefore] looking at different parts of an input audio”
  - “We set the periods to [2, 3, 5, 7, 11] to avoid overlaps as much as possible.”

# HiFiGAN: Ablation Study

Model	MOS (CI)
Ground Truth	4.57 ( $\pm 0.04$ )
Baseline (HiFi-GAN V3)	4.10 ( $\pm 0.05$ )
w/o MPD	2.28 ( $\pm 0.09$ )
w/o MSD	3.74 ( $\pm 0.05$ )
w/o MRF	3.92 ( $\pm 0.05$ )
w/o Mel-Spectrogram Loss	3.25 ( $\pm 0.05$ )
MPD $p=[2,4,8,16,32]$	3.90 ( $\pm 0.05$ )
MelGAN	2.88 ( $\pm 0.08$ )
MelGAN with MPD	3.35 ( $\pm 0.07$ )

Ref: Kong et al., "HiFi-GAN: Generative adversarial networks for efficient and high fidelity speech synthesis," NeurIPS 2020

# GAN-based Models

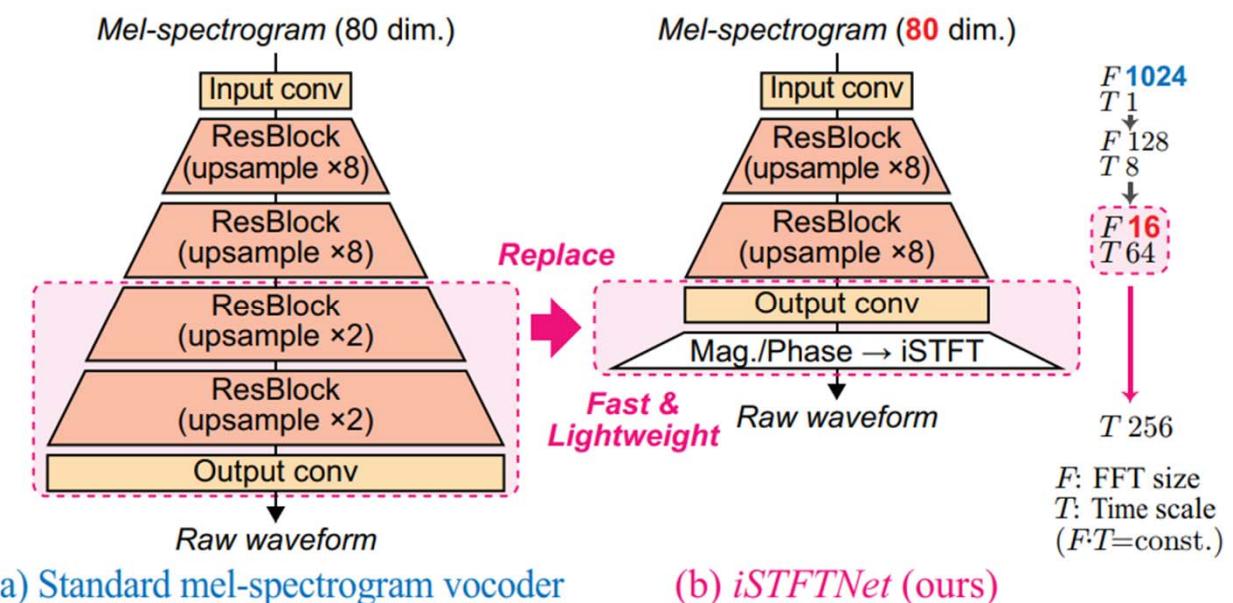
	Generator ( $G$ )	Discriminator ( $D$ ) loss	Auxiliary loss
Parallel WaveGAN	Single scale	Single scale (target waveform)	Multi-reso STFT loss
MelGAN	Multi-scale (multiple up-sampling stages) e.g., duplication, conv1d w/ stride	Multi-scale time domain (average pooling)	Multi-scale feature matching
TFGAN		Multi-scale time & frequency domain	Multi-reso STFT & multi-scale time domain loss
StyleMelGAN		Multiple random framing window & subband $D$	Multi-reso STFT loss
VocGAN		Multi-scale time domain (ave. pooling & output at different scale)	
Multi-band MelGAN		Multi-scale time domain (ave. pooling)	
UnivNet		Multi-scale time domain (ave. pooling & squeeze)	
HiFi-GAN			Single spectral loss

Ref: Figure from <https://www.slideshare.net/jyamagis/advancements-in-neural-vocoders> (page 127)

# iSTFTNet

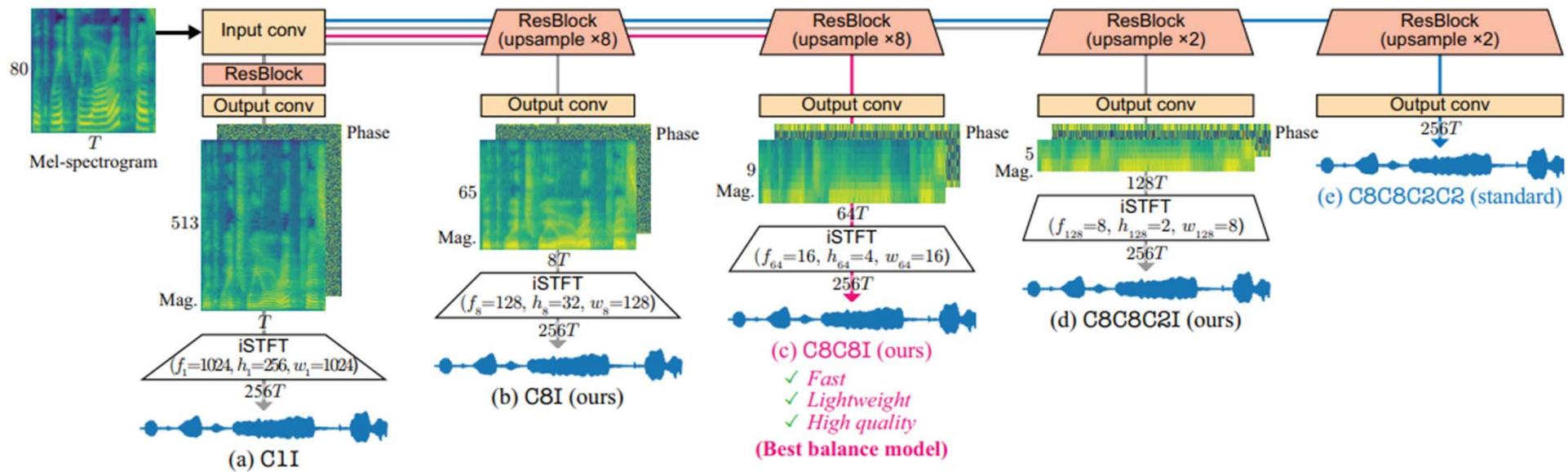
<https://www.kecl.ntt.co.jp/people/kaneko.takuhiro/projects/istftnet/>

- Improved version of HiFiGAN
- Use inverse STFT layers
  - replaces some layers after sufficiently reducing the frequency dimension using upsampling layers
  - reduces the computational cost from black-box modeling



Ref: Kaneko et al, “iSTFTNet: Fast and lightweight Mel-spectrogram vocoder incorporating Inverse Short-Time Fourier Transform,” ICASSP 2022

# iSTFTNet



Ref: Kaneko et al, "iSTFTNet: Fast and lightweight Mel-spectrogram vocoder incorporating Inverse Short-Time Fourier Transform," ICASSP 2022

No.	Model	MOS↑	cFW2VD↓	Speed↑ (GPU)	Speed↑ (CPU)	# Param↓ (M)
1	Ground truth	$4.46 \pm 0.14$	—	—	—	—
2	V1 (original) [12]	$4.22 \pm 0.17$	0.020	$\times 143.59$ (100)	$\times 1.34$ (100)	13.94 (100)
3	V1-C8C8C2I	$4.22 \pm 0.17$	0.018	$\times 179.42$ (125)	$\times 1.63$ (122)	13.80 (99)
4	<b>V1-C8C8I</b>	$4.26 \pm 0.17$	0.020	$\times 245.68$ (171)	$\times 2.33$ (174)	13.26 (95)
5	<u>V1-C8I</u>	$3.32 \pm 0.22$	0.073	$\times 609.43$ (424)	$\times 7.57$ (565)	10.89 (78)
6	<u>V1-C8C1I</u>	$3.82 \pm 0.17$	0.033	$\times 326.39$ (227)	$\times 3.97$ (296)	19.15 (137)

# Outline

- General idea
- DL components: upsampling layers and GAN
- DL-based Mel-vocoders
- **Advanced topics**

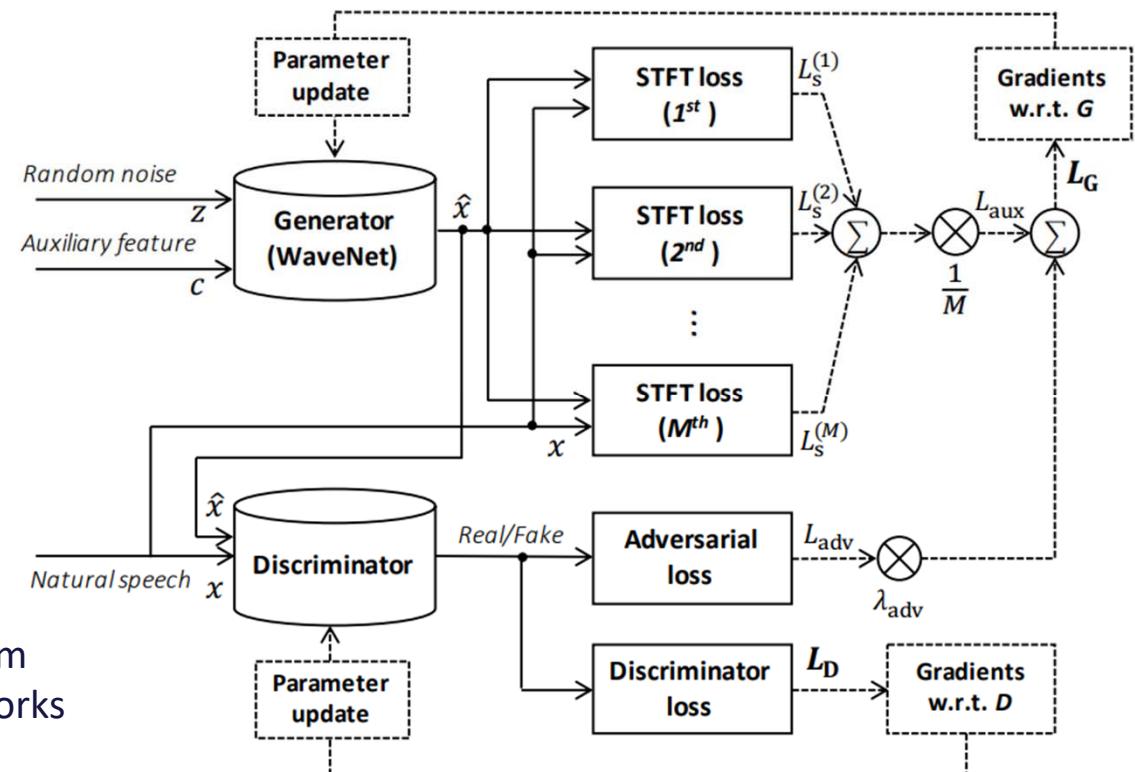
# WaveNet-based Mel-Vocoders

[https://github.com/r9y9/wavenet\\_vocoder](https://github.com/r9y9/wavenet_vocoder)

<https://github.com/kan-bayashi/ParallelWaveGAN>

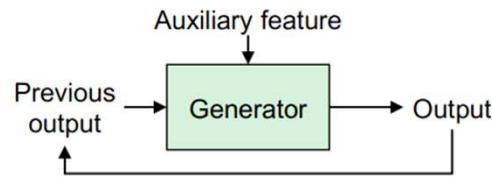
- Parallel WaveGAN (**PWG**)
  - A *non-autoregressive* WaveNet trained by jointly optimizing multi-resolution spectrogram and adversarial loss functions
  - Not the SOTA now
  - More on **WaveNet** in the next lecture

Ref: Yamamoto et al, “Parallel WaveGAN: A fast waveform generation model based on generative adversarial networks with multi-resolution spectrogram,” ICASSP 2020

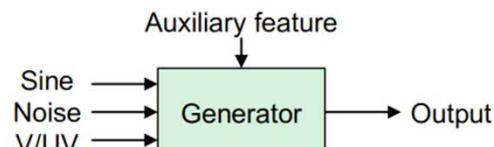


# Source-Filter based Mel-Vocoders

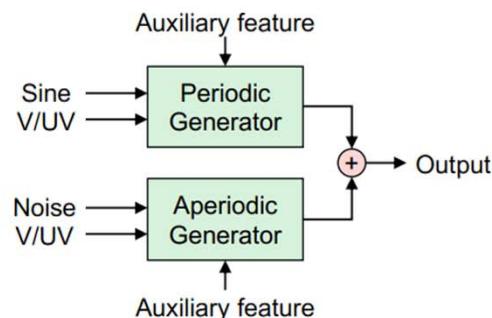
- NSF (ICASSP'19)
- PeriodNet (ICASSP'21)
- DSPGAN (ICASSP'23)



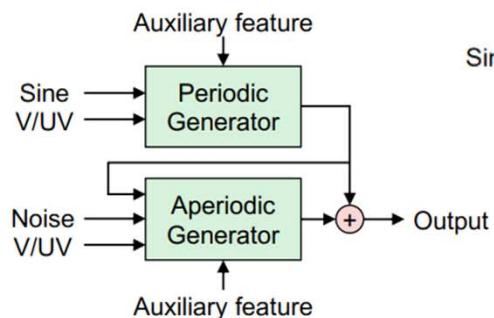
(a) AR model



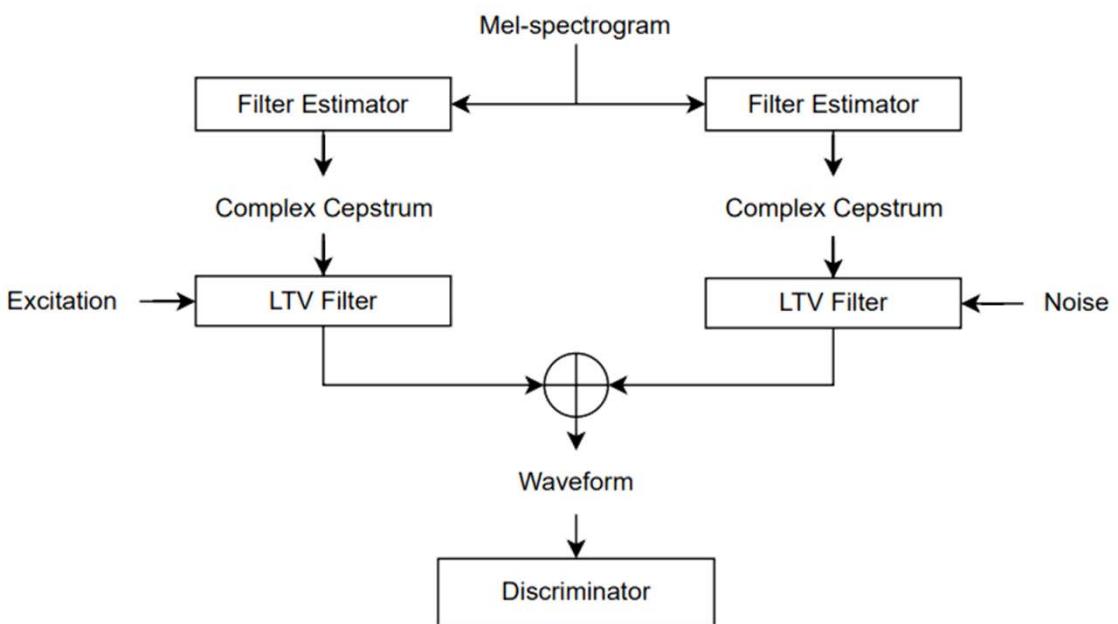
(b) Non-AR baseline model



(c) Non-AR parallel model



(d) Non-AR series model



# Source-Filter based Mel-Vocoders

- **F0 to sine**
  - F0 estimated by pitch estimation tools (see Lecture 7), such as YIN, WORLD, CREPE
  - Convert F0 (instantaneous frequency) to **sine**
- **NSF (ICASSP'19)**
- **Code examples** [ref 1, ref 2]

The input F0 sequence is  $f_{1:T}$ , where  $f_t \in \mathbb{R}_{\geq 0}$  is the F0 value of the  $t$ -th time step, and  $f_t > 0$  and  $f_t = 0$  denote being voiced and unvoiced, respectively. A sine waveform  $e_{1:T}^{<0>}$  with the fundamental frequency can be generated as

$$e_t^{<0>} = \begin{cases} \alpha \sin\left(\sum_{k=1}^t 2\pi \frac{f_k}{N_s} + \phi\right) + n_t, & \text{if } f_t > 0 \\ \frac{\alpha}{3\sigma} n_t, & \text{if } f_t = 0 \end{cases}, \quad (13)$$

Ref 1: <https://github.com/YatingMusic/ddsp-singing-vocoders/blob/f72157cdf9738bb0a14179a0cab13a73f56f5238/ddsp/modules.py#L31>

Ref 2: [https://github.com/kan-bayashi/ParallelWaveGAN/blob/c68b4590ab20eaf55e0b96b82325a90177ffffd5c/parallel\\_wavegan/layers/sine.py#L8](https://github.com/kan-bayashi/ParallelWaveGAN/blob/c68b4590ab20eaf55e0b96b82325a90177ffffd5c/parallel_wavegan/layers/sine.py#L8)

[ddsp-singing-vocoders / ddsp / modules.py](#)

```
# harmonic synth
n_harmonic = amplitudes.shape[-1]
phase = torch.cumsum(2 * np.pi * f0 / self.fs, axis=1) + initial_phase
phases = phase * torch.arange(1, n_harmonic + 1).to(phase)
```

[ParallelWaveGAN / parallel\\_wavegan / layers / sine.py](#)

```
7   class SineGen(torch.nn.Module):
48     def _f02sine(self, f0_values):
56       rad_values = (f0_values / self.sampling_rate) % 1
73       tmp_over_one = torch.cumsum(rad_values, 1) % 1
```

# Source-Filter based Mel-Vocoders

<https://nii-yamagishilab.github.io/samples-nsf/>

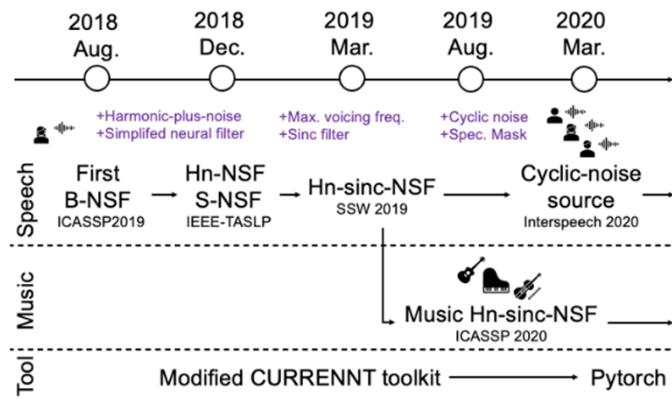
[https://colab.research.google.com/drive/1ekU2YlG-05FaMvWGPEpYIRFvqxSaMsqE?usp=sharing#scrollTo=-X8c2\\_ufjpNH](https://colab.research.google.com/drive/1ekU2YlG-05FaMvWGPEpYIRFvqxSaMsqE?usp=sharing#scrollTo=-X8c2_ufjpNH)

- **NSF-HiFiGAN** Sec.3 Combine HiFiGAN Discriminator with NSF (Generator)

It is possible to replace the HiFiGAN generator with other types of neural waveform model.

NSF is a good choice since it is trained using STFT loss only.

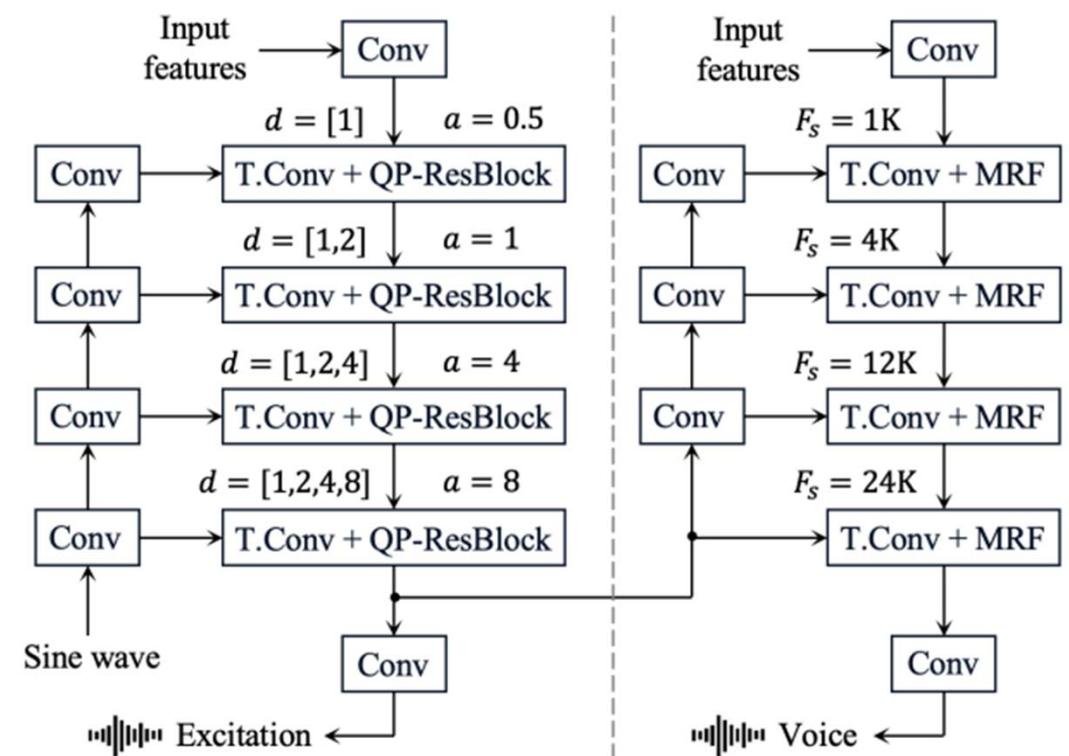
Here, we load the Hn-NSF trained with HiFiGAN discriminator and produce some audio samples.



# Source-Filter based Mel-Vocoders

- **SiFiGAN (ICASSP'23): HiFi-GAN + F0 controllability**

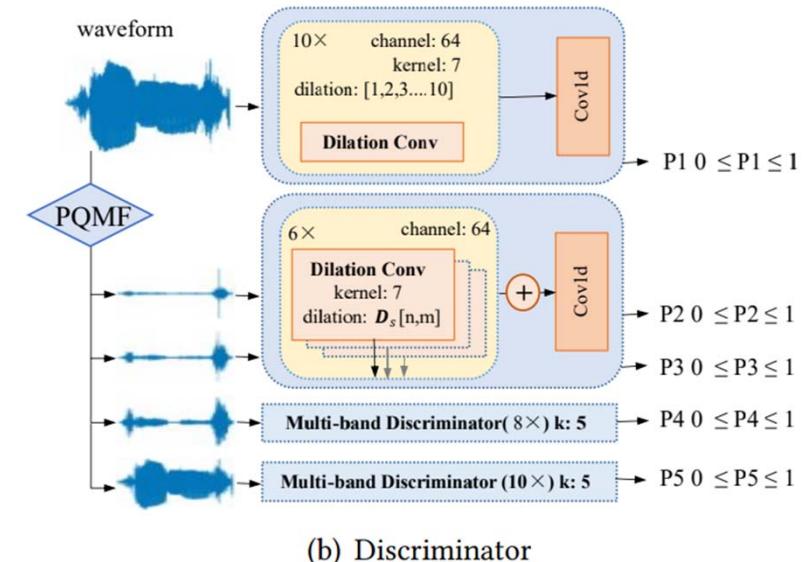
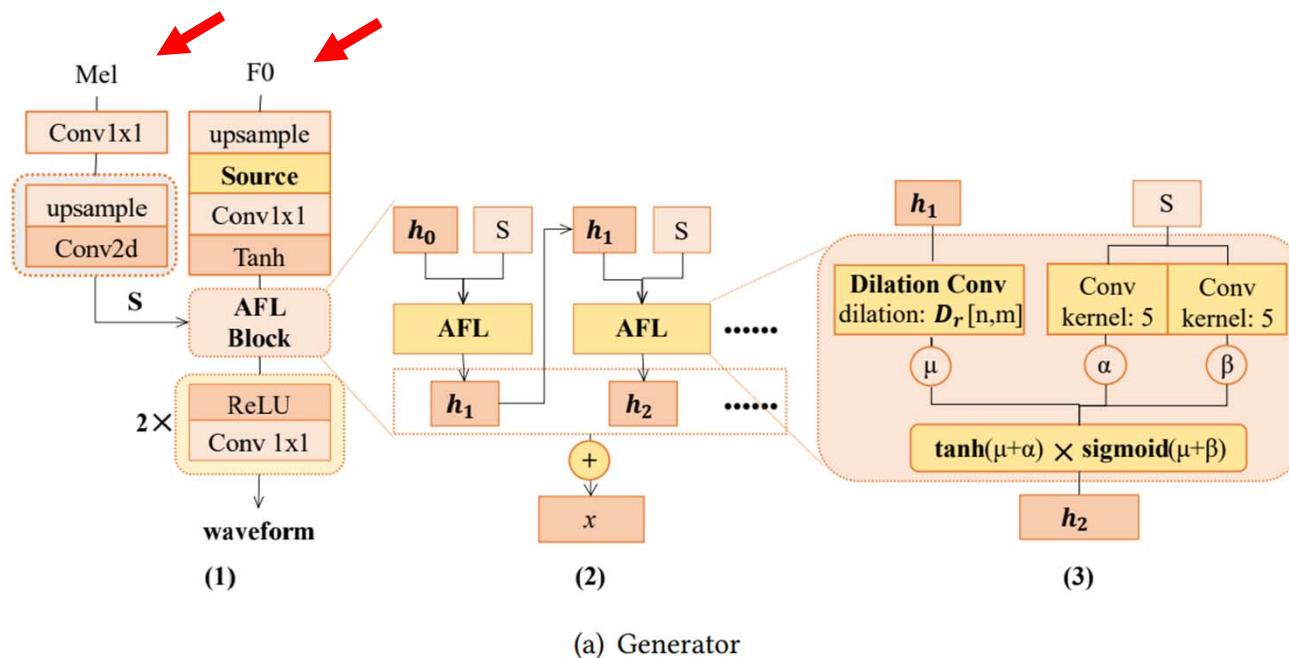
- The given F0 can be different from the F0 in Mel-spectrogram
  - Examples:
    - $0.5 * F_0$
    - $2 * F_0$



Ref: Yoneyama et al, "Source-Filter HiFi-GAN: Fast and pitch controllable high-fidelity neural vocoder," ICASSP 2023

# GAN-based Mel-Vocoders with F0 Input

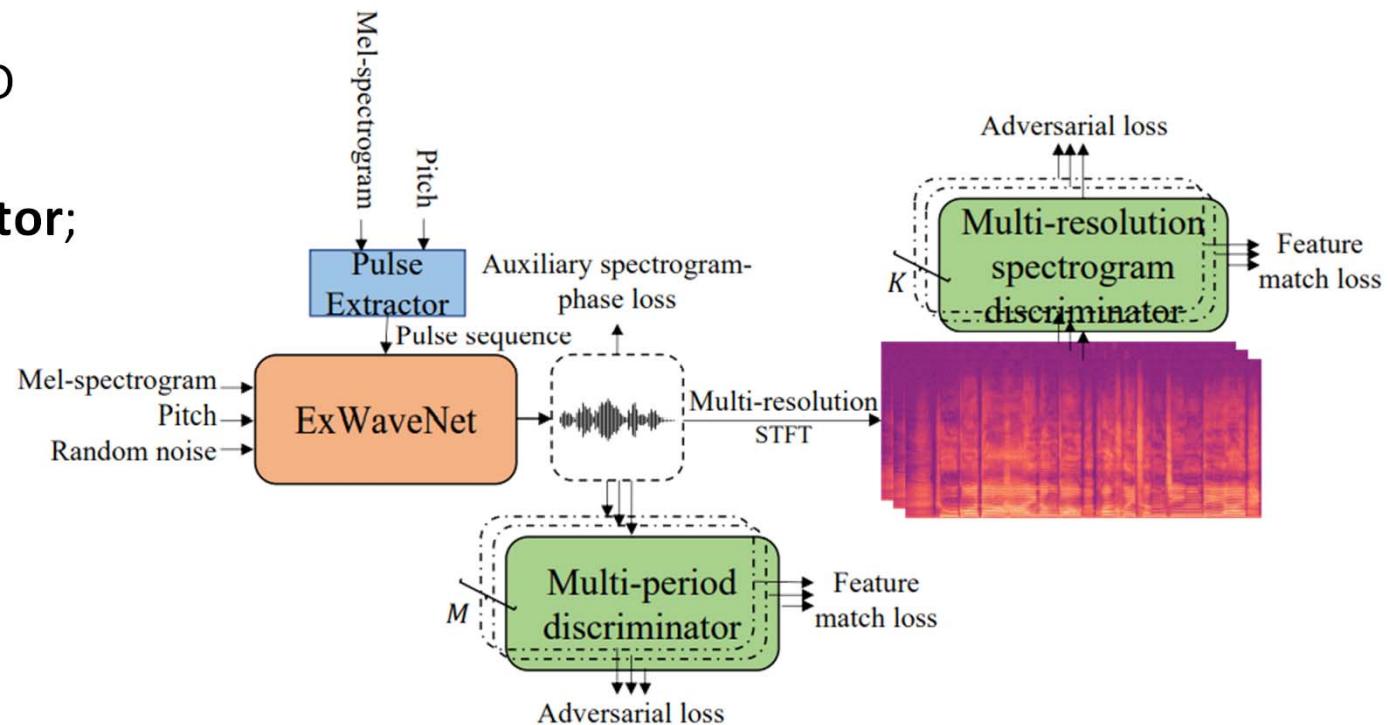
- SingGAN (MM'22)



Ref: Huang et al, "SingGAN: Generative adversarial network for high-fidelity singing voice generation," MM 2022

# GAN-based Mel-Vocoders with F0 Input

- **HiFi-WaveGAN (arXiv'22)**
  - Use MPD (multi-period discriminator) and MRSD (**multi-resolution spectrogram discriminator**; proposed in UnivNet)



Ref: Wang et al, “HiFi-WaveGAN: Generative adversarial network with auxiliary spectrogram-phase loss for high-fidelity singing voice generation,” arXiv 2022

# GAN-free, DDSP-based Mel-Vocoders

<https://github.com/YatingMusic/ddsp-singing-vocoders>

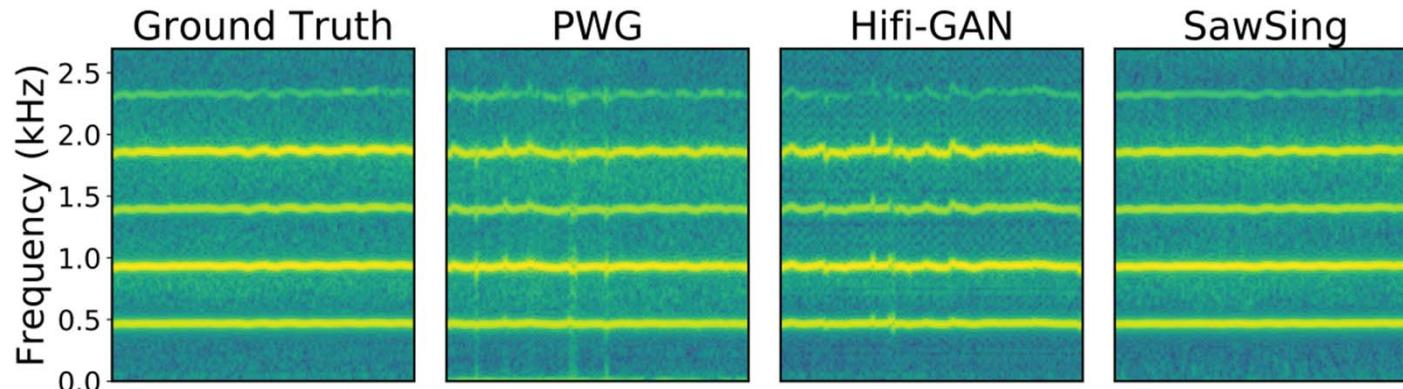
- Use the **source filter** model as an inductive bias for training vocoders
- **No GAN**

All the vocoders we presented are 'harmonic plus noise' models[4]. According to their ways to modeling harmonic parts of singing voices, we have the following models:

Model Name	Synthesizer	Note
SawSinSub	Filtered Sawtooth Synthesizer (Approximated by Harmonic Synthesizer)	proposed SawSing[1]
Sins	Harmonic Synthesizer	[2]
DWS	Wavetable Synthesizer	[3]
Full	Filtered Harmonic Synthesizer	modified from [2]
SawSub	Filtered Sawtooth Synthesizer	modified from [1]

# Source-Filter based Mel-Vocoders

- The use of the sine activation avoids the **glitches** in black-box models such as PWG and HiFiGAN



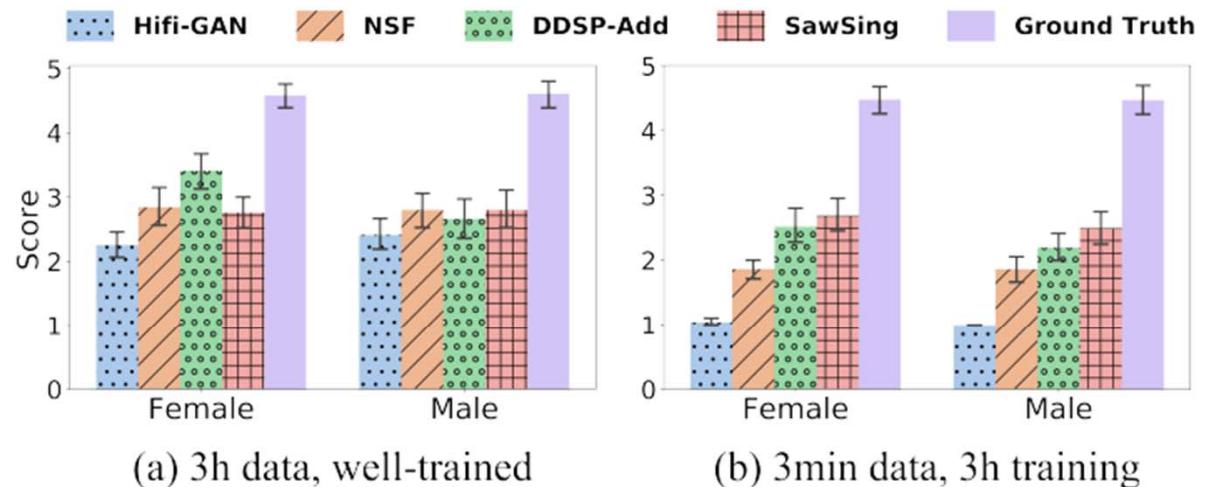
- It's also possible to avoid the glitches for HiFiGAN by using F0 as an additional condition

Ref: Wu et al, "DDSP-based singing vocoders: A new subtractive-based synthesizer and a comprehensive evaluation," ISMIR 2022

# GAN-free, DDSP-based Mel-Vocoders

- The source-filter assumption provides an inductive bias that allows the vocoder to be trained on a **small** amount of data

Model	Para-meters	RTF
FastDiff [21]	15.3M	0.017
HiFi-GAN [15]	13.9M	0.004
PWG [14]	1.5M	0.007
NSF [12]	1.2M	0.006
DDSP-Add [44]	0.5M	0.003
DWTS [27]	0.5M	0.019
SawSing	0.5M	0.003

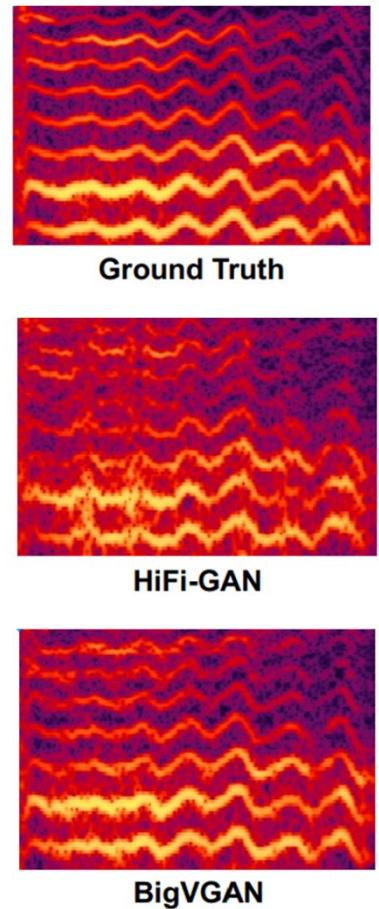


**Figure 3:** MOS with 95% confidence intervals for subjective evaluation of vocoders trained in the two scenarios.

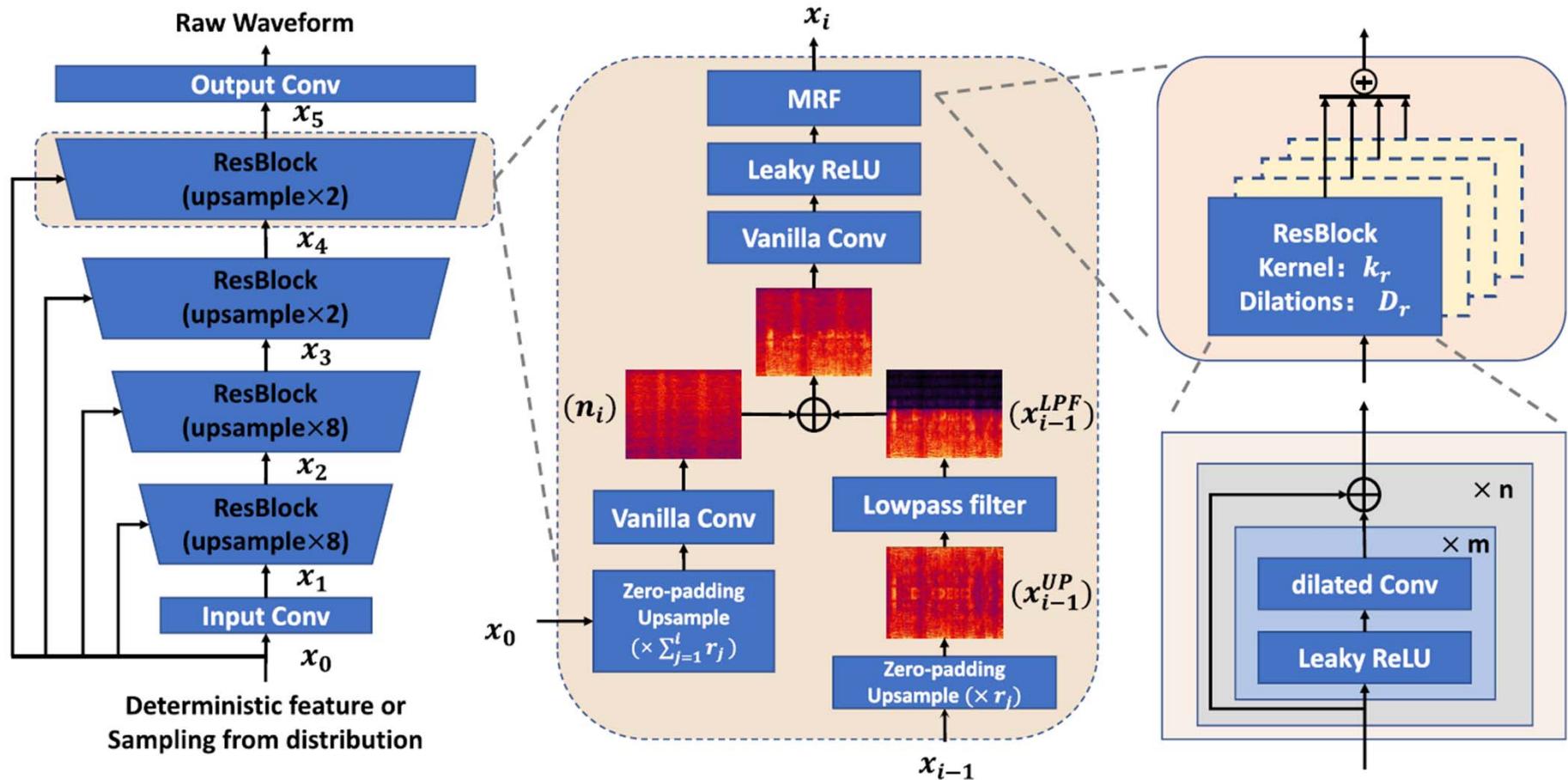
Ref: Wu et al, “DDSP-based singing vocoders: A new subtractive-based synthesizer and a comprehensive evaluation,” ISMIR 2022

# BigVGAN

- A **universal** vocoder that generalizes well for *zero-shot* (out-of-distribution) scenarios without fine-tuning
  - “We introduce **periodic activation function** and **anti-aliased representation** into the GAN generator, which brings the desired inductive bias for audio synthesis and significantly improves audio quality”
  - “We train our GAN vocoder at the largest scale up to **112M** parameters, which is unprecedented in the literature”
  - “BigVGAN trained only on **clean speech** (LibriTTS), achieves the SOTA performance for various zero-shot (out-of-distribution) conditions, including unseen speakers, languages, recording environments, **singing voices**, **music**, and **instrumental audio**”



# Anti-Aliasing



# Diffusion-based Mel-Vocoders

- **DiffWave, WaveGrad, PriorGrad**

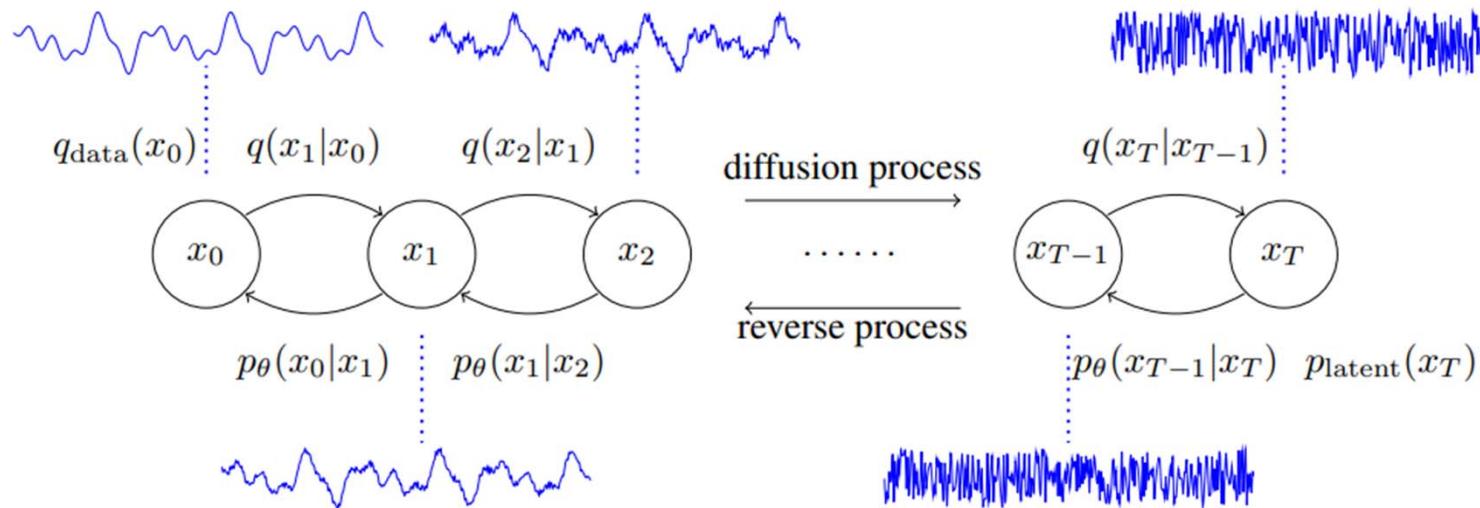
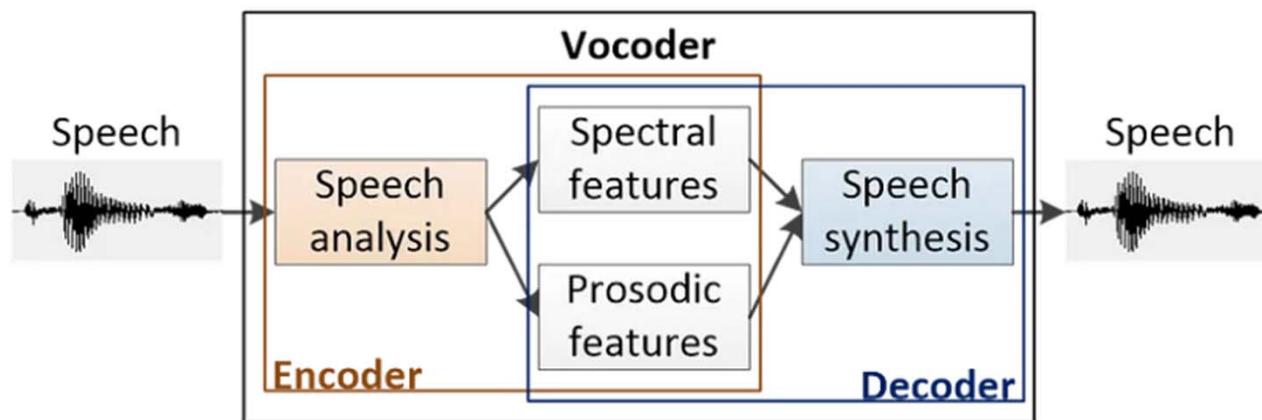


Figure 1: The diffusion and reverse process in diffusion probabilistic models. The reverse process gradually converts the white noise signal into speech waveform through a Markov chain  $p_\theta(x_{t-1}|x_t)$ .

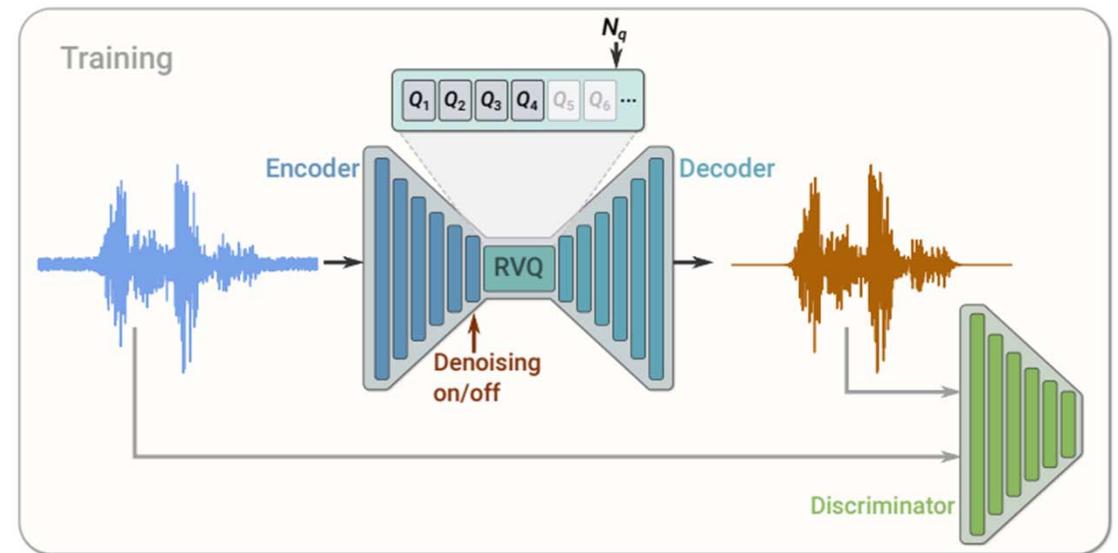
# Audio Codec



- The “acoustic features” used as intermediate representation
  - Many years ago: **F0 + Spectral Envelop + Aperiodicity** → STRAIGHT, WORLD
  - Some years ago: **Mel-spectrogram** → Mel-Vocoders
  - New trend: **Let the model learn** → Audio codec

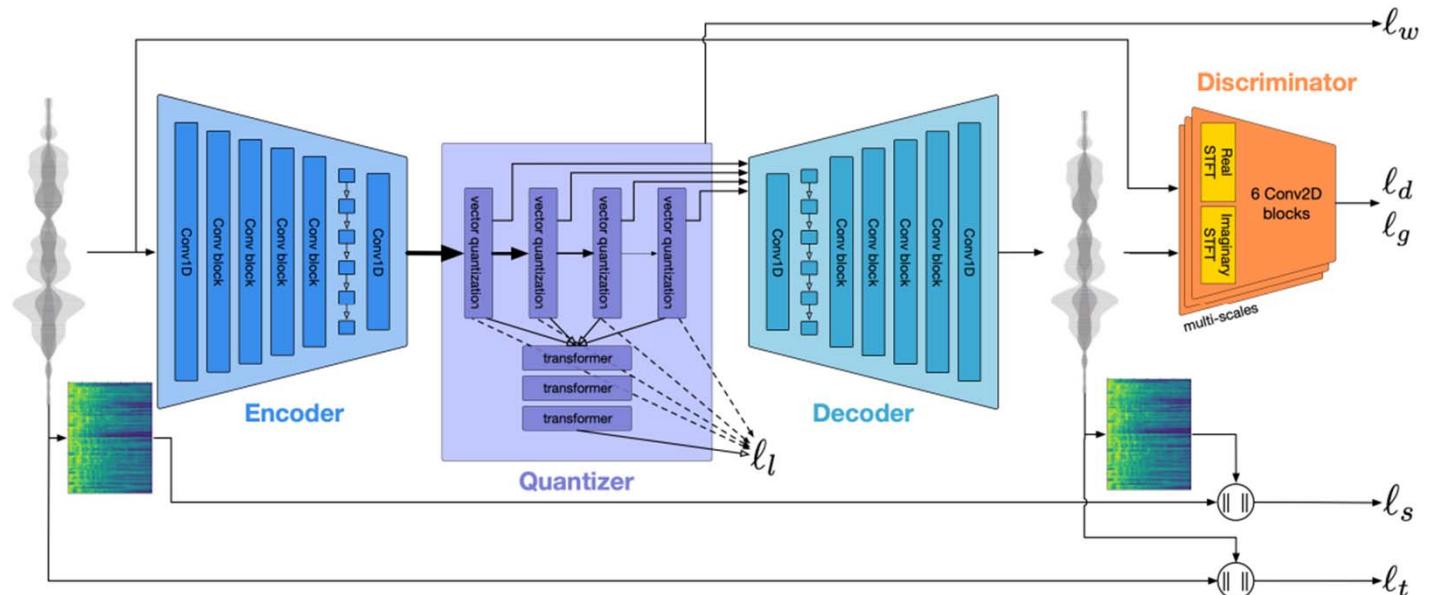
# Audio Codec

- **SoundStream**: An end-to-end neural audio codec (arXiv:2107.03312)
- Initially developed for audio compression
  - Bitrate vs fidelity
  - Computational complexity vs coding efficiency
- Use vector quantization (VQ) for quantization
  - Produce **discrete tokens** that can be used by Transformers for **language modeling**  
Employed by SOTA text-to-music models such as **MusicLM**



# Audio Codec

- Many new models
  - **EnCodec**: High fidelity neural audio compression (arXiv:2210.13438)
  - **HiFi-Codec**: Group-residual vector quantization for high fidelity audio codec (arXiv:2305.02765)
  - High-fidelity audio compression with **improved RVQGAN** (arXiv:2306.06546)



System diagram of  
FB's EnCodec model  
(proposed by the  
Demucs team)

# Audio Codec

- Quantization may not be needed
- **Latent diffusion models** work well with continuous embeddings
- Example: **JEN-1**
  - More on text-to-music models in a future lecture

**High Fidelity Neural Audio Latent Representation.** To facilitate the training on limited computational resources without compromising quality and fidelity, our approach JEN-1 employs a high-fidelity audio autoencoder  $\mathcal{E}$  to compress original audio into latent representations  $z$ . Formally, given a two-channel stereo audio  $x \in \mathbb{R}^{L \times 2}$ , the encoder  $\mathcal{E}$  encodes  $x$  into a latent representation  $z = \mathcal{E}(x)$ , where  $z \in \mathbb{R}^{L/h \times c}$ .  $L$  is the sequence length of given music,  $h$  is the hop size and  $c$  is the dimension of latent embedding. While the decoder reconstructs the audio  $\tilde{x} = \mathcal{D}(z) = \mathcal{D}(\mathcal{E}(x))$  from the latent representation. Our audio compression model is inspired and modified based on previous work (Zeghidour et al., 2021; Défossez et al., 2022), which consists of an autoencoder trained by a combination of a reconstruction loss over both time and frequency domains and a patch-based adversarial objective operating at different resolutions. This ensures that the audio reconstructions are confined to the original audio manifold by enforcing local realism and avoids muffled effects introduced by relying solely on sample-space losses with L1 or L2 objectives. Unlike prior endeavors (Zeghidour et al., 2021; Défossez et al., 2022) that employ a quantization layer to produce the discrete codes, our model directly extracts the continuous embeddings without any quality-reducing loss due to quantization. This utilization of powerful autoencoder representations enables us to achieve a nearly optimal balance between complexity reduction and high-frequency detail preservation, leading to a significant improvement in music fidelity.