Samsung AI Center – Moscow

Audio Synthesis and Bandwidth Extension

Audio Processing Problems

- Text To Speech
- Automatic Speech Recognition
- Acoustic Scene Recognition
  - Source Separation
  - Source Localization
- Audio Enhancement
  - Denoising
  - Bandwidth extension
  - Echo cancellation
- ...

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Introduction to Signal Processing

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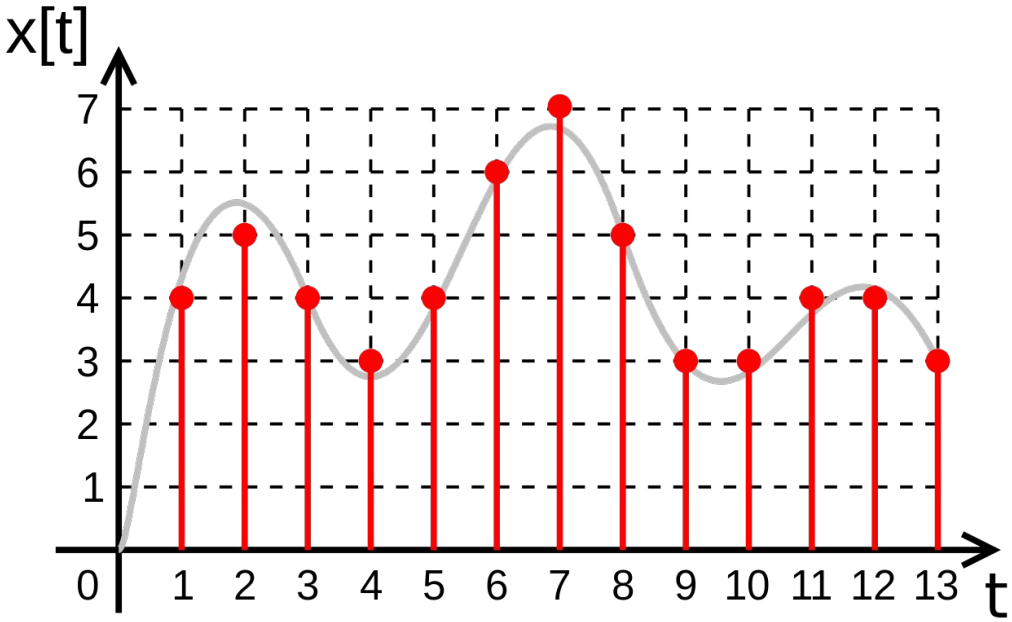
Digital representation of signal



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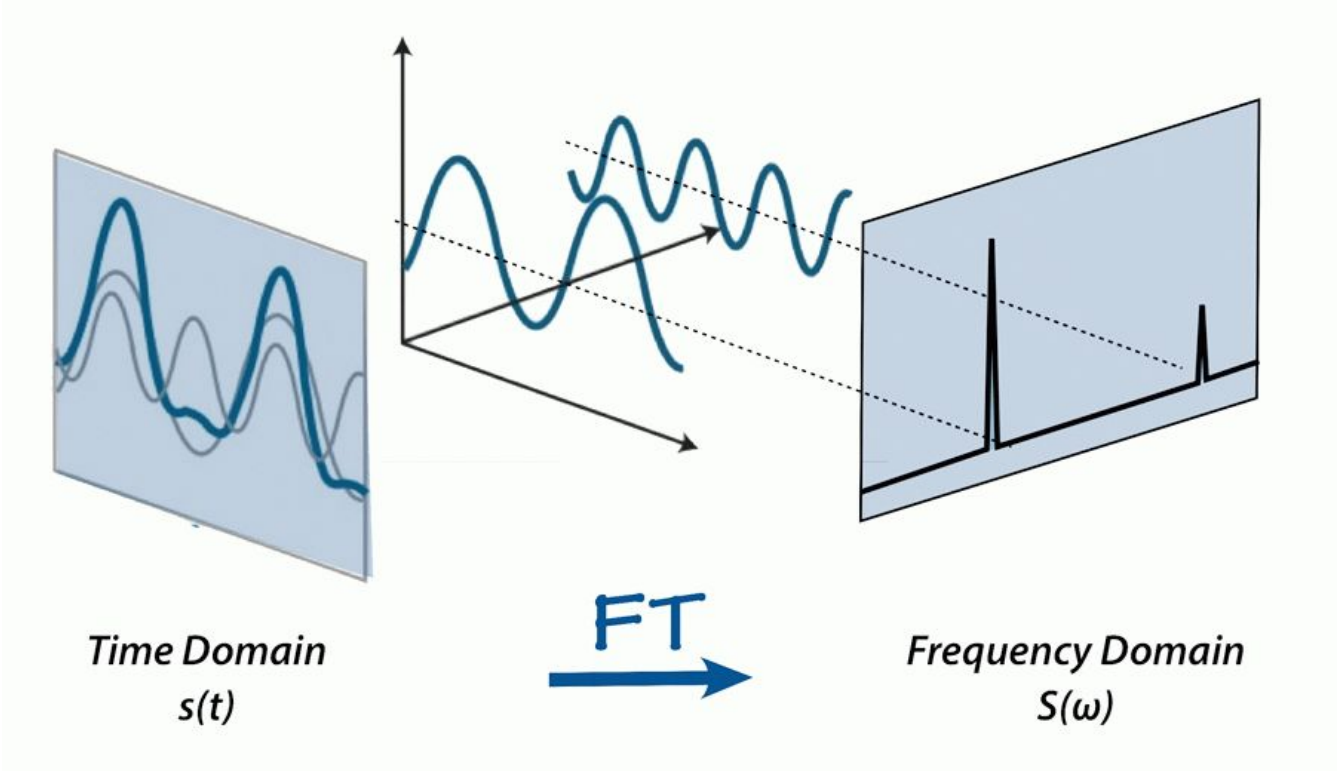
Fourier Transform



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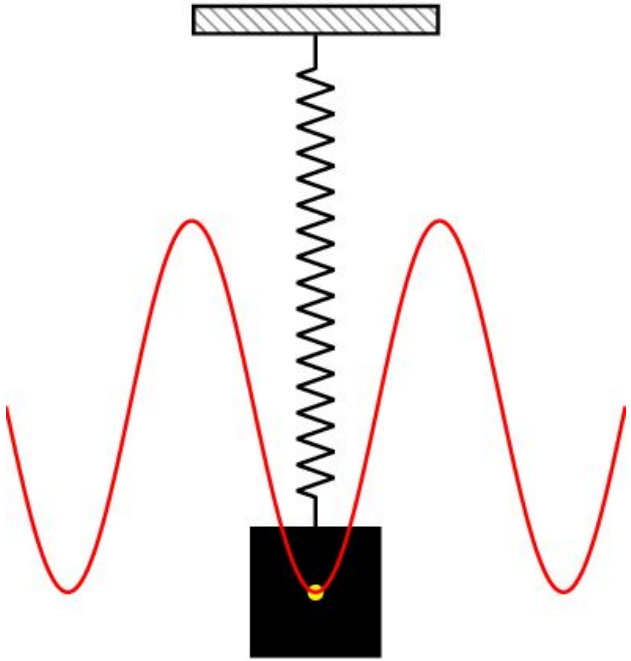
Fourier Transform: physics intuition

$$\frac{\partial^2 x(t)}{\partial t^2} = -\frac{k}{m} x(t)$$

$$x(t) = A\cos(\phi + \omega t)$$

amplitude phase (cycle) frequency



Fourier Transform

$$x(t) = \sum_k A_k \cos(\phi_k + \omega_k t)$$

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Fourier Transform: mathematics strikes back

$$x(t) = \sum_k A_k \cos(\phi_k + \omega_k t)$$

$$e^{i\omega t} = \cos(\omega t) + i \sin(\omega t)$$

$F(\omega_k)$ Fourier coefficient

$$x(t) = \sum_k \overbrace{A_k e^{i\phi_k}} e^{i\omega_k t}$$

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Inverse Fourier Transform

$$x(t) = \sum_k F(\omega_k) e^{i\omega_k t}$$

$$F(\omega_k) = \int x(t) e^{-i\omega_k t} dt$$

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Fourier Transform

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Fourier Transform: Continuous vs. Discrete

Time Duration		
Finite	Infinite	
Discrete FT (DFT)	Discrete Time FT (DTFT)	discr.
$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j\omega_k n}$	$X(\omega) = \sum_{n=-\infty}^{+\infty} x(n) e^{-j\omega n}$	time
$k = 0, 1, \ldots, N-1$	$\omega \in (-\pi, +\pi)$	n
Fourier Series (FS)	Fourier Transform (FT)	cont.
$X(k) = \int_0^P x(t) e^{-j\omega_k t} dt$	$X(\omega) = \int_{-\infty}^{+\infty} x(t) e^{-j\omega t} dt$	time
$k = -\infty, \ldots, +\infty$	$\omega \in (-\infty, +\infty)$	t
discrete freq. k	continuous freq. ω	

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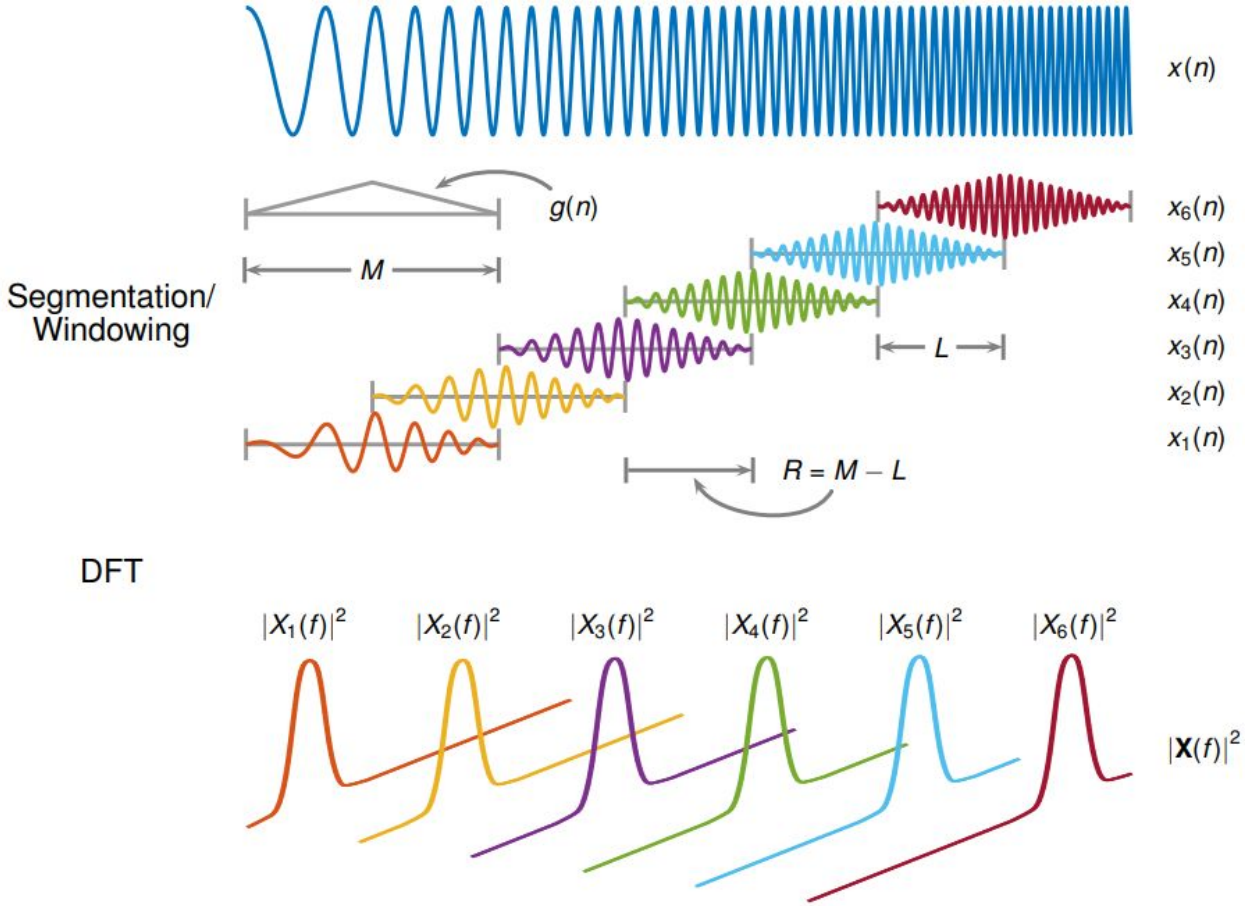
Short-Time Fourier Transform



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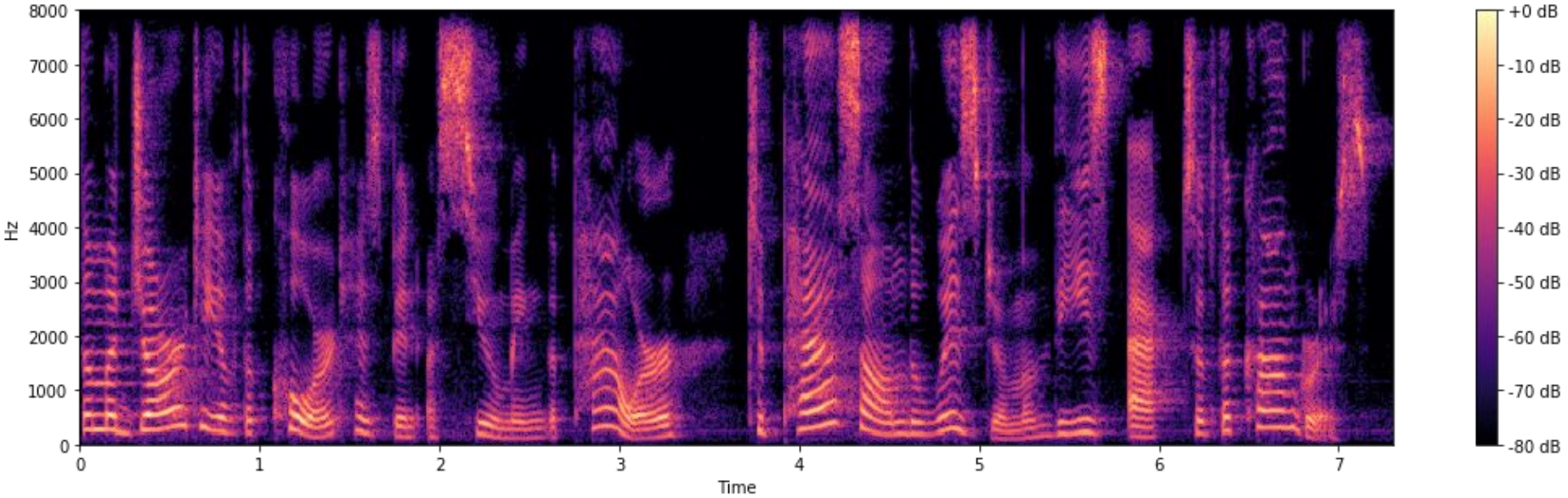
Spectrogram

Amplitude spectrogram



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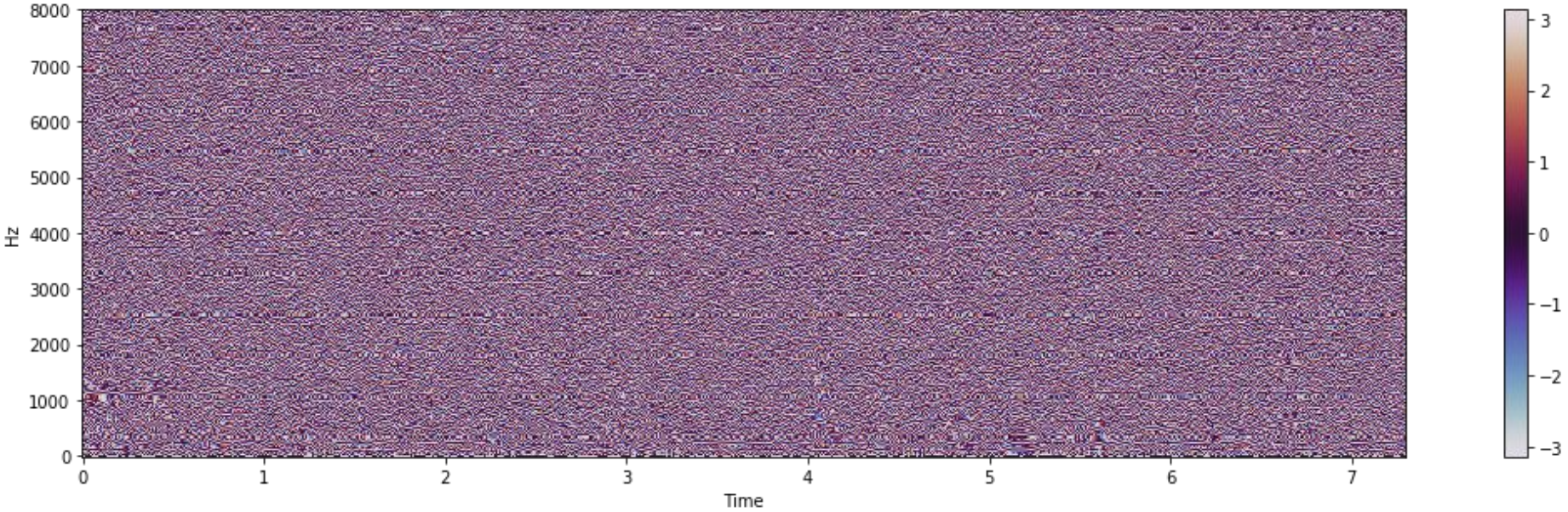
Phase spectrogram



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Inverse Short-Time Fourier Transform

Griffin-Lim

```
def griffin_lim(F, max_iters=32):
    phi = Uniform(0, 2 * pi, size=F.shape)
    for _ in range(max_iters):
        y = ISTFT(F * exp(1j * phi))
        phi = angle(STFT(y))
    return y
```

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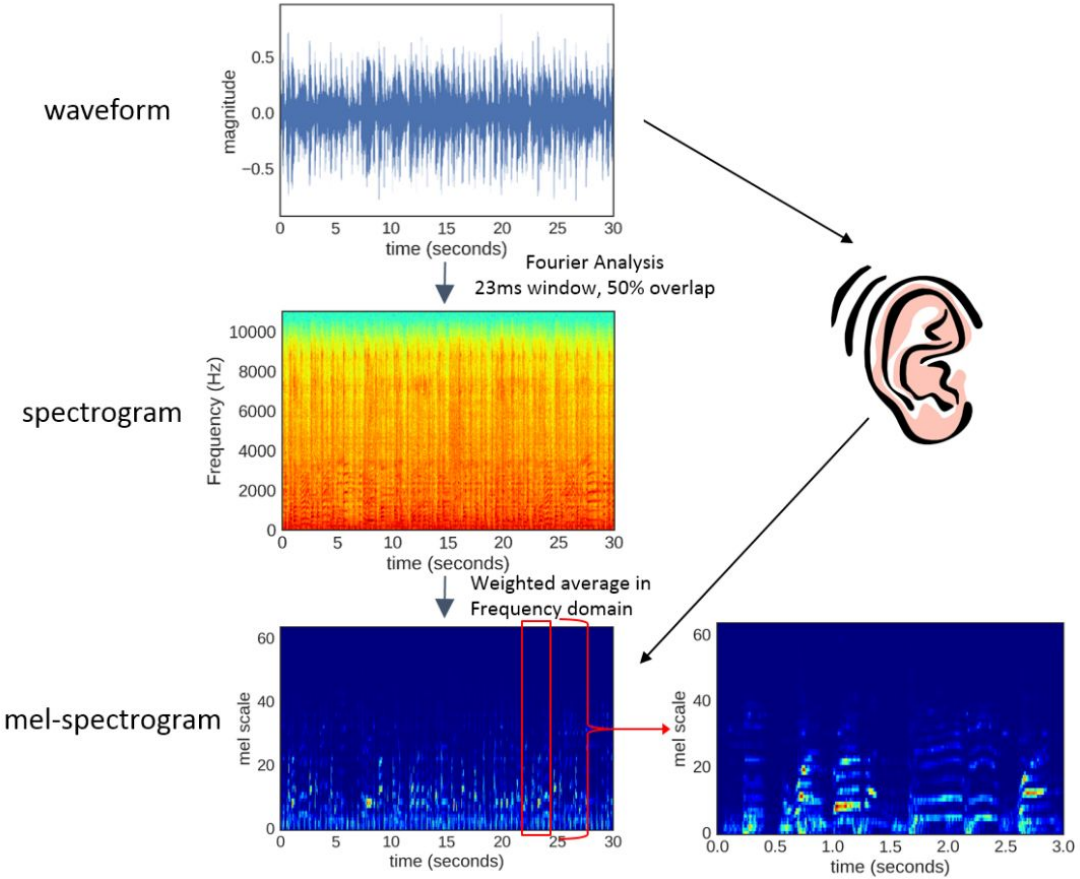
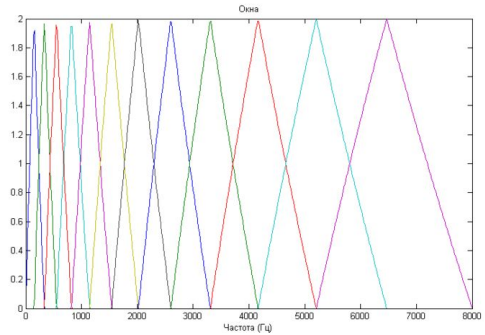
Mel-spectrogram





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Audio Processing Problems

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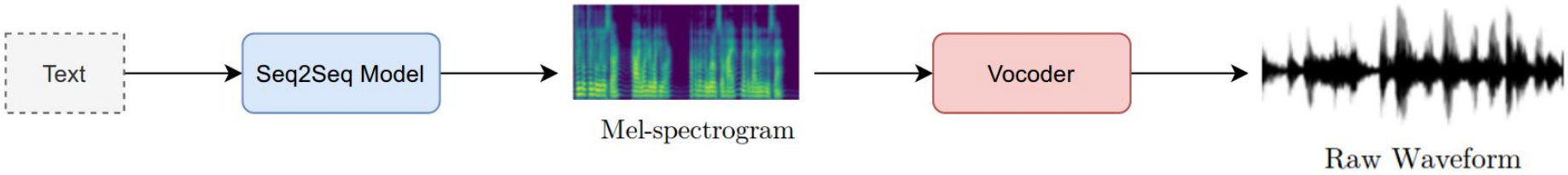
Text-to-speech (TTS)



Mel-spectrogram inversion

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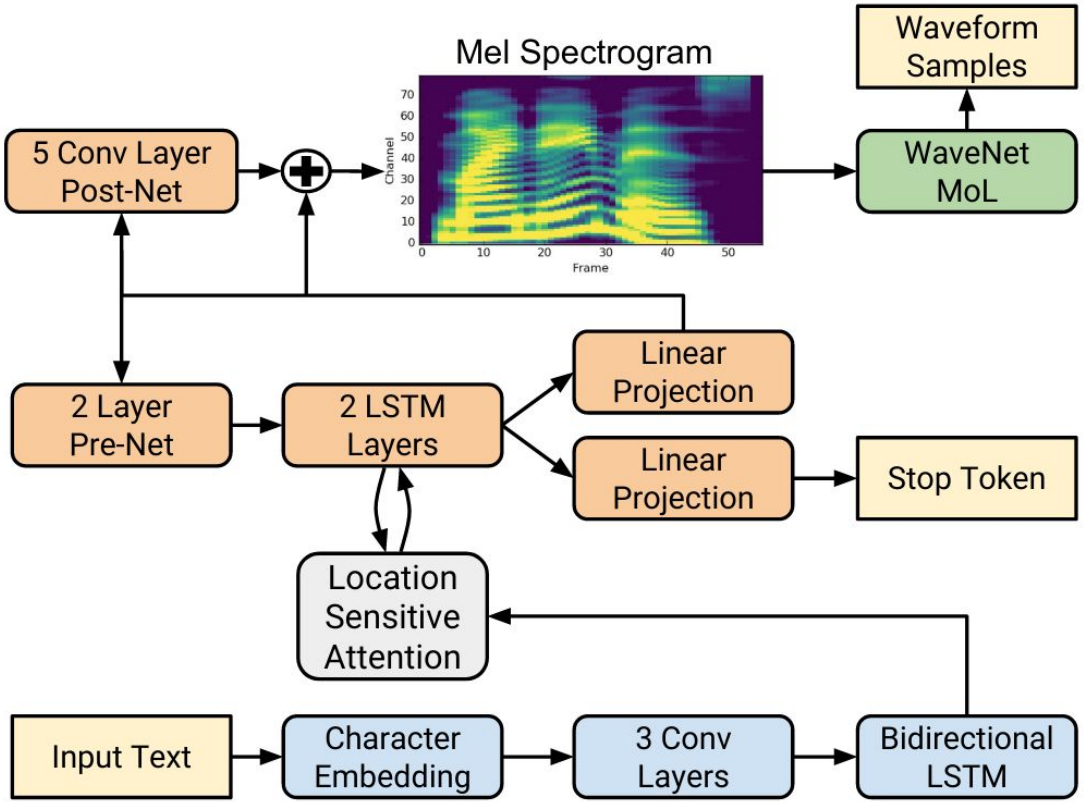
TTS Example - Tacotron 2



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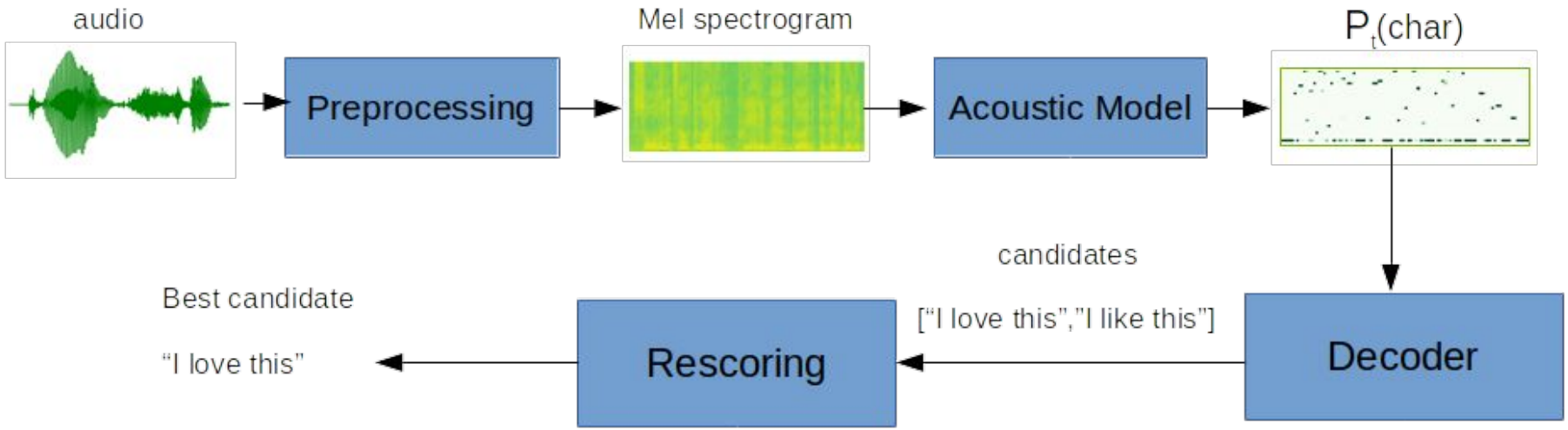
Automatic Speech Recognition (ASR)



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ASR Example - Deep Speech 2

audio

Preprocessing

- Data augmentation
  - additive Gaussian noise
  - time stretch (resampling)
- Windowing 20-25 ms, stride 10 ms
- FFT, log
- Normalization

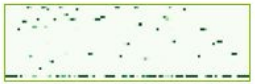
spectrogram

DNN

- 2-3 convolutional layers
  - ch=32, ks=[11, 41], s=[2, 2]
  - ch=32, ks=[11, 21], s=[1, 2]
  - ch=64, ks=[11, 21], s=[1, 2]
- 3-7 bi-/uni- directional GRUs/LSTMs
- 1 row conv layer (for unidirectional)
- 1-2 fully connected layers

- BN/dropout for regularization

$P_t(c)$



training

CTC Loss

inference

Decoder

- greedy (argmax)
- beam search
- beam search with language model (width=2000-8000)

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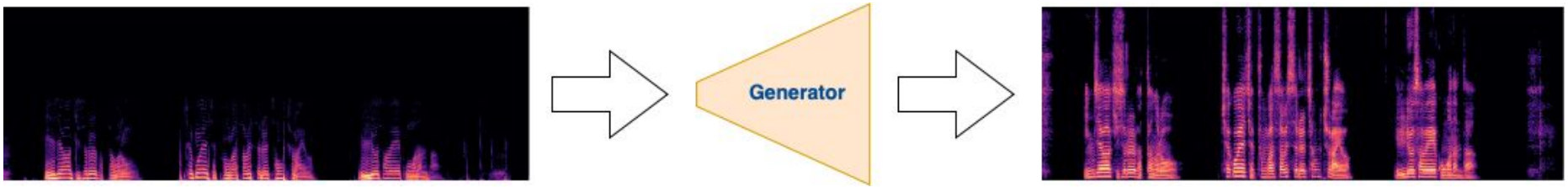
Bandwidth Extension



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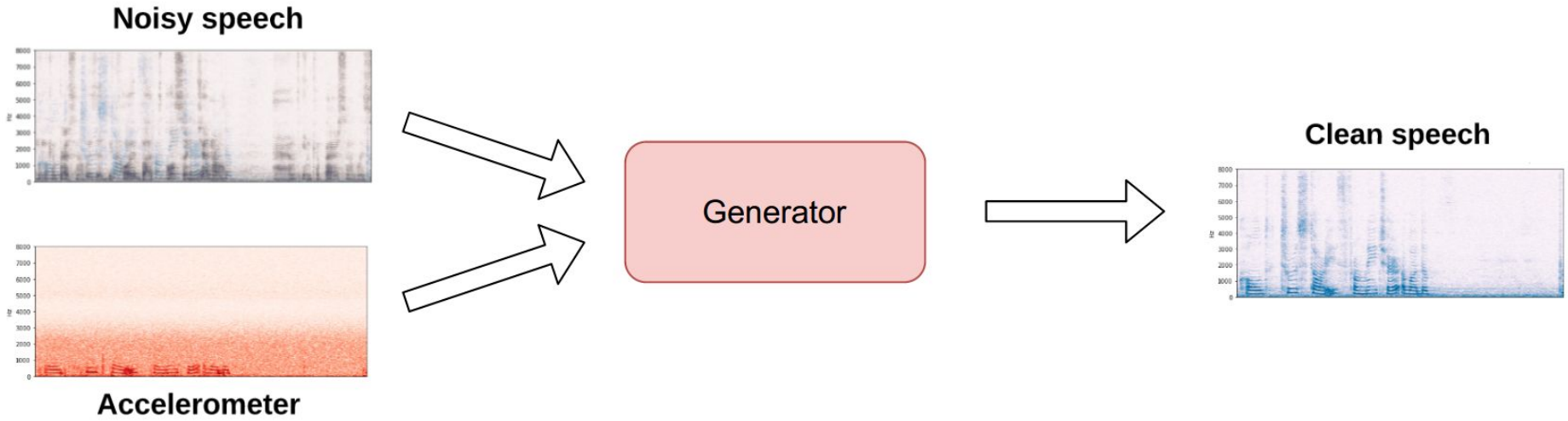
Multi-modal Speech Enhancement



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Architectures

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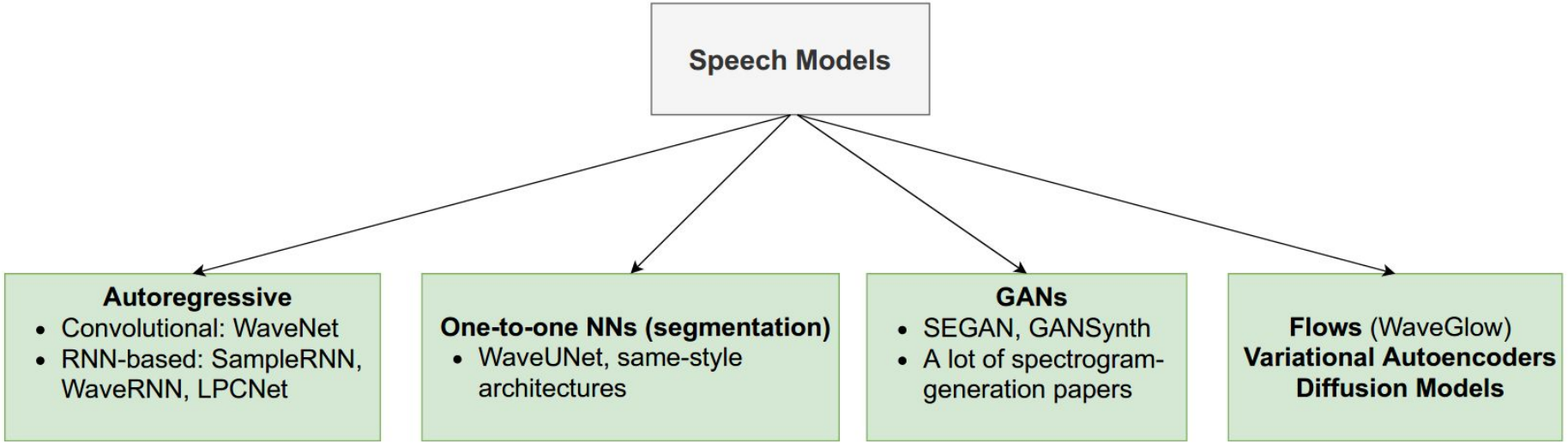
Conditional Generative Models



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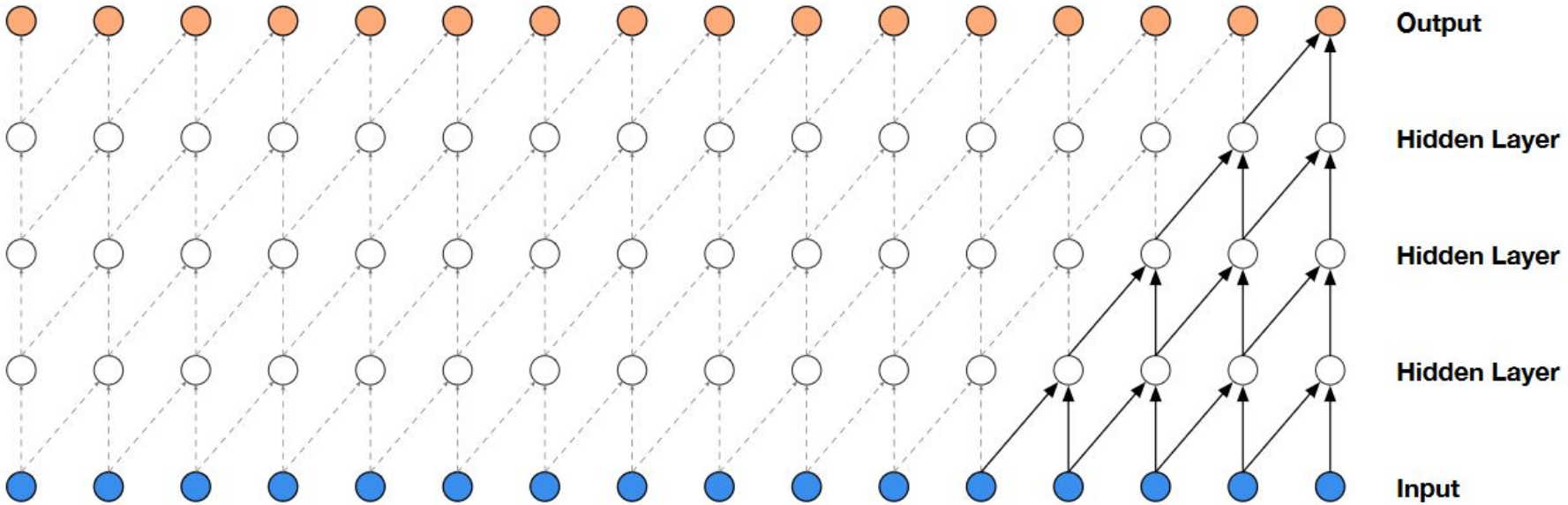
Causal Convolutions have small receptive field



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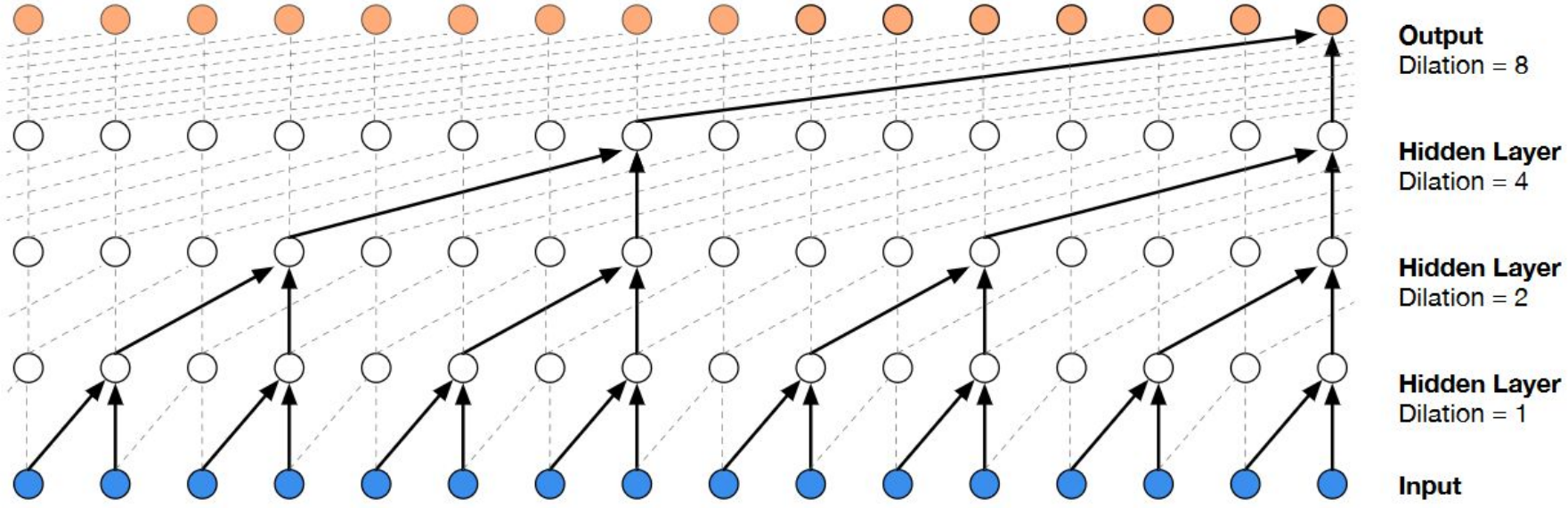
WaveNet

WaveNet uses causal *dilated* convolutions



Dilations grows only up to some limit: 1, 2, 4, …, 512, 1, 2, 4, …, 512, 1, 2, 4, …, 512

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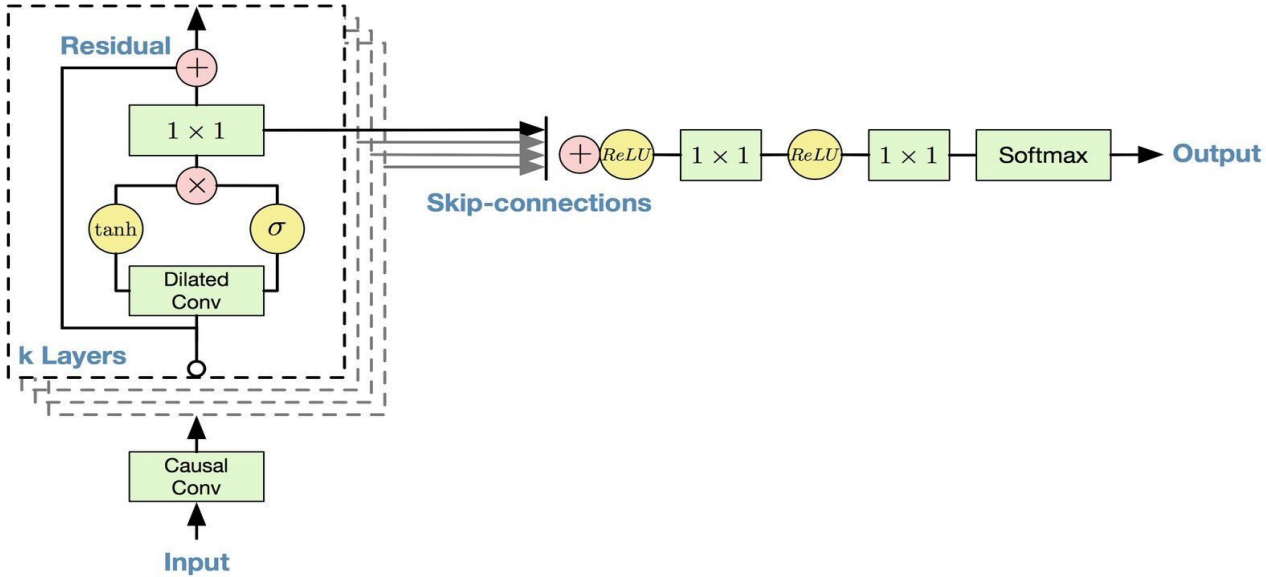
WaveNet: one block structure



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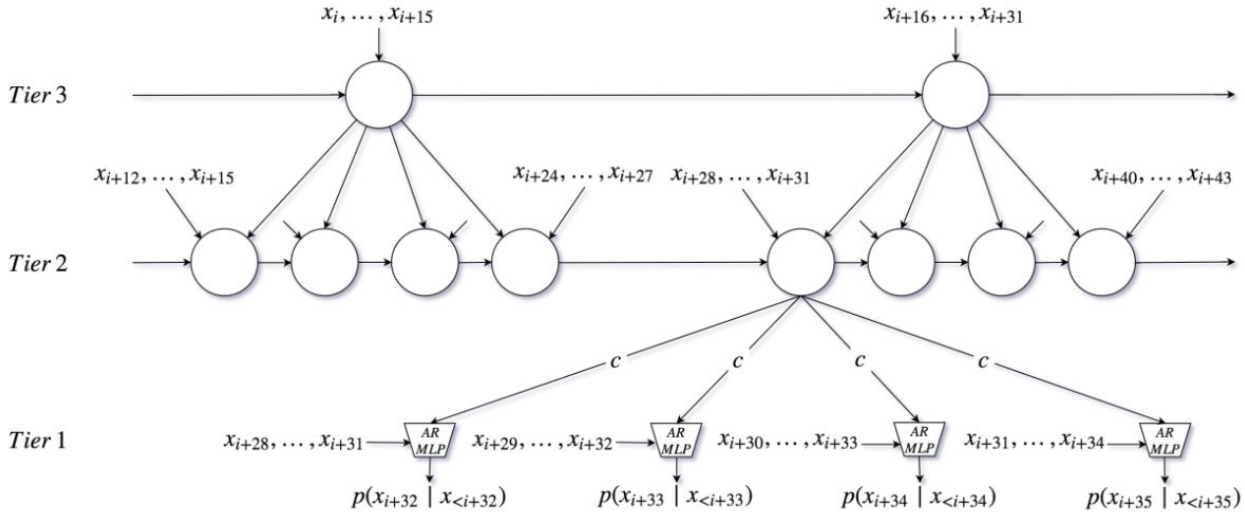
Multiscale RNNs

neither popular nor very effective



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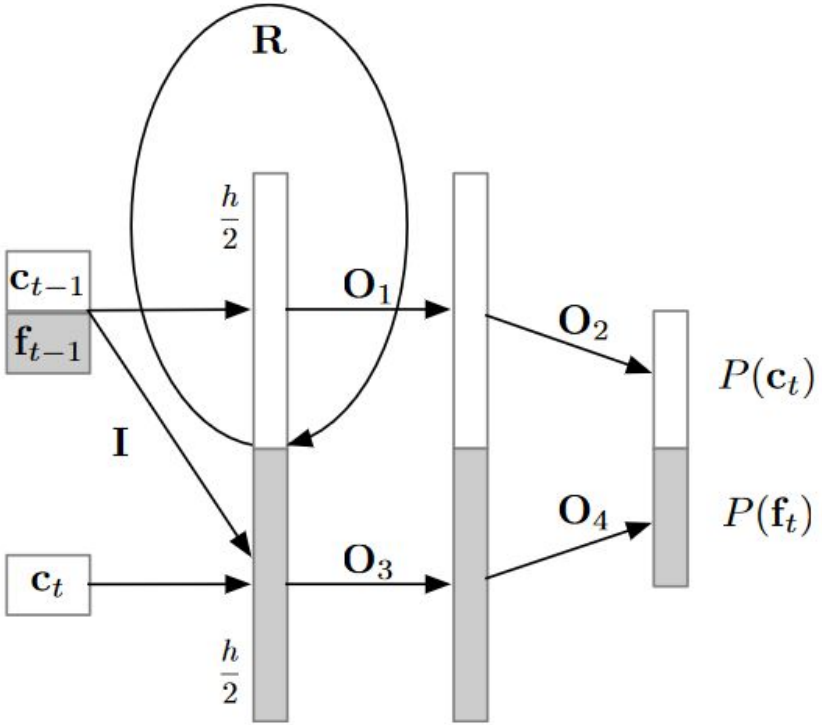
Original net: audio 8bit -> 16bit



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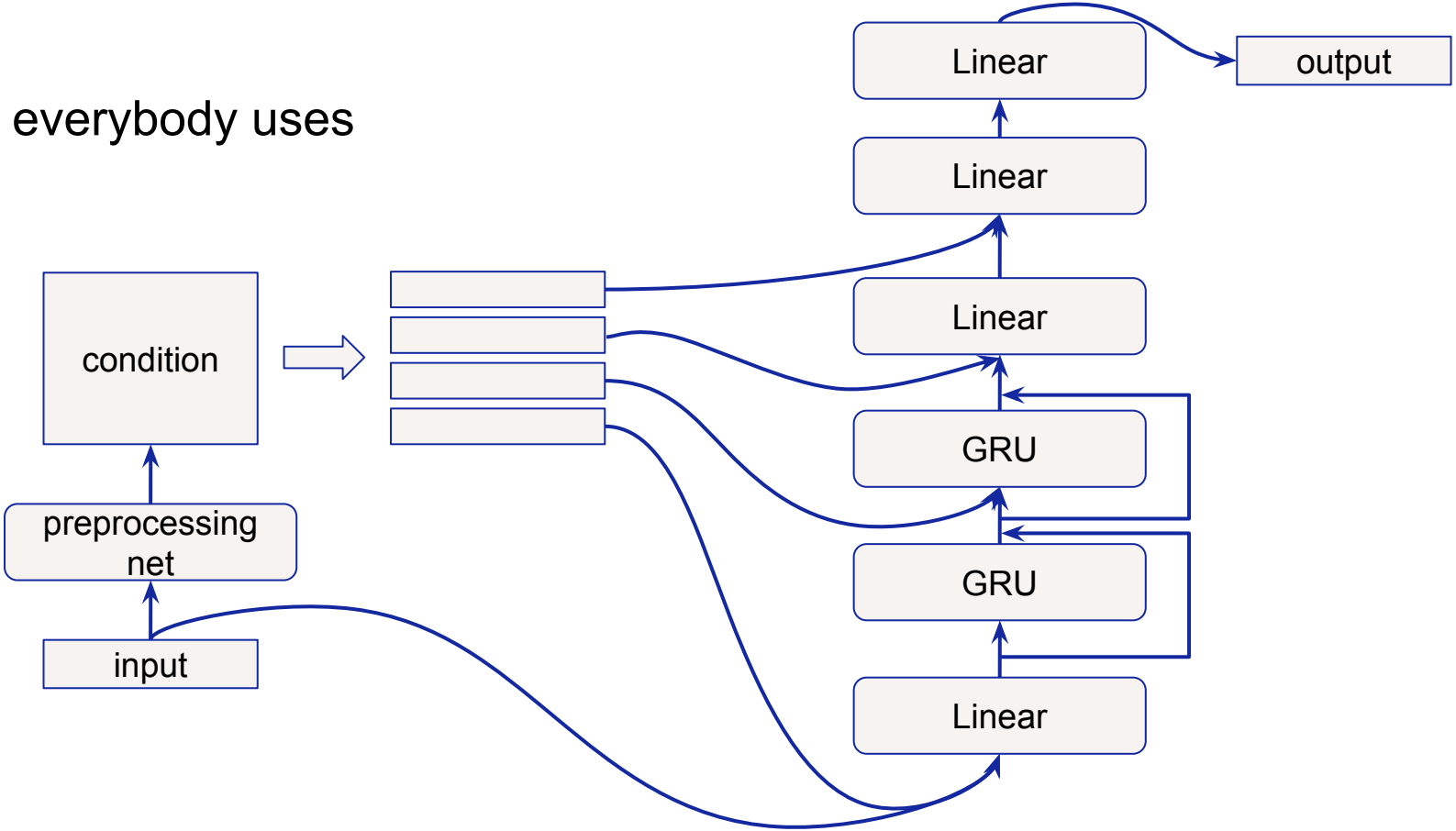
WaveRNN

What everybody uses



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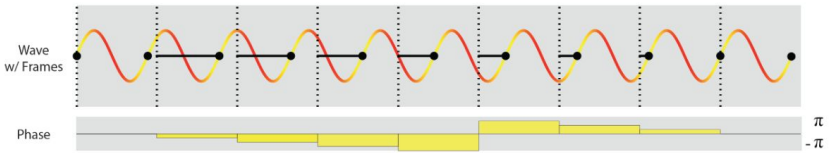
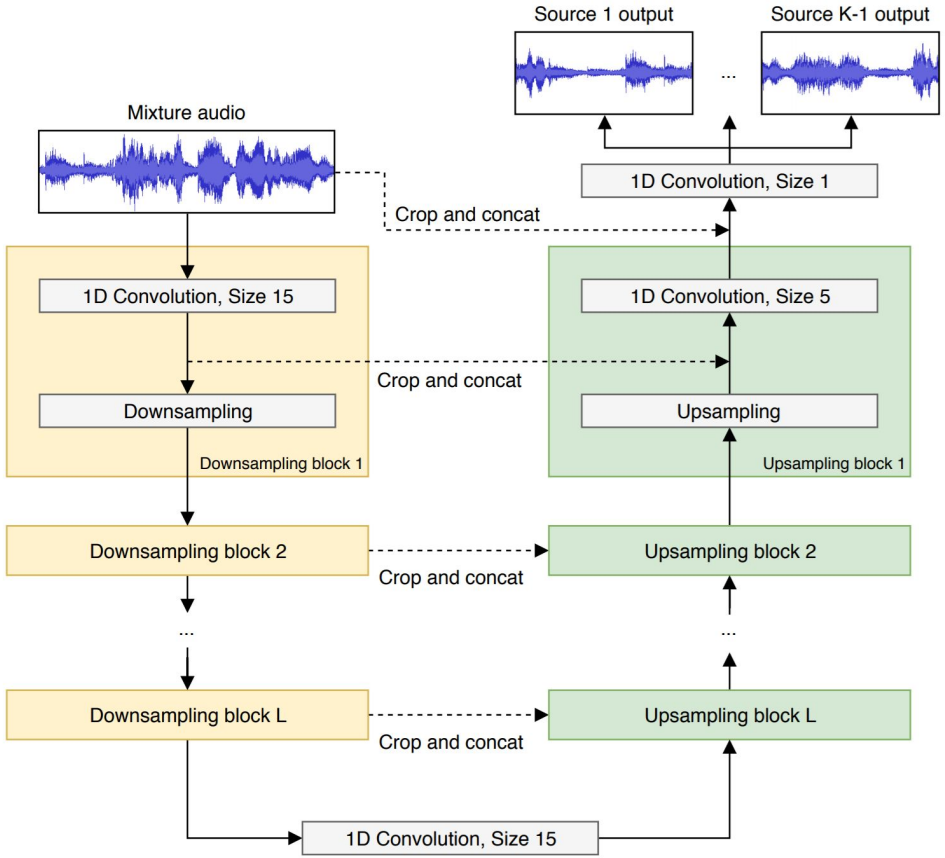
WaveUNet

Pros:

+ lightweight
+ operates on several scales
+ fully convolutional

Cons:





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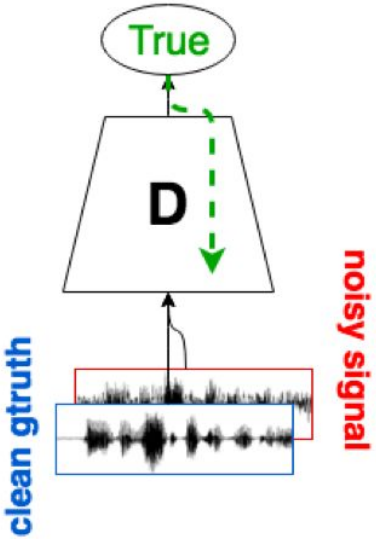
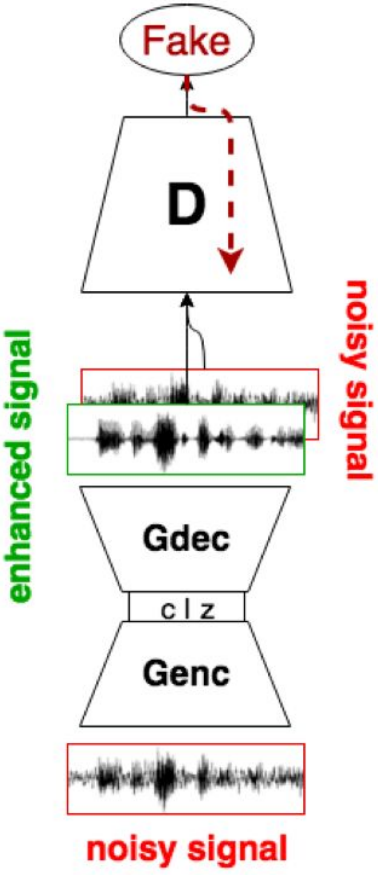
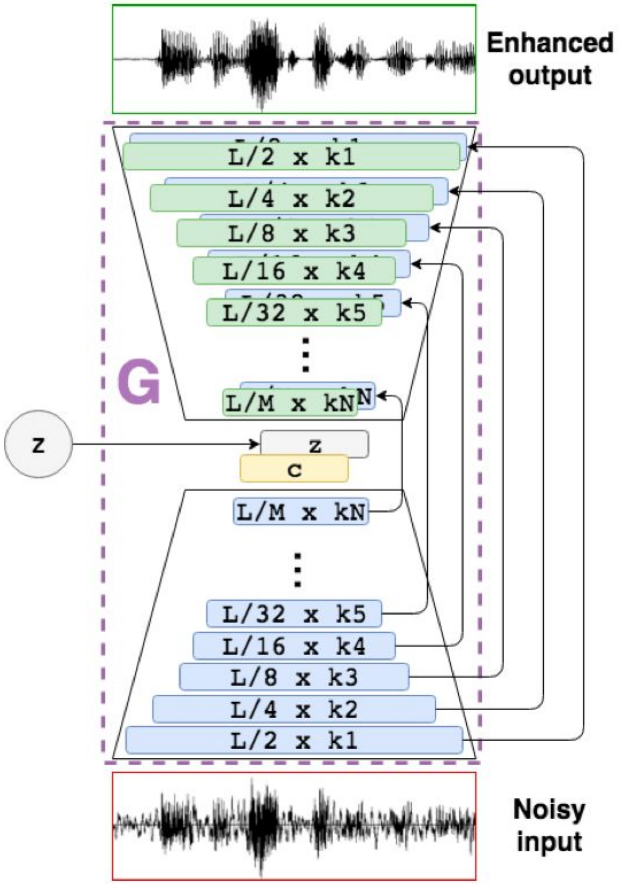
GANs (*)







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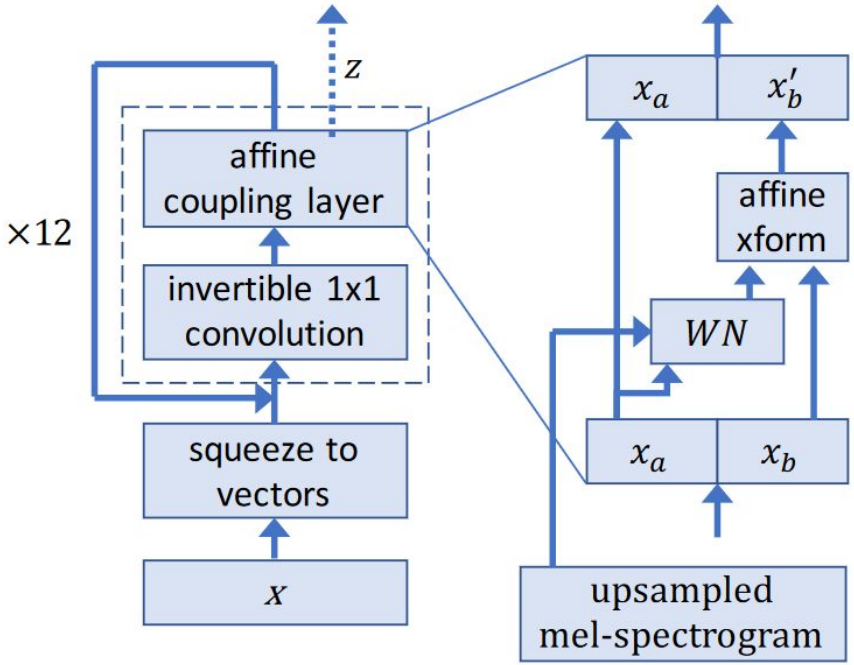
WaveGlow

Pros:
+ highly parallel
+ fast on GPUs

Cons:
- slow on CPUs



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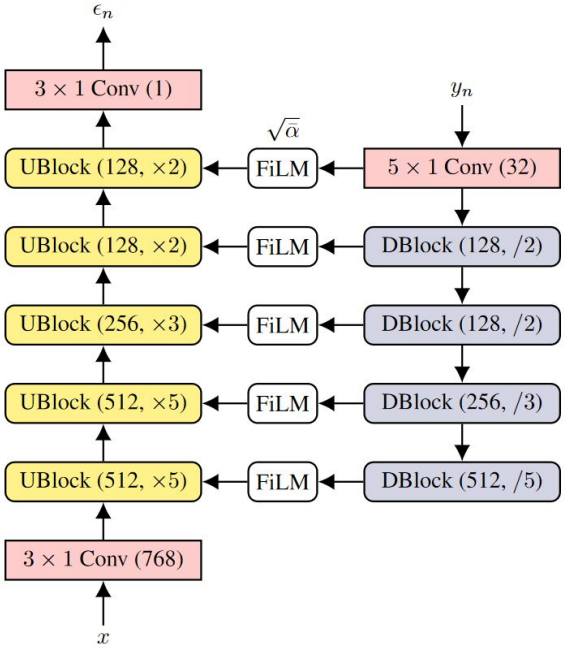
WaveGrad (*)



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Loss Functions

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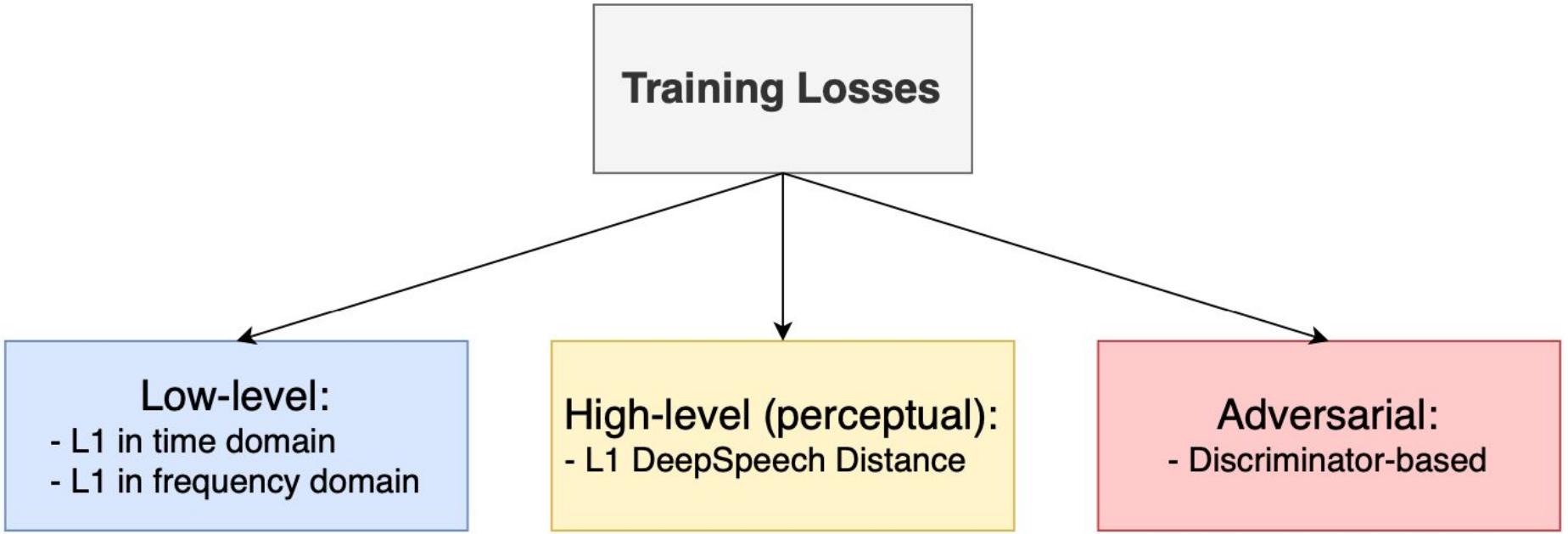
Training Losses



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Low-Level Losses

$$L_1(y, \hat{y}) = \|y - \hat{y}\|_1$$

$$L_1^{stft}(y, \hat{y}) = \|\log(1 + |STFT(y)|) - \log(1 + |STFT(\hat{y})|)\|_1$$

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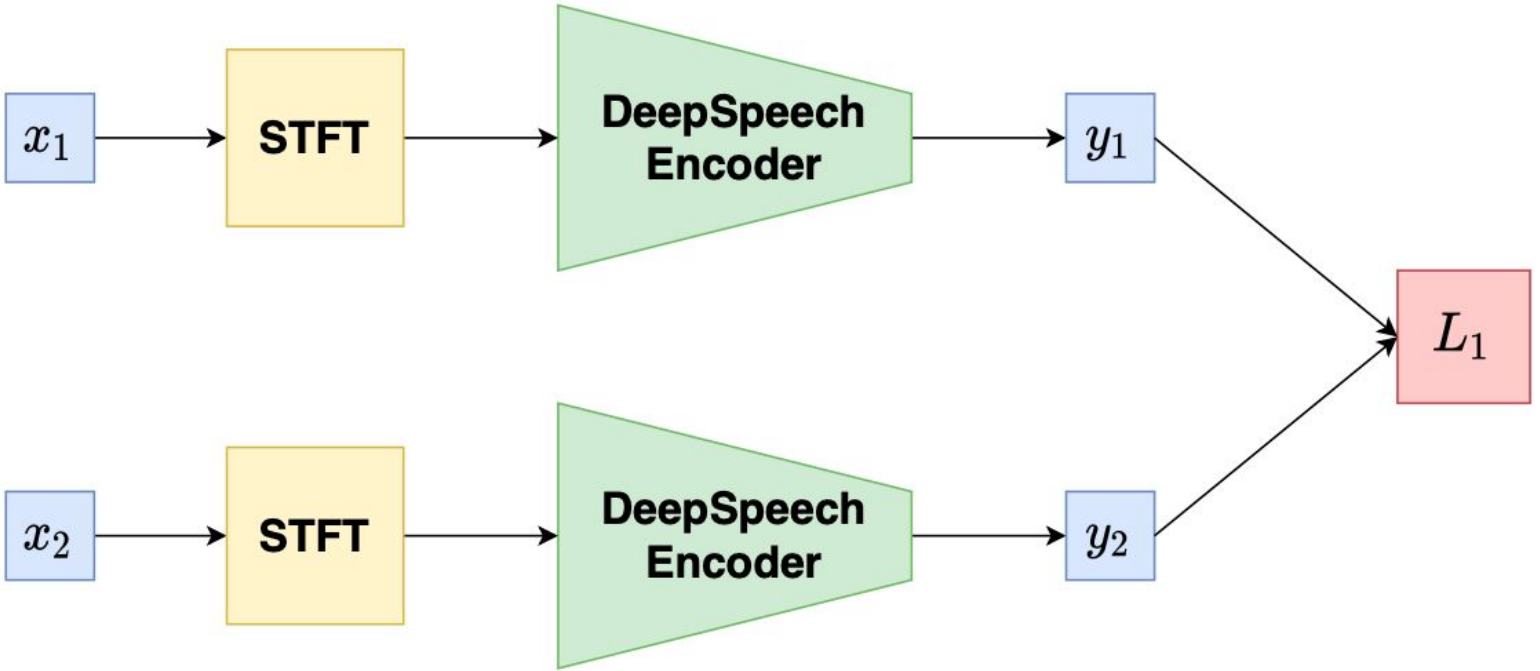
High-Level Loss



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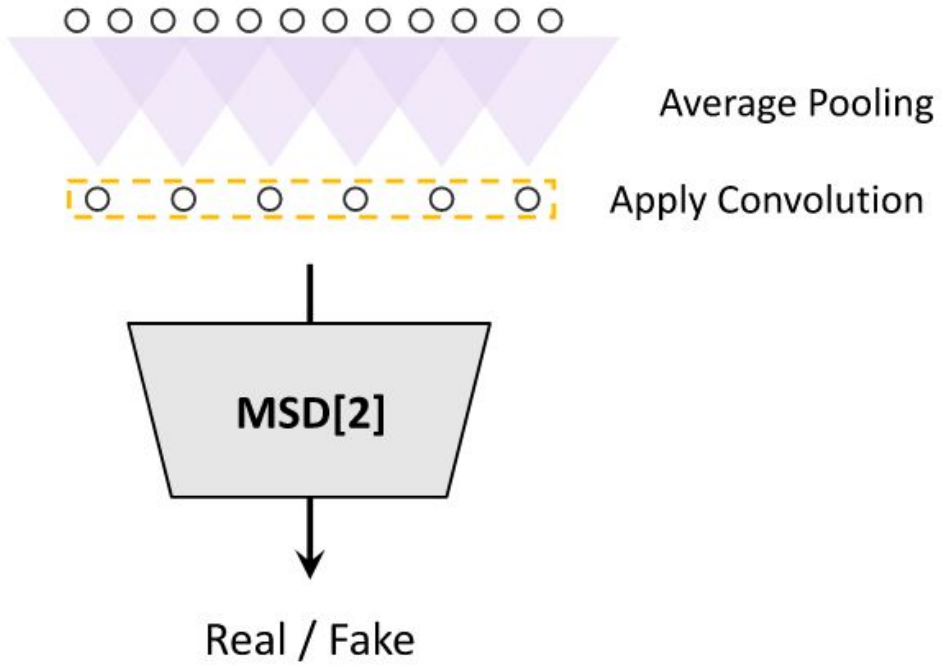
Adversarial Loss

Multi-Scale Discriminators (MSD)



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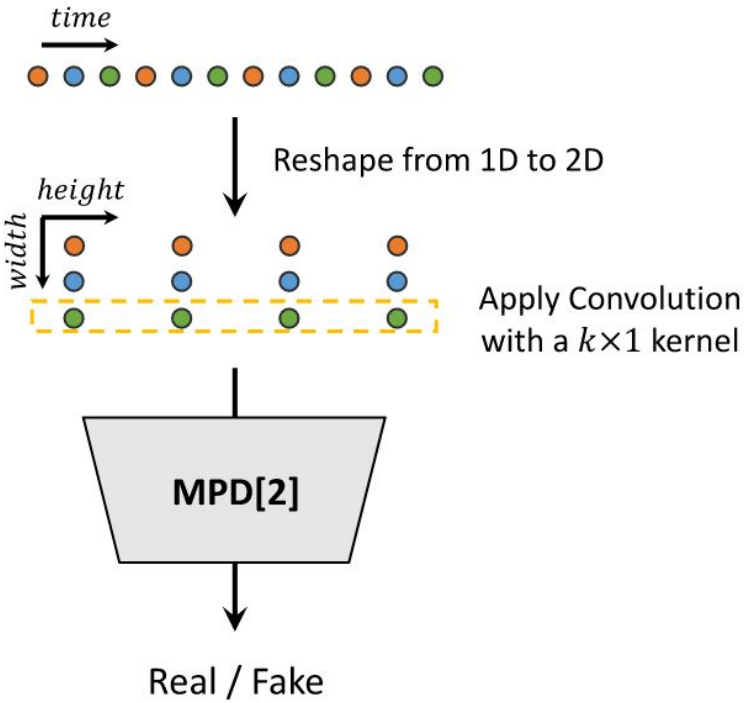
Adversarial Loss

Multi-Period Discriminators (MPD)



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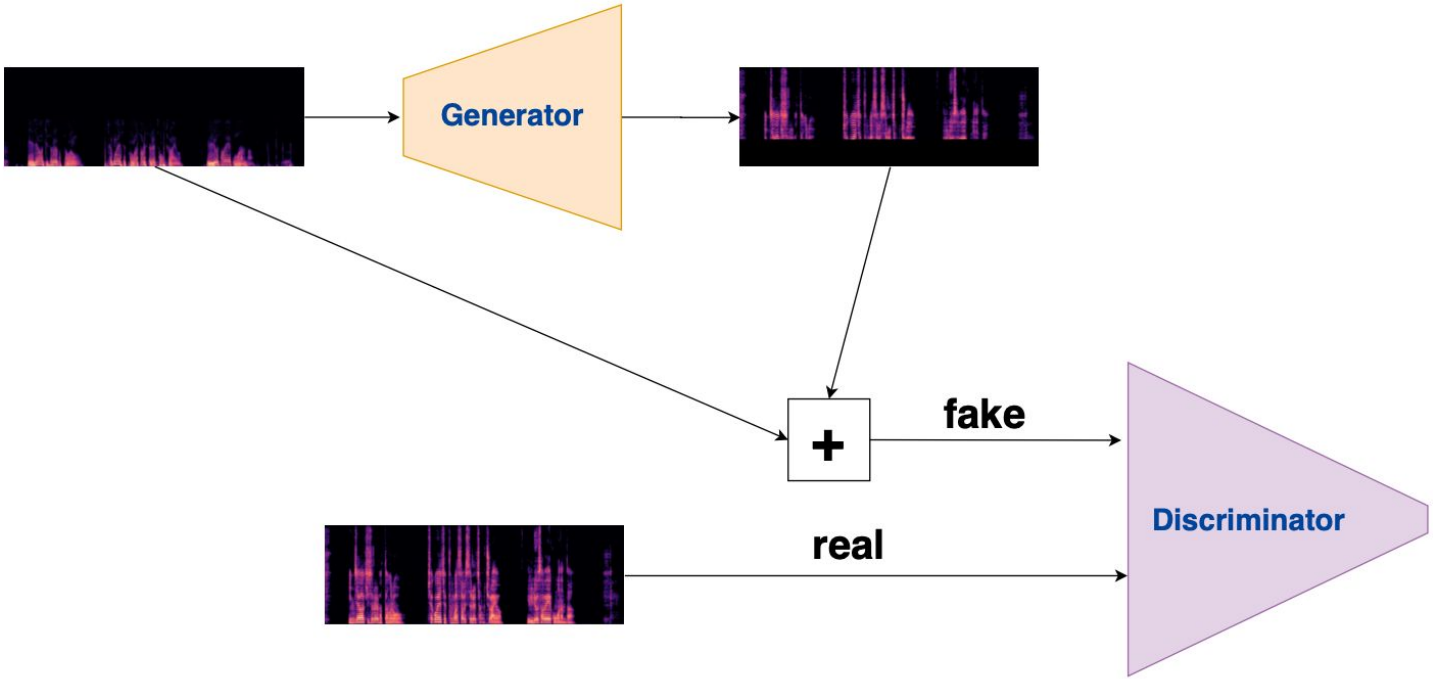
Adversarial Loss (Add more)

Spectrogram-based Discriminators



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Adversarial Objective Functions

Hinge Loss:

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

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

Feature Matching Loss:

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

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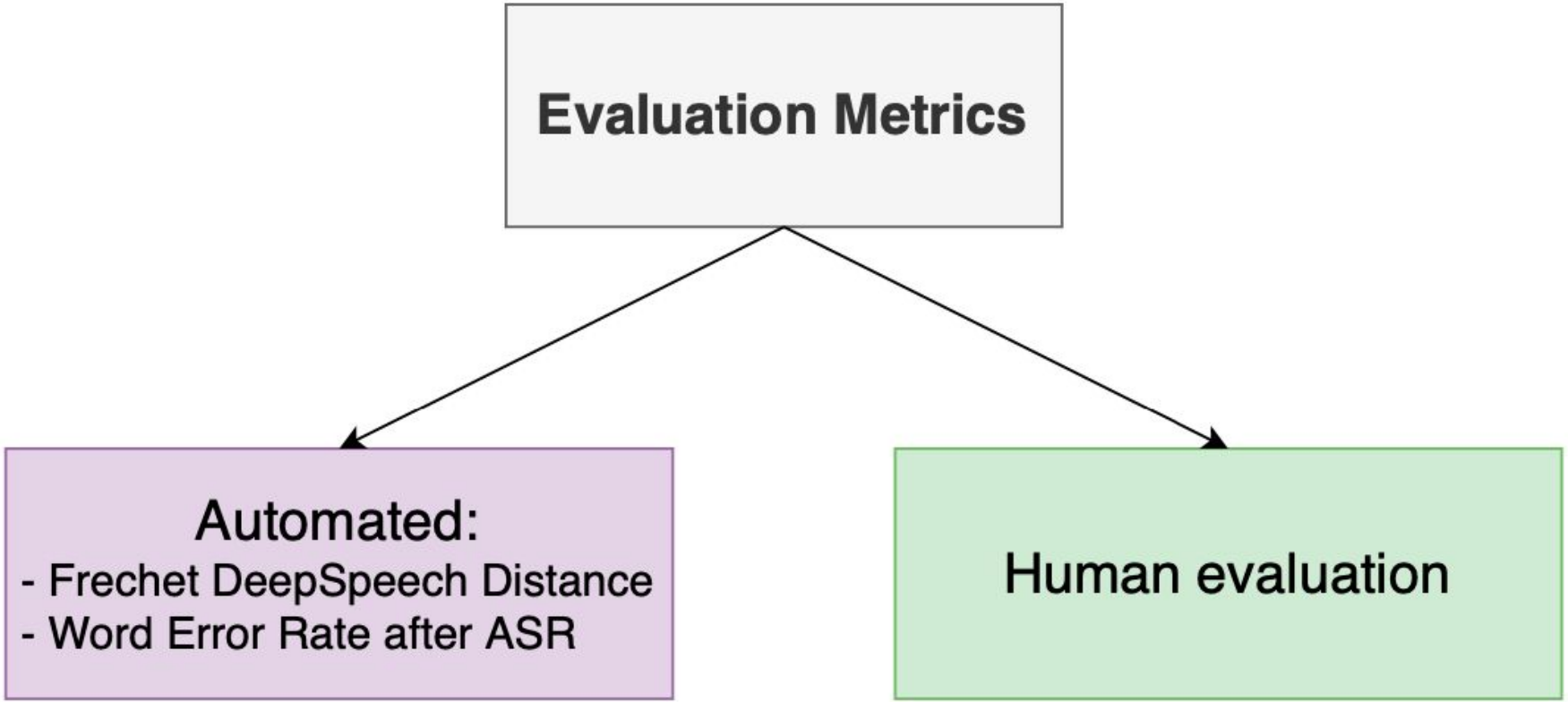
Evaluation Metrics



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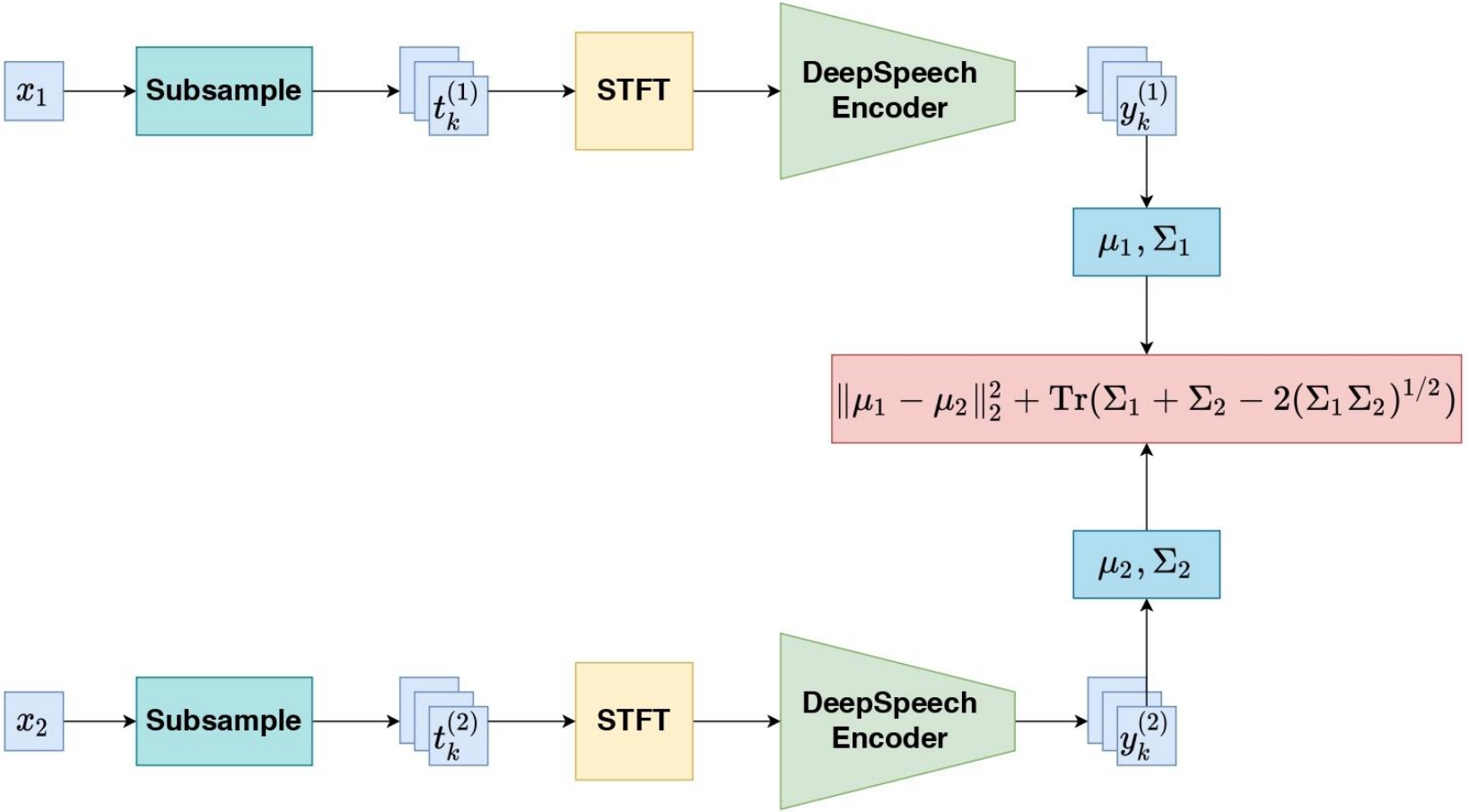
Frechet DeepSpeech Distance



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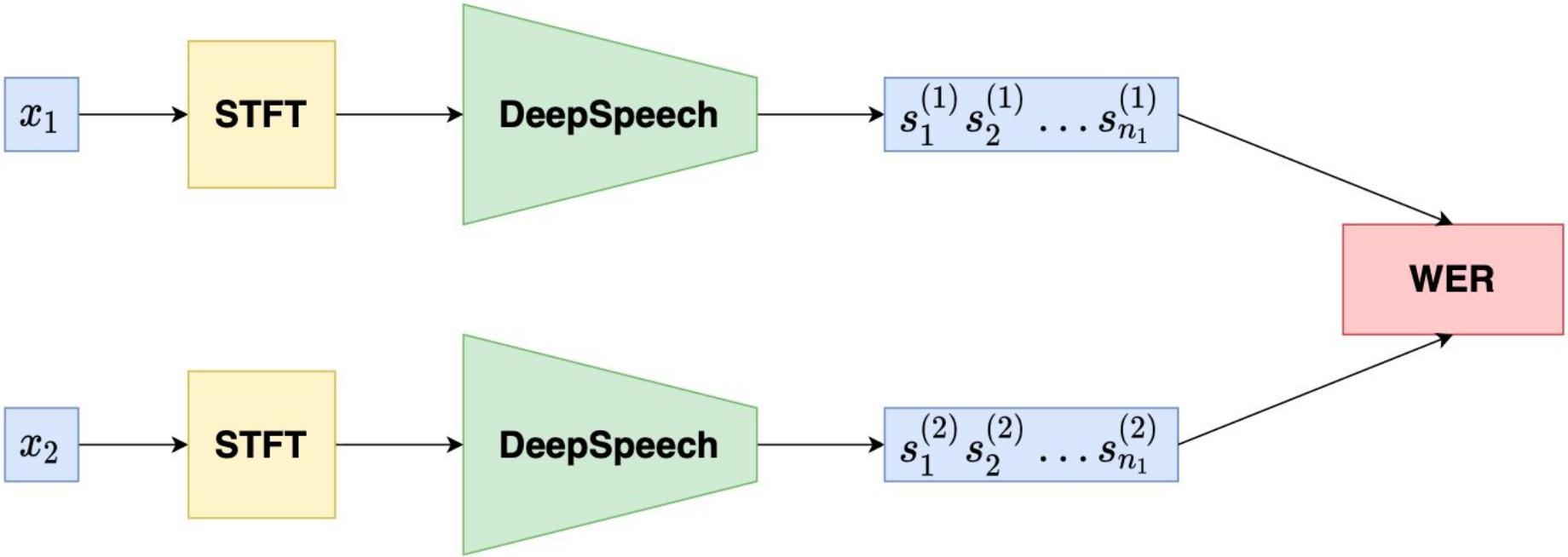
Word Error Rate after ASR



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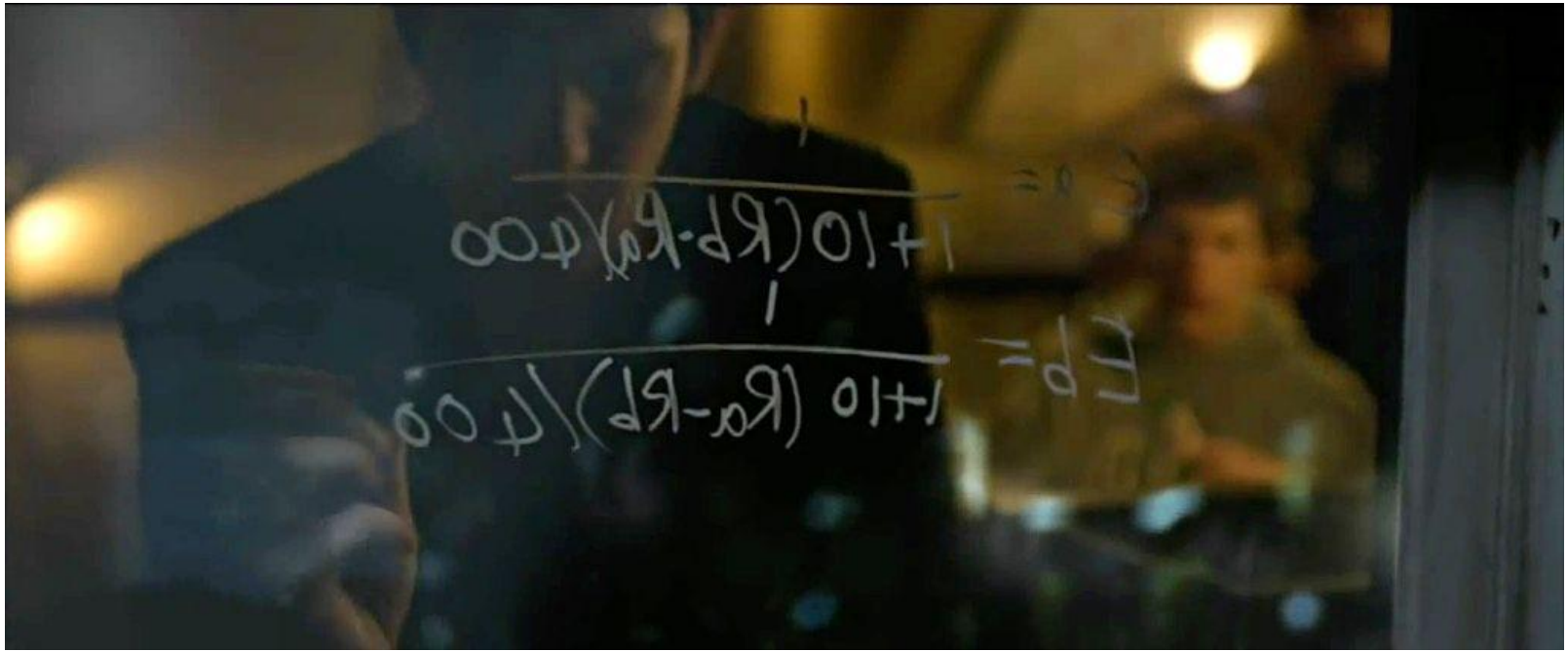
Human Evaluation

Idea: pairwise comparisons



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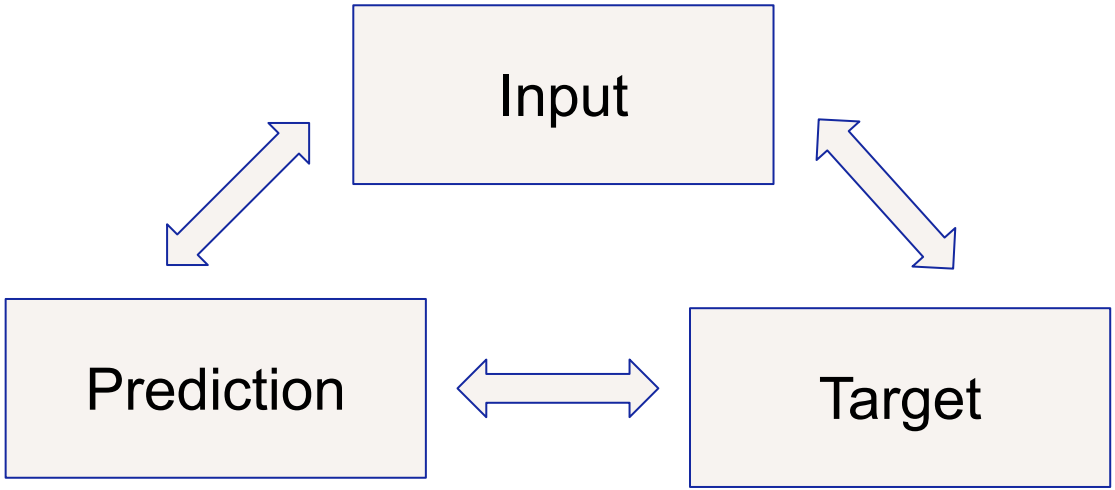
Human Evaluation

Answers: <, >



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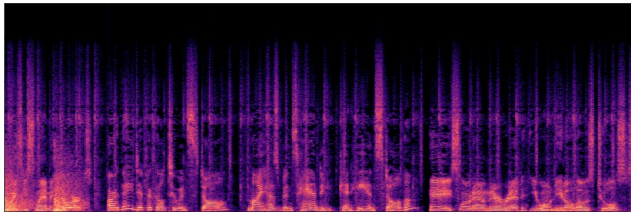
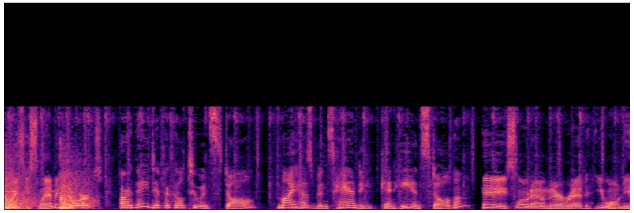
Human Evaluation

Problem





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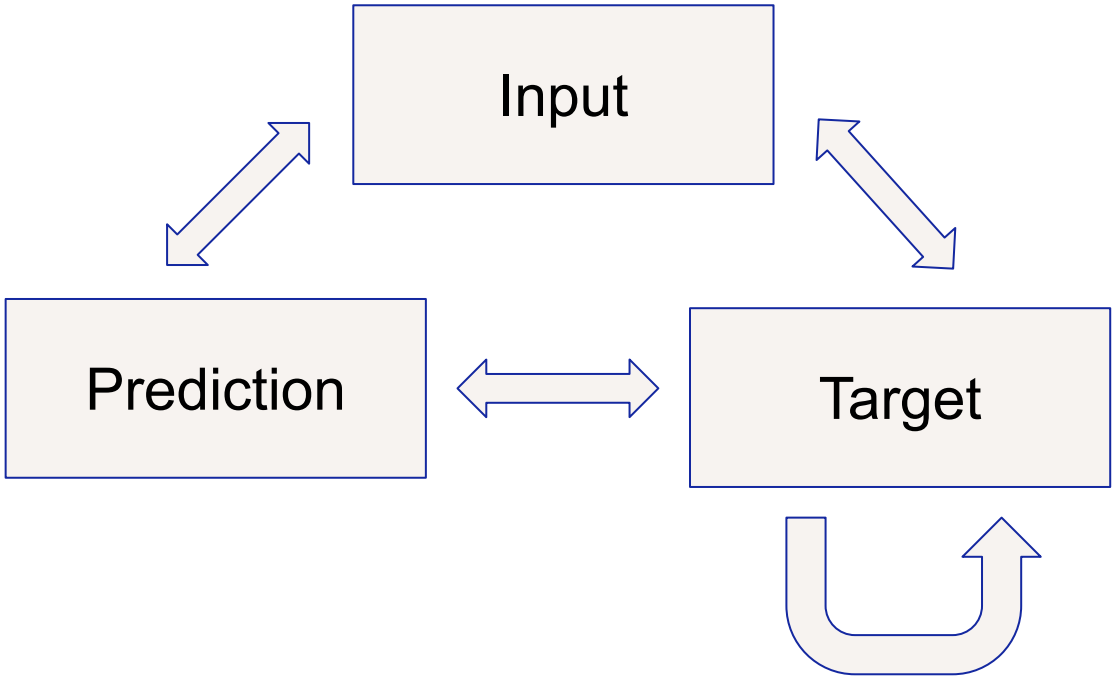
Human Evaluation

Answers: <, >, **=, ≠**



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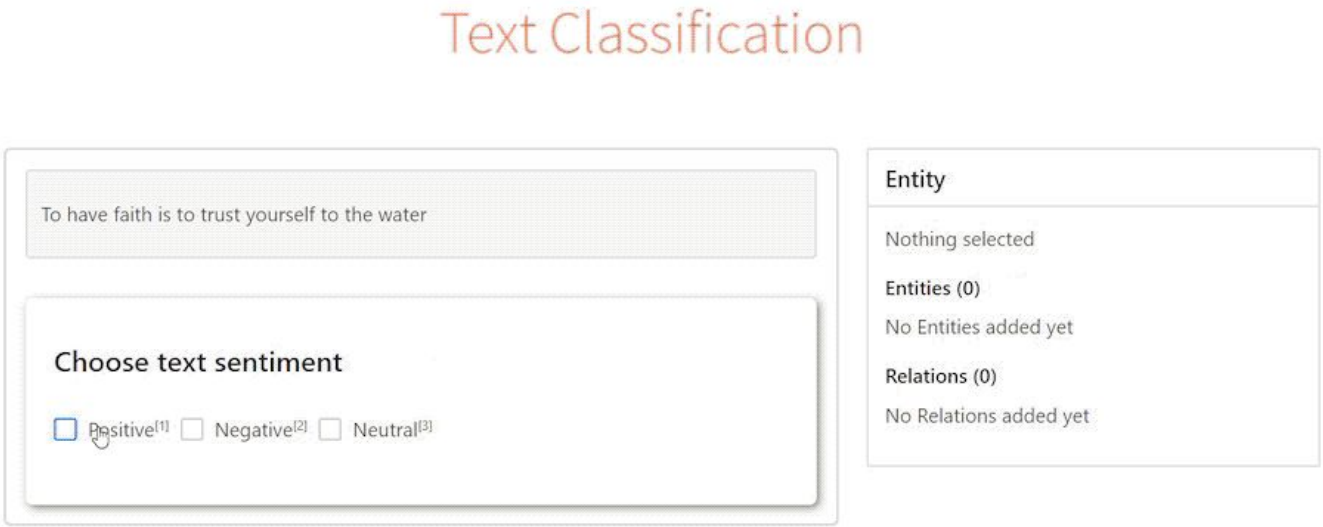
Human Evaluation

Label Studio

https://labelstud.io/



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Datasets

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Speech Datasets

LJ Speech
1 speaker,
~ 24 hours

VCTK
110 speakers
~ 44 hours

Mozilla Common VoiceSet

- Allows commercial usage
- Two months of train data (~64Gb)
- 17 train and 10 validation languages
- Highly imbalanced (languages, genders)

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1 speaker,
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- Credits to Jules

Jules Churkina consulted us while we balanced languages

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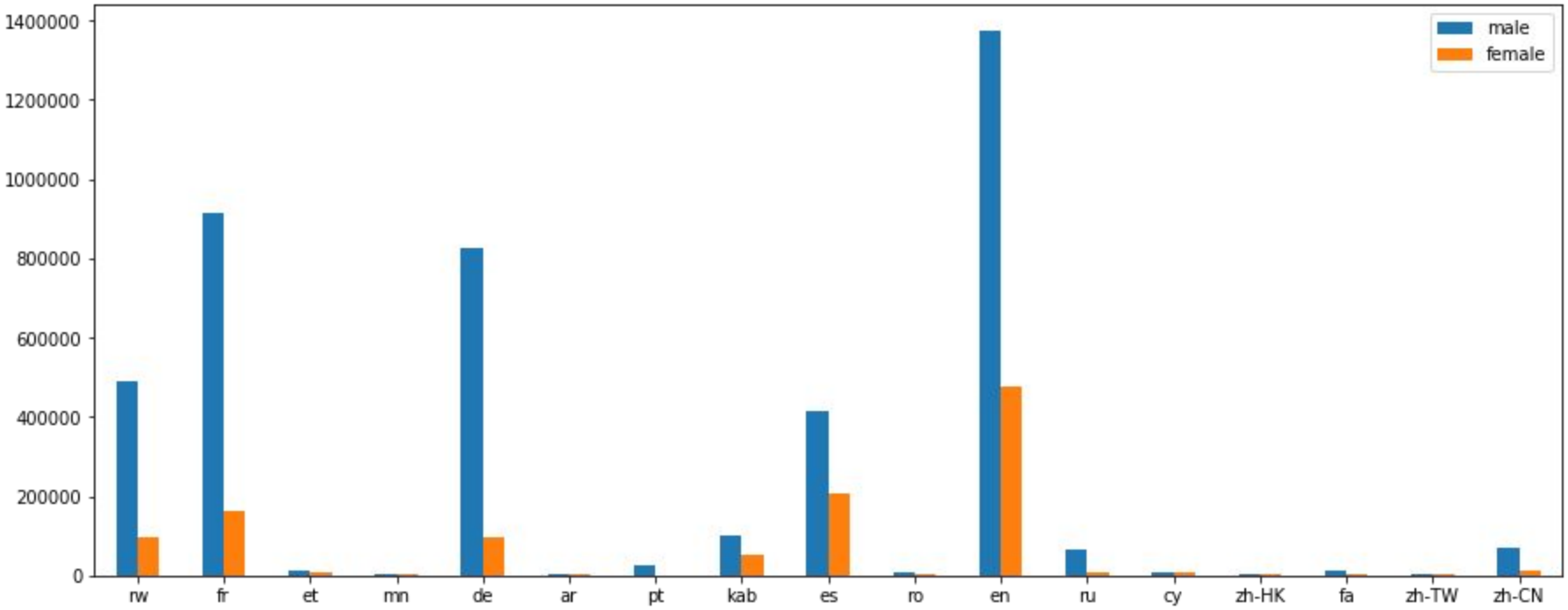
Speech Datasets

VoiseSet Imbalance: Train Set



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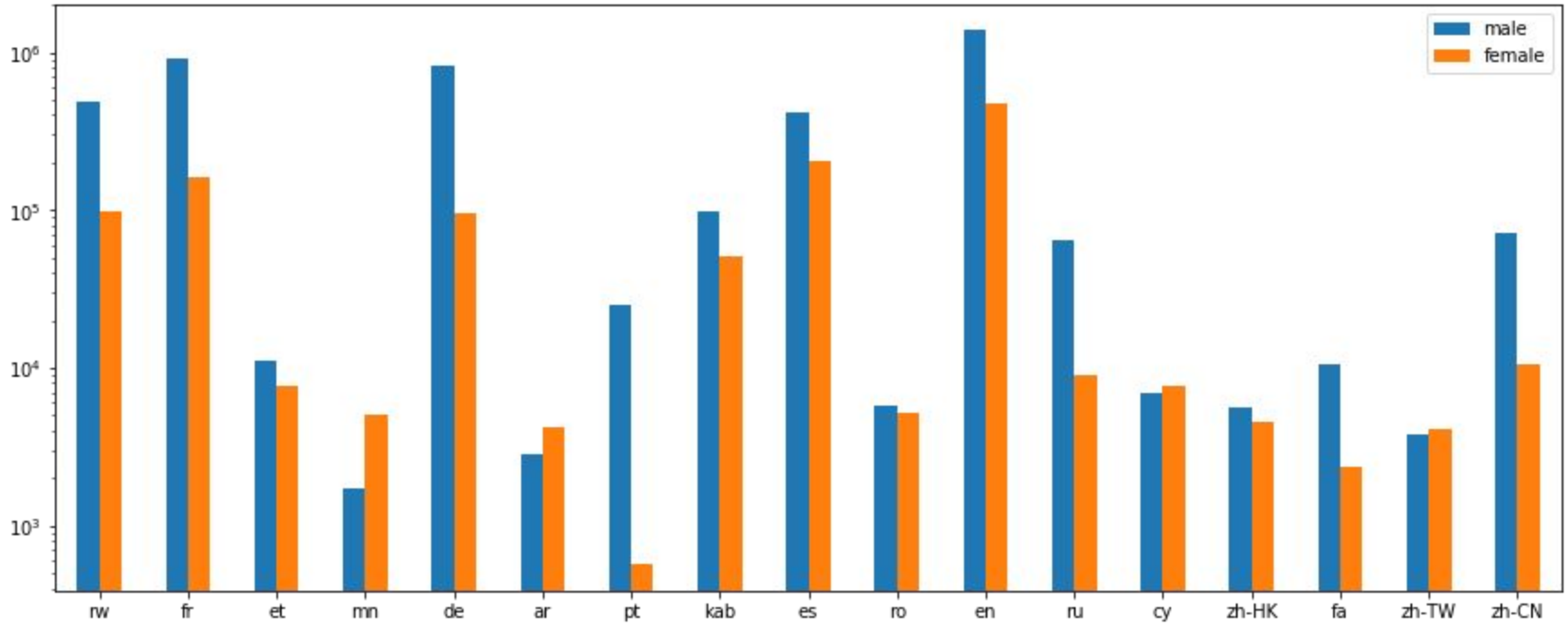
Speech Datasets

VoiseSet Imbalance: Train Set



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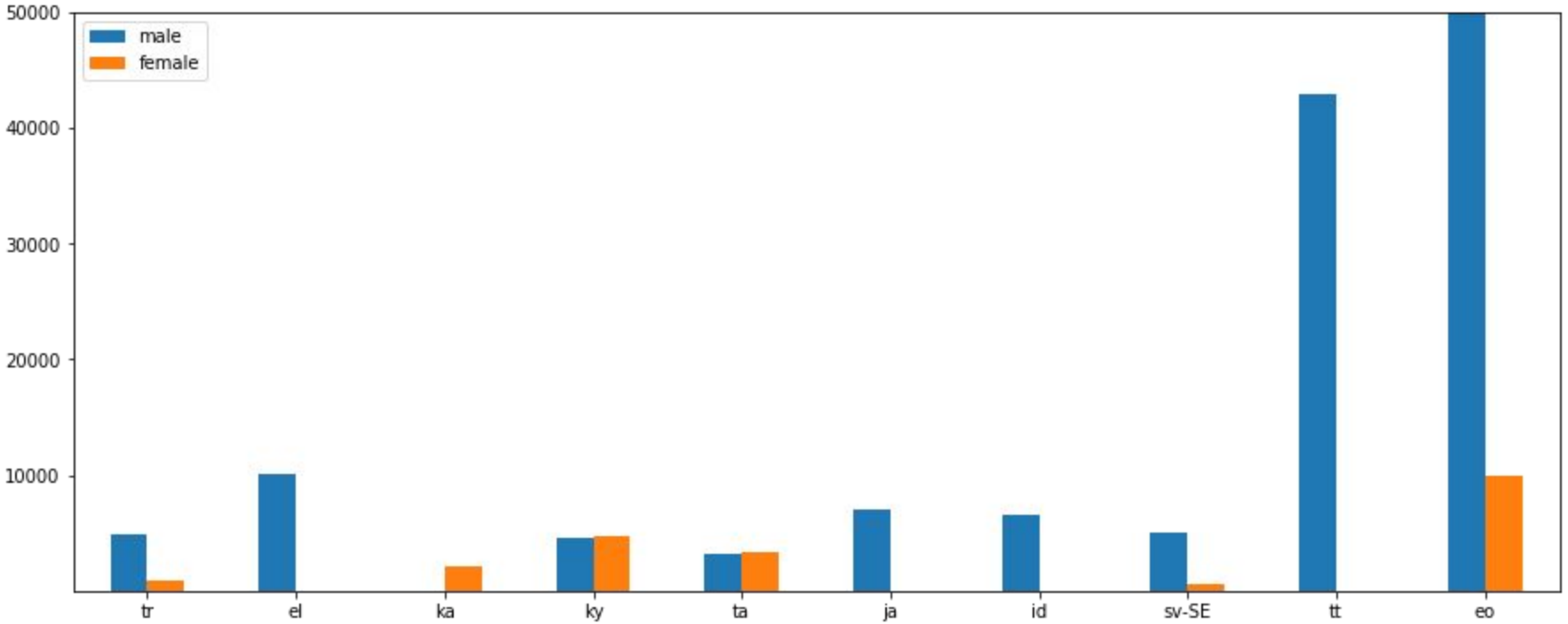
Speech Datasets

VoiseSet Imbalance: Validation Set



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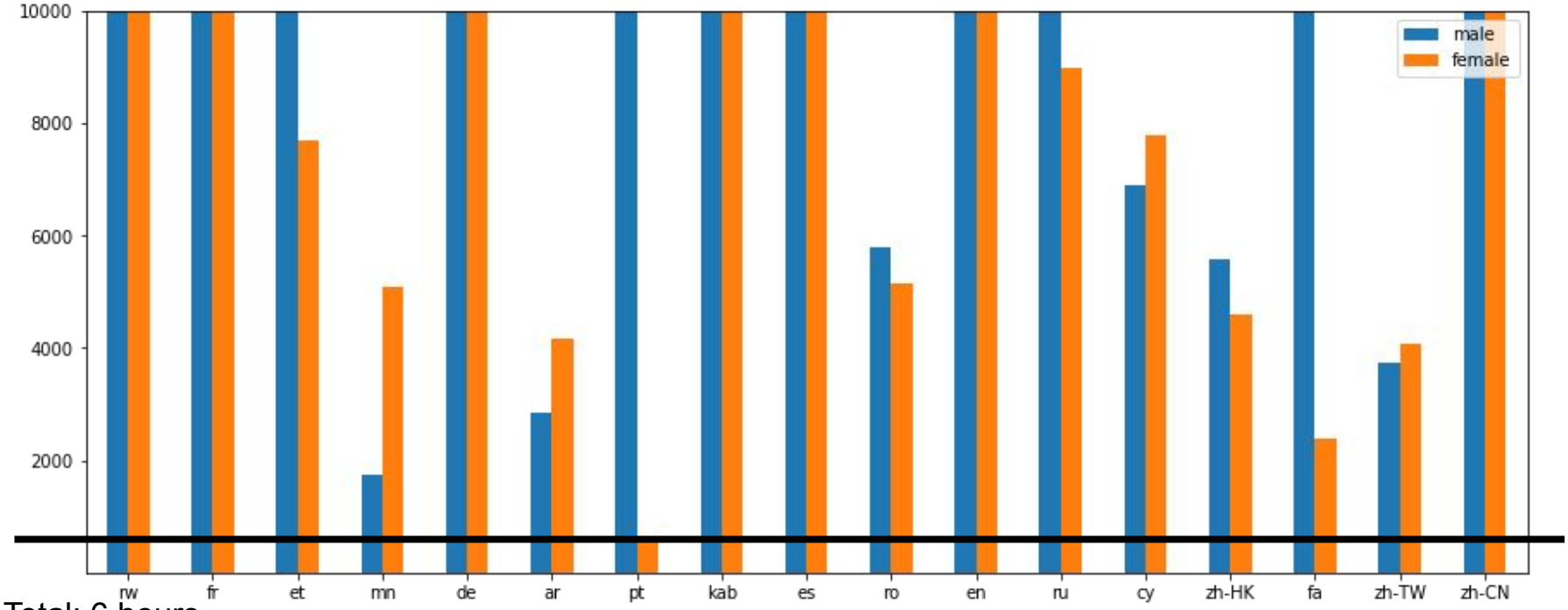
Speech Datasets

VoiseSet Imbalance: Train Set



Total: 6 hours

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Universal Sound Datasets

AudioSet
~ 20K audios
Length of each audio is 10s
Labelling: audio event tags
No raw audio
Downloading is illegal

FreeSound

Each audio is either CC0, CC-BY, Sampling+ or CC-BY-NC
Tags, description and other labels are available
~13Gb of uncompressed filtered wavs
~ 1 day of train set

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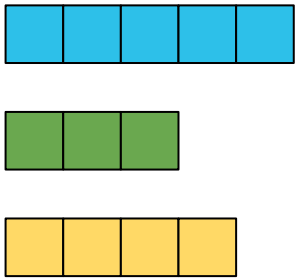
Big Data for Slow FileSystem

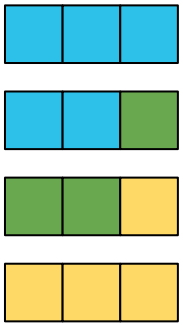
Data Pool

Audios splitted to frames



Batches

All frames of audio are used



- Fast
- Highly correlated batches

One frame per audio is used

- Slow (most read frames are dropped)
- Uncorrelated batches

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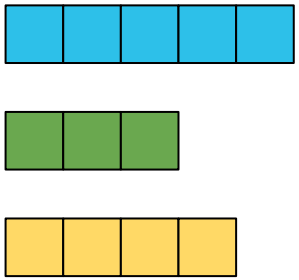
Big Data for Slow FileSystem

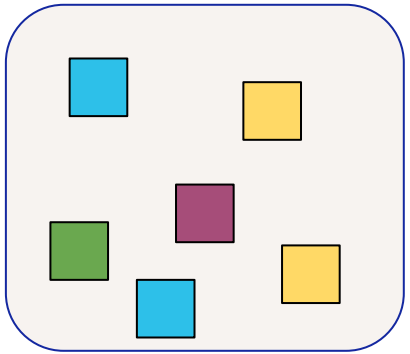
Data Pool

Audios splitted to frames



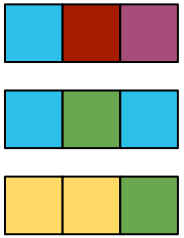
read audios until required pool size is reached

Pool



Invariant:
there are at least K frames in Pool before sampling

sample batches randomly from the pool



- Fast
- Weakly correlated batches

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Big Data for Slow FileSystem

Databases for Large Datasets

File System

HDF5 (Hierarchical Data Format)

LMDB (Lightning Memory-Mapped Database)

WebDataset (https://github.com/tmbdev/webdataset/)

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SOTAs

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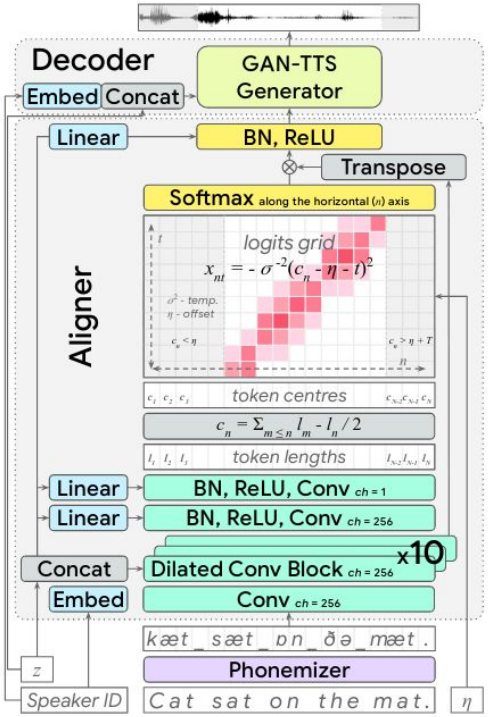
TTS Problem

End-to-End Adversarial Text-to-Speech (ICLR 2021 oral)



- Data - Multispeaker (MS) or Single Speaker (SS)
- Inputs - characters (Ch) or phonemes (Ph)
- Random Window Discriminators (RWD)
- Mel-spectrogram Discriminator (MSD)

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End-to-End Adversarial Text-to-Speech

Model	Data	Inputs	RWD	MSD	$\mathcal{L}_{\text{length}}$	$\mathcal{L}_{\text{pred}}$	Align	MOS
Natural Speech				-				4.55 ± 0.075
GAN-TTS (Bińkowski et al., 2020)				-				4.213 ± 0.046
WaveNet (van den Oord et al., 2016)				-				4.41 ± 0.069
Par. WaveNet (van den Oord et al., 2018)				-				4.41 ± 0.078
Tacotron 2 (Shen et al., 2018)				-				4.526 ± 0.066
No $\mathcal{L}_{\text{length}}$	MS	Ph	✓	✓	×	$\mathcal{L}''_{\text{pred}}$	MI	[does not train]
No $\mathcal{L}_{\text{pred}}$	MS	Ph	✓	✓	✓	×	MI	[does not train]
No Discriminators	MS	Ph	×	×	✓	$\mathcal{L}''_{\text{pred}}$	MI	1.407 ± 0.040
No RWDs	MS	Ph	×	✓	✓	$\mathcal{L}''_{\text{pred}}$	MI	2.526 ± 0.060
No Phonemes	MS	Ch	✓	✓	✓	$\mathcal{L}''_{\text{pred}}$	MI	3.423 ± 0.073
No MelSpecD	MS	Ph	✓	×	✓	$\mathcal{L}''_{\text{pred}}$	MI	3.525 ± 0.057
No Mon. Int.	MS	Ph	✓	✓	✓	$\mathcal{L}''_{\text{pred}}$	Attn	3.551 ± 0.073
No DTW	MS	Ph	✓	✓	✓	$\mathcal{L}_{\text{pred}}$	MI	3.559 ± 0.065
Single Speaker	SS	Ph	✓	✓	✓	$\mathcal{L}''_{\text{pred}}$	MI	3.829 ± 0.055
EATS (Ours)	MS	Ph	✓	✓	✓	$\mathcal{L}''_{\text{pred}}$	MI	4.083 ± 0.049

Input text: *In this work, we take on the challenging task of learning to synthesise speech from normalised text or phonemes in an end-to-end manner, resulting in models which operate directly on character or phoneme input sequences and produce raw speech audio outputs.*

Main model: Single speaker: No RWDs: No MelSpecD: No Discriminators:

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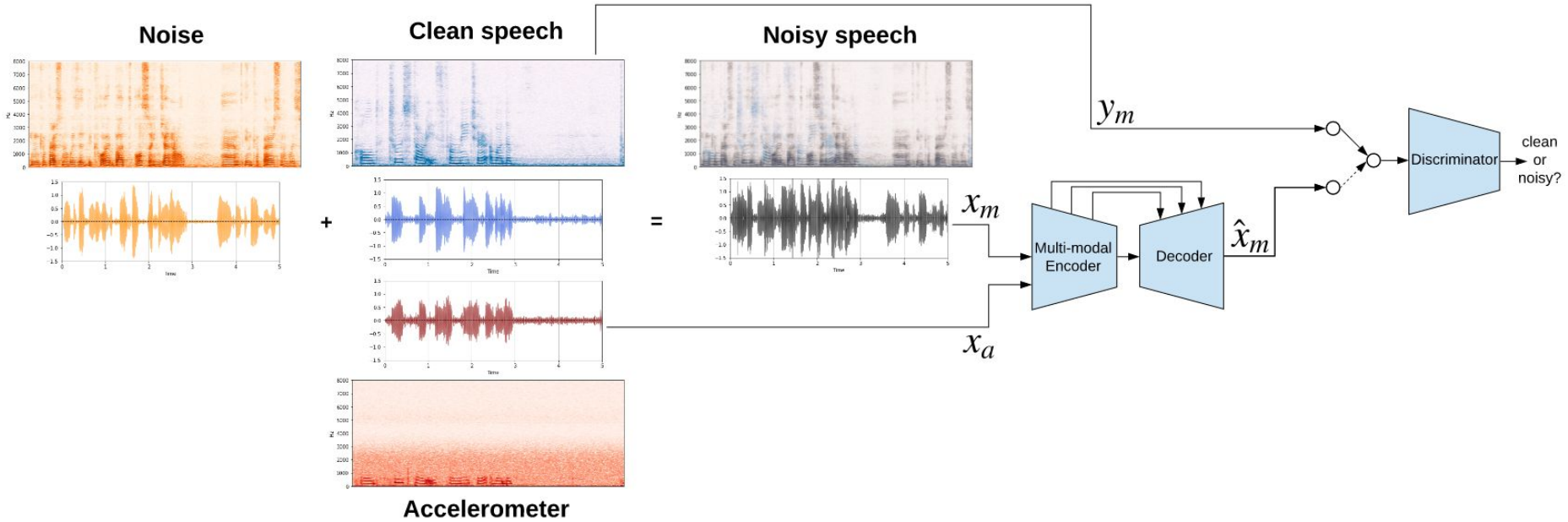
Multi-modal Speech Enhancement

SEANet: A Multi-modal Speech Enhancement Network



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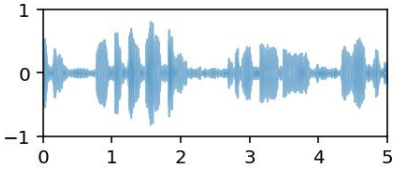
SEANet Results

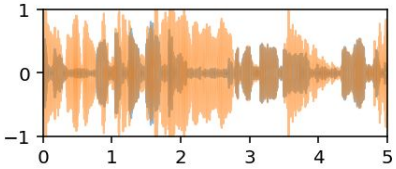
scenario	split	SEANet audio + accel	SEANet audio only
Mixed noise	1	9.9 ± 0.2	8.4 ± 0.2
	2	8.0 ± 0.2	7.9 ± 0.1
	3	8.3 ± 0.1	7.2 ± 0.2
	4	8.8 ± 0.1	8.1 ± 0.1
	5	9.9 ± 0.1	8.4 ± 0.1
	avg.	8.9	8.0
Mixed speech	1	10.1 ± 0.1	-0.9 ± 0.1
	2	8.6 ± 0.1	-0.9 ± 0.1
	3	9.2 ± 0.1	-0.7 ± 0.0
	4	9.0 ± 0.2	-1.0 ± 0.1
	5	11.1 ± 0.2	-0.9 ± 0.1
	avg.	9.6	-0.9

Mixed speech example:

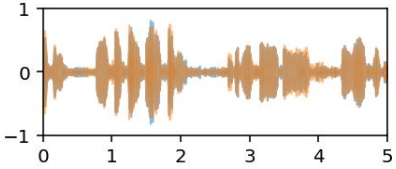
Clean sample:



Noisy sample:



Denoised sample:



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	5	9.9 ± 0.1	8.4 ± 0.1
	avg.	8.9	8.0
Mixed speech	1	10.1 ± 0.1	-0.9 ± 0.1
	2	8.6 ± 0.1	-0.9 ± 0.1
	3	9.2 ± 0.1	-0.7 ± 0.0
	4	9.0 ± 0.2	-1.0 ± 0.1
	5	11.1 ± 0.2	-0.9 ± 0.1
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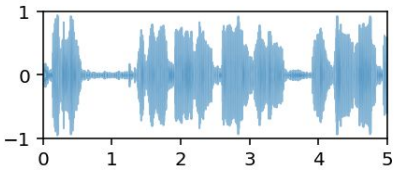
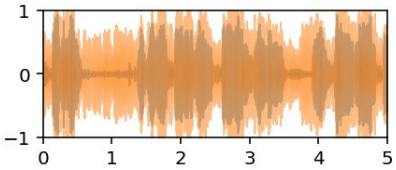
Mixed noise example:

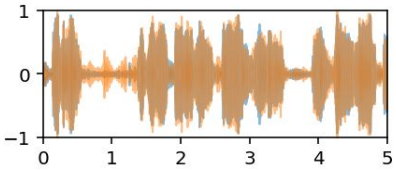
Clean sample:



Noisy sample:



Denoised sample:



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Diffusion Models

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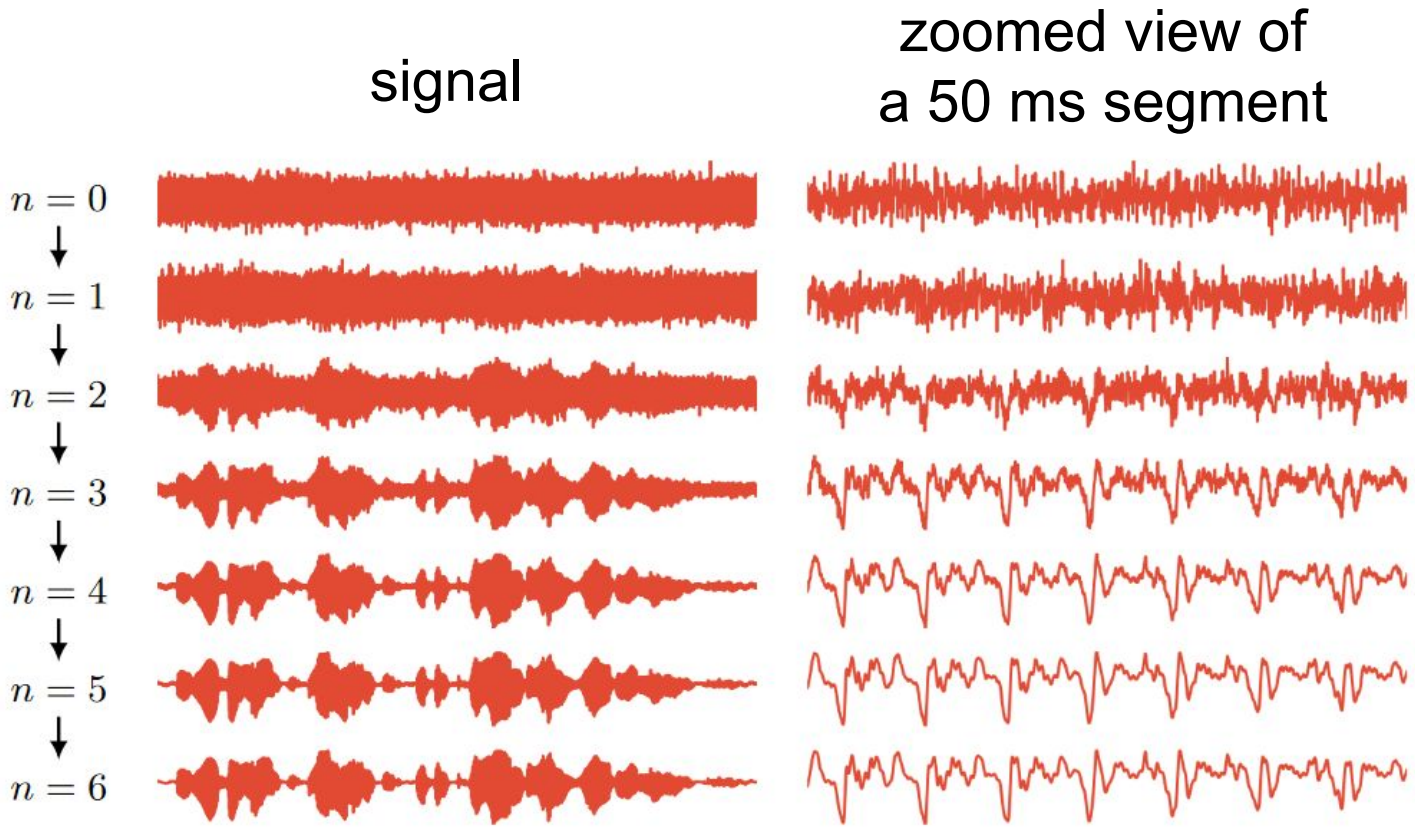
Diffusion Models



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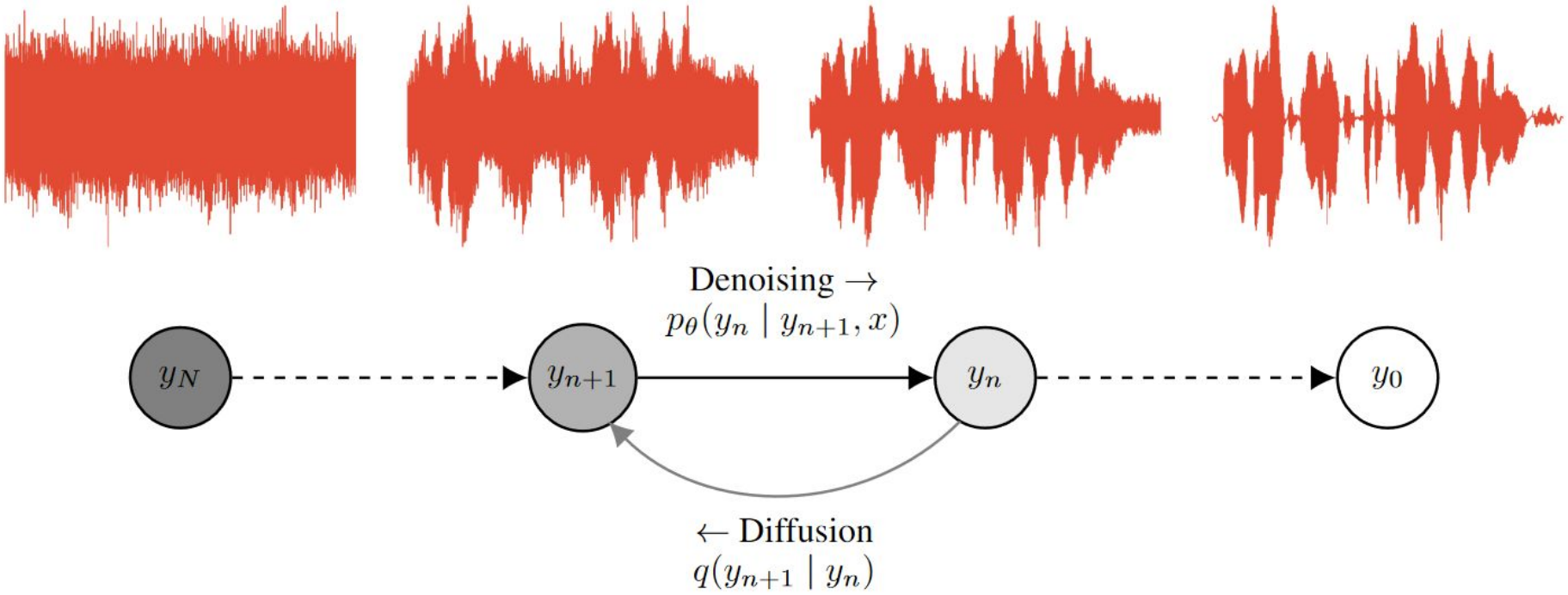
Diffusion Models



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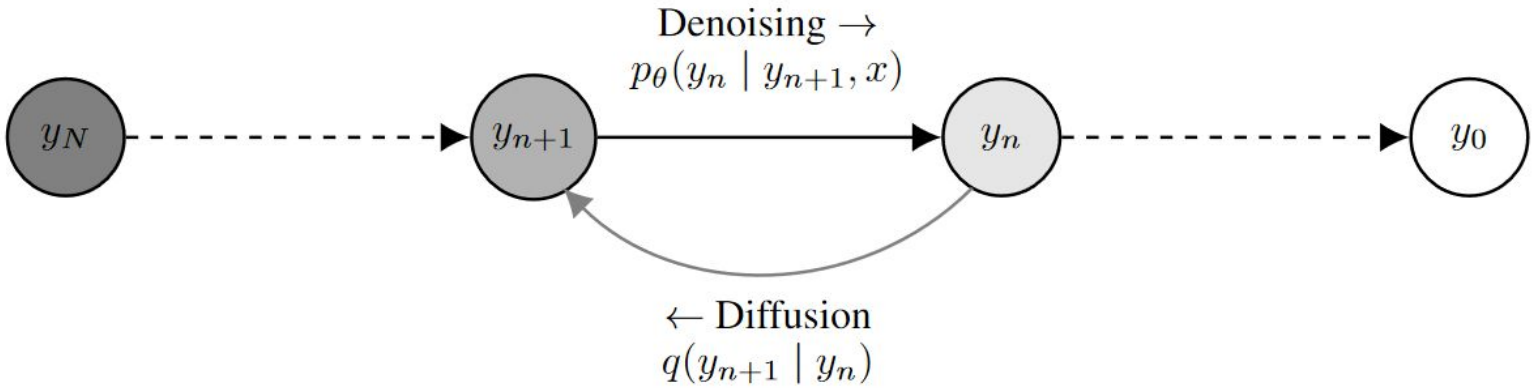
Diffusion Models



$$q(y_{n+1}|y_n) = \mathcal{N}(y_{n+1}|\sqrt{1-\beta_n}y_n, \beta_n I)$$

$$p(y_n|y_{n+1}) = \mathcal{N}(y_n|\mu(y_{n+1}, n), \sigma(y_{n+1}, n)^2 I)$$

$$p(y_N) = \mathcal{N}(y_N|0, I)$$

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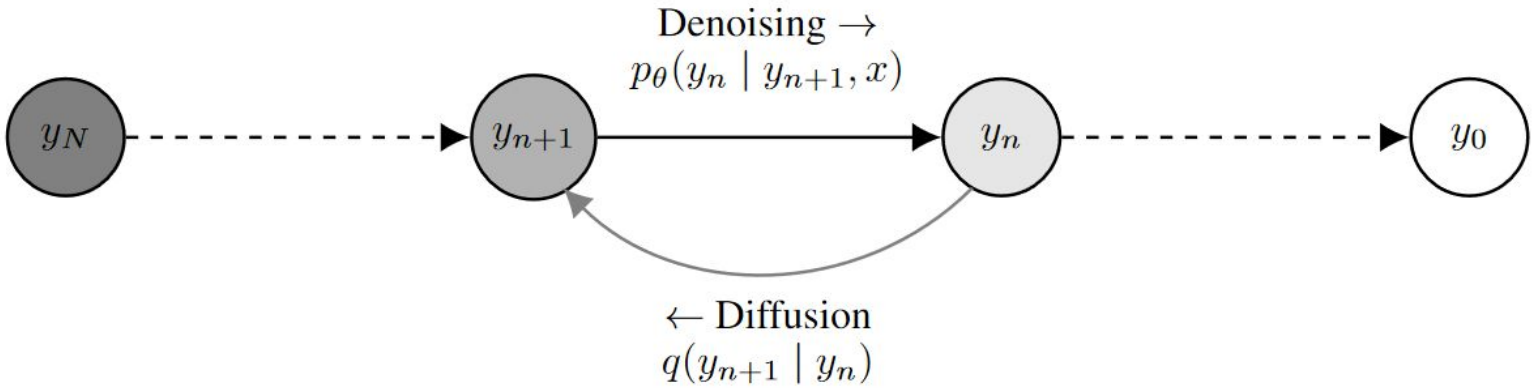
Diffusion Models



$$p_\theta(y_0) \geq \mathbb{E}_{y_1,\ldots,y_N \sim q(y_1,\ldots,y_N|y_0)} \log \frac{p_\theta(y_0, y_1, \ldots, y_N)}{q(y_1, \ldots, y_N|y_0)}$$

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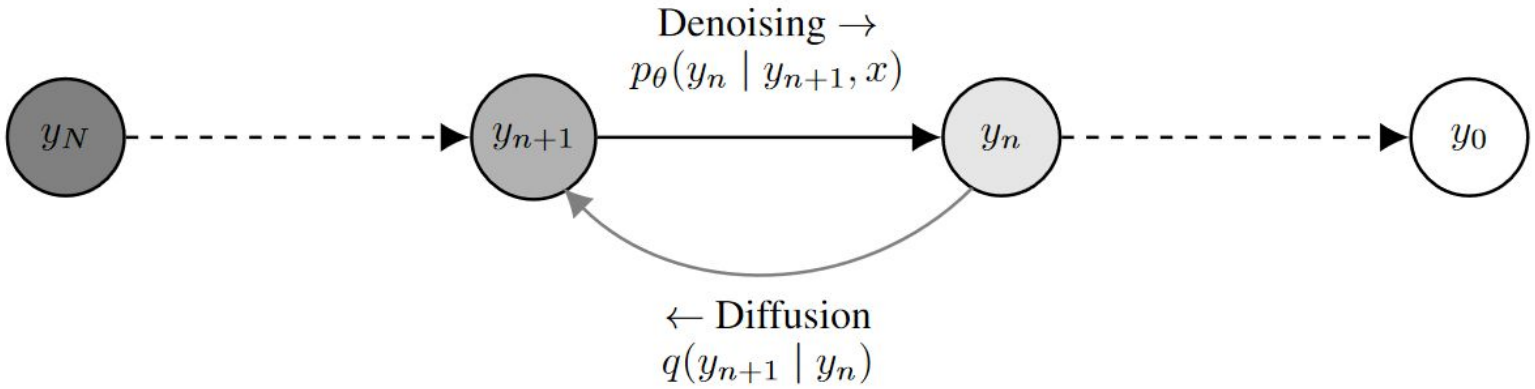
Diffusion Models



$$\mathbb{E}_{y_1,\dots,y_N \sim q(y_1,\dots,y_N|y_0)} \log \frac{p(y_N)p_\theta(y_{N-1}|y_N)\cdots p_\theta(y_0|y_1)}{q(y_1|y_0)\cdots q(y_N|y_{N-1})}$$

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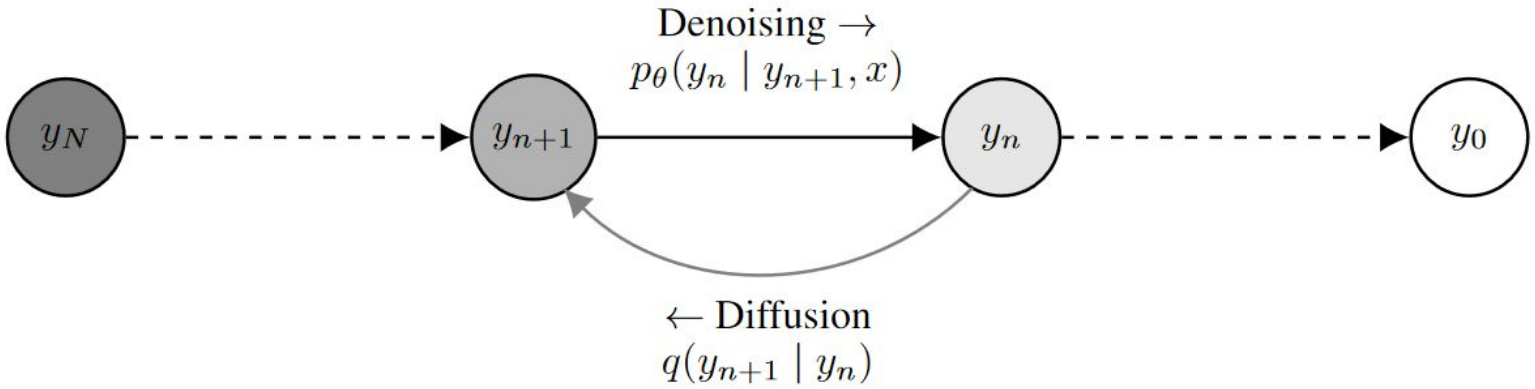
Diffusion Models



$$\mathbb{E}_{y_1,\dots,y_N \sim q(y_1,\dots,y_N|y_0)} \left(\sum_{n=0}^{N-1} \log \frac{p_\theta(y_n|y_{n+1})}{q(y_{n+1}|y_n)} + p(y_N) \right)$$

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References (ICLR 2021)

- WaveGrad (Google Brain)
- DiffWave (Baidu Research, NVIDIA)
- For images: Score-based Generative Modeling Through Stochastic Differential Equations (Stanford University, Google Brain)

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Thank You

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