Deep Learning Audio

Lecture 7

Pavel Severilov

Moscow Institute of Physics and Technology

2022

Outline

1. Neural Vocoders
2. WaveNet
3. Parallel WaveGAN
4. DiffWave

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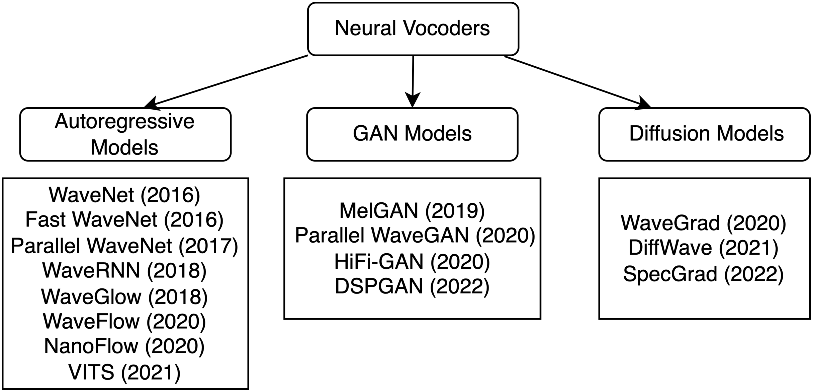
Neural Vocoders



Neural Vocoders

Model type	Model	MOS on LJ Speech
Autoregressive	WaveNet	3.68
	WaveRNN	3.96
GAN	MelGAN	3.73
	Parallel WaveGAN	3.99
Diffusion	WaveGrad	3.85
	DiffWave	**4.07**
	Griffin-Lim	3.68
	Ground Truth	**4.10**

AlBadawy et al., Vocbench: A Neural Vocoder Benchmark for Speech Synthesis, IEEE ICASSP, 2022

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WaveNet

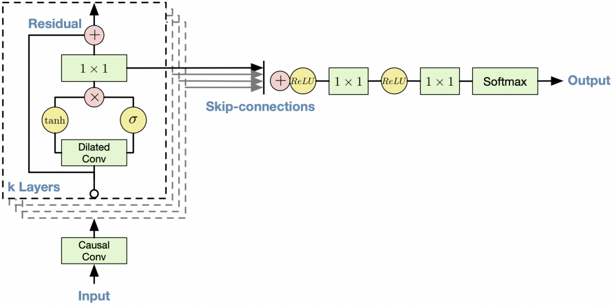


Figure: WaveNet architecture: uses **causal** dilated convolutions

- The joint probability of a waveform $x = \{x_1, \cdots, x_T\}$: $p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t \mid x_{1:t-1})$
- Each conditional $p(x_t \mid x_{1:t-1})$ models the distribution for the timestamp t

Oord et al., WaveNet: A Generative Model for Raw Audio, 2016

Causal Convolution

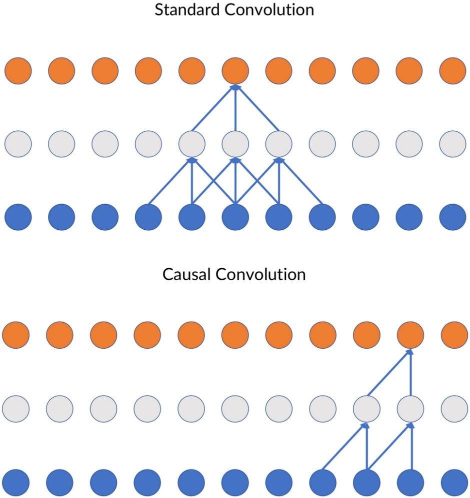


Figure: Standard vs causal convolutions. Causal makes convs autoregressive

Dilated Convolution

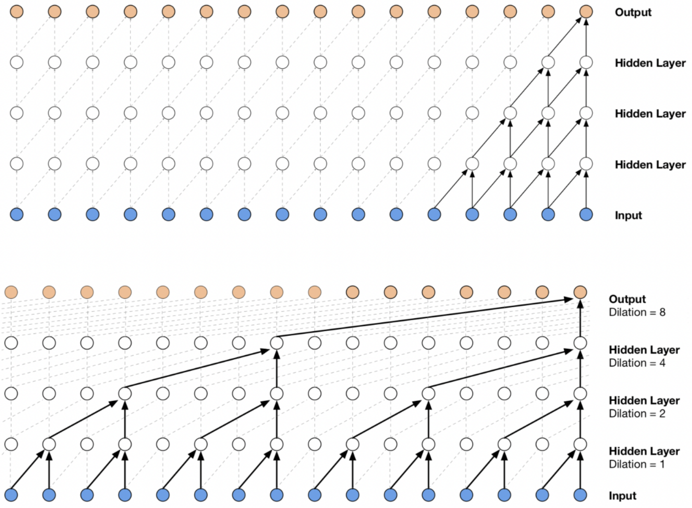
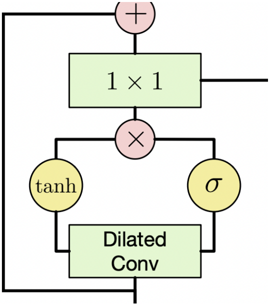


Figure: Non-dilated vs dilated causal convolutions. Dilated convs increase receptive fields

Conditional gated units

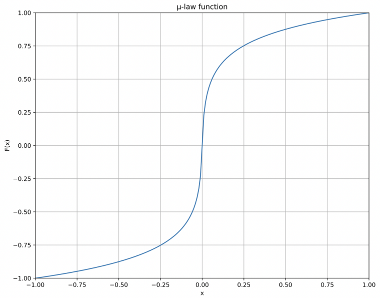


Gated activation unit as used in the gated PixelCNN + condition $\mathbf{y}$

$$\mathbf{z} = \tanh\left(W_{f,k} * \mathbf{x} + V_{f,k} * \mathbf{y}\right) \odot \sigma\left(W_{g,k} * \mathbf{x} + V_{g,k} * \mathbf{y}\right).$$

$*$ – convolution, $\odot$ – element-wise multiplication, $\sigma(\cdot)$ – sigmoid function, f and g – filter and gate, respectively, W – learnable convolution filter, V – learnable linear projection

Mu Law Encoding



- Raw audio $\sim$ 16-bit integer values $\Rightarrow$ softmax layer need to output 65,536 probabilities per timestep
- Solution: apply a μ-law transformation to the data, and then quantize it to 256 possible values:

$$f\left(x_t\right) = \operatorname{sign}(x_t)\frac{\ln\left(1+\mu\left|x_t\right|\right)}{\ln\left(1+\mu\right)}, \quad -1 < x_t < 1, \mu = 255$$

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Parallel WaveGAN

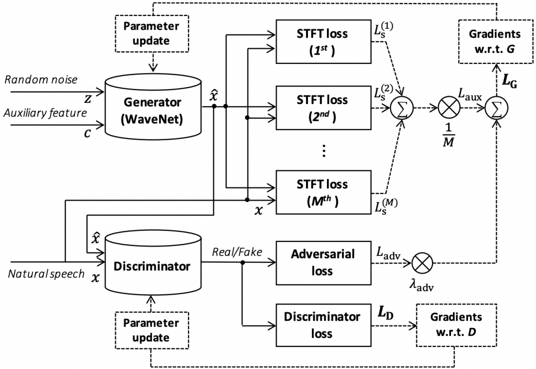
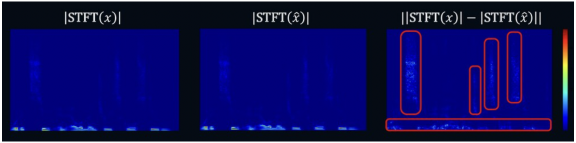


Figure: Parallel WaveGAN

Yamamoto et al., Parallel Wavegan: A Fast Waveform Generation Model Based on Generative Adversarial Networks with Multi-Resolution Spectrogram, IEEE ICASSP, 2020

STFT Loss



$$\mathcal{L}_{\mathrm{s}}(G) = \mathbb{E}_{\mathbf{z}\sim p(\mathbf{z}),\mathbf{x}\sim p_{data}}\left[\mathcal{L}_{\mathrm{sc}}(\mathbf{x},\hat{\mathbf{x}}) + \mathcal{L}_{\mathrm{mag}}(\mathbf{x},\hat{\mathbf{x}})\right]$$

$$\mathcal{L}_{\mathrm{sc}}(\mathbf{x},\hat{\mathbf{x}}) = \frac{\left\| |\mathrm{STFT}(\mathbf{x})| - \left|\mathrm{STFT}^{\mathrm{T}}(\hat{\mathbf{x}})\right| \right\|}{\| |STFT(\mathbf{x})| \|_F}$$

$$\mathcal{L}_{\mathrm{mag}}(\mathbf{x},\hat{\mathbf{x}}) = \frac{1}{N}\left\| \log|\mathrm{STFT}(\mathbf{x})| - \log|\mathrm{STFT}(\hat{\mathbf{x}})| \right\|_1$$

$$\mathcal{L}_{\mathrm{aux}}(G) = \frac{1}{M}\sum_{m=1}^{M}\mathcal{L}_{\mathrm{s}}^{(m)}(G), \mathrm{M} - \text{number of STFT losses}$$

Takaki et al., STFT Spectral Loss for Training a Neural Speech Waveform Model, IEEE ICASSP, 2019

GAN Loss

- Discriminator Loss:

$$\mathcal{L}_{\mathrm{D}}(G, D) = \mathbb{E}_{\mathbf{x} \sim p_{\mathrm{data}}}[(1 - D(\mathbf{x}))^2] + \mathbb{E}_{\mathbf{z} \sim N(0,I)}[D(G(\mathbf{z}))^2]$$

- Generator Loss

$$L_{\mathrm{adv}}(G, D) = \mathbb{E}_{\mathbf{z} \sim N(0,I)} \left[(1 - D(G(\mathbf{z})))^2\right]$$

$$L_{\mathrm{G}}(G, D) = L_{\mathrm{aux}}(G) + \lambda_{\mathrm{adv}} L_{\mathrm{adv}}(G, D)$$

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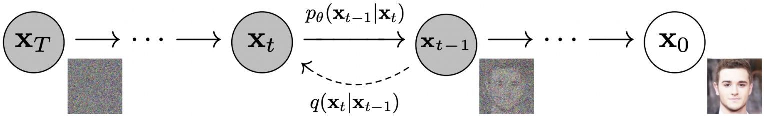
Diffusion models idea



- **Diffusion probabilistic model**: parameterized Markov chain from data x_0 to the latent variable x_T

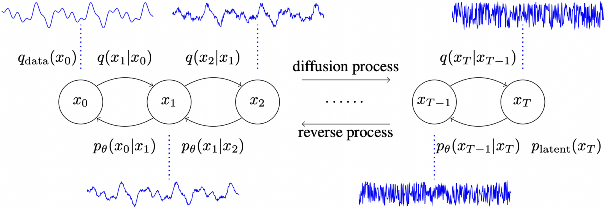
$$q(x_1, \cdots \cdot x_T|x_0) = \prod_{t=1}^{T} q(x_t|x_{t-1})$$

- **Reverse process**: Markov chain from x_T to x_0 parameterized by θ:

$$p_{\mathrm{latent}}(x_T) = \mathcal{N}(0, I), \quad p_\theta(x_0, \cdots, x_{T-1}|x_T) = \prod_{t=1}^{T} p_\theta(x_{t-1}|x_t)$$

Ho et al., Denoising Diffusion Probabilistic Models, NeurIPS Proceedings, 2020

DiffWave



- **Sampling**: reverse process $x_T \sim \mathcal{N}(0, I)$, $x_{t-1} \sim p_\theta(x_{t-1}|x_t)$ for $t = T, T-1, \cdots, 1$. x_0 – sampled data.
- **Training**: $p_\theta(x_0) = \int p_\theta(x_0, \cdots, x_{T-1}|x_T) \cdot p_{\text{latent}}(x_T) \mathbf{d}x_{1:T}$ (likelihood) is intractable to calculate $\Rightarrow$ model trained by maximizing its variational lower bound (ELBO):

$$\mathbb{E}_{q_{\text{data}}(x_0)} \log p_\theta(x_0) \geq$$
$$\geq \mathbb{E}_{q(x_0, \cdots, x_T)} \log \frac{p_\theta(x_0, \cdots, x_{T-1}|x_T) \cdot p_{\text{latent}}(x_T)}{q(x_1, \cdots, x_T|x_0)} := \text{ELBO}$$

Kong et al., DiffWave: A Versatile Diffusion Model for Audio Synthesis, ICLR, 2021

DiffWave: advantages

- **Non-autoregressive**: much faster than WaveNet
- **Compact model**: smaller footprint than flow-based models
- No auxiliary losses in training (e.g., spectrogram-based losses): **no mode collapse** like in GANs/VAEs