Diffusion-based Vocoding for Real-Time Text-To-Speech

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LTH

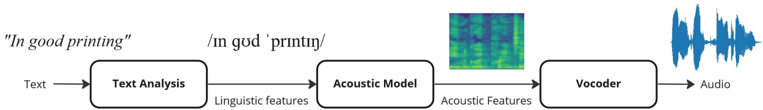
March 21, 2023

Presentation Layout

- Problem Introduction
- Past Work
- Problem Statement / Goals
- Quick background
- TODO: Add more

Typical TTS Pipeline

Text $\longrightarrow$ Speech



Text Analysis Acoustic Model Vocoder

The Phase Reconstruction Problem

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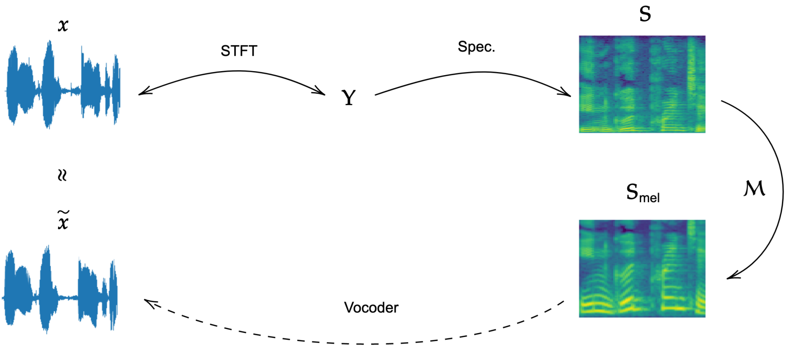

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- GANs (HiFi-GAN)
- Diffusion (DiffWave)
- ...and more

Diffusion

- Main idea
- Where do Neural Networks come in?
- How can it be used for vocoding?

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- Also easy to *destroy* data into noise, hard to do the inverse
- Teach a model to perform each "denoising" step

Forward Process

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Variance schedule $\beta_t \in [0,1]$: At which "rate" we tend towards a unit Gaussian

Forward Process

Quick way to get a noisy sample $\boldsymbol{x}_t$:

$$
\begin{aligned}
\bar{\alpha}_t &= \prod_{i=1}^{T}(1-\beta_i) \\
\boldsymbol{x}_t &\sim q(\boldsymbol{x}_t \mid \boldsymbol{x}_0) = \mathcal{N}(\boldsymbol{x}_t\,;\,\sqrt{\bar{\alpha}_t}\boldsymbol{x}_0, \sqrt{1-\bar{\alpha}_t}\boldsymbol{I}), \\
\boldsymbol{x} &= \sqrt{\bar{\alpha}_t}\boldsymbol{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\varepsilon}, \quad \boldsymbol{\varepsilon} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})
\end{aligned}
$$

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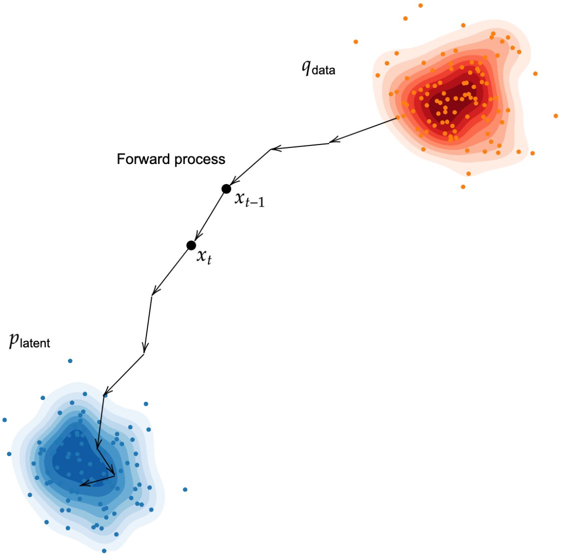

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- Model each transition as $p_\theta(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_{\boldsymbol{t}}) = \mathcal{N}(\boldsymbol{x}_{t-1}\,;\, \boldsymbol{\mu}_\theta(\boldsymbol{x}_t, t), \boldsymbol{\Sigma}_\theta(\boldsymbol{x}_t, t))$

Backward Process