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

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LTH

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Presentation Layout

- Problem Introduction
- Past Work
- Problem Statement
- Diffusion Models
- Improvements
- Method & Results
- Discussion & Future Work

Typical TTS Pipeline

Text $\longrightarrow$ Speech

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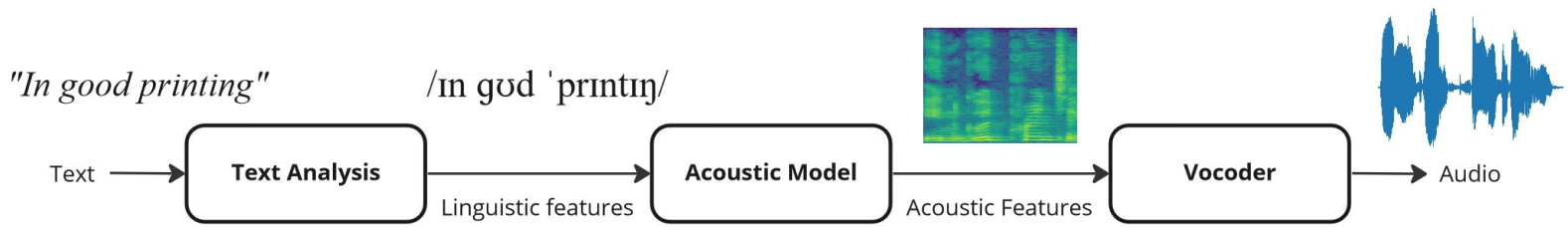

Text Analysis Acoustic Model Vocoder

The Phase Reconstruction Problem

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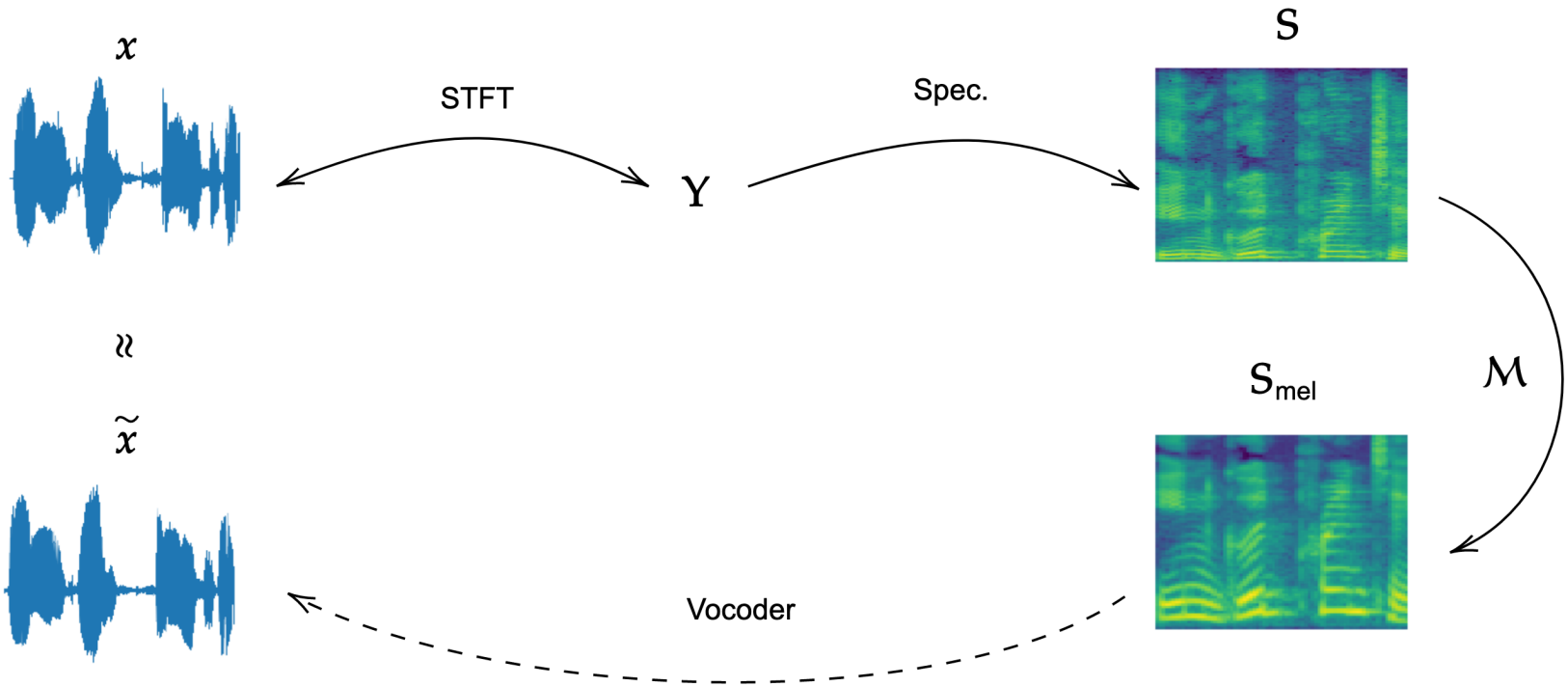

The Phase Reconstruction Problem

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- Diffusion (DiffWave)
- ...and more

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  - Variance schedule
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  - Noise prior
- How does a vocoder trained on audio from one speaker generalize to another?
- Can such a model generate audio faster than real-time?

Diffusion

- How can it be used for vocoding?

Diffusion

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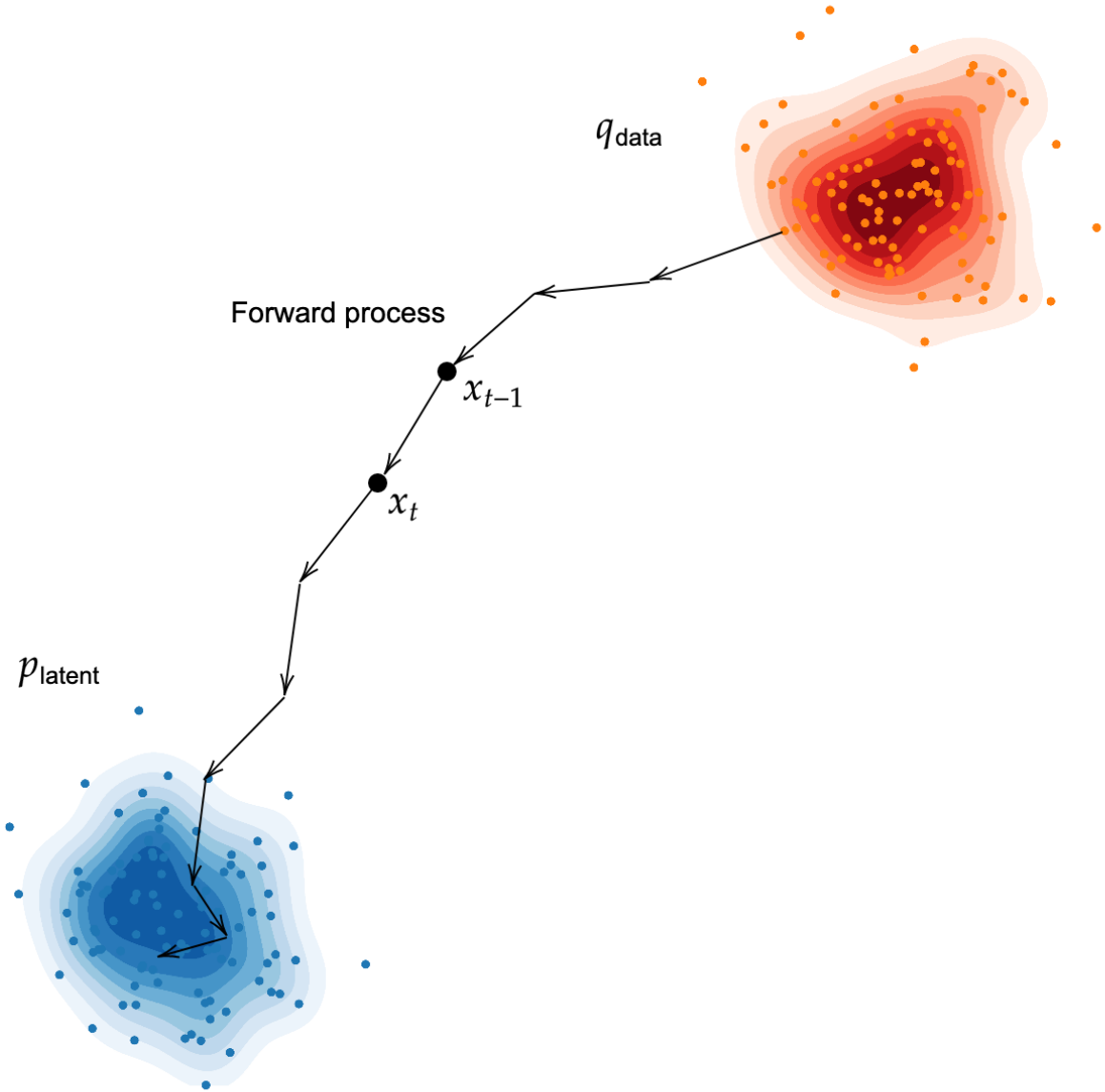
- Teach a model to perform the inverse transformation in several steps

Forward Process



Forward Process

- Choose a number of diffusion steps T
- Decide how "big" steps we take via a variance schedule β_t
- Each sample is drawn as
  $q(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-1}) = \mathcal{N}(\boldsymbol{x}_t\,; \sqrt{1-\beta_t}\boldsymbol{x}_{t-1}, \beta_t \boldsymbol{I})$

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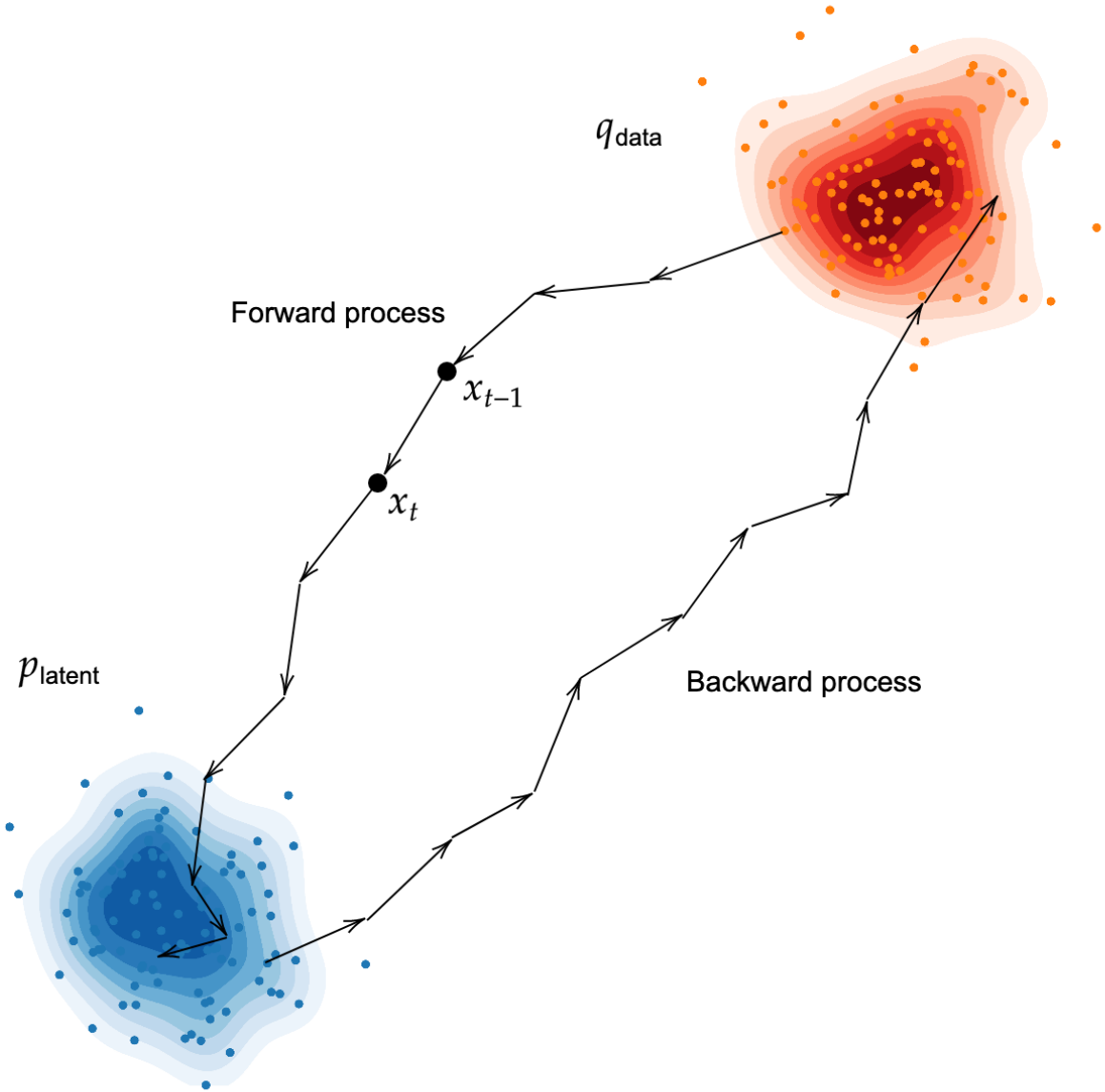
- Training: sample t uniformly over $[1, T]$

Backward Process



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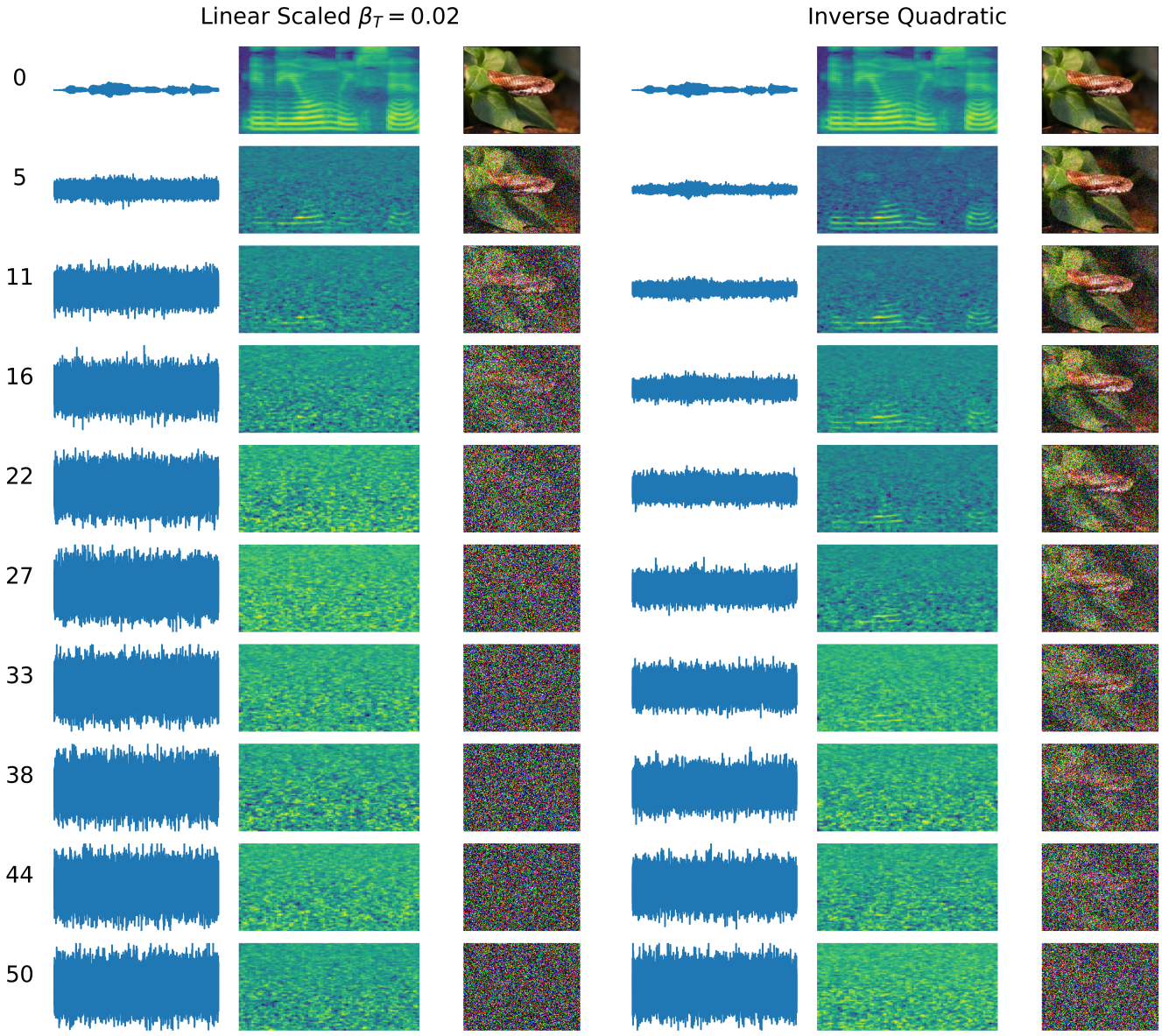

Main Considerations

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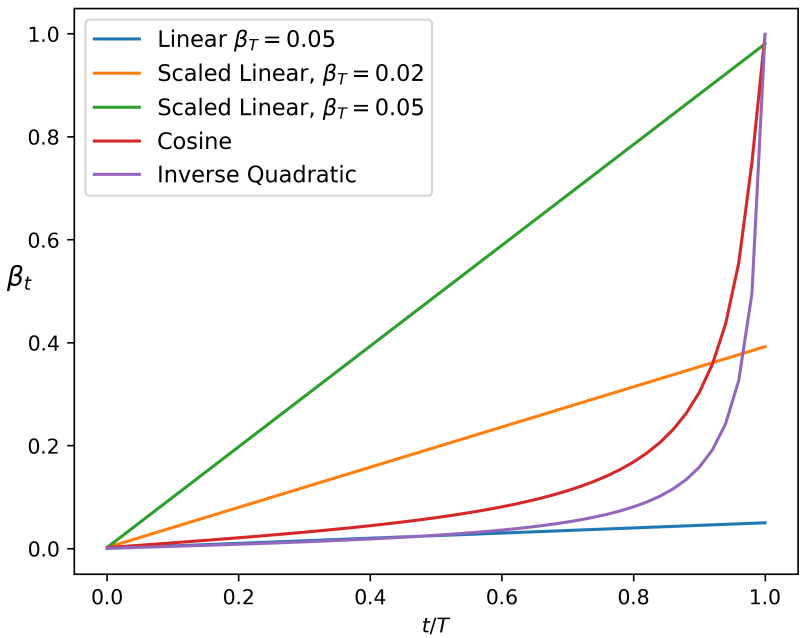
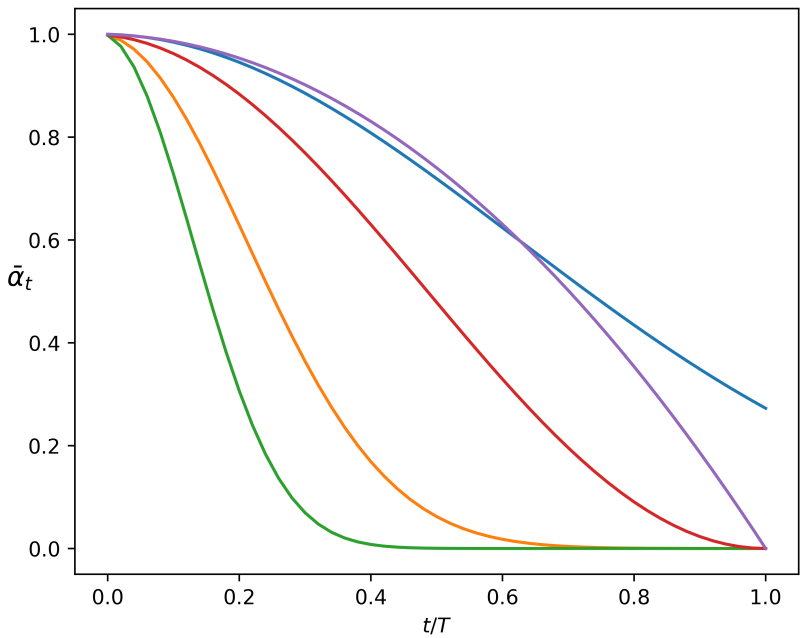
- Uniform vs importance sampling of t

Variance Schedule

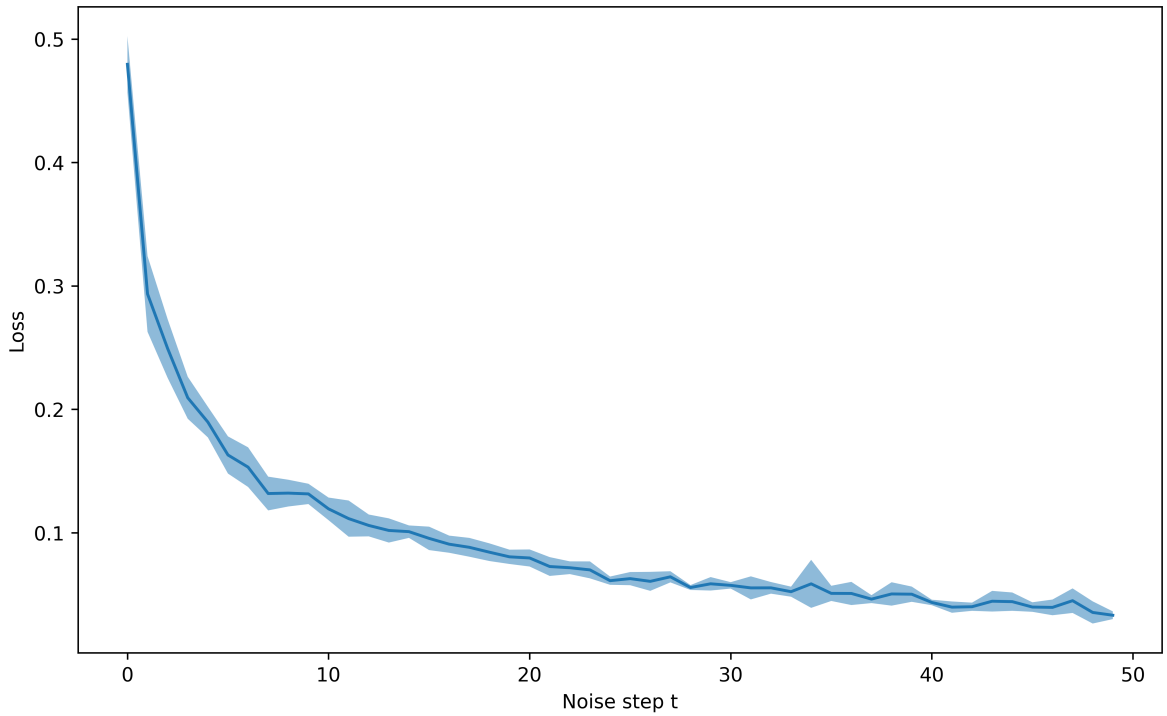
- We do not want to reach white noise too early
- Smooth transition from data to noise





Importance Sampling

Gradient is noisy when training! Most likely from a skewed loss:



Hypothesis: some steps are harder to learn than others

Idea: sample t weighted by the loss

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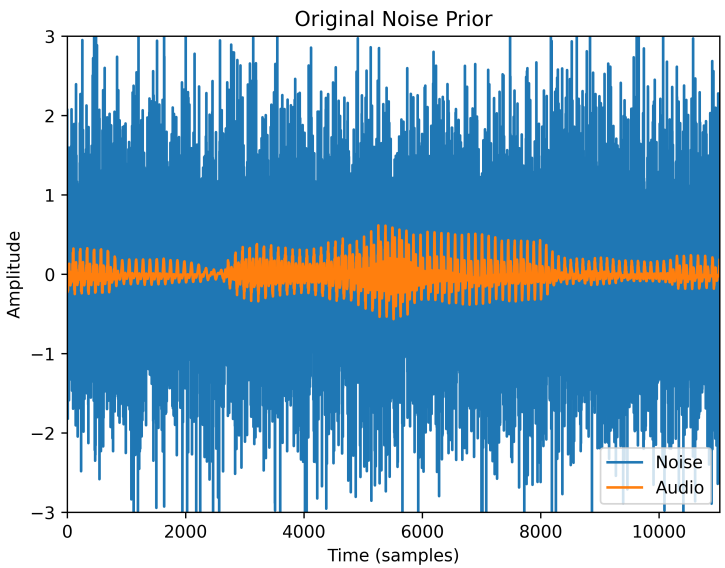

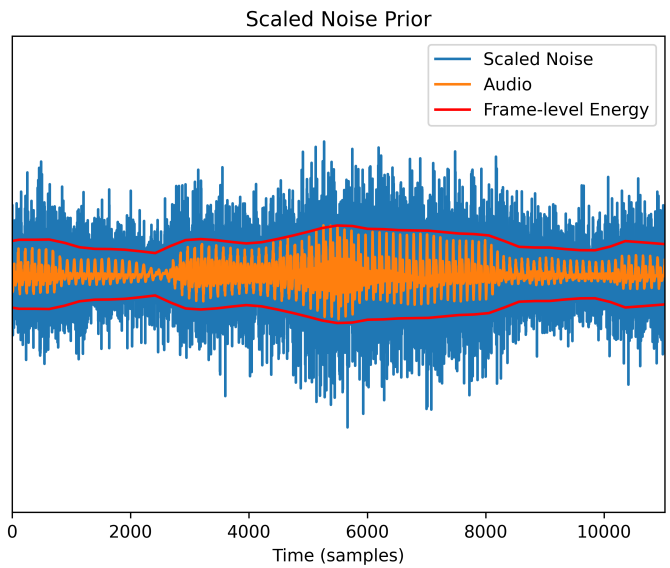

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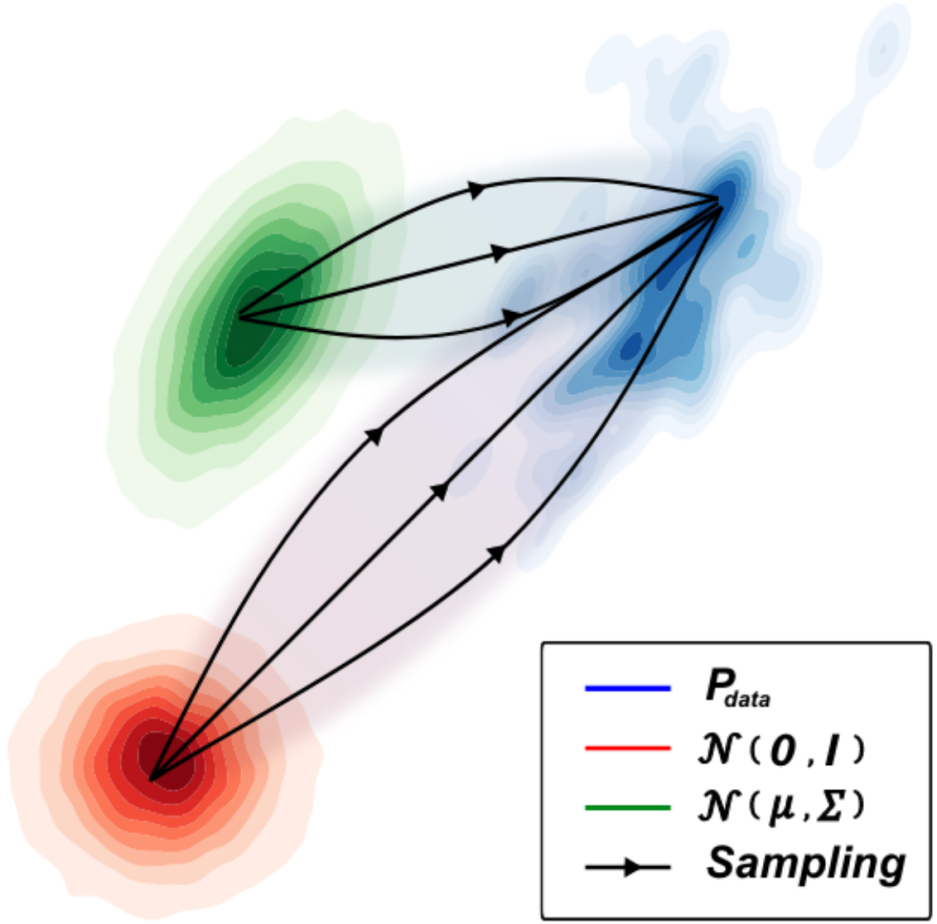

Metrics

- Approximate Mean Opinion Score (AMOS)
  - Scale 1-5, finetuned audio model
- Log-mel Spectrogram Mean Absolute Error (LS-MAE)
- Peak Signal-to-Noise Ratio (PSNR)
- Multi-resolution STFT Error (MRSE)

Data

- LJ Speech
  - Training set
  - 24 hours of speech from audiobooks
  - 13 100 audio files, 95 in test set
  - Sample rate: 22 050 Hz
- LibriTTS
  - Test set of other speaker
  - 515 audio files

Model

- DiffWave, based on dilated convolutions
- 2.6M parameters, $T = 50$
- Short inference schedule with $T = 6$

Method & Results

Experiments

- Variance Schedules
- Time-step Sampling
- Noise Prior
- Model Size
- Inference Speed
- Longer Training

Method & Results: Variance Schedule

Objective Metrics:

	LJ-test			Libri-test		
Model	**LS-MAE ↓**	**PSNR ↑**	**MRSE ↓**	**LS-MAE ↓**	**PSNR ↑**	**MRSE ↓**
Griffin-Lim	0.302	25.517	1.131	0.227	27.011	1.027
Linear $\beta_T = 0.05$	0.550	20.331	1.279	0.680	23.510	1.341
Scaled Linear $\beta_T = 0.05$	0.779	17.340	1.593	0.818	20.510	1.522
Scaled Linear $\beta_T = 0.02$	0.727	18.077	1.511	0.812	21.056	1.483
Cosine	0.699	17.829	1.512	0.712	20.982	1.463
Inverse Quadratic	0.541	20.190	1.270	0.698	23.524	1.345

Method & Results: Variance Schedule

Subjective Metrics:

Model	**AMOS** ↑ (LJ-test)	**AMOS** ↑ (Libri-test)
Ground Truth	3.63 ± 0.26	2.68 ± 0.38
Griffin-Lim	1.57 ± 0.15	1.35 ± 0.18
Linear $\beta_T = 0.05$	2.88 ± 0.23	2.14 ± 0.26
Scaled Linear $\beta_T = 0.05$	2.27 ± 0.17	1.77 ± 0.26
Scaled Linear $\beta_T = 0.02$	2.40 ± 0.21	1.82 ± 0.25
Cosine	2.39 ± 0.19	1.83 ± 0.27
Inverse quadratic	2.89 ± 0.23	2.17 ± 0.27

Method & Results: Variance Schedule

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- Original Linear and Inverse Quadratic best
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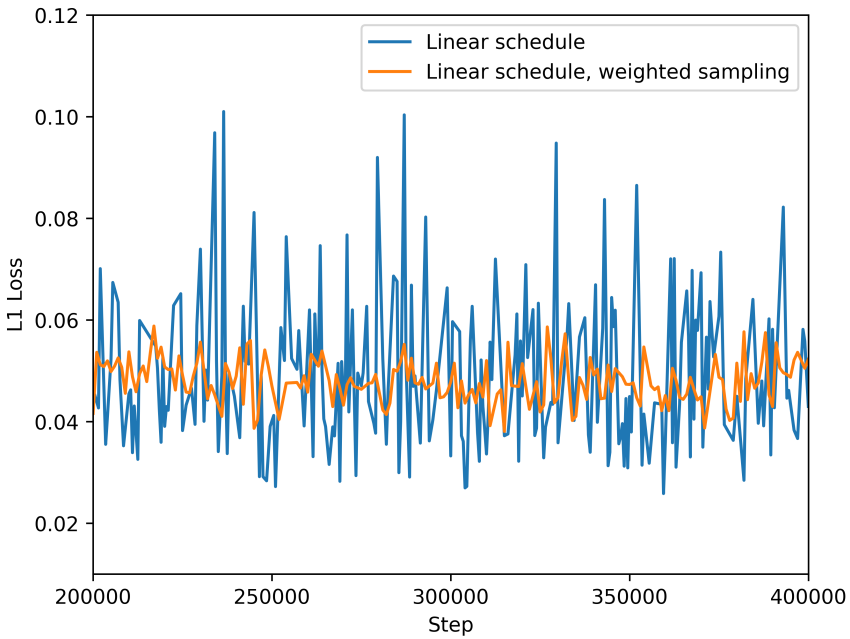
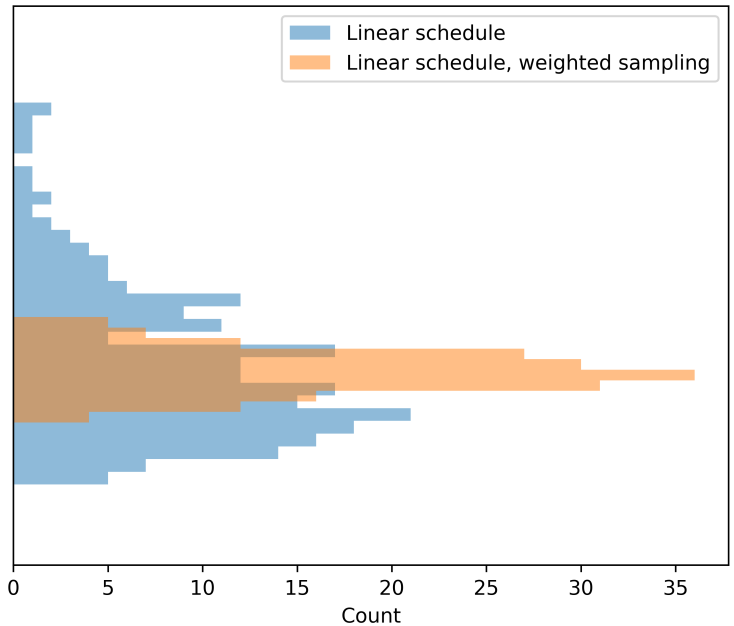
- Griffin Lim best objective metrics, worst AMOS

Method & Results: Time-step Sampling





Method & Results: Time-step Sampling

Objective Metrics:

	LJ-test			Libri-test		
Model	**LS-MAE ↓**	**PSNR ↑**	**MRSE ↓**	**LS-MAE ↓**	**PSNR ↑**	**MRSE ↓**
Uniform sampling	0.550	20.331	1.279	0.680	23.510	1.341
Uniform sampling (fast)	0.562	20.069	1.314	0.684	23.461	1.379
Importance sampling	0.519	19.494	1.285	0.605	23.485	1.287
Importance sampling (fast)	0.518	19.333	1.318	0.587	23.318	1.309

Method & Results: Time-step Sampling

Subjective Metrics:

Model	**AMOS** ↑ (LJ-test)	**AMOS** ↑ (Libri-test)
Ground truth	3.63 ± 0.26	2.68 ± 0.38
Uniform sampling	2.88 ± 0.23	2.14 ± 0.26
Uniform sampling (fast)	2.75 ± 0.24	2.07 ± 0.25
Importance sampling	2.87 ± 0.25	2.15 ± 0.28
Importance sampling (fast)	2.78 ± 0.24	2.09 ± 0.27

Method & Results: Time-step Sampling

- Loss variance reduced

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Method & Results: Time-step Sampling

- Loss variance reduced
- Both objective & subjective scores similar
- Not significantly more robust to shorter schedule

Method & Results: Noise Prior

Objective Metrics:

	LJ-test			Libri-test		
Model	**LS-MAE ↓**	**PSNR ↑**	**MRSE ↓**	**LS-MAE ↓**	**PSNR ↑**	**MRSE ↓**
DiffWave	0.550	20.331	1.279	0.680	23.510	1.341
DiffWave (fast)	0.562	20.069	1.314	0.684	23.461	1.379
PriorGrad	0.474	27.499	1.343	0.615	24.731	1.564
PriorGrad (fast)	0.455	27.236	1.336	0.567	24.798	1.518

Method & Results: Noise Prior

Subjective Metrics:

Model	**AMOS** ↑ (LJ-test)	**AMOS** ↑ (Libri-test)
Ground truth	3.63 ± 0.26	2.68 ± 0.38
DiffWave	2.88 ± 0.23	2.14 ± 0.26
DiffWave (fast)	2.75 ± 0.24	2.07 ± 0.25
PriorGrad	3.00 ± 0.29	2.19 ± 0.33
PriorGrad (fast)	2.74 ± 0.29	2.00 ± 0.28

Method & Results: Noise Prior

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- Slightly worse performance for short schedule

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- Slightly worse performance for short schedule
- Higher MRSE might indicate overfitting

Method & Results: Model Size

How does model size affect performance?

Objective Metrics:

	LJ-test			Libri-test		
Model	**LS-MAE ↓**	**PSNR ↑**	**MRSE ↓**	**LS-MAE ↓**	**PSNR ↑**	**MRSE ↓**
Base	0.550	20.331	1.279	0.680	23.510	1.341
Base + IQ + IS	0.616	19.154	1.381	0.745	23.197	1.389
Base (fast)	0.562	20.069	1.314	0.684	23.461	1.379
Base + IQ + IS (fast)	0.634	18.800	1.421	0.766	23.145	1.437
Small	0.547	19.860	1.311	0.692	22.752	1.409
Small + IQ + IS	0.611	18.945	1.330	0.736	23.170	1.392
Small (fast)	0.535	19.678	1.342	0.691	22.787	1.408
Small + IQ + IS (fast)	0.615	18.907	1.358	0.730	23.160	1.420

Method & Results: Model Size

Subjective Metrics:

Model	**RTF** ↓ (CPU)	**RTF** ↓ (GPU)	**AMOS** ↑ (LJ-test)	**AMOS** ↑ (Libri-test)
Base	44.38	0.57	2.88 ± 0.23	2.14 ± 0.26
Base + IQ + IS	48.61	0.56	2.74 ± 0.23	2.12 ± 0.26
Base (fast)	5.26	0.061	2.75 ± 0.24	2.07 ± 0.25
Base + IQ + IS (fast)	5.44	0.061	2.68 ± 0.22	2.06 ± 0.25
Small	33.07	0.43	2.76 ± 0.22	2.07 ± 0.26
Small + IQ + IS	33.28	0.41	2.76 ± 0.21	2.09 ± 0.27
Small (fast)	4.04	0.046	2.65 ± 0.22	2.07 ± 0.27
Small + IQ + IS (fast)	4.10	0.046	2.63 ± 0.22	2.00 ± 0.25

Method & Results: Model Size

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Method & Results: Model Size

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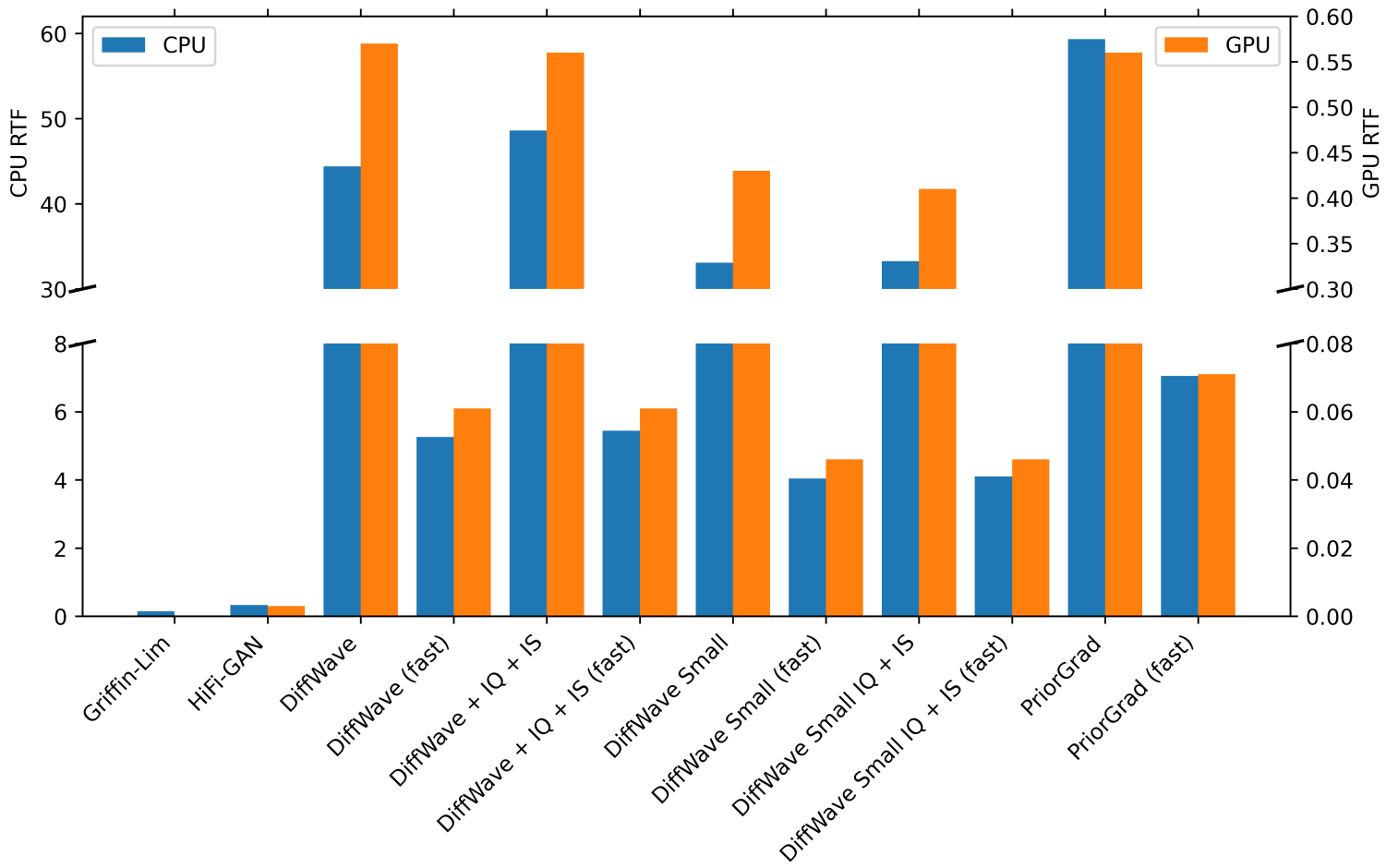
- Minimal difference in audio quality
- IQ + IS did not result in a better smaller model

Method & Results: Inference Speed

How do the models compare in terms of inference speed?



Method & Results: Inference Speed

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- Fast sampling: 12% of steps, 9x speedup
- Still 15 times slower than HiFi-GAN

Method & Results: Longer Training

How does longer training affect performance?

Objective Metrics:

	LJ-test			Libri-test		
Model	**LS-MAE**	**PSNR**	**MRSE**	**LS-MAE**	**PSNR**	**MRSE**
HiFi-GAN (2.5M)	0.345	23.854	1.236	0.261	27.673	1.155
DiffWave (500k)	0.550	20.331	1.279	0.680	23.510	1.341
DiffWave (2.5M)	0.568	21.049	1.250	0.759	23.678	1.370
DiffWave (2.5M) (fast)	0.561	20.963	1.259	0.745	23.745	1.383
DiffWave + IQ + IS (2.5M)	0.577	21.282	1.252	0.791	23.754	1.379
DiffWave + IQ + IS (2.5M) (fast)	0.576	21.143	1.271	0.781	23.822	1.392

Method & Results: Longer Training

Subjective Metrics:

Model	**AMOS** (LJ-test)	**AMOS** (Libri-test)
Ground truth	3.63 ± 0.26	2.68 ± 0.38
HiFi-GAN (2.5M)	2.70 ± 0.25	2.29 ± 0.38
DiffWave (500K)	2.88 ± 0.23	2.14 ± 0.26
DiffWave (2.5M)	3.05 ± 0.25	2.31 ± 0.30
DiffWave (2.5M) (fast)	2.99 ± 0.23	2.24 ± 0.29
DiffWave + IQ + IS (2.5M)	3.05 ± 0.25	2.30 ± 0.29
DiffWave + IQ + IS (2.5M) (fast)	2.98 ± 0.42	2.23 ± 0.27

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- IQ + IS resulted in similar scores to base

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Main takeaways:

- Possible to perform vocoding using diffusion on GPU, slow on CPU, further speedup possible

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- Objective Metrics not always reliable

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- Possible to perform vocoding using diffusion on GPU, slow on CPU, further speedup possible
- Choice of schedule important, should not reach noise too early
- Importance sampling: not more robust, but better variance
- Able to generalize to another speaker, AMOS hard to interpret
- Objective Metrics not always reliable
- Similar quality to HiFi-GAN, but slower

Future Work

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- Higher sample rate, Distillation, Super-resolution

Thank you!