Generative Diffusion Models for Audio Inpainting

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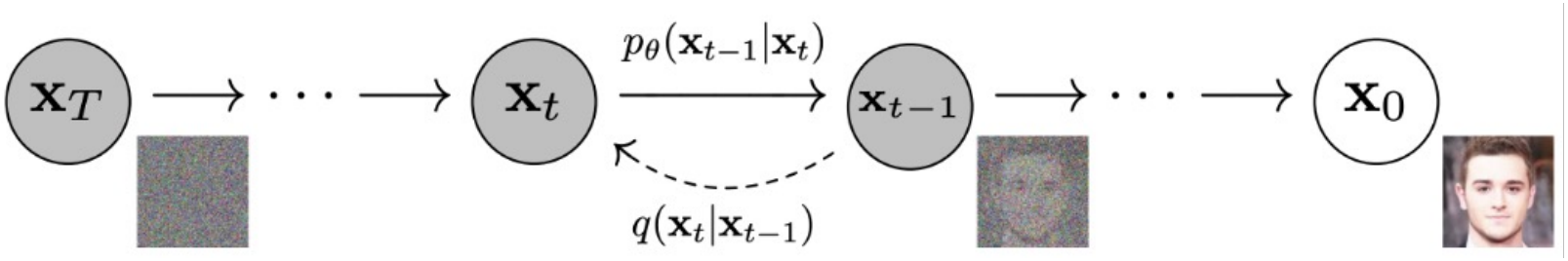
Diffusion models

Main concepts

- Iteratively transform an initial noise distribution into a target distribution
- Generate high-quality samples and perform denoising and inpainting



Forward process: using a variance schedule, small amount of Gaussian noise is added to the sample for *T* steps

$$q(\mathbf{x}_t|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t}\mathbf{x}_0, (1-\bar{\alpha}_t)\mathbf{I})$$

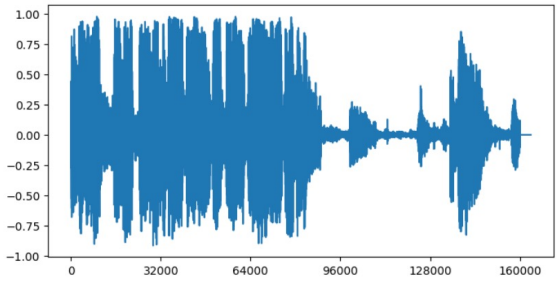
Reverse process: the noise added at each step of the forward process is predicted and removed from the sample

$$q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\mu}(\mathbf{x}_t, \mathbf{x}_0), \tilde{\beta}_t\mathbf{I})$$

Spectrograms

A **spectrogram** is a visual representation that displays the frequency content of an audio signal over time

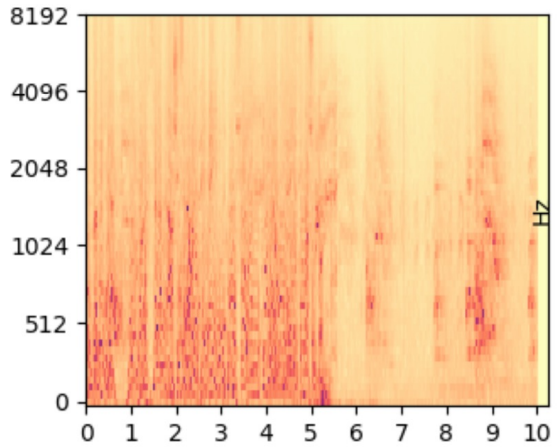
Vector 1 x 160000 (10 seconds)



(a) Audio wave

Sparsity → Computationally demanding and Risk of overfitting

Matrix 1024 x 64 (10 seconds)



(b) Spectrogram

Dense representation → Capture long term dependencies and Efficient training

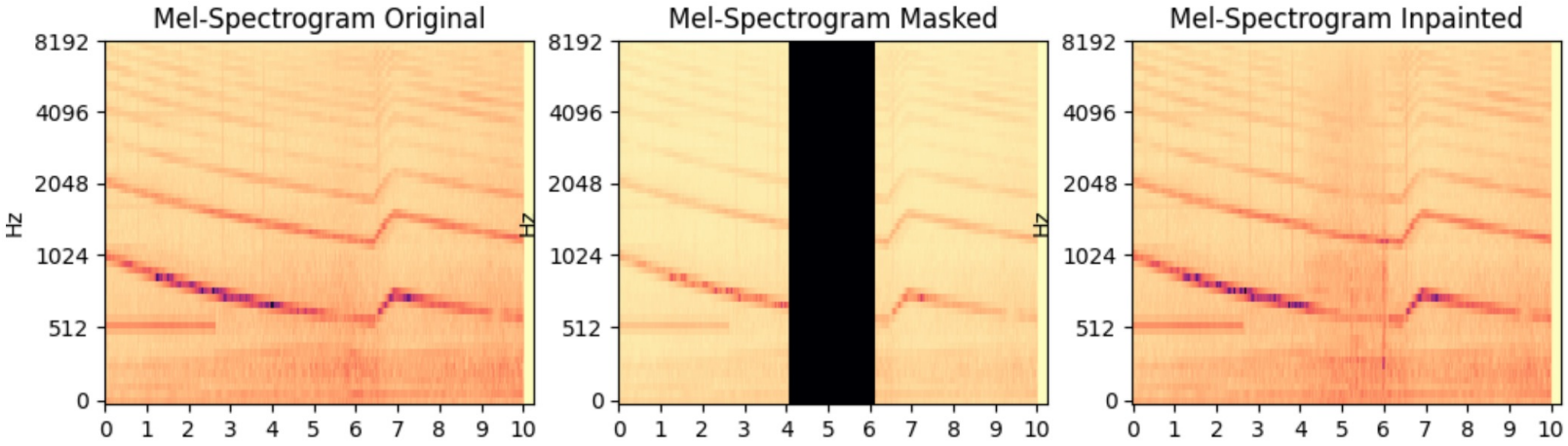
Audio generation and Audio inpainting

Audio Generation

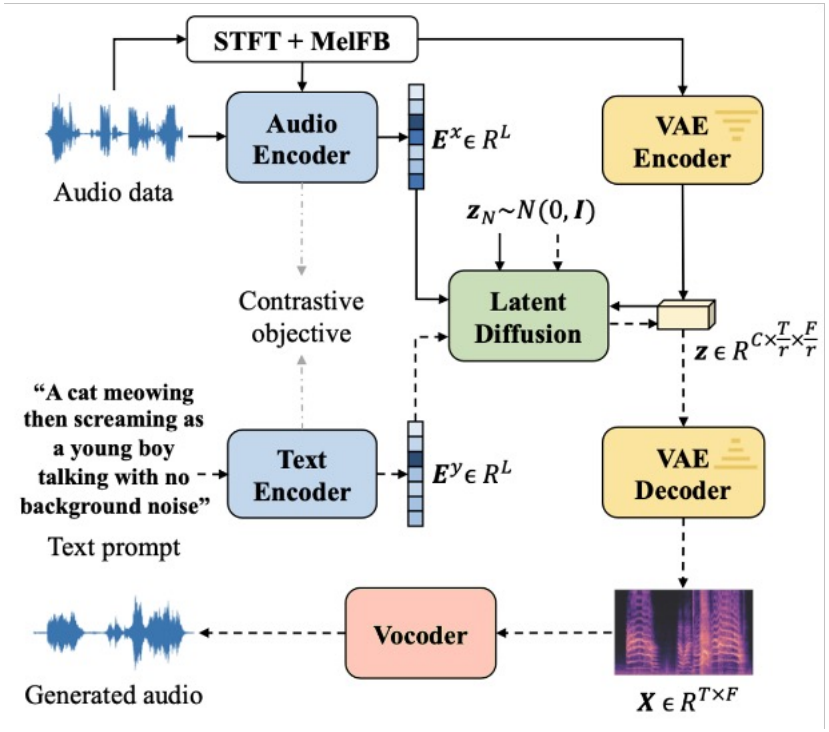
- Produce audio from textual descriptions that is indistinguishable from human-created or real-world audio
- Generate audio samples with similar characteristics to the training data, also showcasing innovative attributes

Audio Inpainting

- Reconstruct missing or corrupted portions of audio signals and restore the original audio content



State-of-the-Art: AudioLDM

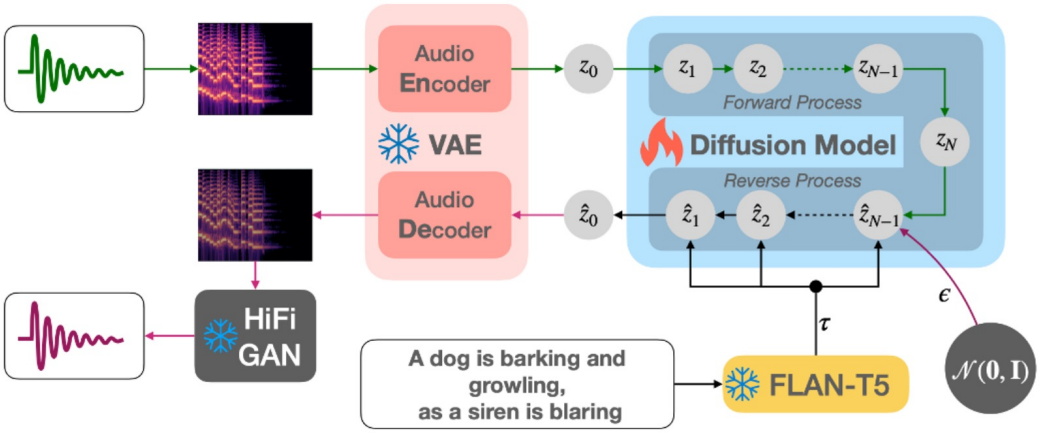


- **CLAP** (Contrastive Language-Audio Pretraining): encode audio descriptions and audio clips into a shared audio-text embedding space
- **VAE** (Variational Autoencoder): compress the spectrogram into a compact latent space
- **Latent Diffusion**: the conditioning information is integrated into the feature extraction process
- **Vocoder**: HiFi-GAN is employed to synthesize the audio waveform from the generated spectrogram

Inpainting: at each step of the reverse process, the latent representation z_{n-1} is modified using the mask m, the generated z_{n-1} and the known part of the audio z^{ob}

$$z'_{n-1} = (1 - m) \odot z_{n-1} + m \odot z^{ob}_{n-1}$$

State-of-the-Art: Tango



- **FLAN-T5**:
  - Instruction-tuned LLM architecture used as text encoder
  - Trained on a large-scale chain-of-thought and instruction-based dataset
  - Can learn new tasks mimicking gradient descent through attention weights

TANGO achieves comparable results compared to AudioLDM while extremely reducing the training dataset and time

Inpainting:

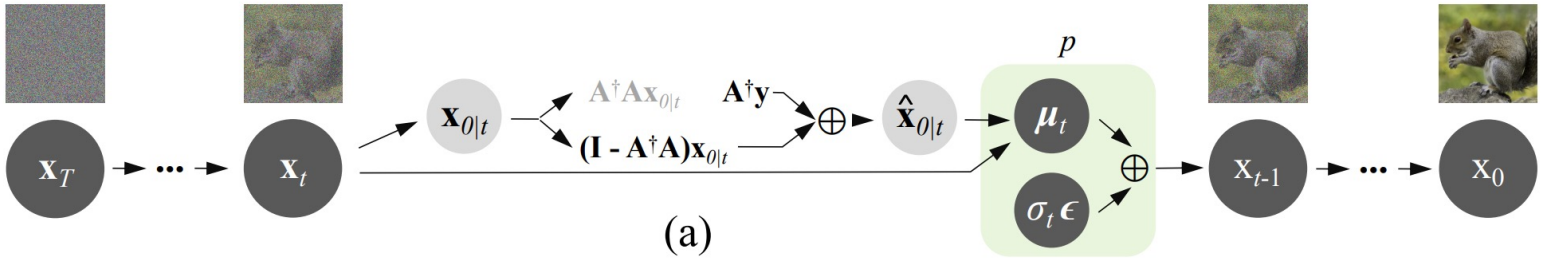
- x^{known} is sampled from the known part
- $x^{unknown}$ is sampled from the model

The two components are combined using the mask *m*

$$x_{t-1} = m \odot x_{t-1}^{known} + (1 - m) \odot x_{t-1}^{unknown}$$

Selected Approaches: DDNM and DDNM+

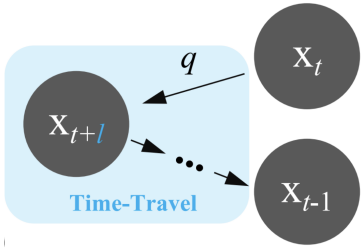
DDNM (Denoising Diffusion Null-Space Model) is a framework for image restoration which refines the null-space content during the reverse diffusion process to produce results that satisfy data consistency and realism



Task: reconstruct $\hat{x}$ from y where $y = Ax$

$\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
for $t = T, \ldots, 1$ **do**
  $\mathbf{x}_{0|t} = \frac{1}{\sqrt{\bar{\alpha}_t}}\left(\mathbf{x}_t - \mathcal{Z}_{\boldsymbol{\theta}}(\mathbf{x}_t, t)\sqrt{1-\bar{\alpha}_t}\right)$
  $\hat{\mathbf{x}}_{0|t} = \mathbf{A}^\dagger\mathbf{y} + (\mathbf{I} - \mathbf{A}^\dagger\mathbf{A})\mathbf{x}_{0|t}$
  $\mathbf{x}_{t-1} \sim p(\mathbf{x}_{t-1}|\mathbf{x}_t, \hat{\mathbf{x}}_{0|t})$
return $\mathbf{x}_0$

DDNM+: Through the time-travel trick we generate a better “past”, which in turn leads to a better “future”



Selected Approaches: RePaint and RePaint+

RePaint: sample the unmasked regions using the available information as conditioning during the diffusion process

$$x_{t-1}^{known} \sim \mathcal{N}(\sqrt{\bar{\alpha}_t}x_0, (1-\bar{\alpha}_t)\mathbf{I})$$

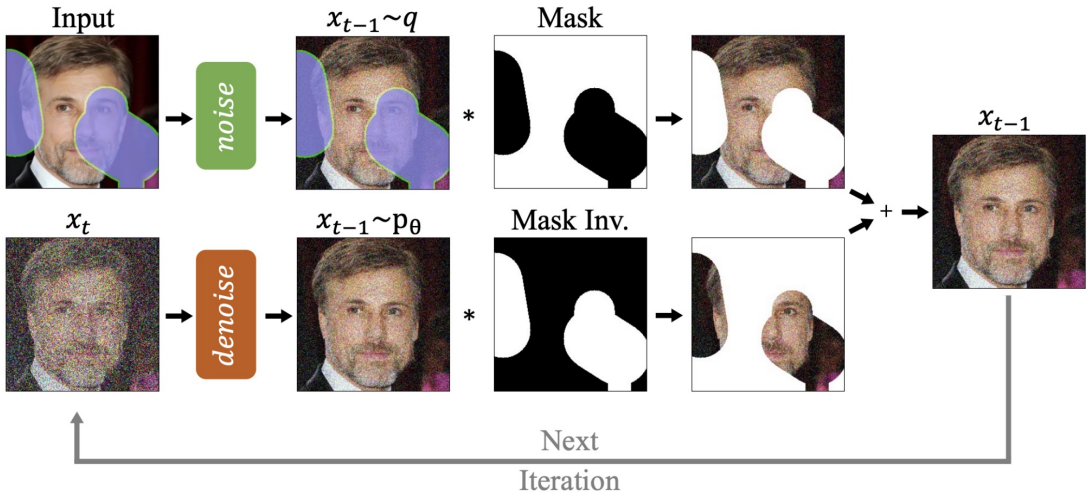
$$x_{t-1}^{unknown} \sim \mathcal{N}(\mu_\theta(x_t, t), \Sigma_\theta(x_t, t))$$

$$x_{t-1} = m \odot x_{t-1}^{known} + (1-m) \odot x_{t-1}^{unknown}$$

x_{t-1} is diffused back to x_t

$$x_t \sim \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I})$$

the denoising step is performed again



The model has **more time** to effectively incorporate the provided information with the generated part

RePaint+: The latent representation is diffused back to multiple previous steps and then all of them are sequentially performed again

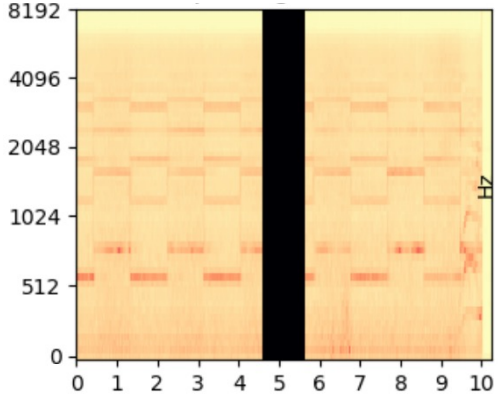
Audio samples and Inference details

Tests were done using 24 audio clips from the **AudioCaps** dataset

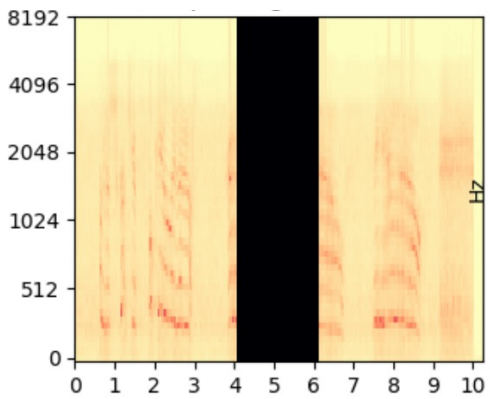
“Female and male are having conversation”

“An emergency vehicles’ siren with a brief male yell”

“Duck quacking repeatedly”



1 second gap



2 seconds gap

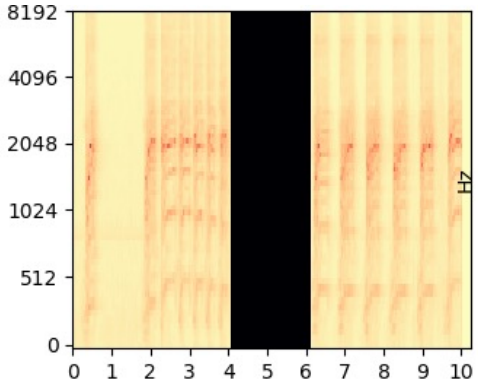
	1 Clip	Batch of 8 Clips
AudioLDM	1	4
Tango	10	40
Tango + DDNM	10	40
Tango + DDNM$^+$	120	480
Tango + RePaint	100	400
Tango + RePaint$^+$	100	400

Inference times in minutes using one GPU NVIDIA Tesla T4

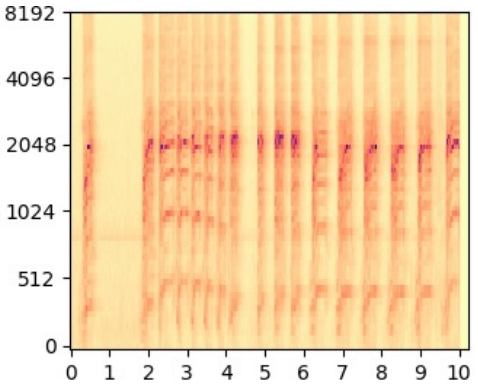
Listen to the audio clips at: https://www.andrearodriguez.it/inpainting

Results

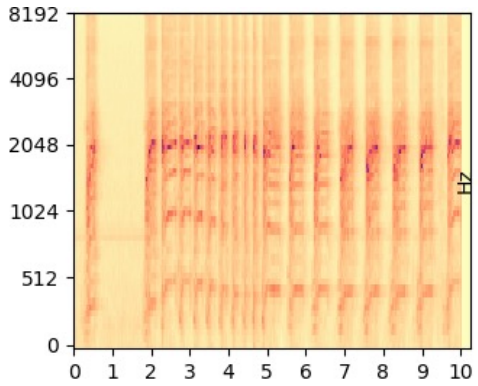
“Duck quacking repeatedly”



Masked

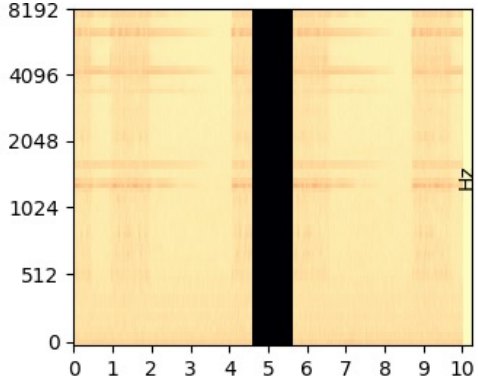


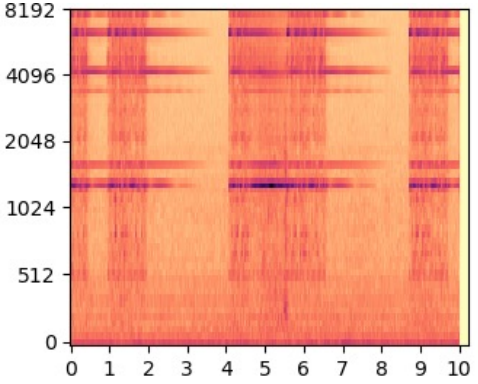
Inpainted using RePaint

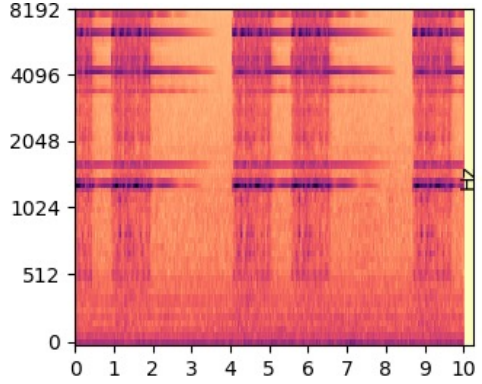


Original

“A telephone ringing”







Metrics

- SDR = Signal Distortion Ratio
- SNR = Signal Noise Ratio
- PSNR = Peak Signal Noise Ratio
- SSIM = Structural Similarity Index Measure

1 second gap

4.5-5.5	AudioLDM	Tango	Tango DDNM	Tango DDNM$^+$	Tango RePaint	Tango RePaint$^+$
SDR	-3.27	5.48	5.03	5.47	**5.96**	4.97
SNR	-0.25	5.73	5.39	5.71	**6.17**	5.28
PSNR	39.46	43.35	42.44	43.22	**44.08**	42.38
SSIM	98.40	99.25	99.21	**99.28**	99.18	99.14

2 seconds gap

4-6	AudioLDM	Tango	Tango DDNM	Tango DDNM$^+$	Tango RePaint	Tango RePaint$^+$
SDR	-4.97	1.48	1.53	**1.99**	1.64	1.48
SNR	-1.45	2.82	**2.90**	2.21	2.71	2.02
PSNR	35.44	39.74	39.85	38.61	**39.92**	38.56
SSIM	97.84	98.34	98.46	98.45	**98.59**	98.56

* SSIM values are multiplied by 100

Audio inpainting in communication scenarios

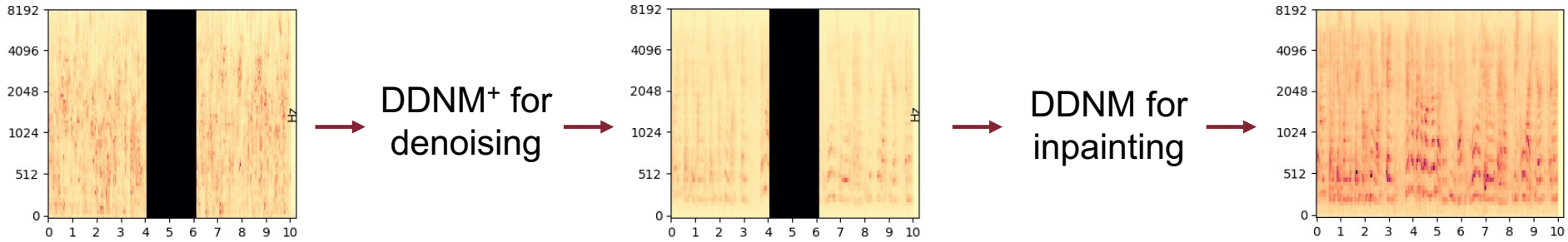
We tested the technique adding white **Gaussian noise** to some audio clips and then trying to remove it

We worked with **PSNR** 20 and 30

$$\hat{x}_{0|t} = \Sigma_t A^\dagger y + (I - \Sigma_t A^\dagger A) x_{0|t}$$

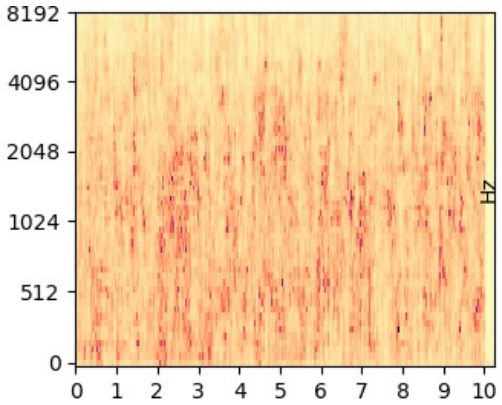
$$x_{t-1} = \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1-\bar{\alpha}_t}\hat{x}_{0|t} + \frac{\sqrt{\alpha_t}(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t}x_t + \sqrt{\Phi_t}\epsilon$$

DDNM+: introduces a new parameter σ_y which represents the estimated noise level that we aim to eliminate from the audio signal

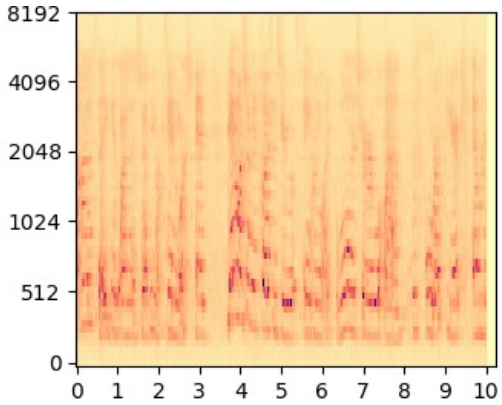


Results

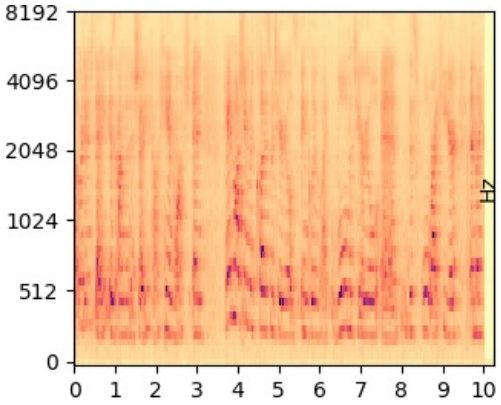
“An adult female is speaking in a quiet environment”



Noisy



Denoised



Original

SNR

PSNR 20	Clip 1	Clip 2	Clip 3	Clip 4
Noisy	-9.80	-9.11	-8.61	-10.10
Denoised	-2.47	-3.80	-2.64	-2.58

SNR

PSNR 30	Clip 1	Clip 2	Clip 3	Clip 4
Noisy	-3.53	-2.45	-3.54	-3.61
Denoised	-1.82	-1.14	-1.32	-2.20

Conclusions

- The proposed techniques achieve **better results** than the two baslines
- **RePaint** consistently achieves superior results compared to the other methodologies
- It is crucial to consider the **trade-off** between quality and inference time

and Future works

- Create an **automated communication system** which performs denoising and intelligently identifies and inpaints problematic segments
- **Remove conditioning** from text and perform inpainting based only on the known portion of audio

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