

Music generation with Diffusion models - updates

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Agenda

- Progress
- Future work

Progress

Progress

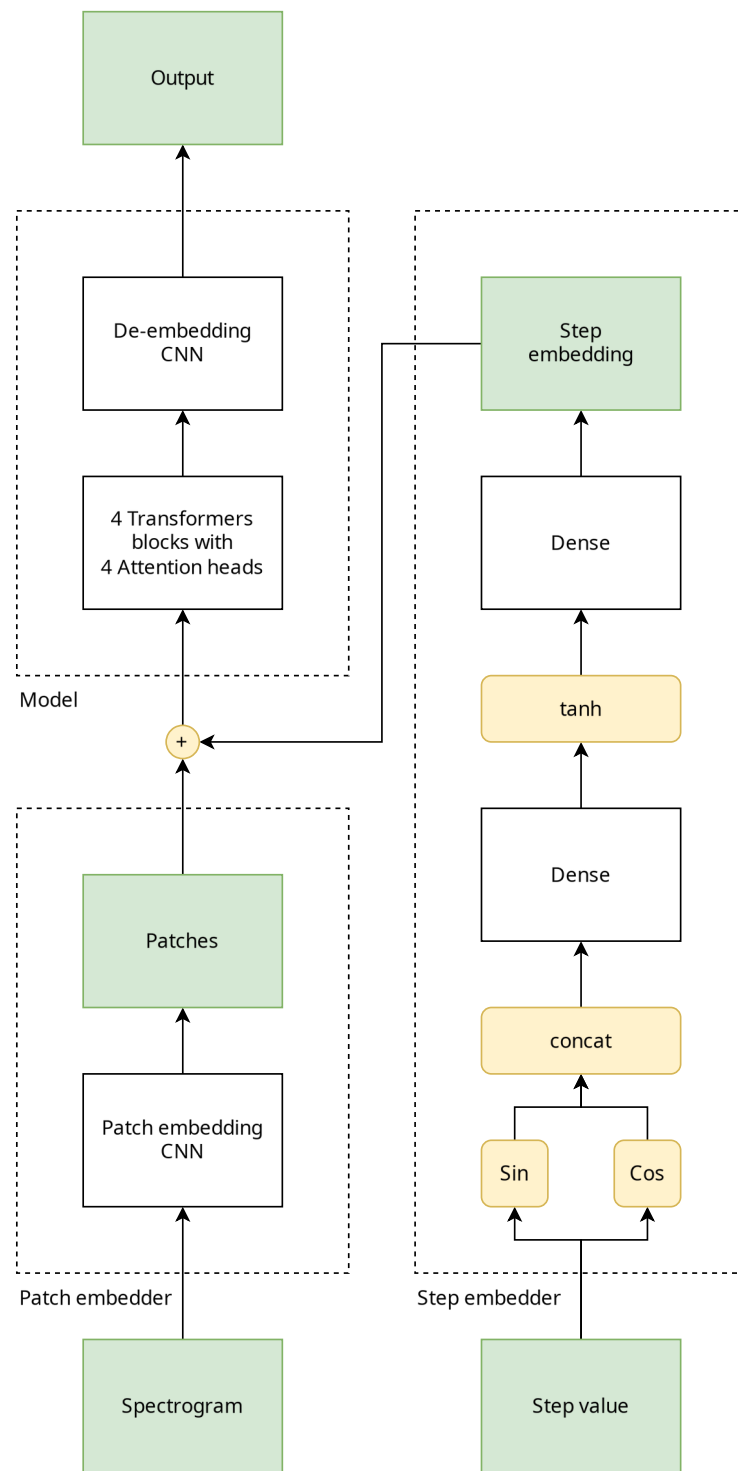
- Data
- Model
- Pipeline:
 - Preprocessing
 - Training loop

Data

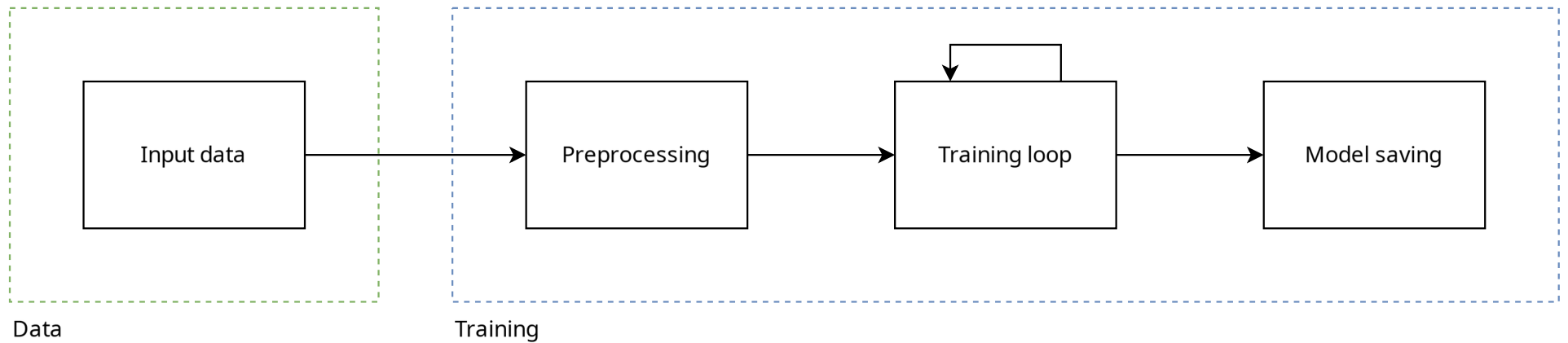
- The dataset is composed of:
 - 710 songs, with different genres, some with lyrics
 - 1106 labels, with multiple labels per song
- The dataset is freely available on *Huggingface*

Model

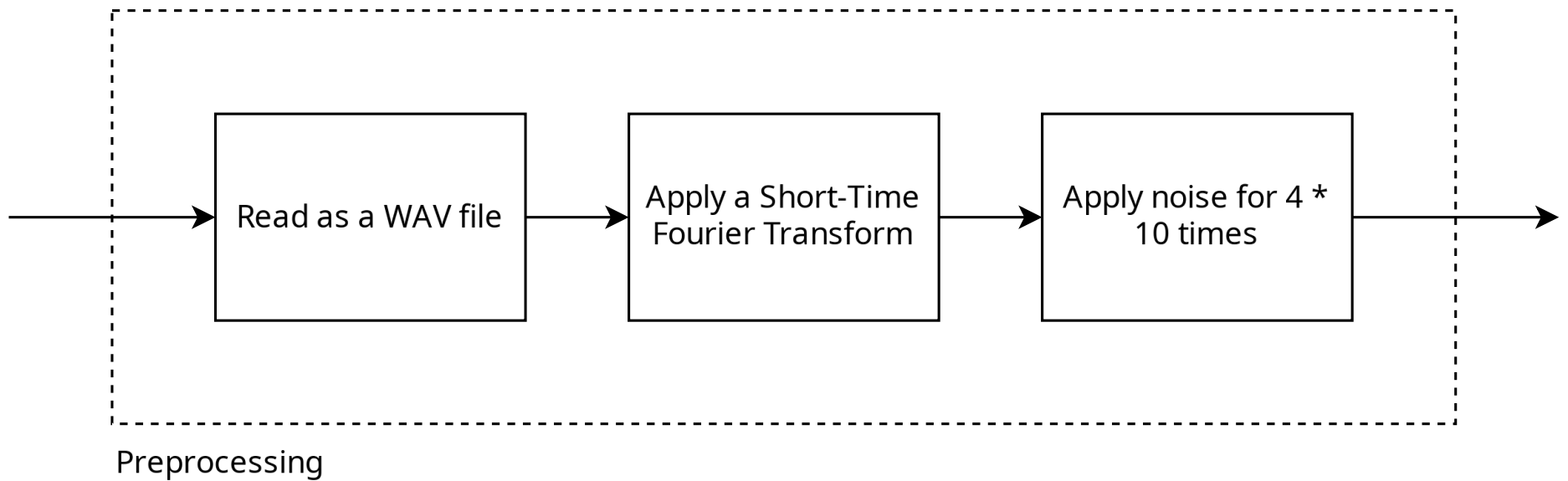
- Currently, the model is a “*Diffusion Transformer*”, with:
 - 4 Transformer blocks, with 4 Attention heads each
 - Patch **embedding** and **de-embedding** is done using CNNs
 - Timestep **embedding** and is done via a Dense network
- Number of parameters is 5 388 802



Pipeline

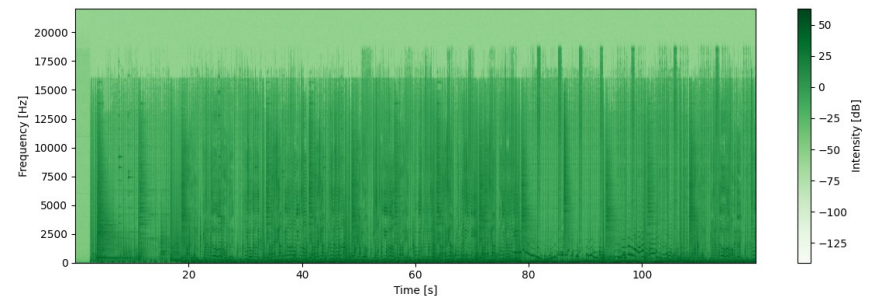
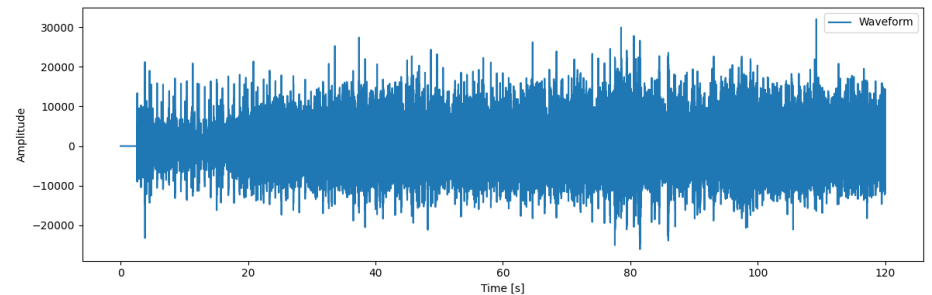


Preprocessing



Preprocessing

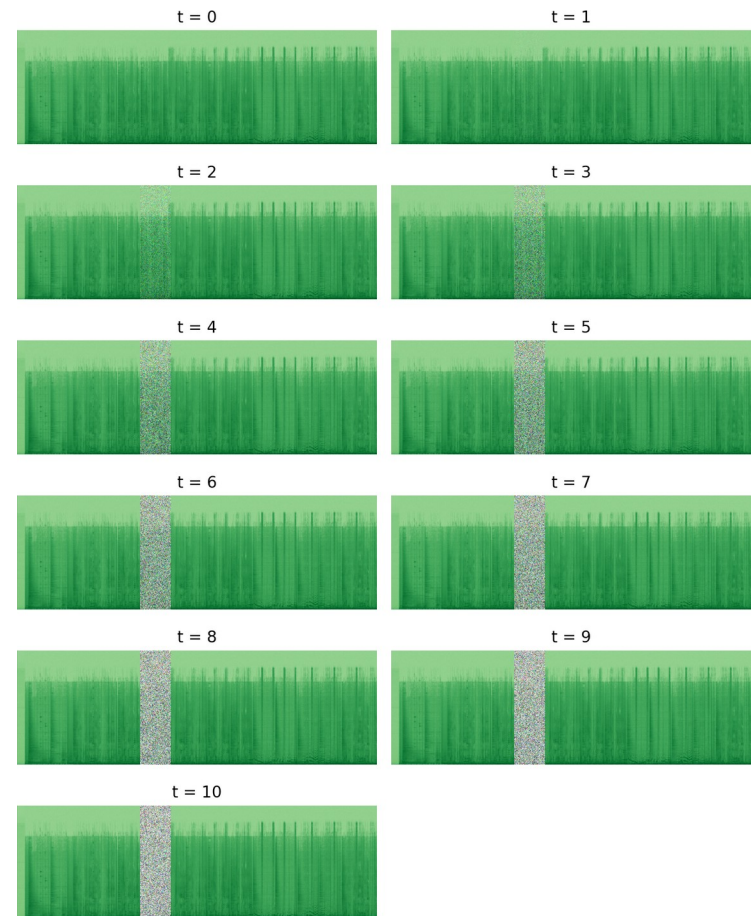
- Given a **waveform**, a Short-Time Fourier Transform is applied
- A **spectrogram** is given as a result
- The spectrogram is saved as a tensor



Preprocessing

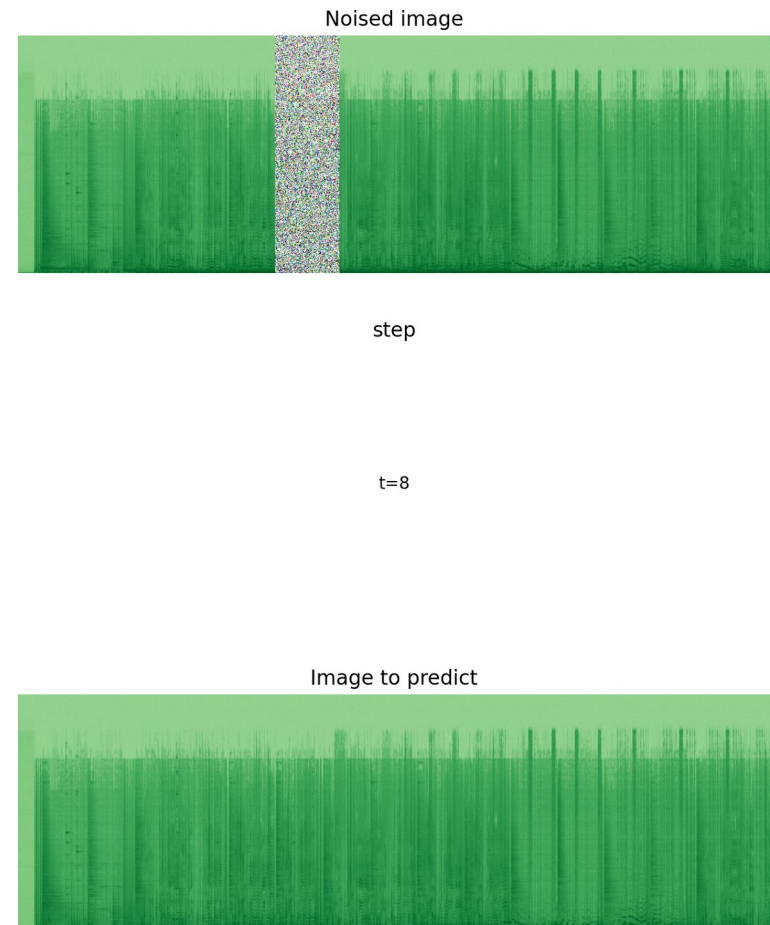
- The **spectrogram** is gradually “noised”:
 - Start with an unnoised spectrogram
 - For t iterations, add more noise
- To get a better result, the noise scheduling process described in the “*Denoising Diffusion Probabilistic Models*” (Ho et al.) paper is used
- The formula is:

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(0, \mathbf{I})$$



Training loop

- At training, the model is given:
 - A noised spectrogram
 - A timestep value
- The model is tasked to predict the original image
 - **Motivation:** the model does not need to capture intermediary denoising steps, as it introduces noise
- The loss is influenced by the difference between:
 - The predicted denoised spectrogram
 - The actual spectrogram



Training loop

- Training loss: MSE
- Training optimizer: Adam
- Training statistics:
 - Uses about 8GB of VRAM for training
 - Training takes 5 epochs * 450s \approx 2250s on 1 GPU

Future work

Future work

- Add:
 - support for text-driven generation
- Explore with:
 - different input tensor shapes and sizes
 - different learning parameters
 - different model sizes
 - different model configurations
- Training:
 - run training multiple times

Thank you!