Deep Learning for Audio

Lecture 10

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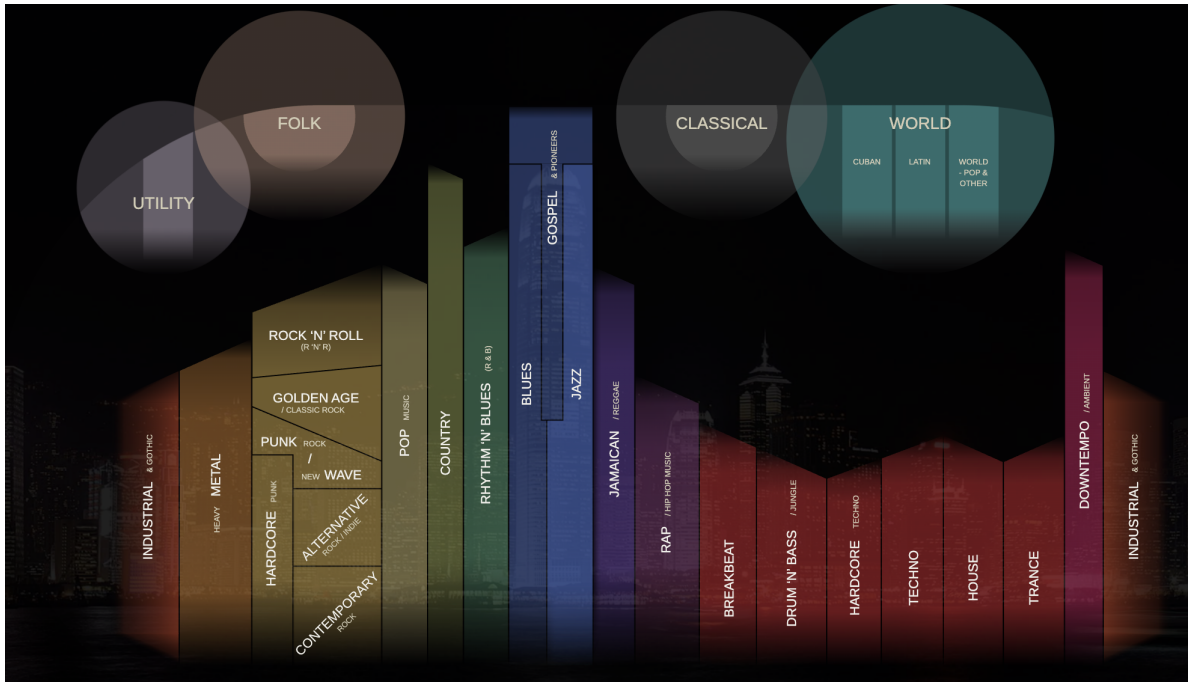
AI Masters

2023

Outline

Outline

Problems with generating music



- Should NNs compose music by following the same logic and process as humans do?
- Are current evaluation methods good enough to compare and measure the creativity of the composed music?
- Difficult to collect data due to copyright
- Music is subjective
- Each music Genre has its own rules

Datasets

- JSB Chorales Dataset (chorales by Johann Sebastian Bach)
- Maestro Dataset (200 hours of virtuosic piano performances with fine alignment between note labels and audio waveforms)
- The Lakh MIDI Dataset (176,581 unique MIDI files)
- MetaMIDI Dataset (436,631 MIDI files)

Labs, apps, ideas

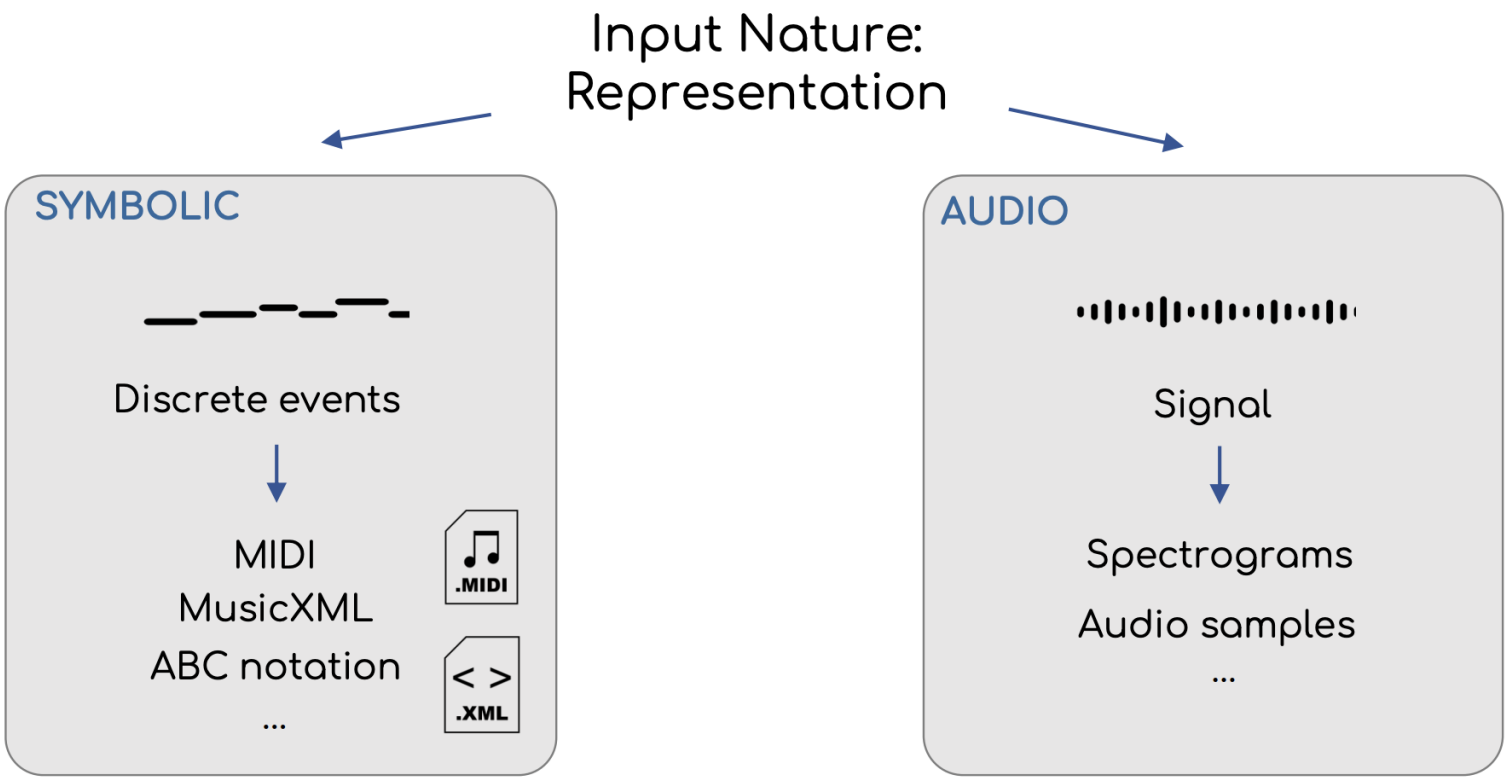
Research Groups and Labs:

- Google Magenta
- Audiolabs Erlangen
- Music Informatics Group
- Music and Artificial Intelligence Lab
- Metacreation Lab

Apps:

- AIVA
- Amper Music
- Ecrett Music
- Humtap
- Amadeus Code
- Computoser
- Brain.fm

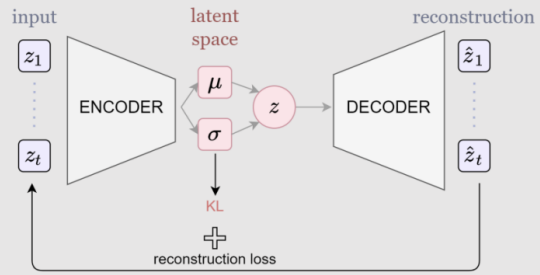
Input representations



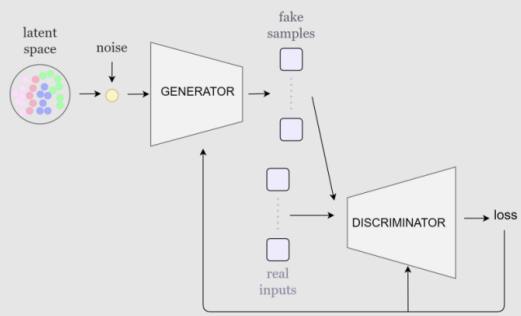
History: before 2019

Generative Models

VAEs



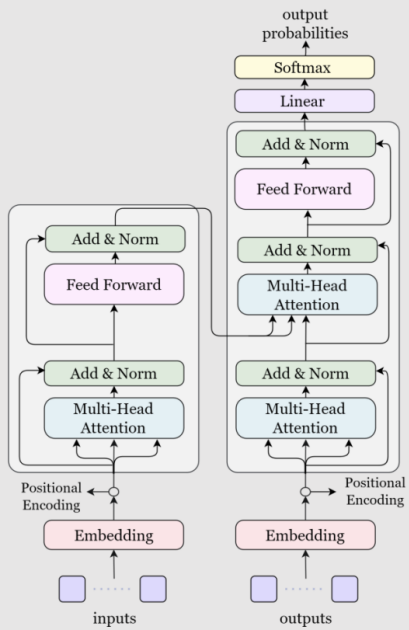
GANs



Sequence Models

Recurrent Neural Networks (RNNs)

Transformers



MuseNet

- Learn to predict the next token
- Uses GPT-2
- MIDI format
- Sparse Transformer to train a 72-layer network with 24 attention heads
- Long context: full attention over a context of 4096 tokens

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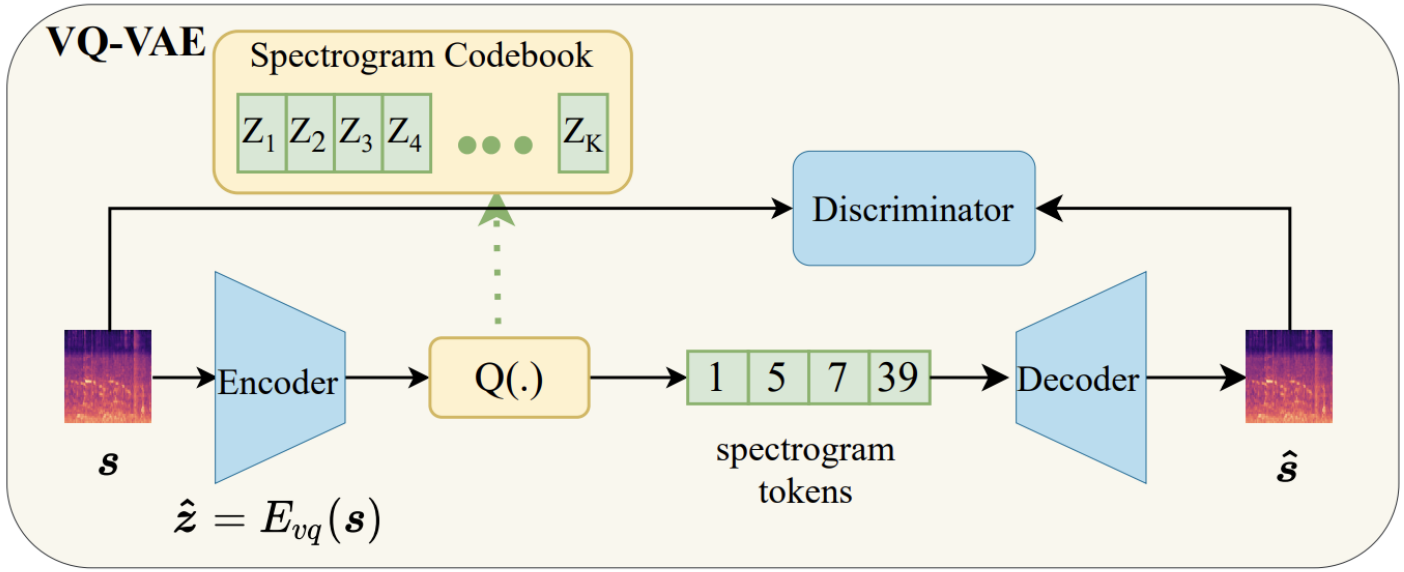
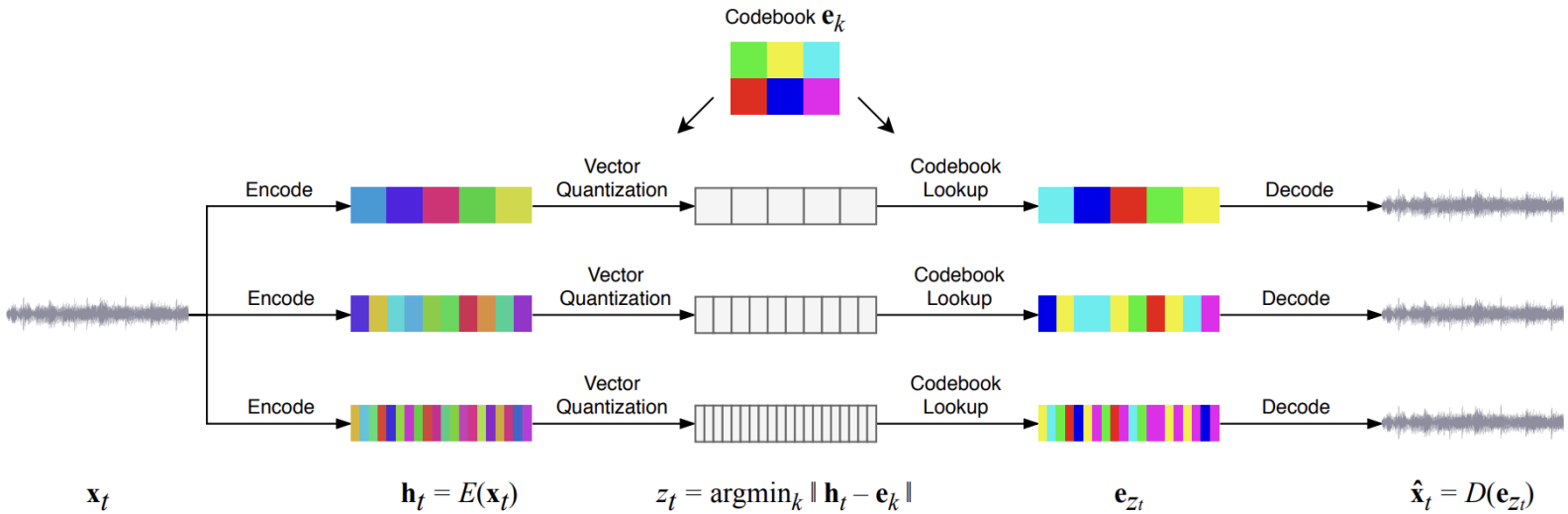
VQ-VAE



- Encoder extracts the representation z from the mel-spectrogram
- Codebook contains a finite number of embedding vectors
- Decoder reconstructs the mel-spectrogram based on mel-spectrogram tokens
- Discriminator distinguishes the mel-spectrogram is original or reconstructed
- $Q(\cdot)$ denotes a spatial-wise quantizer that maps each features z_{ij} into its closest codebook entry z_k

Jukebox



- Based on VQ-VAE
- Separated autoencoders with different temporal resolutions
- Spectral loss

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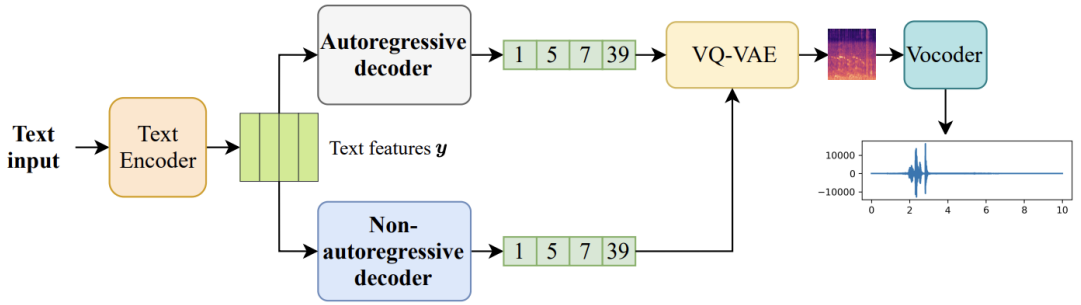
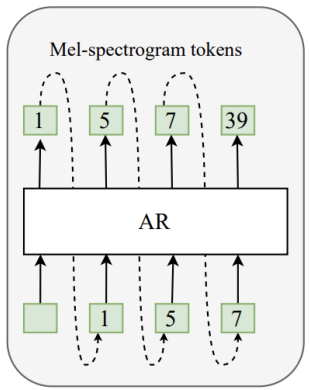
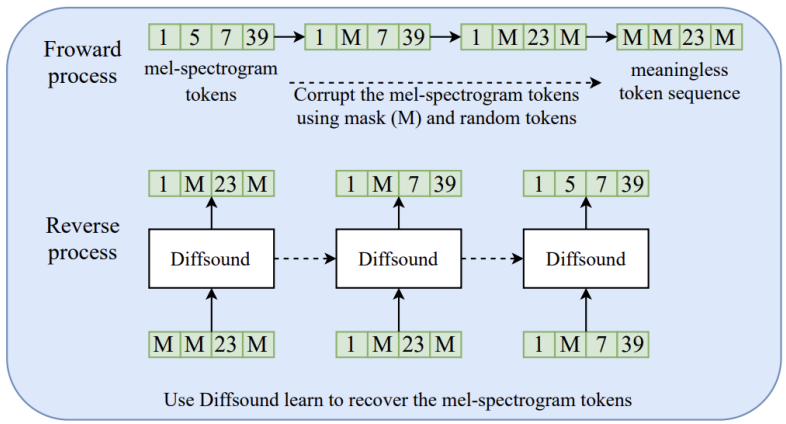
Diffsound





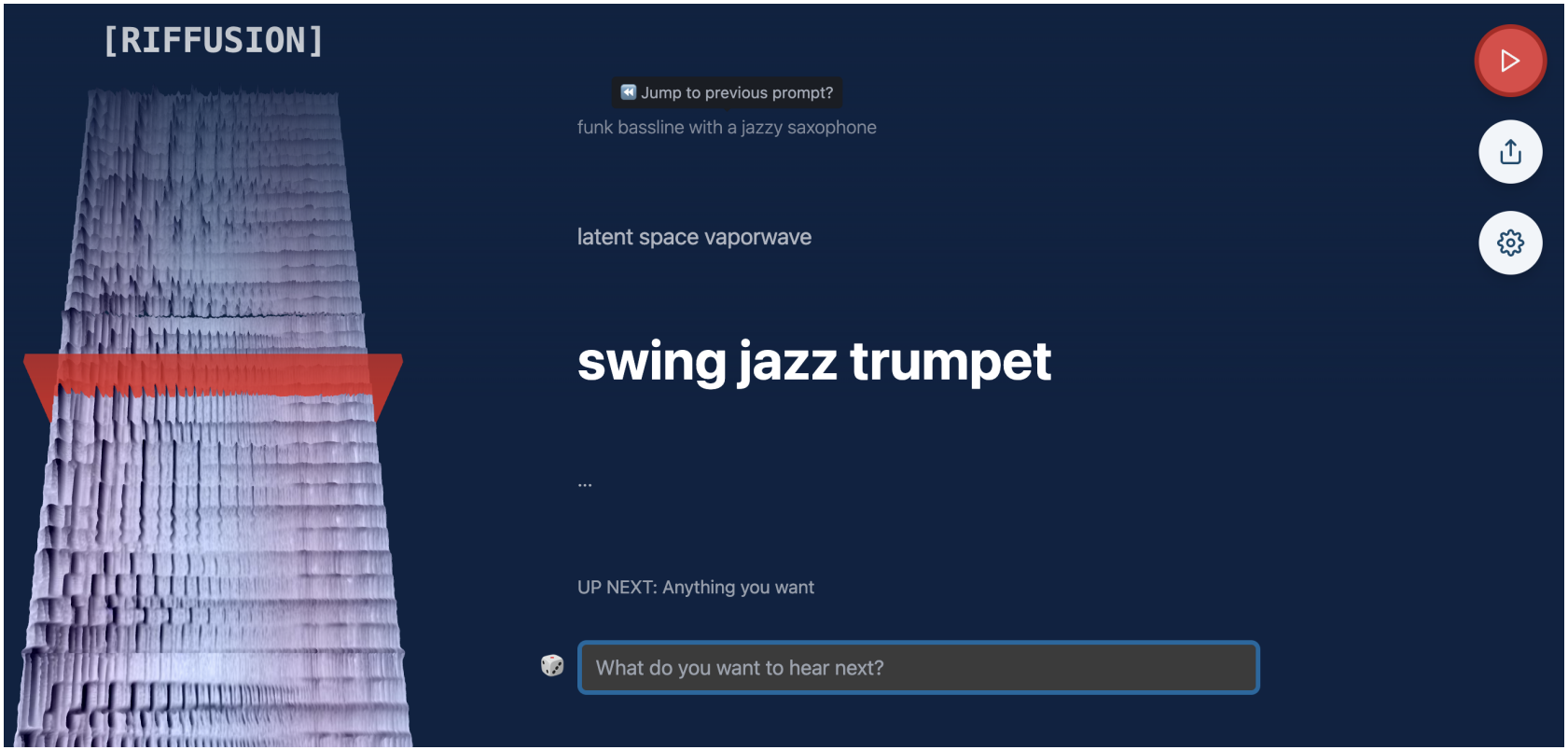
An example of autoregressive spectrogram tokens generation



An example of non-autoregressive spectrogram tokens generation.

- Text encoder (CLIP) extracts text features from the text input
- Decoder generates mel-spectrogram tokens
- Pre-trained VQ-VAE transforms the tokens into mel-spectrogram
- Vocoder transforms mel-spectrogram into waveform

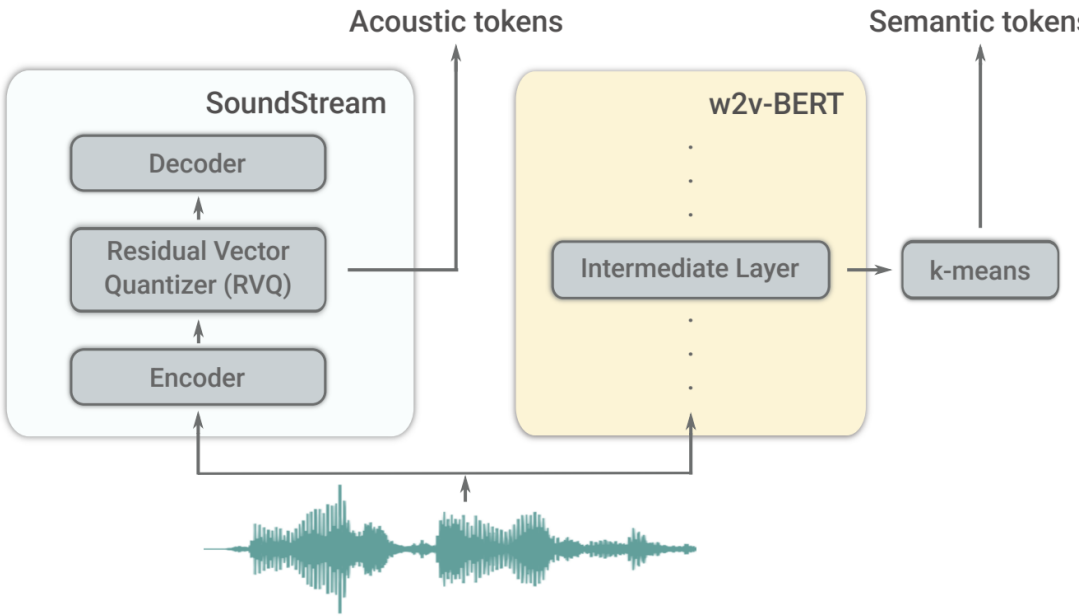
Riffsound



- Real-time music generation with stable diffusion
- Fine-tuned the model to generate images of spectrograms
- Combine short clips by sampling the latent space between a prompt with two different seeds, or two different prompts with the same seed

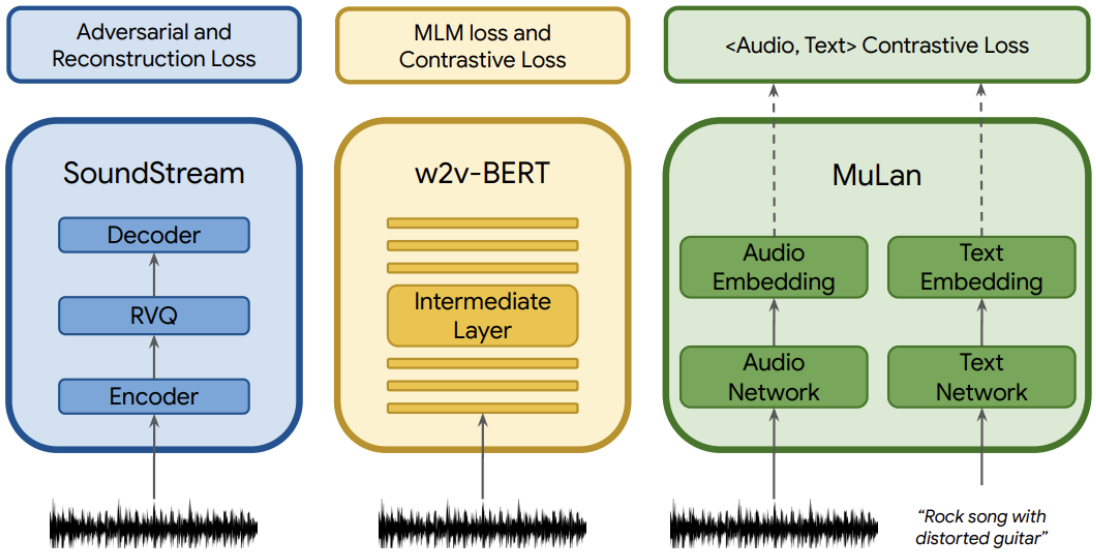
Outline

AudioLM



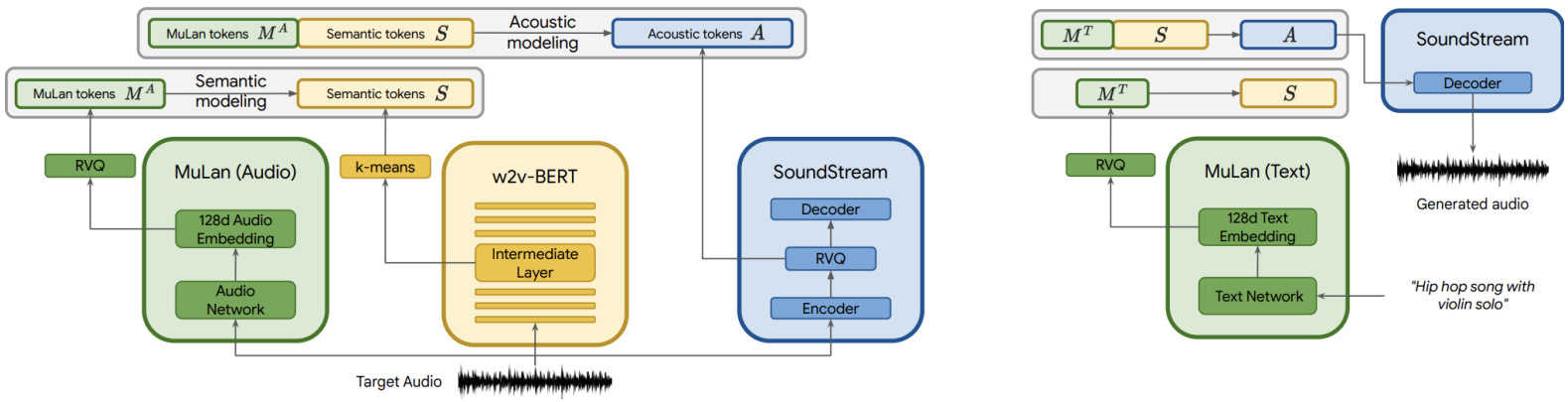
- SoundStream: 24 kHz audio to 50 Hz embeddings (Autoencoder codec with vector quantizers)
- w2v-BERT: extract embeddings from the 7th layer and quantize them using the centroids of a learned k-means over the embeddings

MusicLM



- Based on AudioLM: SoundStream + w2v-BERT + MuLan
- MuLan tokens
- Metrics Frechet Audio Distance (FAD), KL

MusicLM


MuLan tokens M^A
Semantic tokens S
Acoustic modeling
Acoustic tokens A
MuLan tokens M^A
Semantic modeling
Semantic tokens S
RVQ
MuLan (Audio)
128d Audio Embedding
Audio Network
k-means
w2v-BERT
Intermediate Layer
SoundStream
Decoder
RVQ
Encoder
Target Audio
M^T
S
A
SoundStream
Decoder
M^T
S
RVQ
MuLan (Text)
128d Text Embedding
Text Network
Generated audio
"Hip hop song with violin solo"