# Deep Learning for Audio

## Lecture 10

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AI Masters

2024

# Outline

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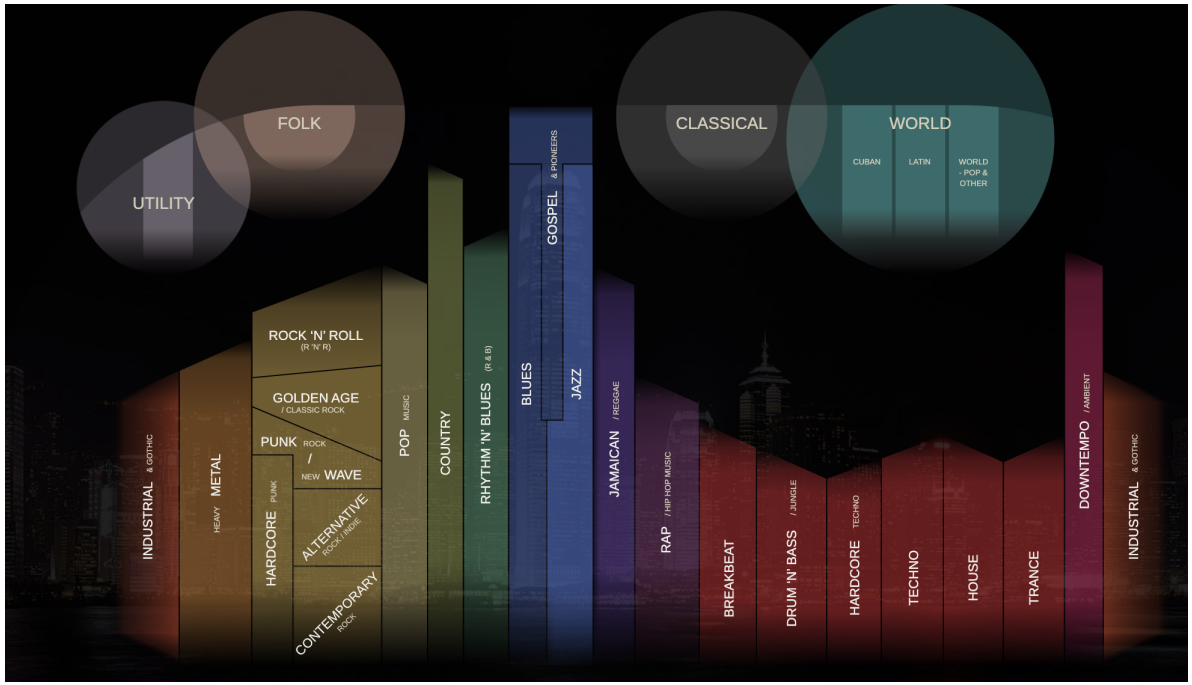
# Problems with generating music




- 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

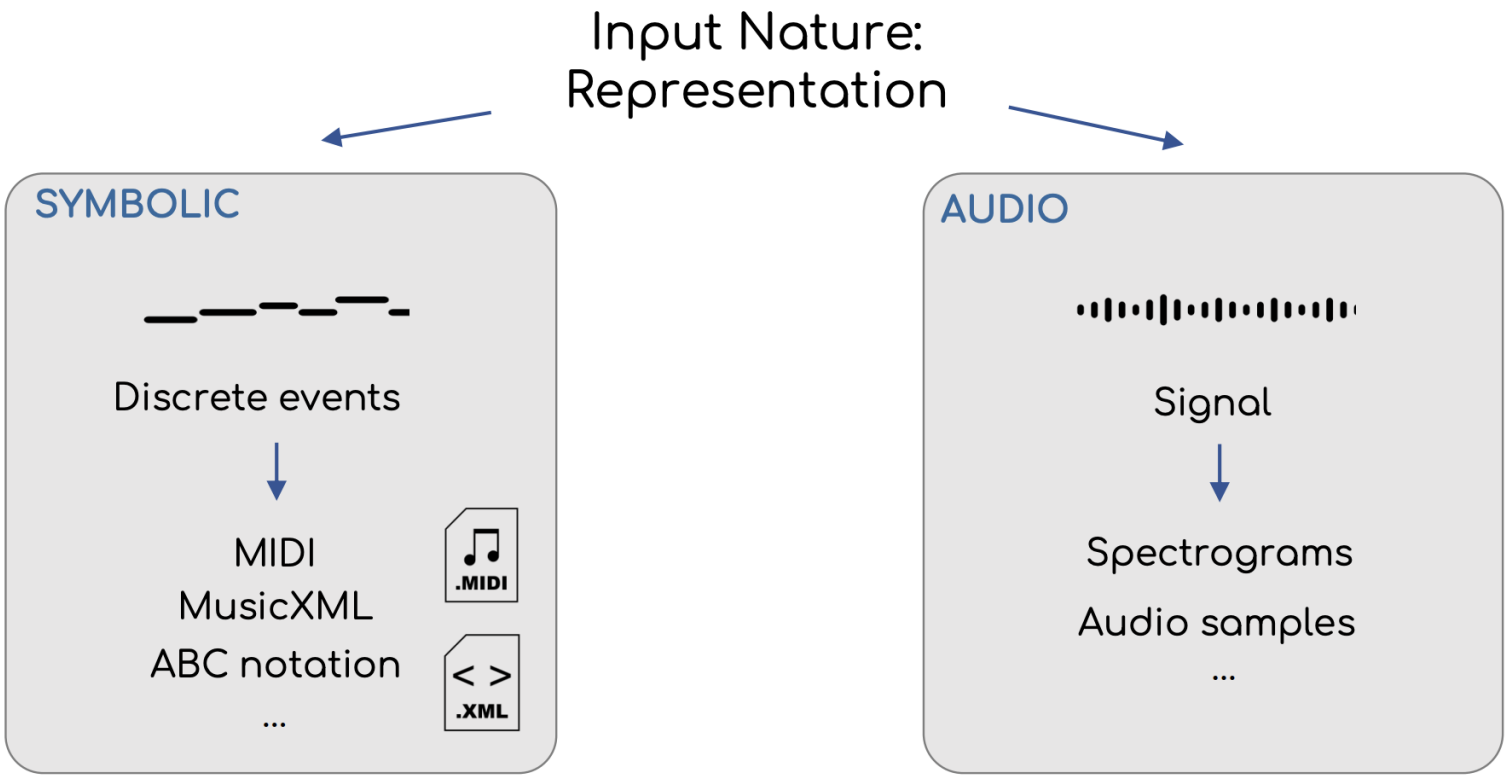
Research Groups and Labs:

- 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

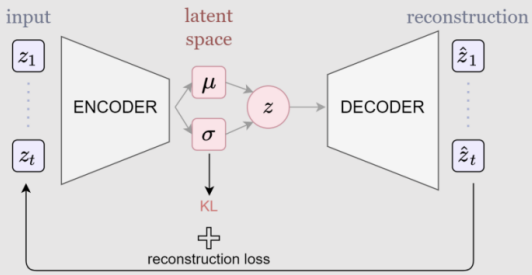
# Input representations



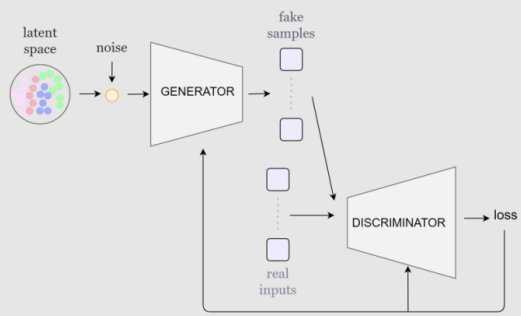
# History: before 2019

## Generative Models

VAEs



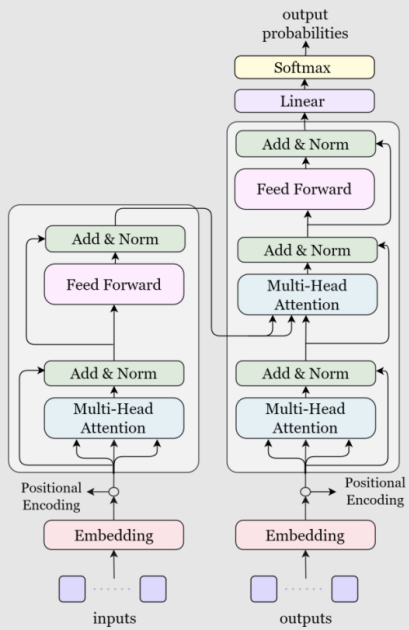

GANs




## Sequence Models

Recurrent Neural Networks (RNNs)

Transformers

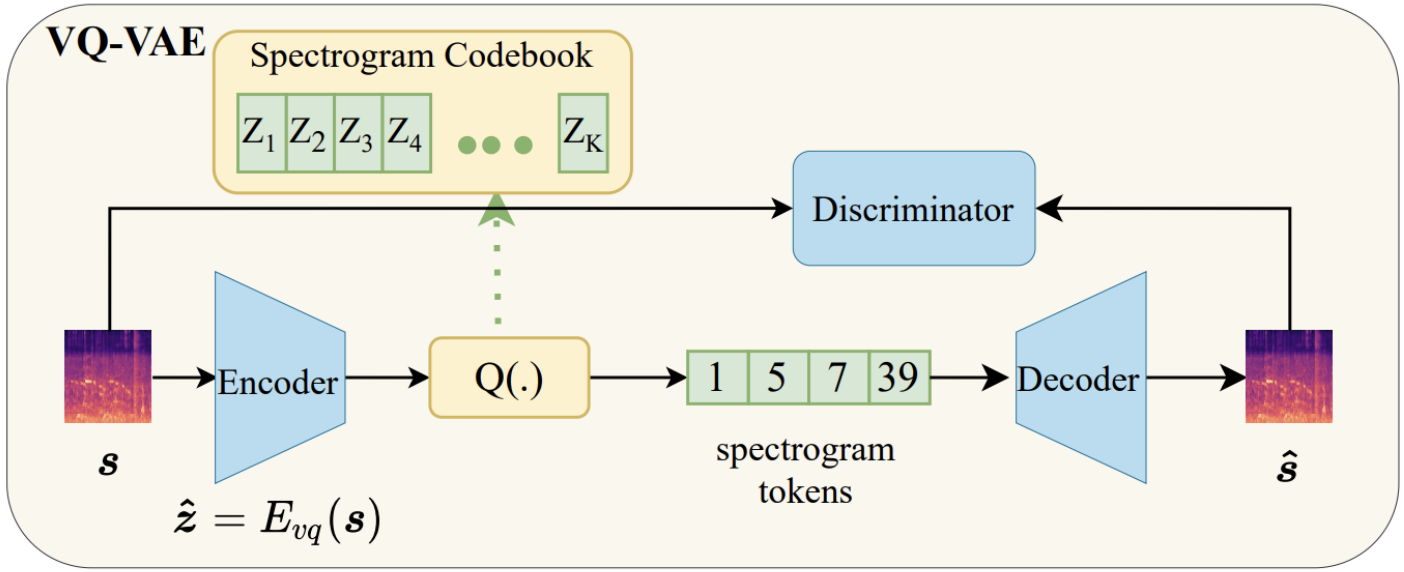


# MuseNet


- 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

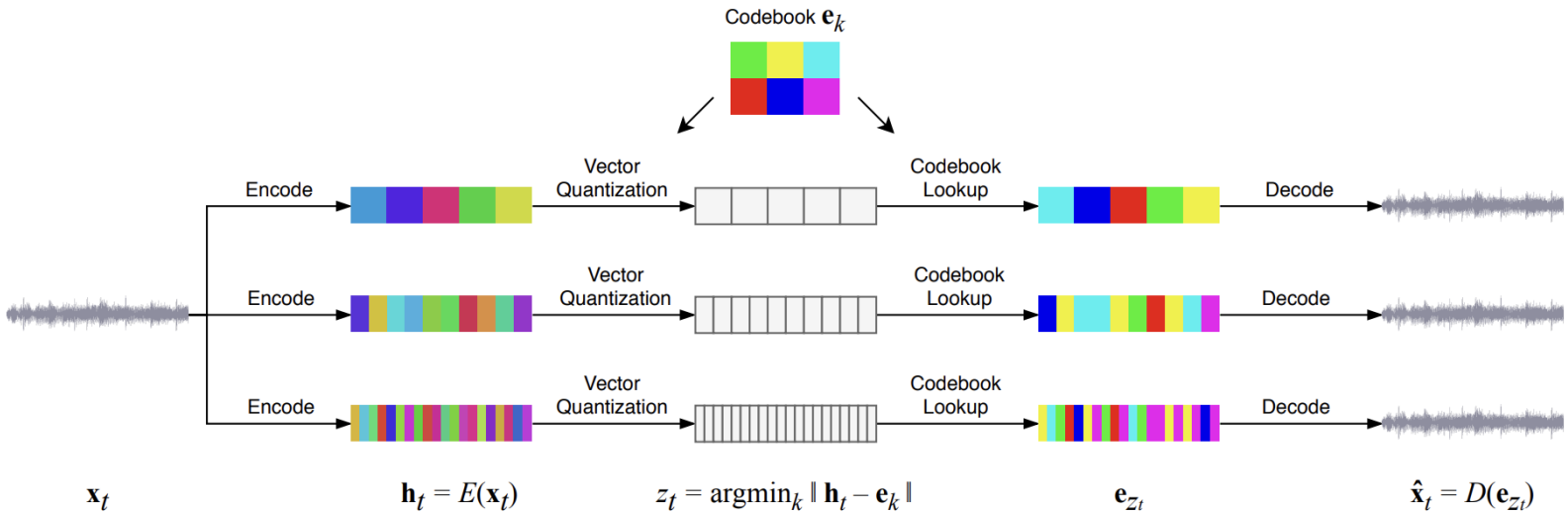
# Outline

# 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 $z_k$

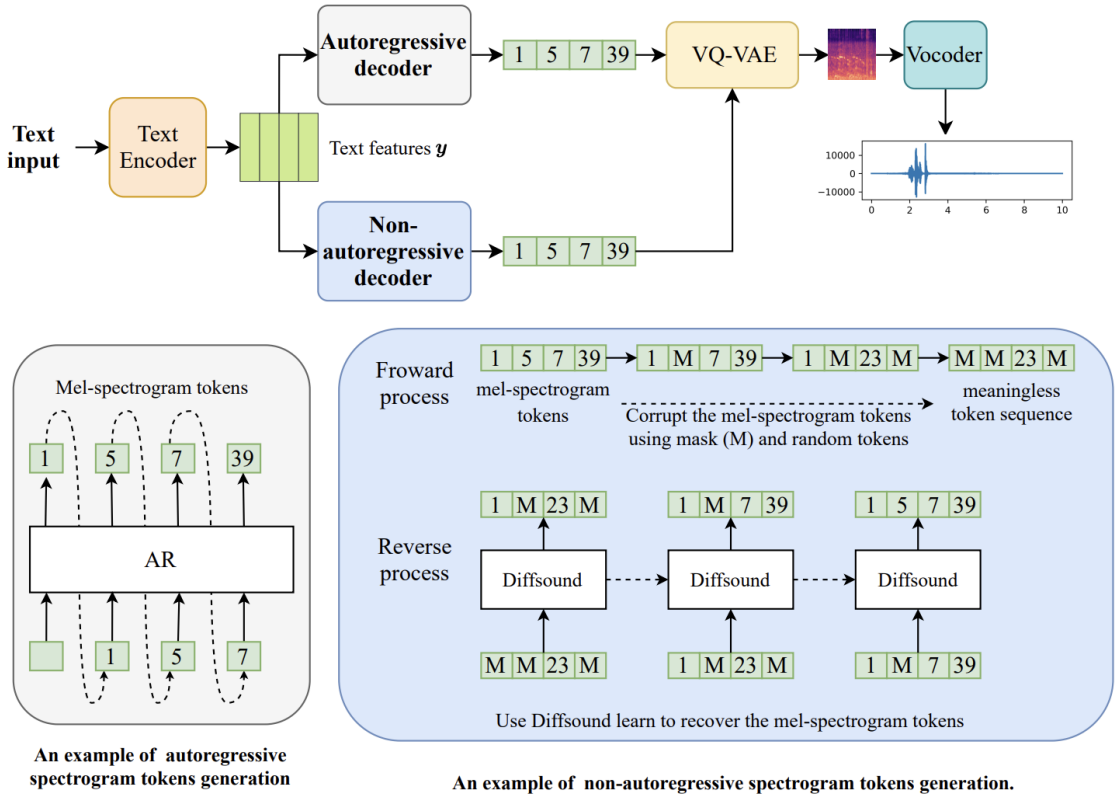
# Jukebox




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

# Outline

# Diffsound

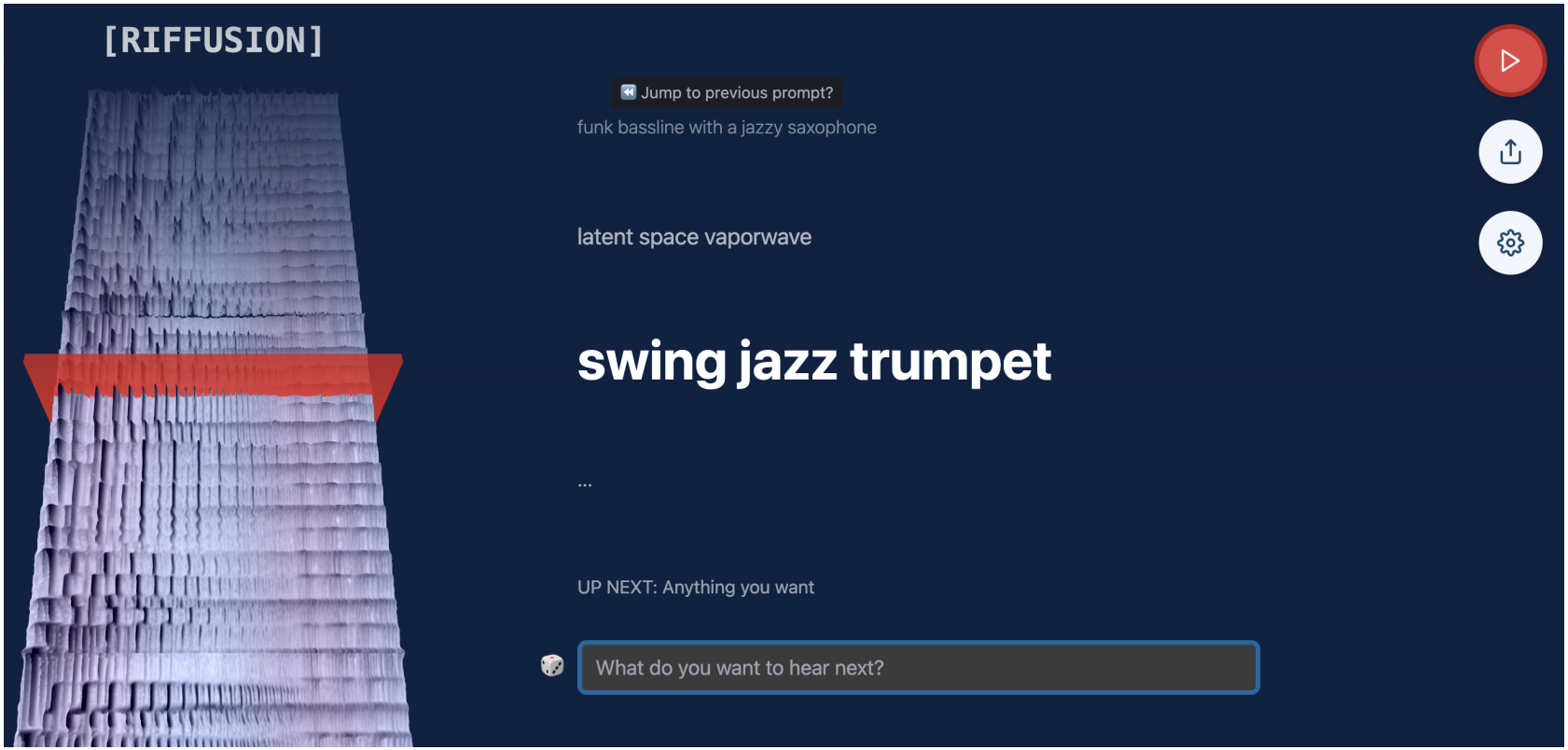



An example of autoregressive spectrogram tokens generation

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

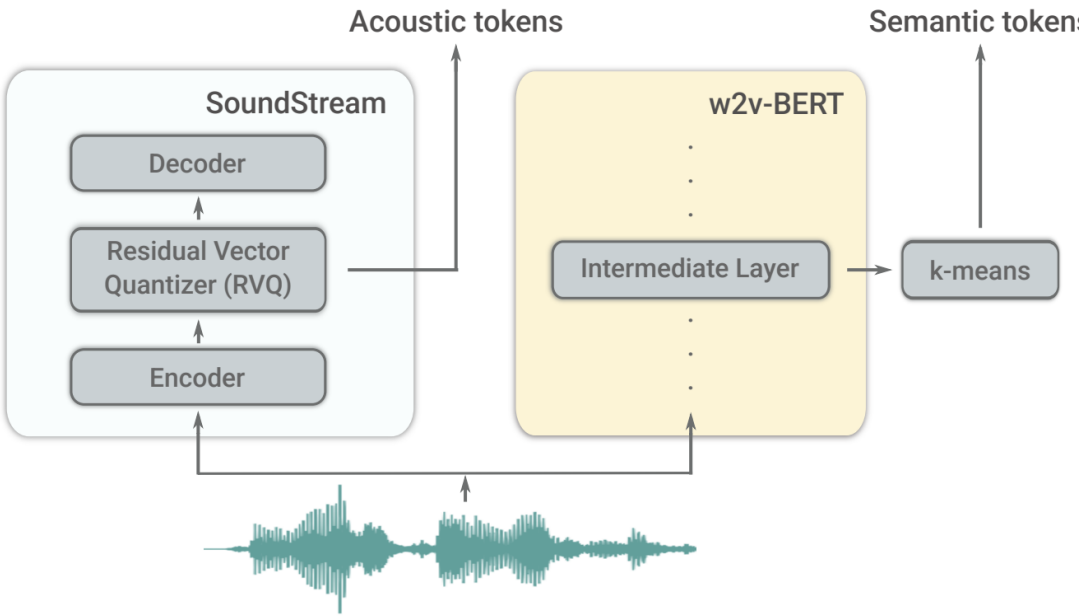
# Riffsound




- 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

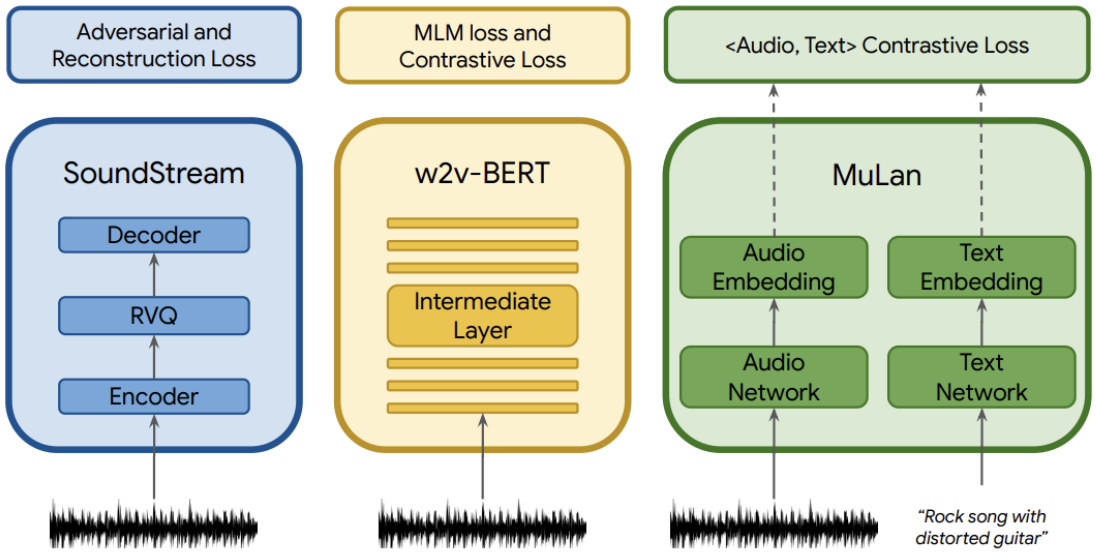
# Outline

# AudioLM



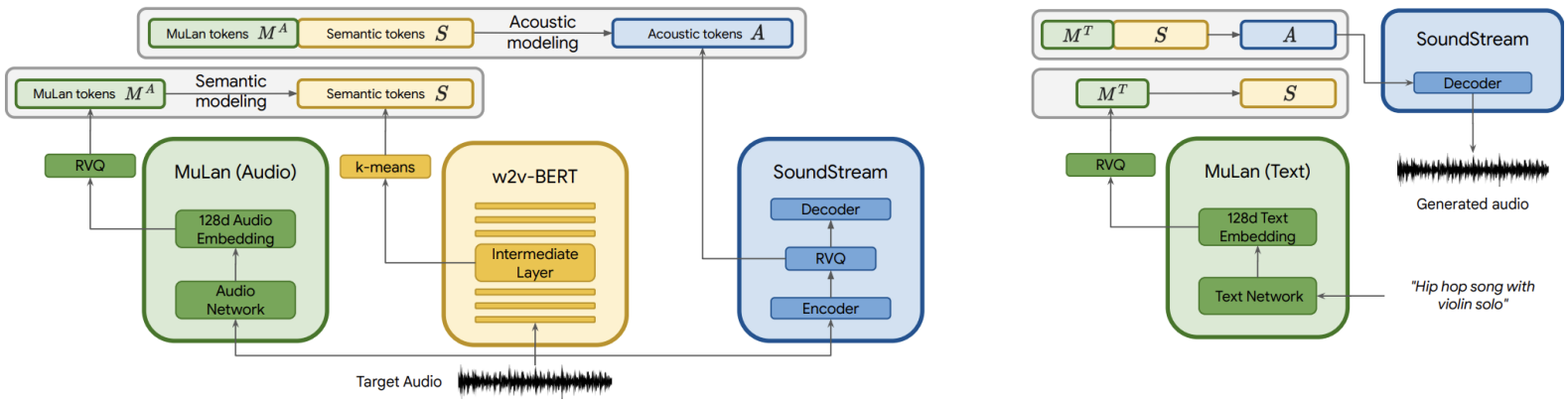

- SoundStream: 24 kHz audio to 50 Hz embeddings (Autoencoder codec with vector quantizers)
- w2v-BERT: extract embeddings from the 7th layer and quantize them using the centroids of a learned k-means over the embeddings

# MusicLM



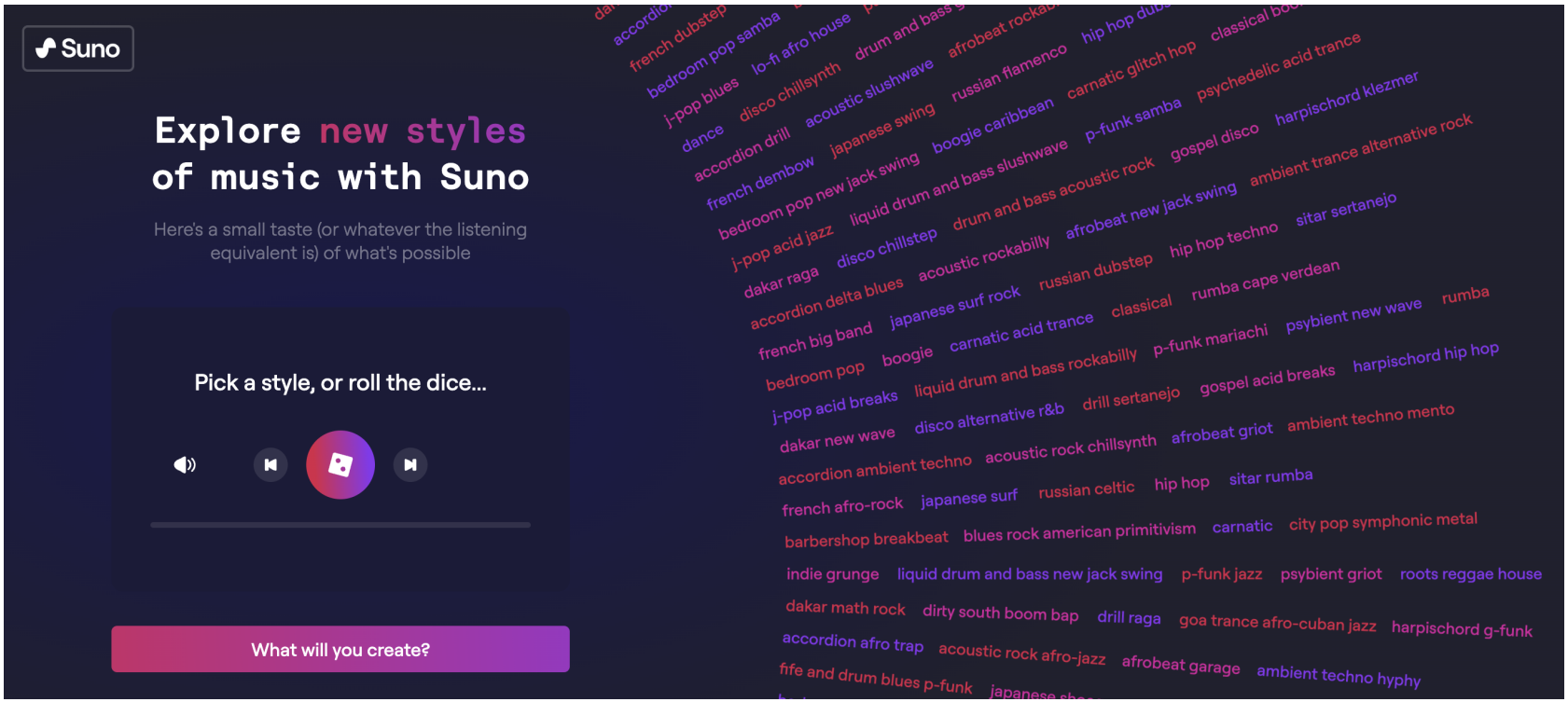

- Based on AudioLM: SoundStream + w2v-BERT + MuLan
- MuLan tokens
- Metrics Frechet Audio Distance (FAD), KL

# MusicLM: training




- training

# Suno: Bark




- architecturally very similar to Google's AudioLM

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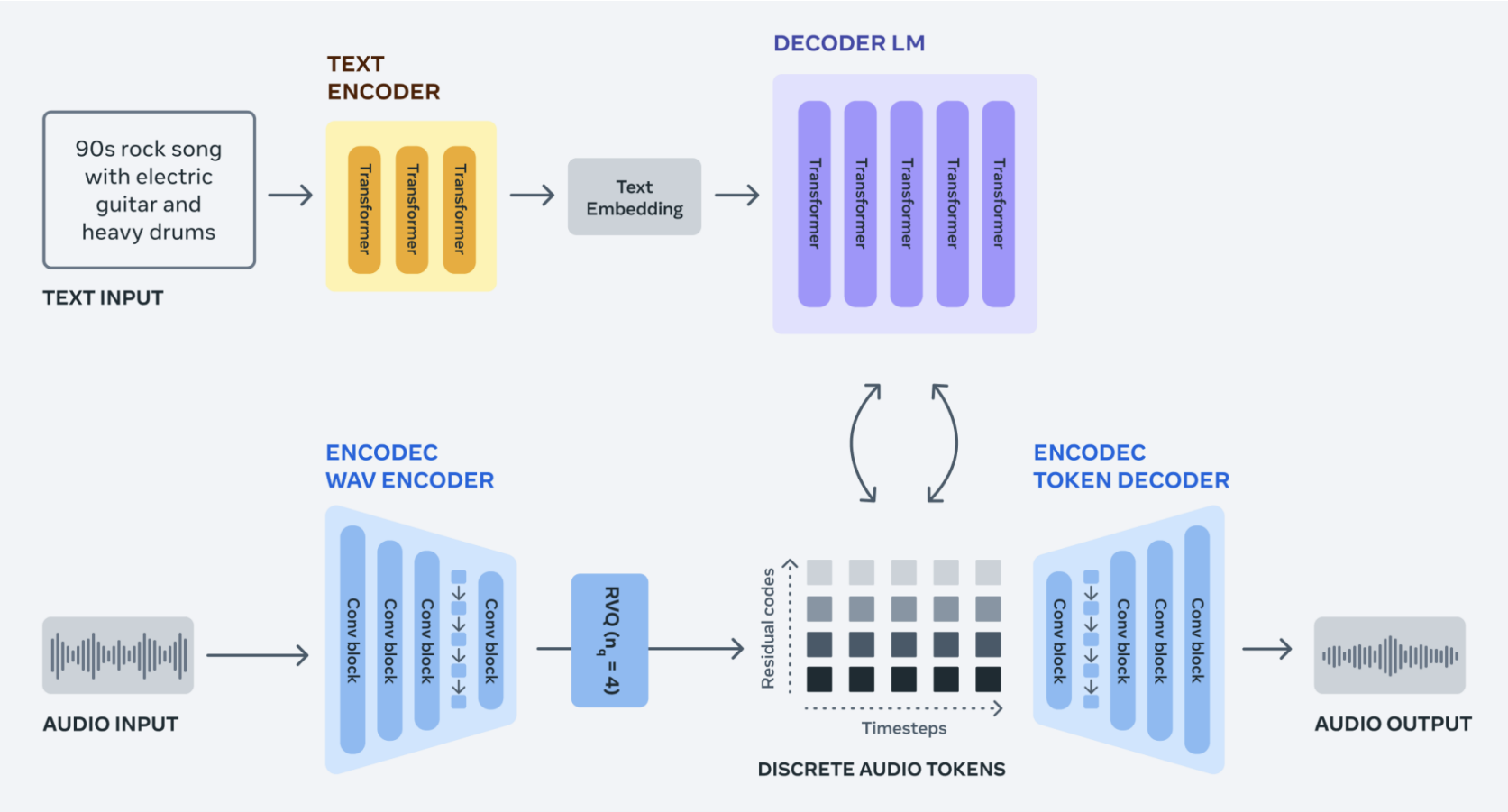
# AudioCraft




- model from Meta