2024 edition

Deep Learning for Music Analysis and Generation

Text-to-music Generation

(text → audio)

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Reference: ISMIR 2024 Tutorial

https://ismir2024.ismir.net/tutorials

Connecting Music Audio and Natural Language

Seung Heon Doh, Ilaria Manco, Zachary Novack, JongWook Kim and Ke Chen

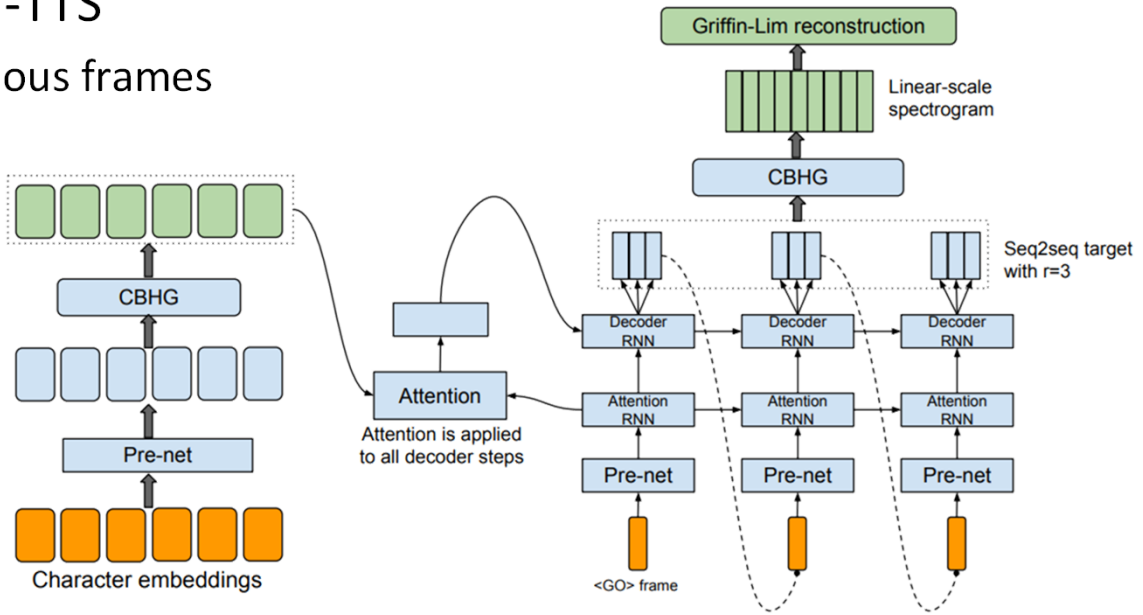
Timeline	Content
09:00 - 09:05	Chapter 1. Introduction / Motivation [SeungHeon]
09:05 - 09:40	Chapter 2. Overview of Language Models [Jong Wook]
09:40 - 10:30	Chapter 3. Music Description [Ilaria]
10:30 - 11:00	Coffee Break
11:00 - 11:40	Chapter 4. Text-to-Music Retrieval For Music Discovery [SeungHeon]
11:40 - 12:20	Chapter 5. Text-to-Music Generation for New Sound [Zachary & Ke]
12:20 - 12:30	Chapter 6. Conclusion

Outline

- **Image/audio tokenization and generation via VQVAE**
- Audio codec models
- Text-to-music: linking text and musical audio
  - Transformer-based approach
  - Diffusion-based approach

Building an LM for Audio

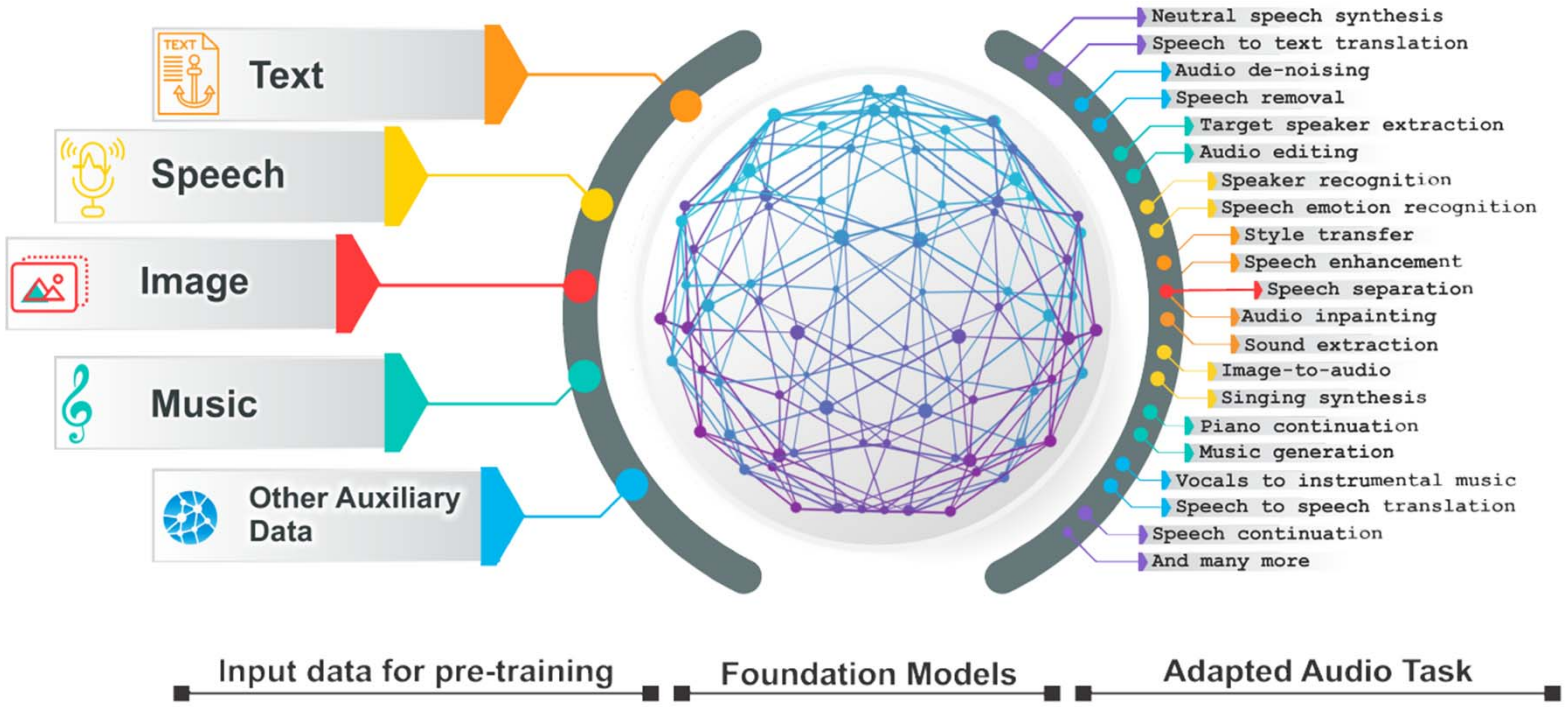
- MIDI events are by nature **discrete**; easy to build an LM for MIDI
- Audio files (waveforms or spectrograms) are **continuous** so it's trickier
- We can still build an autoregressive model for audio
  - Example: TacoTron or Transformer-TTS
    - Predict the next frame given the previous frames



(Figure from Wang et al, "Tacotron: Towards end-to-end speech synthesis," INTERSPEECH 2017)

Building an LM for Audio

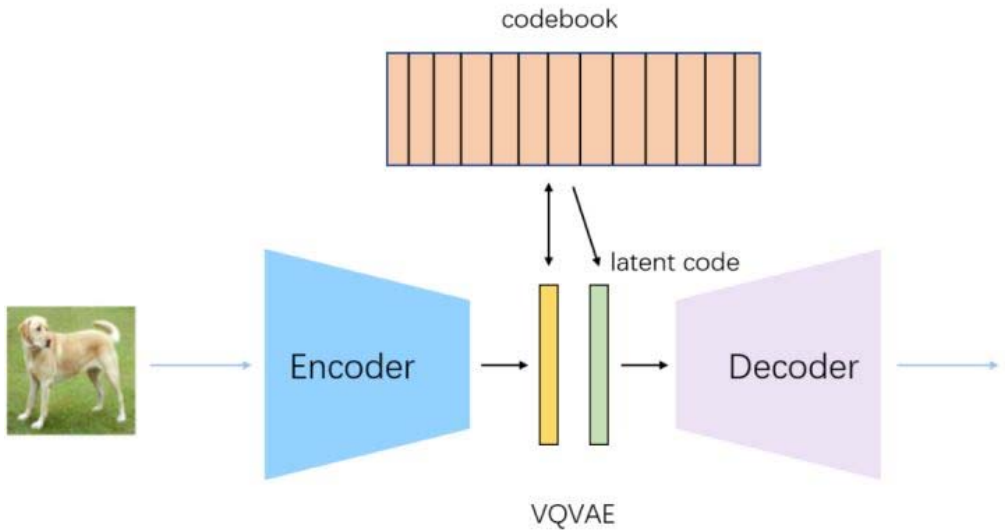
- But, easier to build a multimodal LM if *everything* is **discrete**



(Figure from Latif et al, "Sparks of large audio models: A survey and outlook," arXiv 2023)

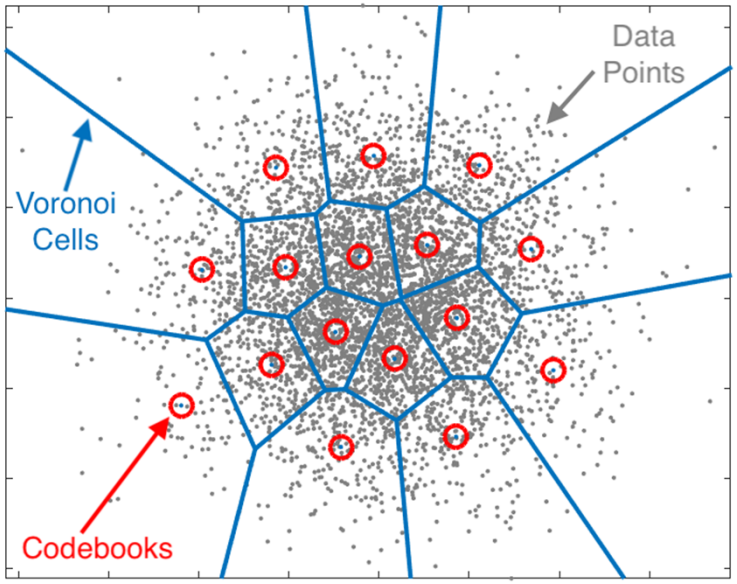
Language Modeling (LM) in Music Audio

- **Audio domain**
  - use some encoder/decoder to convert audio into "**audio tokens**"
  - **for example: VQ-VAE**
  - then build an LM



https://zhuanlan.zhihu.com/p/388299884

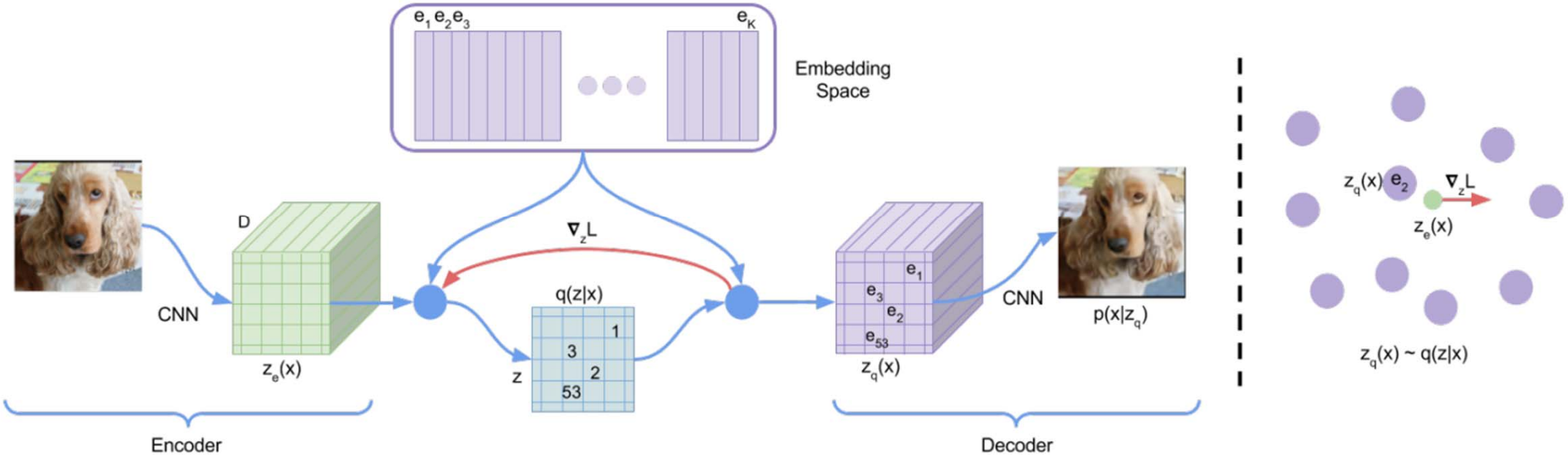
Illustration of vector quantization (VQ)



https://towardsdatascience.com/improving-vector-quantization-in-vector-quantized-variational-autoencoders-vq-vae-9158814b5ce

Image Tokenization by VQVAE

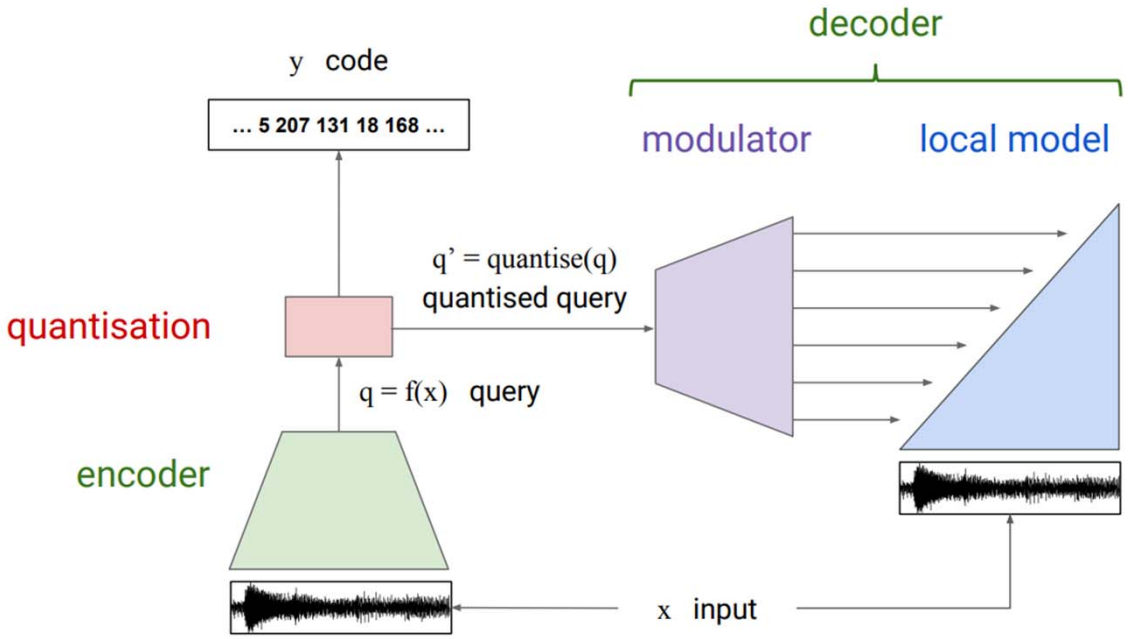
- We can obtain **discrete tokens of continuous data** by doing **vector quantization** at the output of an image **encoder** (Oord et al., 2017)



Ref: Oord et al, "Neural discrete representation learning, NeurIPS 2017

Audio Tokenization by VQVAE

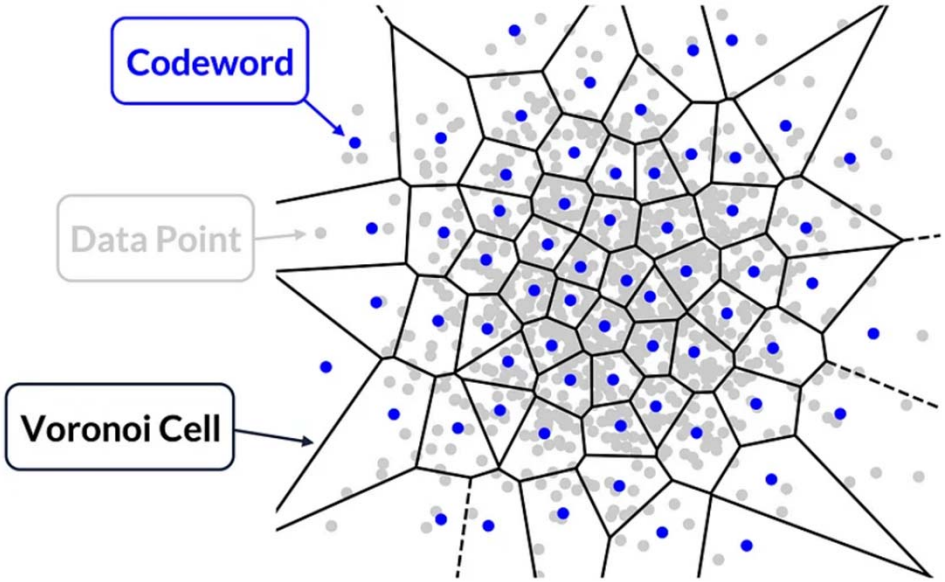
- Similarly, doing **vector quantization** at the output of an audio **encoder** (Dieleman et al., 2018)



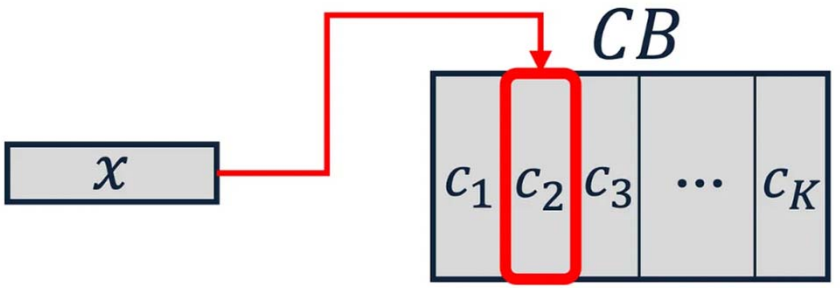
Ref: Dieleman et al, "The challenge of realistic music generation: modelling raw audio at scale," NeurIPS 2018

Vector Quantization

- Form a codebook by **clustering** in an embedding space from an encoder



Vector Quantization Operation (image by author)



$$x_{quantized} = c_{i^*} \; ; \; i^* = \arg\min_i \|x - c_i\|^2 \; ; \; i \in \{1, ..., K\}$$

$$in\ this\ case : x_{quantized} = c_2$$

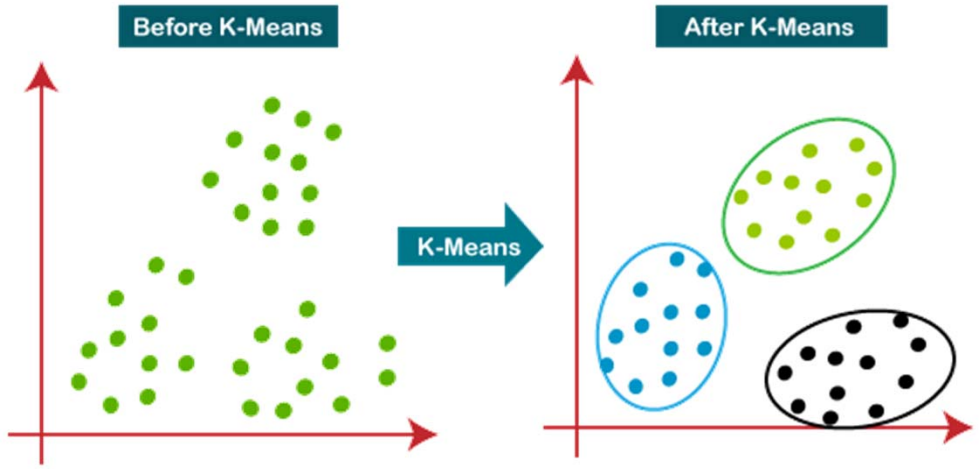
(Figure from: https://towardsdatascience.com/optimizing-vector-quantization-methods-by-machine-learning-algorithms-77c436d0749d)

K-Means Clustering

https://towardsdatascience.com/clear-and-visual-explanation-of-the-k-means-algorithm-applied-to-image-compression-b7fdc547e410

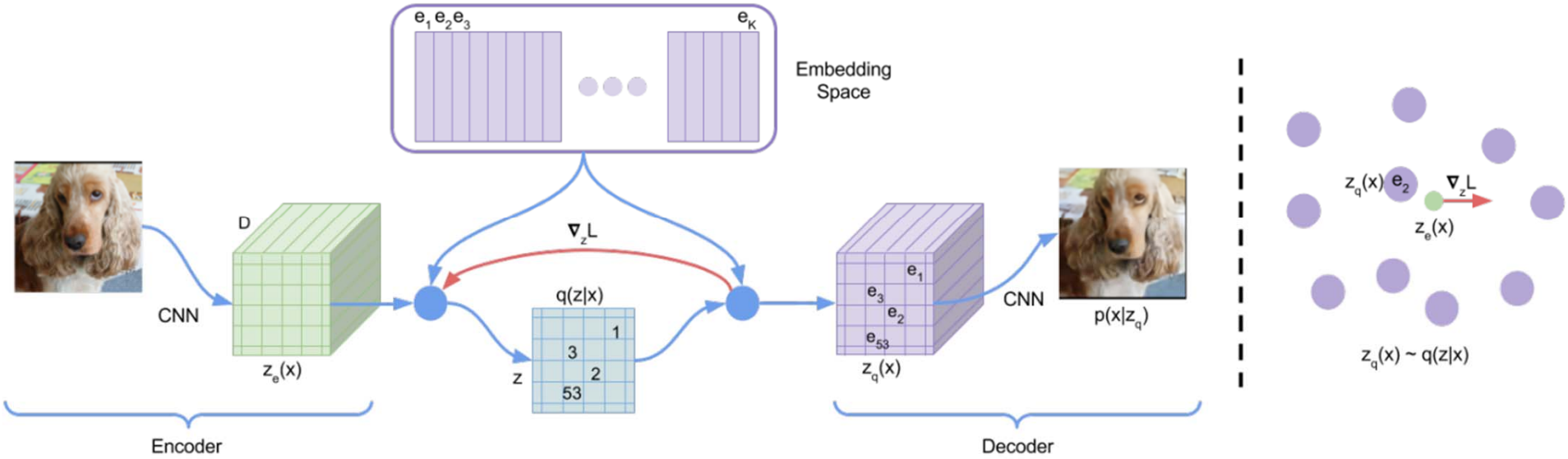
- K-Means algorithm
  - Initializing a set of cluster centroids
  - Assigning observations to clusters
  - Updating the clusters

- Difference between K-Means and VQVAE
  - In K-Means, the feature space is ***given***
  - In VQVAE, the feature space is ***learned***



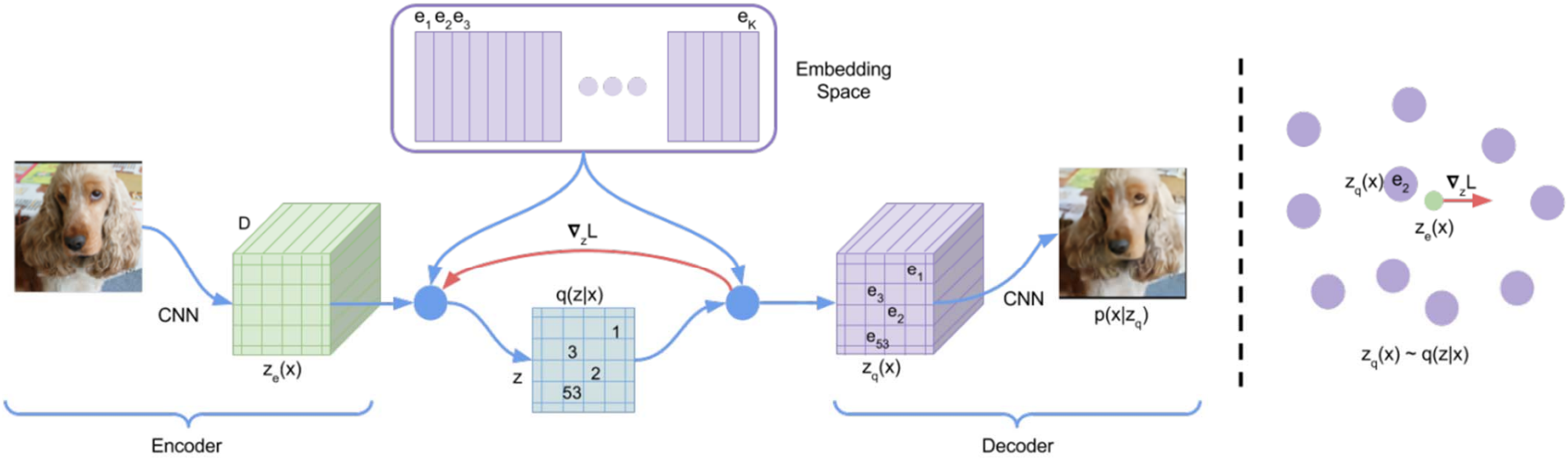
https://keytodatascience.com/k-means-clustering-algorithm/

VQVAE



- Encoder output: $z_e(\mathbf{x})$
- VQ: find the codeword $\mathbf{e}$ from a learned codebook $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_K\}$ that is closest to $z_e(\mathbf{x})$ to represent $z_e(\mathbf{x})$
- Decoder input: $z_q(\mathbf{x}) \triangleq \mathbf{e}$

VQVAE



$$L = \log p(x|z_q(x)) + \|\mathrm{sg}[z_e(x)] - e\|_2^2 + \beta\|z_e(x) - \mathrm{sg}[e]\|_2^2,$$

Reconstruction loss

Optimizes the encoder and decoder

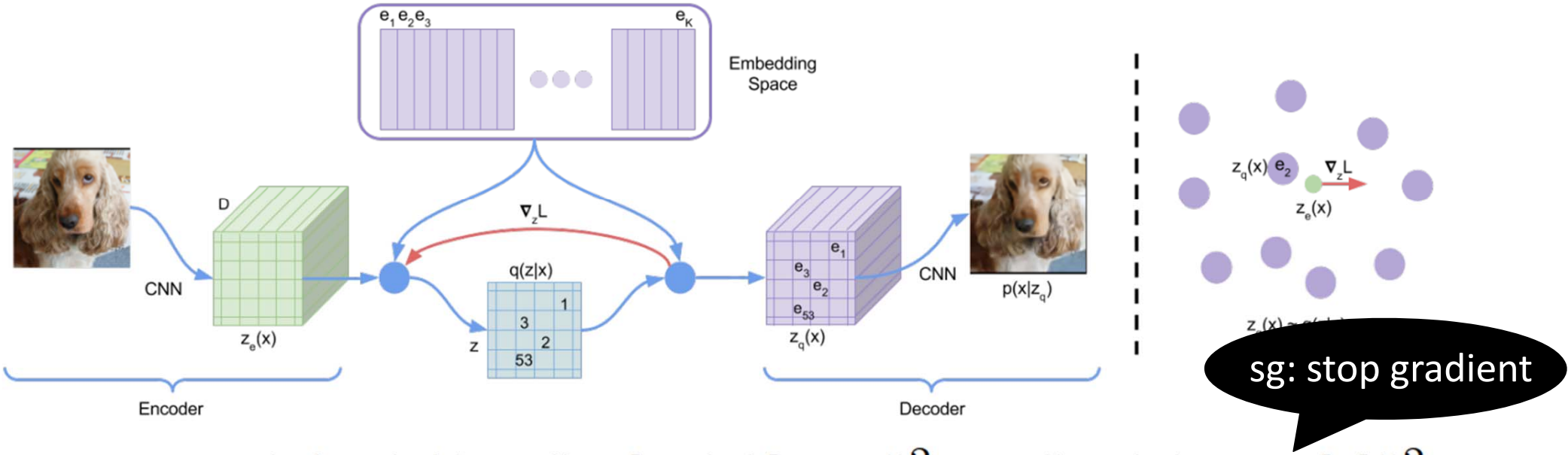
Codebook loss

Optimizes the codebook (move the codewords towards the encoder outputs)

commitment loss

Optimizes the encoder (move the encoder outputs towards the codewords)

VQVAE



$$L = \log p(x|z_q(x)) + \|\mathrm{sg}[z_e(x)] - e\|_2^2 + \beta\|z_e(x) - \mathrm{sg}[e]\|_2^2,$$

Reconstruction loss

Codebook loss

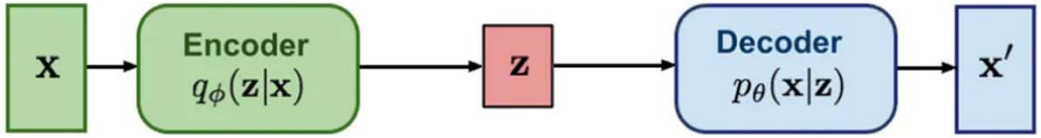
commitment loss

Decoder needs to recover the input from a quantized latent

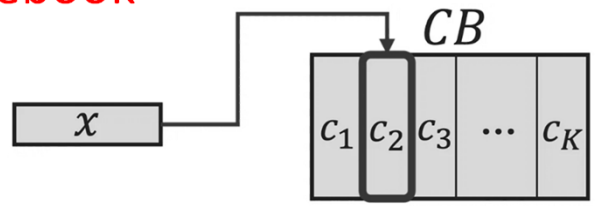
Commitment loss helps improves convergence because the encoder output would “commit” to some codewords instead of changing the codewords too frequently

VQVAE vs VAE

VAE: maximize variational lower bound



- **VQVAE produces discrete codes** (indices for a fixed number of latents)
  - **Encoder output**: an arbitrary continuous latent $q_\phi(\mathbf{z}|\mathbf{x})$
  - **Decoder input**: a *continuous* latent *selected* from the codebook
  - **Codebook size** K → only *K* possible decoder input
  - **The latent** $\mathbf{z}$ → one-hot index vector of dimension K



- **VAE produces continuous latent**
  - **Encoder output**: mean and STD
  - **Decoder input**: sampled continuous latent $\mathbf{z}$ from the mean and STD

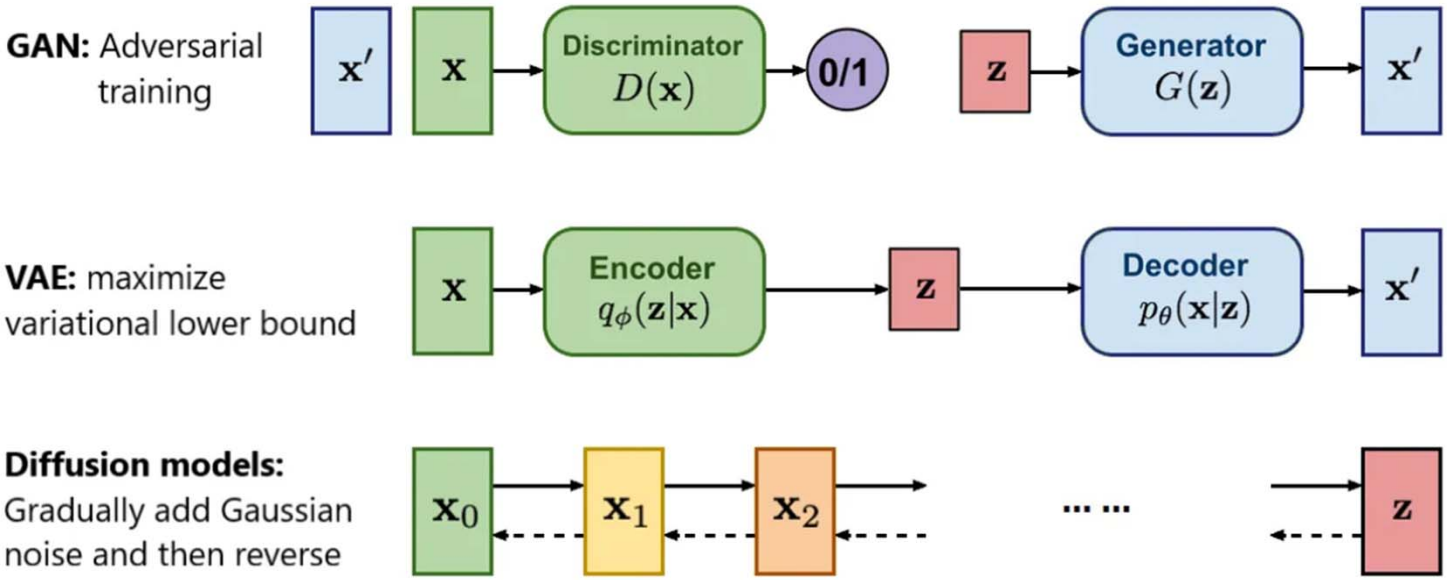
$$x_{quantized} = c_{i^*} \; ; \; i^* = \arg\min_i \|x - c_i\|^2 \; ; \; i \in \{1, \ldots, K\}$$

$$in\ this\ case : x_{quantized} = c_2$$

(Figure from: https://pub.towardsai.net/diffusion-models-vs-gans-vs-vaes-comparison-of-deep-generative-models-67ab93e0d9ae)

VQVAE vs VAE

- Both have an "**information bottleneck**"
- VQVAE produces **discrete codes** (indices for a fixed number of latents), while VAE produces **continuous latent**

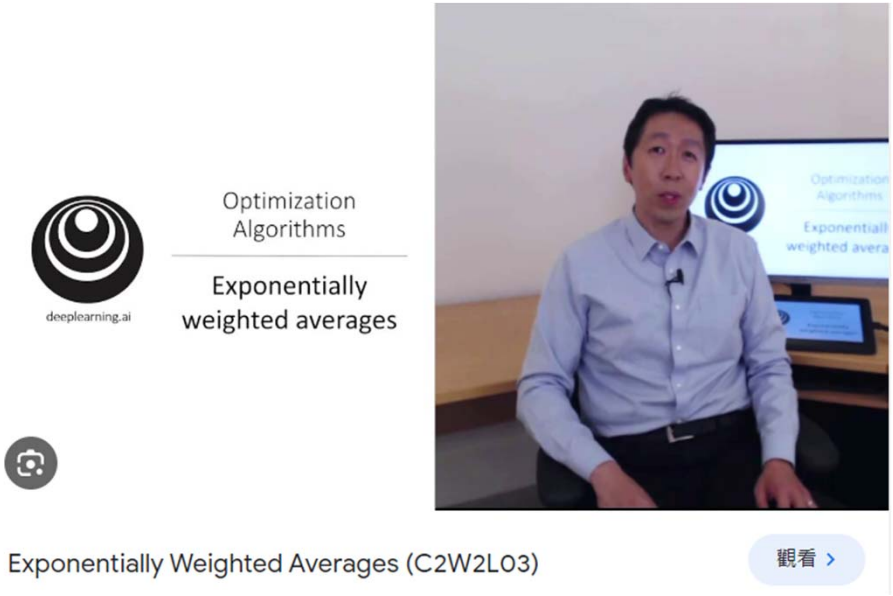


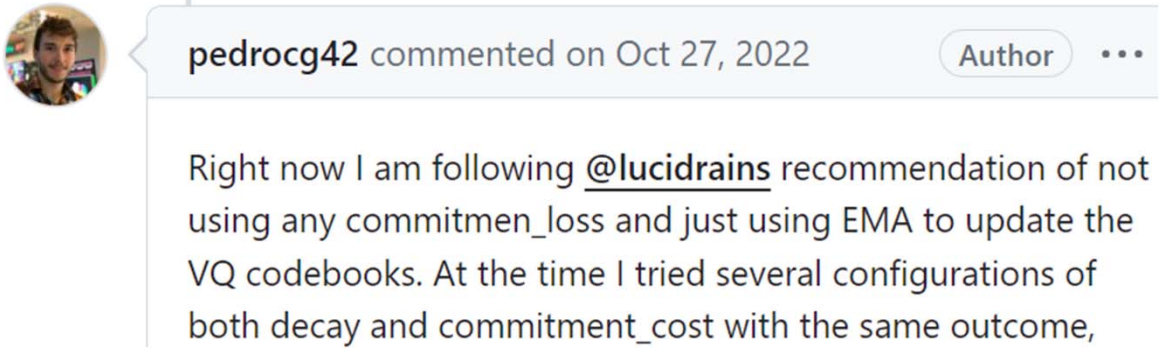
(Figure from: https://pub.towardsai.net/diffusion-models-vs-gans-vs-vaes-comparison-of-deep-generative-models-67ab93e0d9ae)

VQVAE Training Tips: Exponential Moving Average (EMA)

$$L = \log p(x|z_q(x)) + \|\text{sg}[z_e(x)] - e\|_2^2 + \beta\|z_e(x) - \text{sg}[e]\|_2^2,$$

Reconstruction loss | Codebook loss (EMA update) | commitment loss



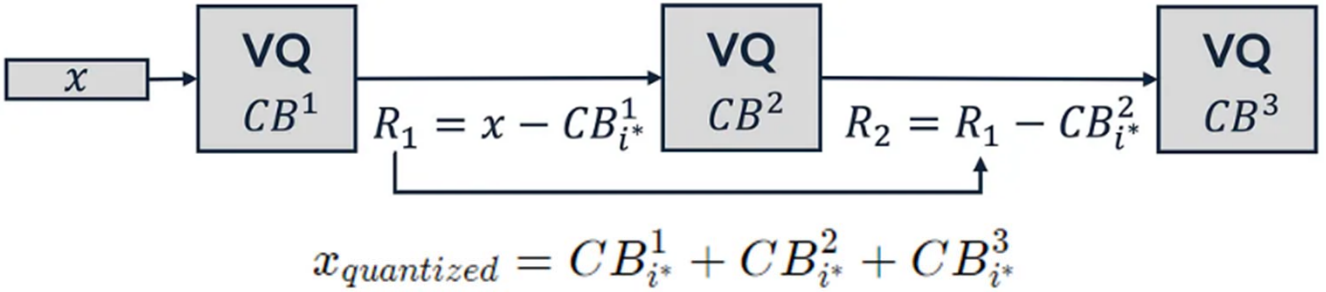


Some people said that we don't need the commitment loss if we use EMA
(https://github.com/lucidrains/vector-quantize-pytorch/issues/27)

Ref: Oord et al, "Neural discrete representation learning, NeurIPS 2017

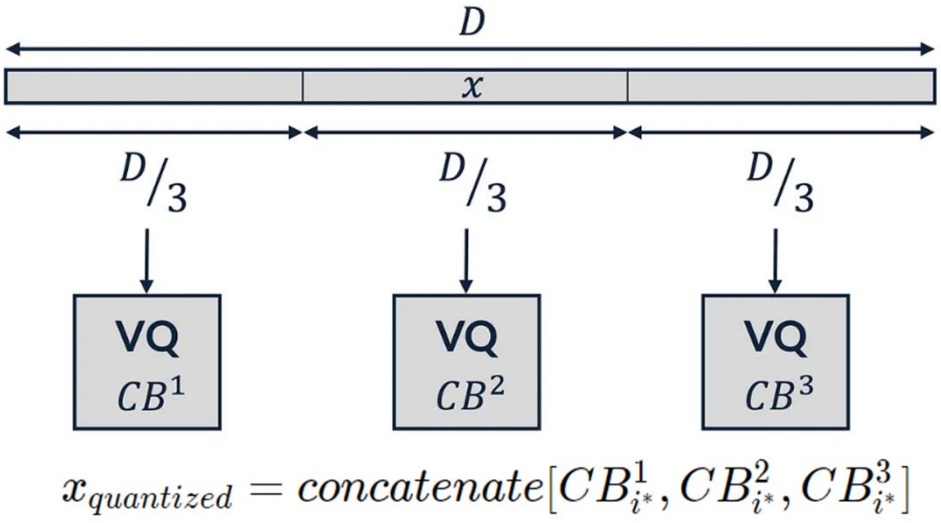
Variants of VQ

- Residual VQ (**RVQ**)



- Product VQ (PVQ)

  (a.k.a., decomposed VQ; DVQ)



- More… (e.g., additive VQ)

(Figure from: https://towardsdatascience.com/optimizing-vector-quantization-methods-by-machine-learning-algorithms-77c436d0749d)

VQVQE Library

https://github.com/lucidrains/vector-quantize-pytorch

vector-quantize-pytorch

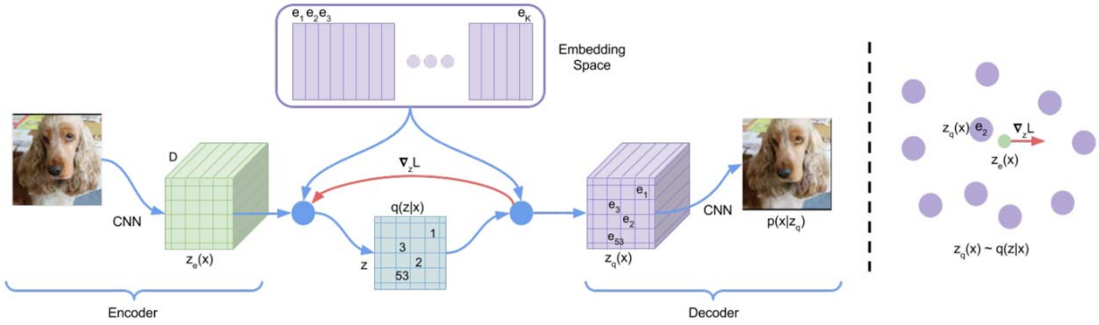
- Initialization
- **Lower codebook dimension**
- Cosine similarity
- **Expiring stale codes**
- Orthogonal regularization loss
- Multi-headed VQ
- Random Projection Quantizer
- Finite Scalar Quantization
- Lookup Free Quantization

VQVAE Training Tips: Increasing Codebook Usage

https://github.com/lucidrains/vector-quantize-pytorch

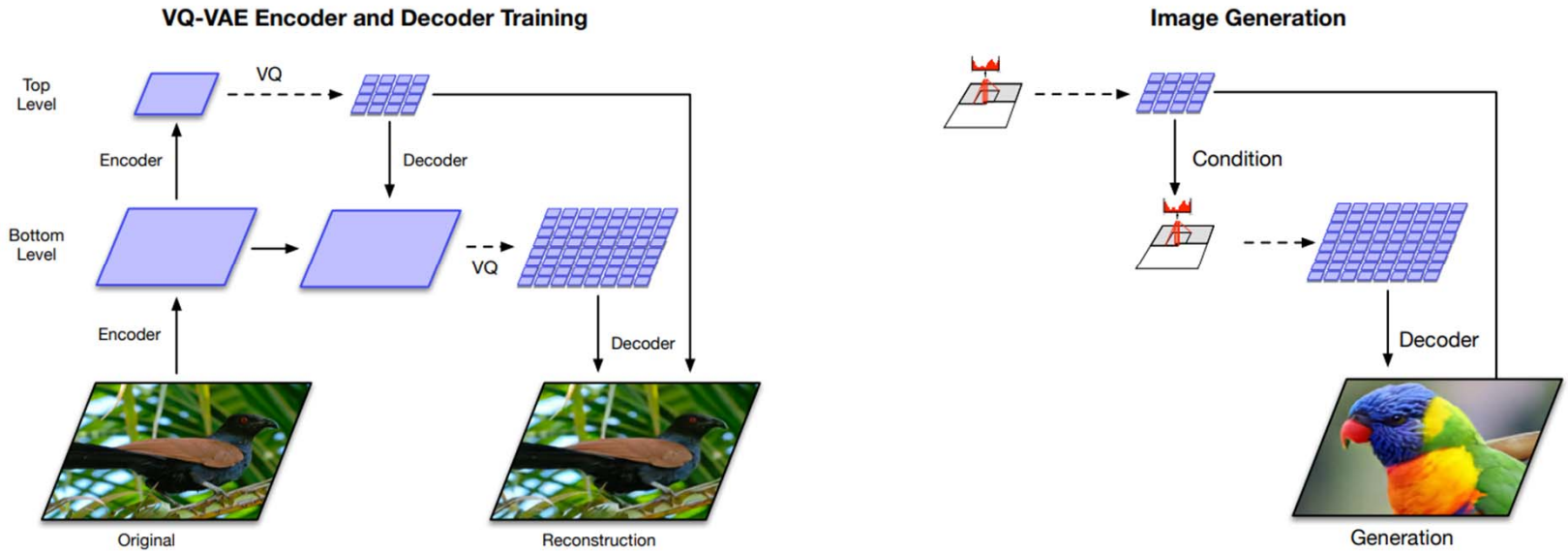
vector-quantize-pytorch

- Techniques to combat “dead” codebook entries (*index collapse*), which is a common problem when using vector quantizers
- **Lower codebook dimension**
  - Do VQ in a lower-dim space
  - The encoder values are projected down before being projected back to high dim after quantization



VQVAE 2: Hierarchical VQ

- The input to the model is a 256×256 image that is compressed to quantized latent maps of size 64×64 and 32×32 for the bottom and top levels, respectively. The decoder reconstructs the image from the two latent maps.



Ref: Razavi et al, "Generating diverse high-fidelity images with VQ-VAE-2," NeurIPS 2019

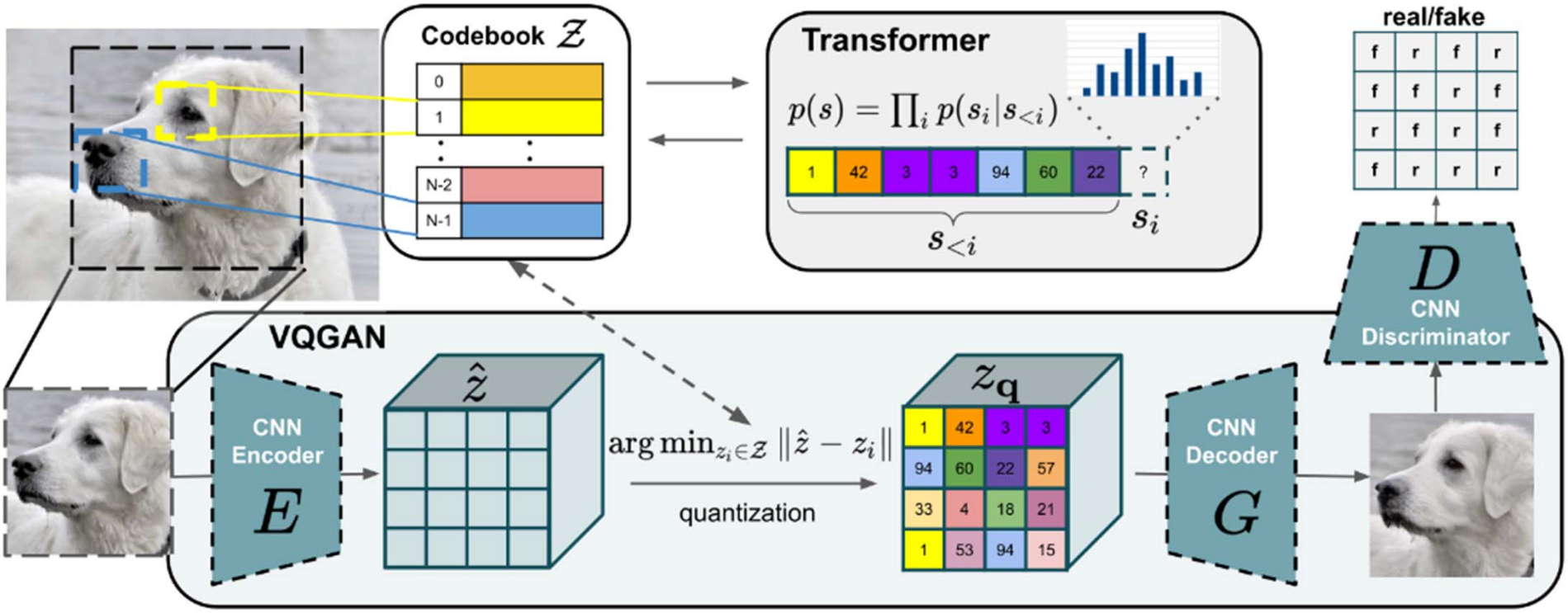
Summary

- We can use **VQVAE** to convert continuous data to discrete tokens
- What we get from VQVAE: **encoder**, **decoder**, and **codebook**

- We can then train a Transformer **LM** over the codeword sequences
  - Image generation: VQGAN
  - Music generation: Jukebox, KaraSinger, JukeDrummer, SingSong

- The VQVAE and the Transformer LM are trained separately

VQVAE-based Image Generation: VQGAN

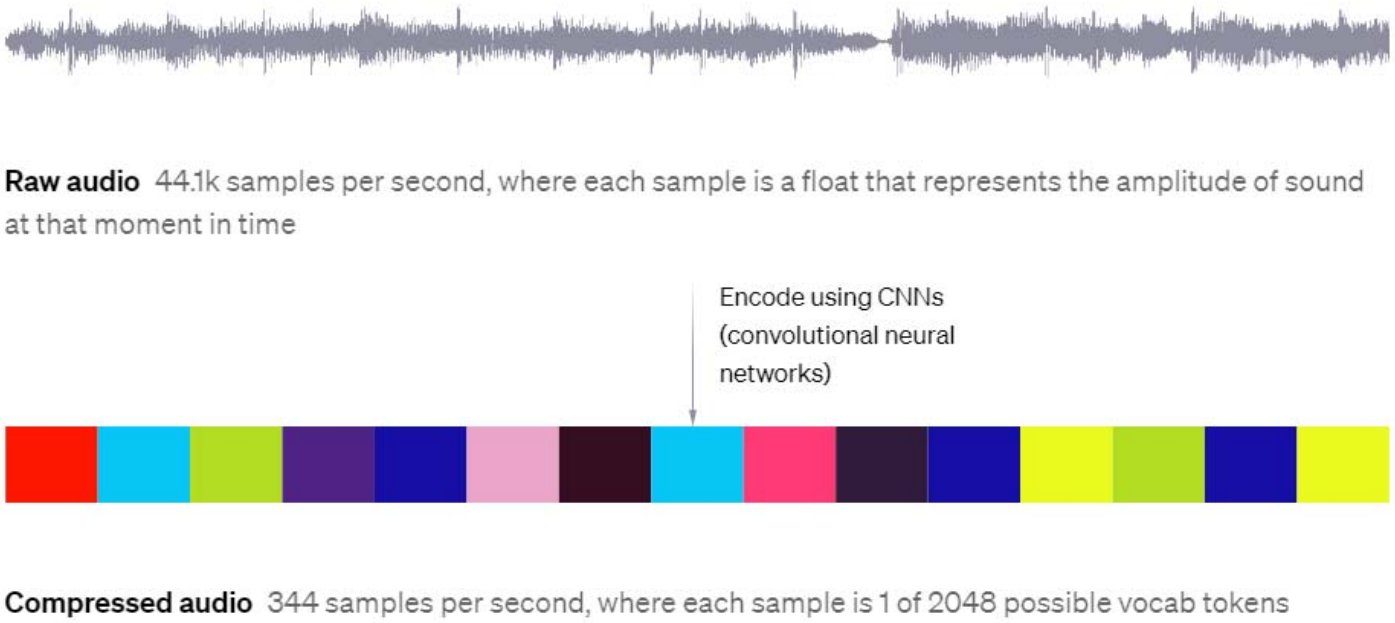


Ref: Esser et al, "Taming Transformers for high-resolution image synthesis," CVPR 2021
Ref: Yu et al, "Vector-quantized Image Modeling with Improved VQGAN," ICLR 2022

VQVAE-based Music Generation: JukeBox

https://openai.com/research/jukebox

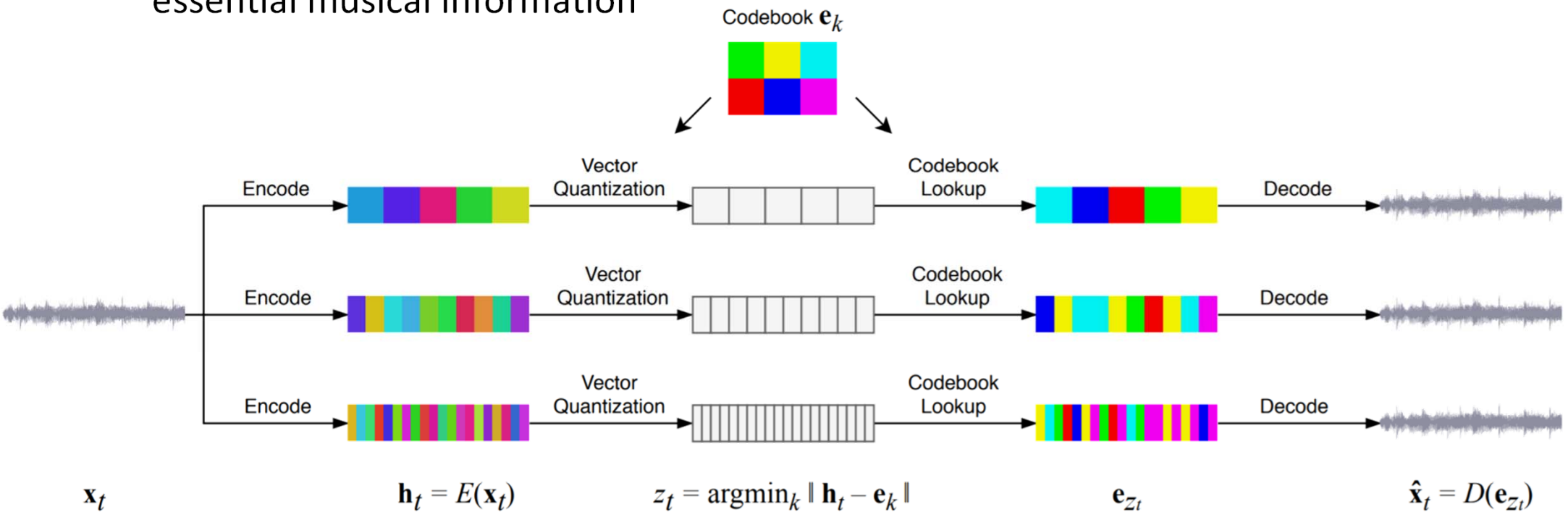
- Use **vector quantization** (VQ) to model waveforms as "**acoustic tokens**"



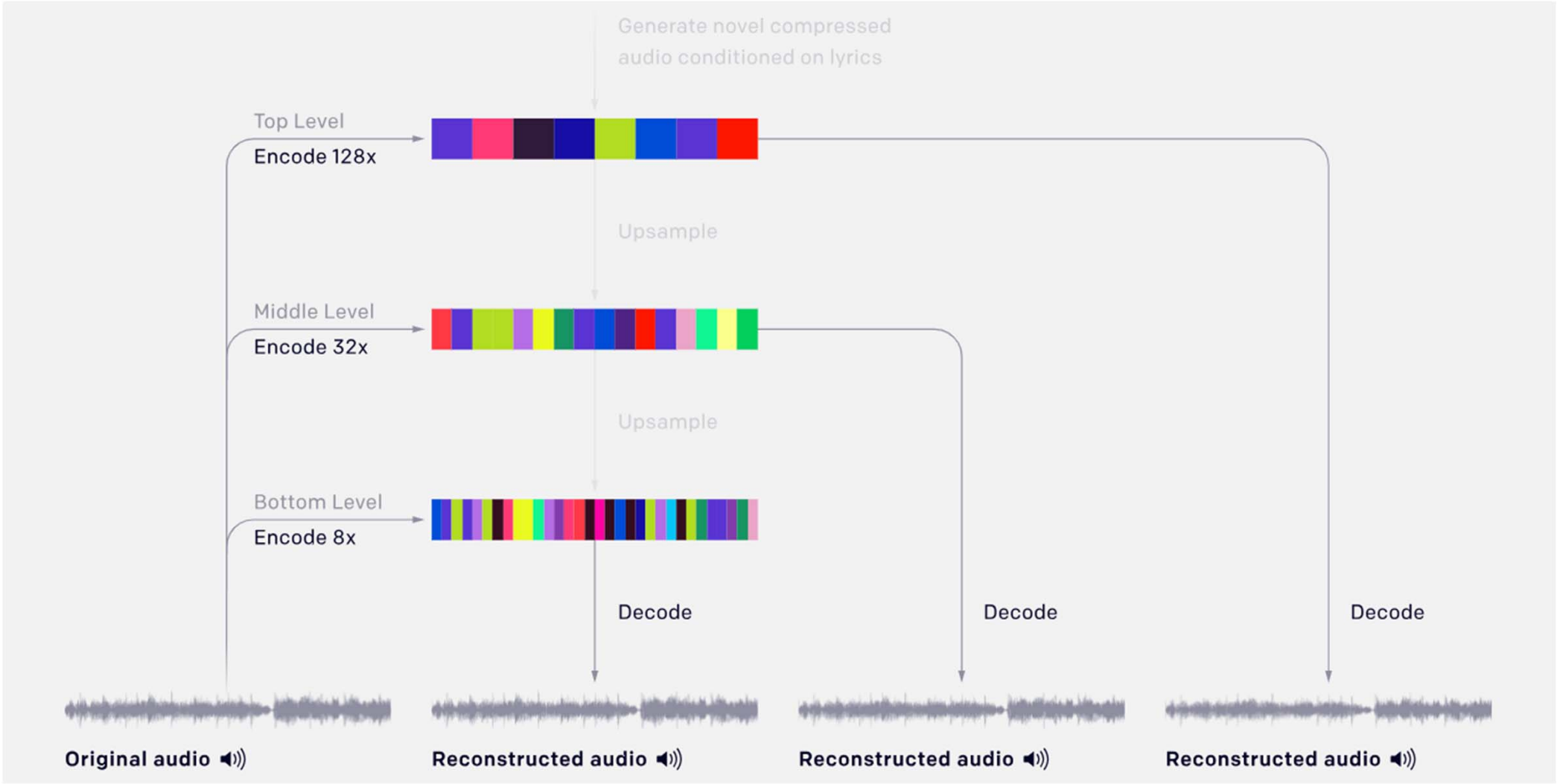
Ref: Dhariwal et al, "Jukebox: A generative model for music," arXiv 2020

VQVAE-based Music Generation: JukeBox

- Three layers of VQ for fidelity (like VQVAE 2): **top**, **middle**, **bottom**
  - Each VQ-VAE level independently encodes the input
  - **Bottom** produces the highest quality reconstruction, while **top** retains only the essential musical information

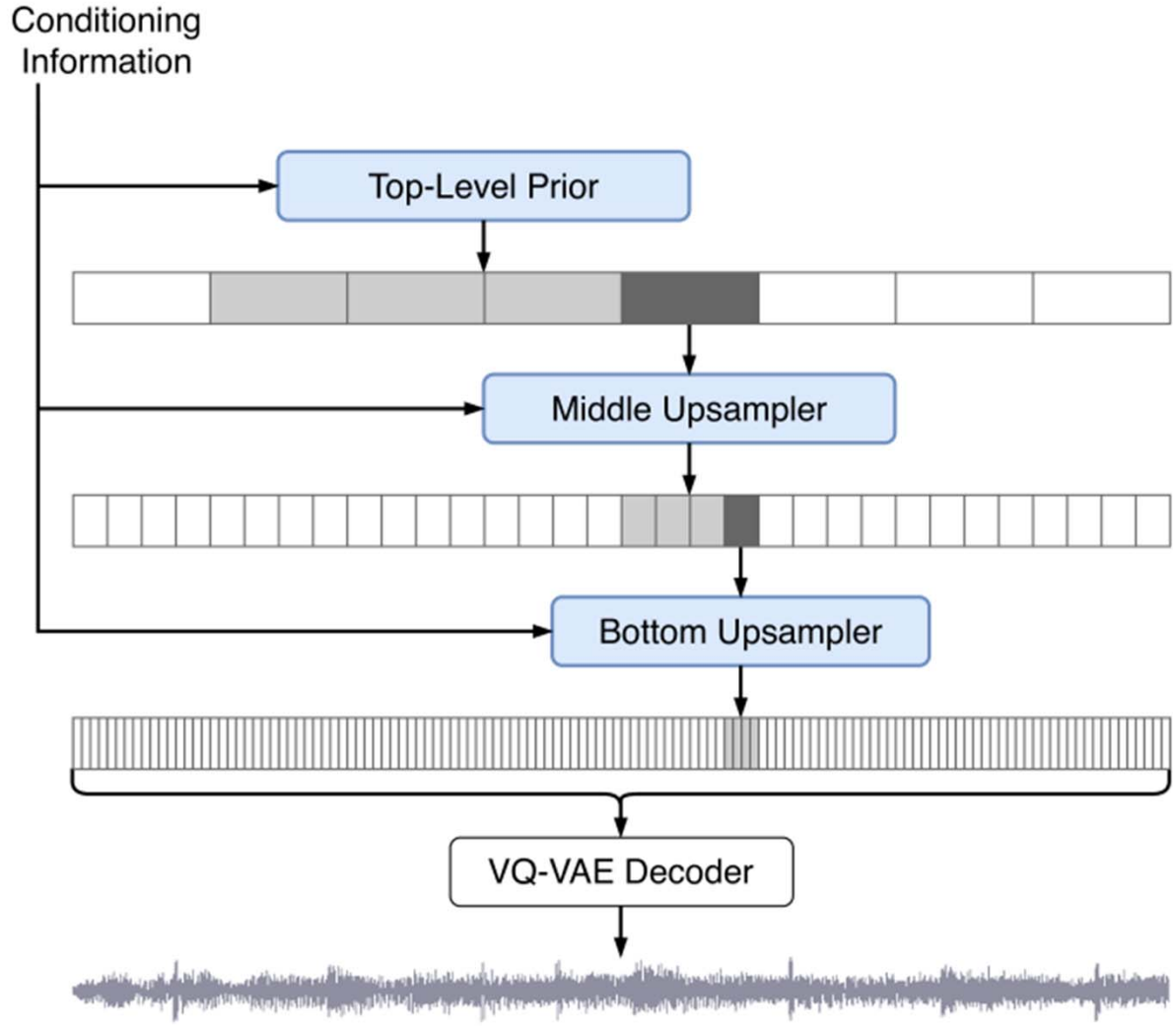


VQVAE-based Music Generation: JukeBox

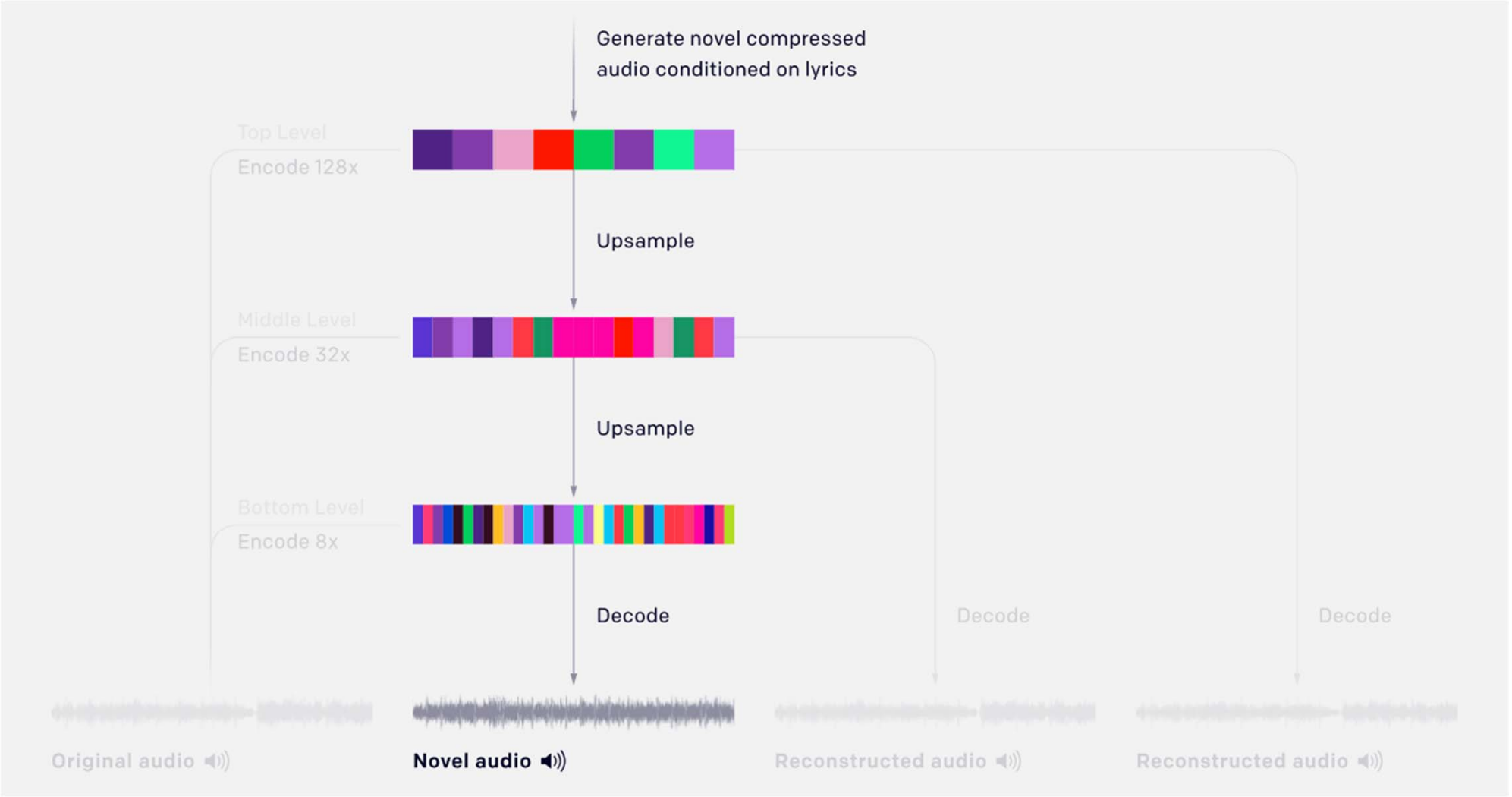


VQVAE-based Music Generation: JukeBox

- Take **lyrics** as condition
  - Given lyrics, generate **top-level** tokens
  - Given lyrics+top, generate **mid-level** tokens
  - Given lyrics+mid, generate **bottom-level** tokens
- Generate music waveforms that contain both **vocal** and **instrumental background** (mixed together)

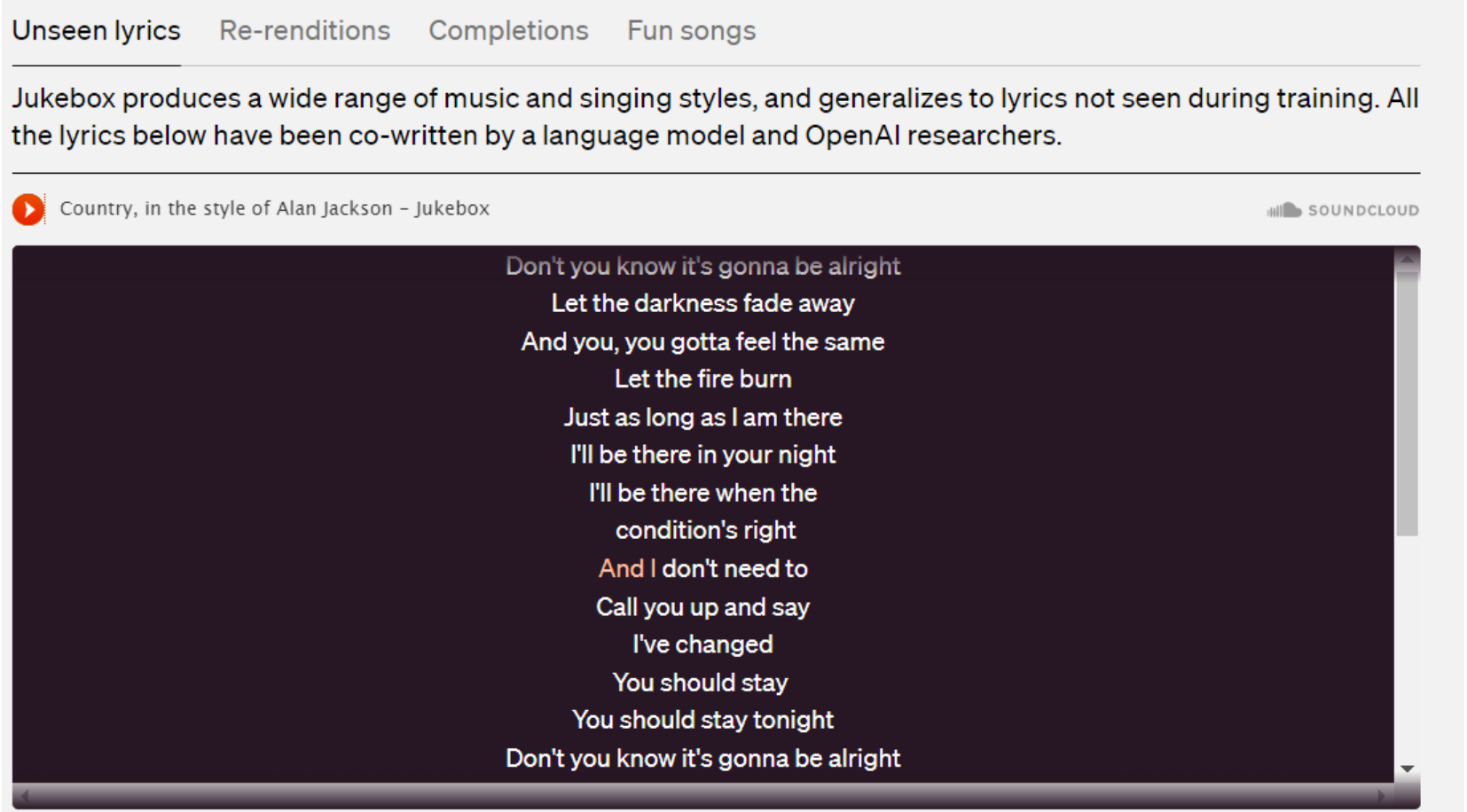


VQVAE-based Music Generation: JukeBox



VQVAE-based Music Generation: JukeBox

https://openai.com/research/jukebox



Issues of OpenAI's Jukebox

- **GPU-intensive**
  - **1M** proprietary songs as training data & **512 V100s** & total training time **>6 weeks** (i.e., around >60 years of single V100 time)

trained on 128 V100s for 2 weeks, and the top-level prior has 5 billion parameters and is trained on 512 V100s for 4 weeks. We use Adam with learning rate 0.00015 and weight decay of 0.002. For lyrics conditioning, we reuse the prior and add a small encoder, after which we train the model on 512 V100s for 2 weeks. The detailed hyperparameters for our models and training are provided in Appendix B.3.

The current model takes around an hour to generate 1 minute of top level tokens. The upsampling process is very slow, as it proceeds sequentially through the sample. Currently it takes around 8 hours to upsample one minute of top level tokens. We can create a human-in-the-loop co-composition process at the top level only, using the VQ-VAE decoders

- **Low controllability**
  - The only control signal is the lyrics

Outline

- Image/audio tokenization and generation via VQVAE
- **Audio codec models**
- Text-to-music: linking text and musical audio
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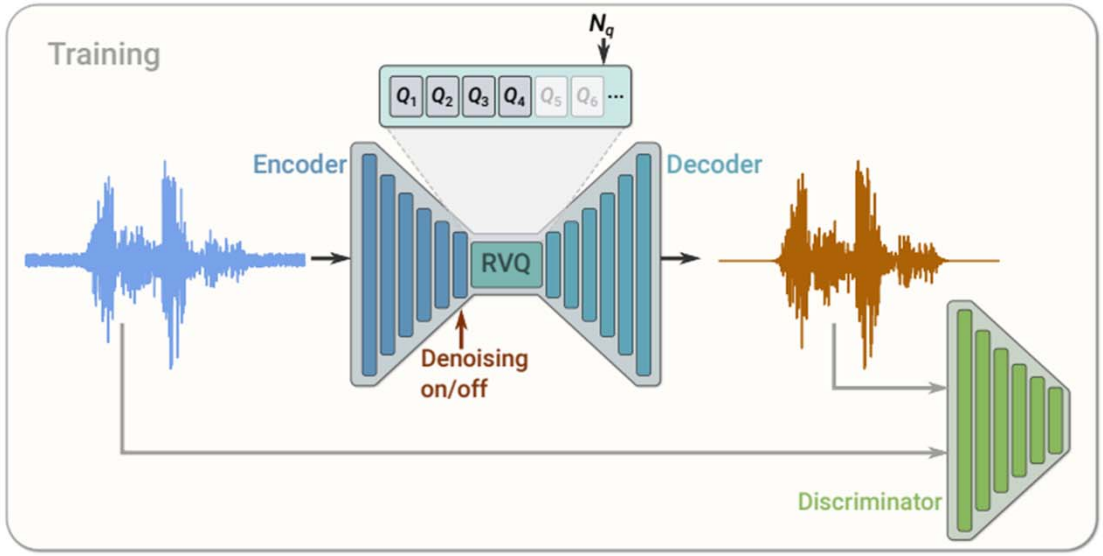
  - Diffusion-based approach

Audio Codec

- **Use raw waveforms for VQ-VAE** (like OpenAI's JukeBox)
- Initially developed for **audio compression**
  - ***Bitrate*** vs ***fidelity***
  - Computational complexity vs coding efficiency

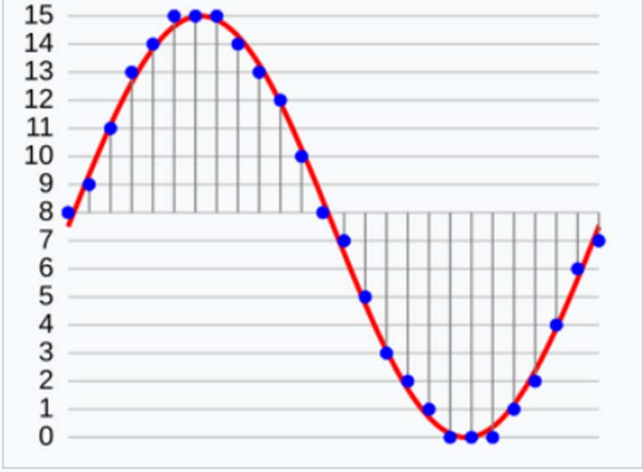


- Use vector quantization (VQ) for quantization
  - Produce **discrete tokens** that can be used for building a Transformer LM, though training LMs is not the focus of these audio compression papers

Ref: Zeghidour et al, "SoundStream: An end-to-end neural audio codec," IEEE TASLP 2021

Bitrate

- Pulse-code modulation (PCM)
  - 4bits: 16 possible values
  - 16bits: 65,536 possible values

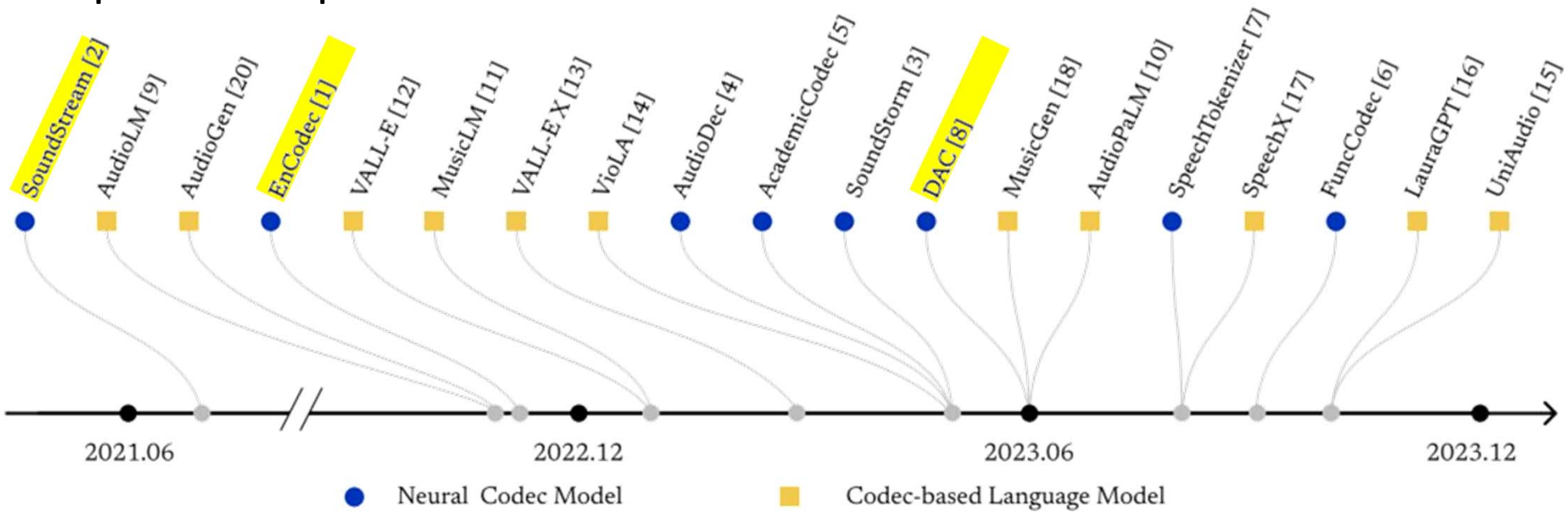


Sampling and quantization of a signal (red) for 4-bit LPCM over a time domain at specific frequency

- For 16bits 44.1kHz audio
  - 705.6 kbits per second (**kbps**)
  - 42.336 Mbits per minute

Audio Codec

- Rapid development



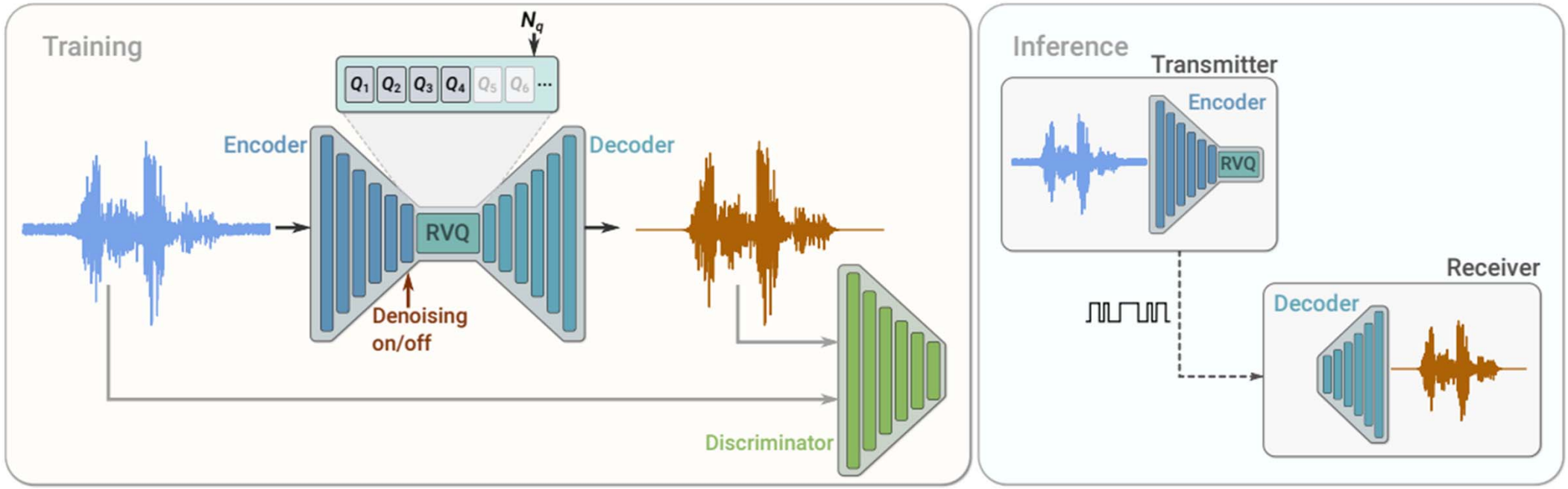
Towards audio language modeling - an overview

Haibin Wu[1], Xuanjun Chen[1*], Yi-Cheng Lin[1*], Kai-wei Chang[1], Ho-Lam Chung[1],
Alexander H. Liu[2], Hung-yi Lee[1]

https://arxiv.org/pdf/2402.13236

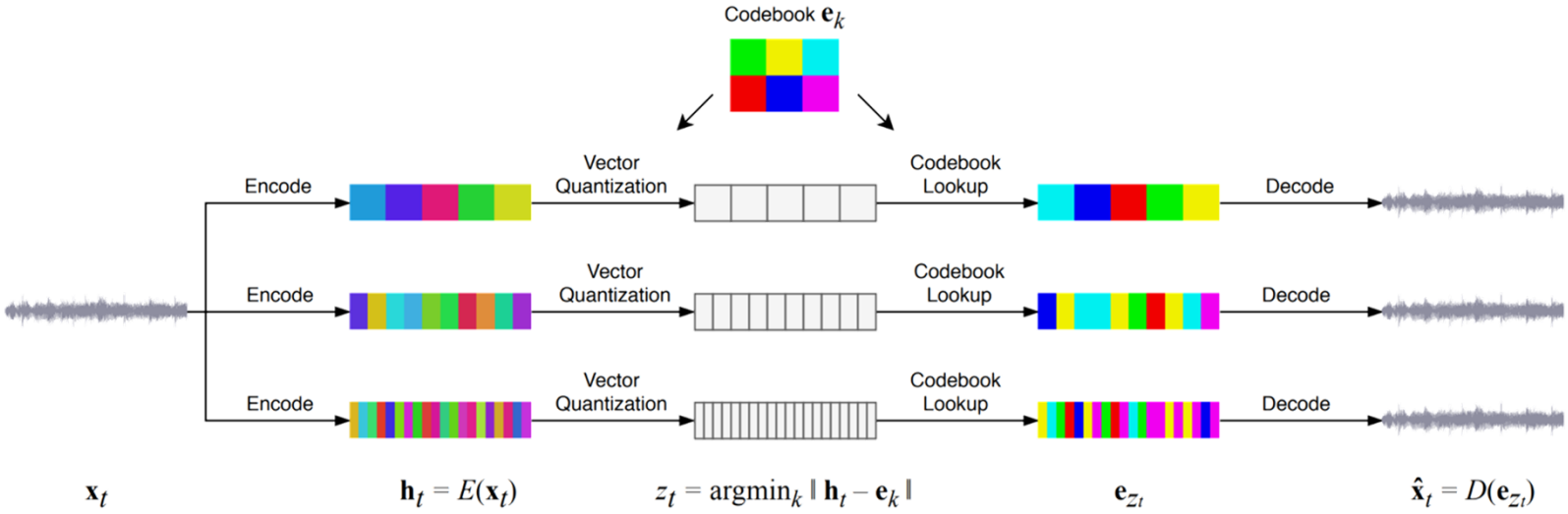
SoundStream (from Google)

- Use RVQ
  - The same audio chunk is **recursively** VQed by different codebooks

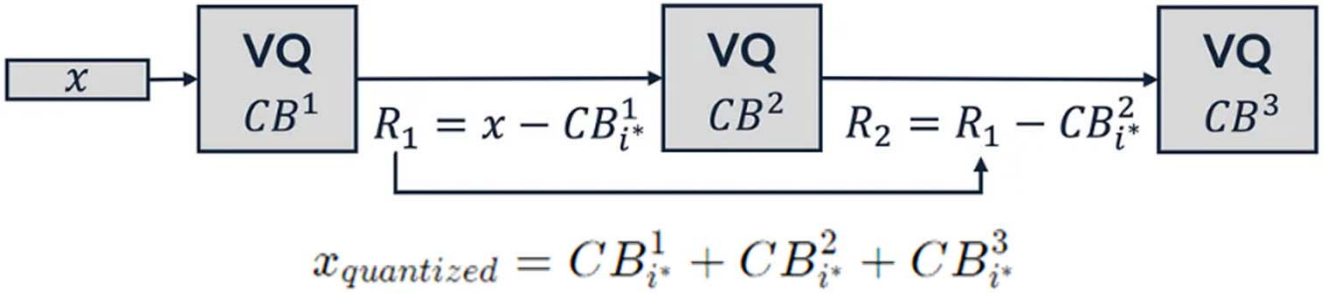


Ref: Zeghidour et al, "SoundStream: An end-to-end neural audio codec," IEEE TASLP 2021

Hierarchical VQ vs RVQ



- **RVQ** is found to be superior in audio codec research



RVQ Demonstration

- Use descript audio codec (DAC) → see later slides

- Adding more quantizers (codebook layers) improve fidelity
  - At the cost of increased bitrate (therefore less compression rate)

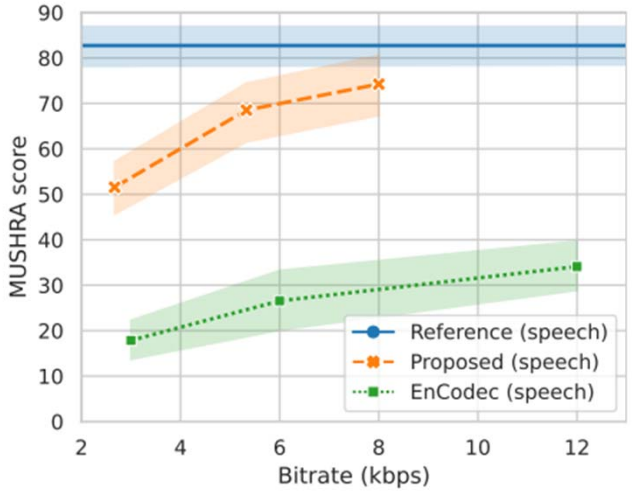
9 layers

6 layers

3 layers

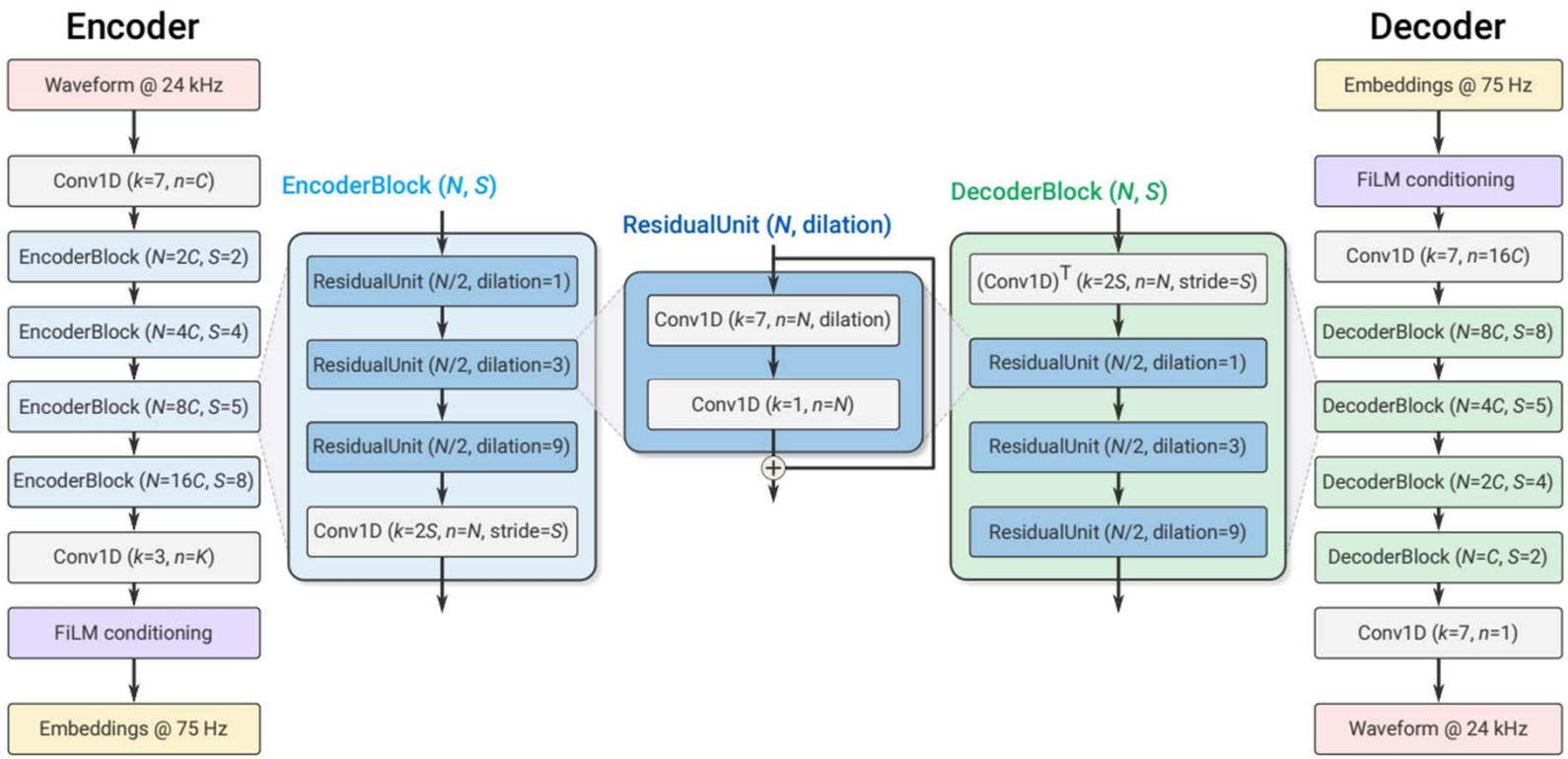
2 layers

1 layer



SoundStream (from Google)

- **Convolutional** encoder/decoder



Ref: Zeghidour et al, "SoundStream: An end-to-end neural audio codec," IEEE TASLP 2021

SoundStream (from Google)

- Use both a waveform-domain discriminator and an STFT-based discriminator, which receives as input the complex-valued STFT of the input waveform, expressed in terms of real and imaginary parts

- Both discriminators are fully **convolutional**

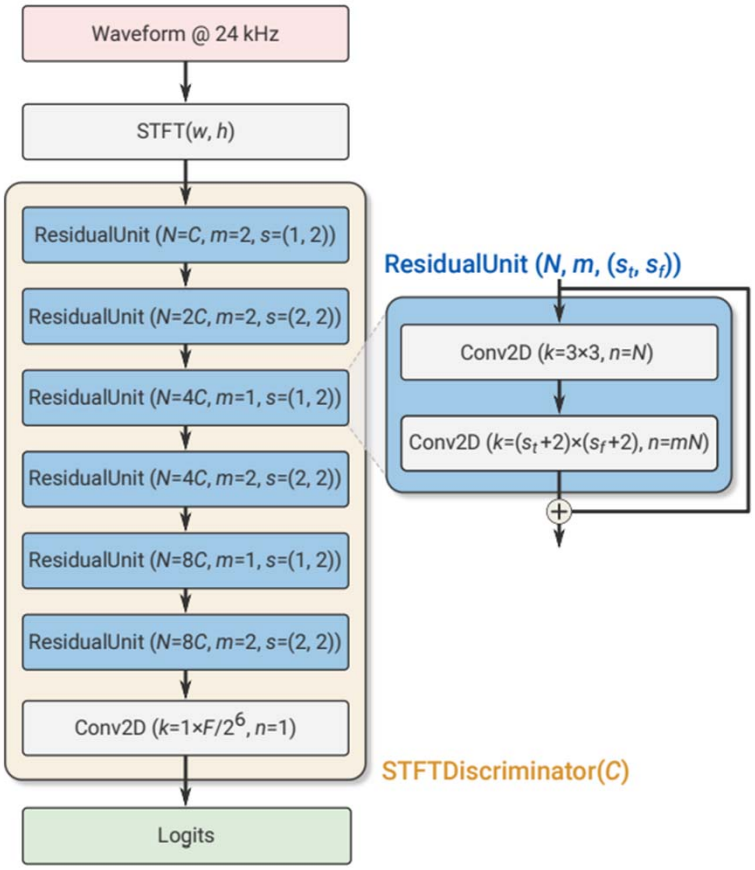


Fig. 4: STFT-based discriminator architecture.

Ref: Zeghidour et al, "SoundStream: An end-to-end neural audio codec," IEEE TASLP 2021

SoundStream (from Google)

- Use **8** layers of RVQ
- Codebook size set to **1024** (2^{10}) for each quantizer
- Evaluation metric: Google's **ViSQOL** (Virtual Speech Quality Objective Listener)
- **Not open source**

TABLE II: Trade-off between residual vector quantizer depth and codebook size at 6 kbps.

Number of quantizers N_q	8	16	80
Codebook size N	1024	32	2
ViSQOL	4.01 ± 0.03	3.98 ± 0.03	3.92 ± 0.03

(the effective number of unique codewords of these three configurations is all $\mathbf{2^{80}}$, why?)

Ref: Zeghidour et al, "SoundStream: An end-to-end neural audio codec," IEEE TASLP 2021

EnCodec (from Meta)

Open source https://github.com/facebookresearch/encodec

- A causal model operating at 24 kHz on monophonic audio trained on a variety of audio data.
- A non-causal model operating at 48 kHz on stereophonic audio trained on music-only data.

The 24 kHz model can compress to 1.5, 3, 6, 12 or 24 kbps, while the 48 kHz model support 3, 6, 12 and 24 kbps. We also provide a pre-trained language model for each of the models, that can further compress the representation by up to 40% without any further loss of quality.

Compression

```
encodec [-b TARGET_BANDWIDTH] [-f] [--hq] [--lm] INPUT_FILE [OUTPUT_FILE]
```

Decompression

```
encodec [-f] [-r] ENCODEC_FILE [OUTPUT_WAV_FILE]
```

Ref: Défossez et al, “High fidelity neural audio compression,” TMLR 2023

EnCodec (from Meta)

Extracting discrete representations

```python
from encodec import EncodecModel
from encodec.utils import convert_audio
```

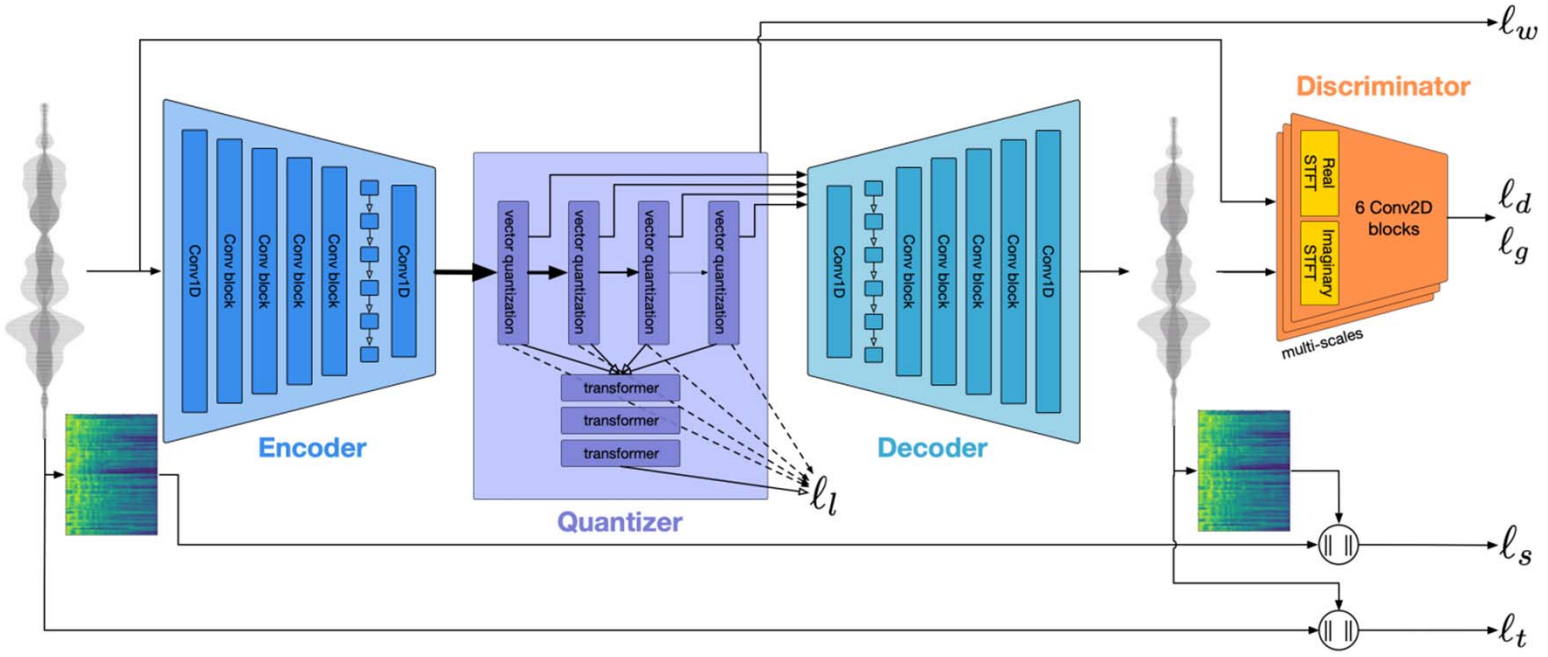
```python
# Instantiate a pretrained EnCodec model
model = EncodecModel.encodec_model_24khz()
# The number of codebooks used will be determined bythe bandwidth selected.
# E.g. for a bandwidth of 6kbps, `n_q = 8` codebooks are used.
# Supported bandwidths are 1.5kbps (n_q = 2), 3 kbps (n_q = 4), 6 kbps (n_q = 8) and 12 kbps (n_q =16) and 24
# For the 48 kHz model, only 3, 6, 12, and 24 kbps are supported. The number
# of codebooks for each is half that of the 24 kHz model as the frame rate is twice as much.
model.set_target_bandwidth(6.0)

# Load and pre-process the audio waveform
wav, sr = torchaudio.load("<PATH_TO_AUDIO_FILE>")
wav = convert_audio(wav, sr, model.sample_rate, model.channels)
wav = wav.unsqueeze(0)

# Extract discrete codes from EnCodec
with torch.no_grad():
    encoded_frames = model.encode(wav)
codes = torch.cat([encoded[0] for encoded in encoded_frames], dim=-1)  # [B, n_q, T]
```

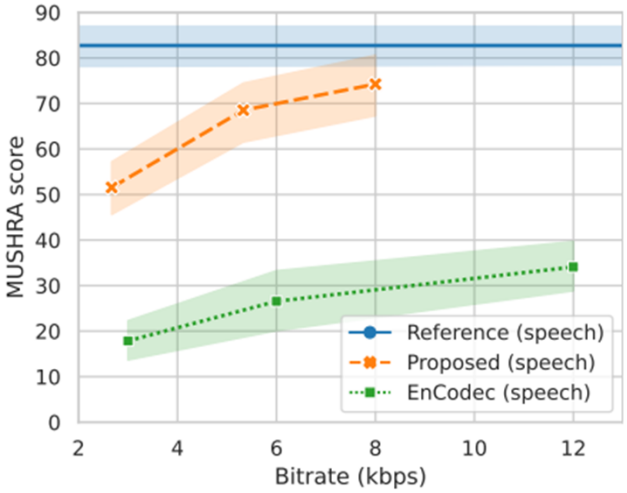
Encodec

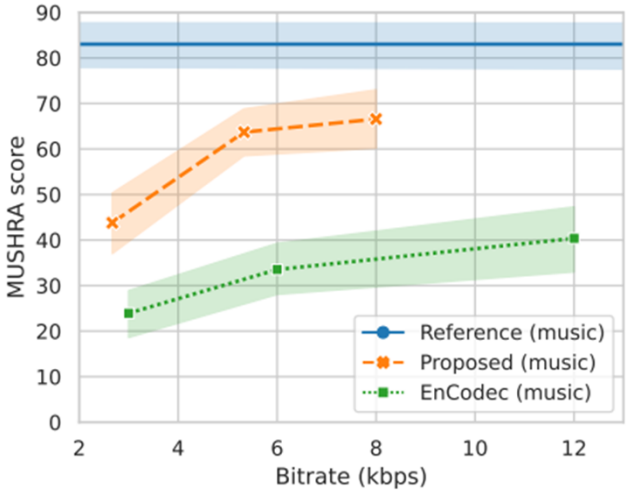
- RVQVAE+GAN, convolutional encoder/decoder
- Trained using **8 A100 GPUs** for 300 epochs
- Use the Jamendo dataset for the music version of Encodec



Descript Audio Codec (DAC)

- Can compress 44.1 KHz audio into discrete codes at **8 kbps** bitrate (~90x compression)
  - Why 90x? (16bits 44.1kHz audio: 705.6 kbps)
- Outperform EnCodec in both objective and subjective evaluations





Codec	Bitrate (kbps)	Bandwidth (kHz	Mel distance ↓	STFT distance ↓	ViSQOL ↑	SI-SDR ↑
Proposed	1.78	22.05	1.39	1.95	3.76	2.16
	2.67	22.05	1.28	1.85	3.90	4.41
	5.33	22.05	1.07	1.69	4.09	8.13
	8	22.05	0.93	1.60	4.18	10.75
EnCodec	1.5	12	2.11	4.30	2.82	-0.02
	3	12	1.97	4.19	2.94	2.94
	6	12	1.83	4.10	3.05	5.99
	12	12	1.70	4.02	3.13	8.36
	24	12	1.61	3.97	3.16	9.59
Lyra	9.2	8	2.71	4.86	2.19	-14.52
Opus	8	4	3.60	5.72	2.06	5.68
	14	16	1.23	2.14	4.02	8.02
	24	16	0.88	1.90	4.15	11.65

Ref: Kumar et al, “High-fidelity audio compression with improved RVQGAN,” NeurIPS 2023

Descript Audio Codec (DAC)

Improved RVQGAN

Ablation on	Decoder dim.	Activation	Multi-period	Single-scale	# of STFT bands	Multi-scale mel.	Latent dim	Quant. method	Quant. dropout	Bitrate (kbps)	Balanced samp.	Mel distance ↓	STFT distance ↓	ViSQOL ↑	SI-SDR ↑	Bitrate efficiency ↑
	1536	snake	✓	✗	5	✓	8	Proj.	1.0	8	✓	1.09	1.82	3.96	9.12	99%
Architecture	512	snake	✓	✗	5	✓	8	Proj.	1.0	8	✓	1.11	1.83	3.91	8.72	99%
	1024	snake	✓	✗	5	✓	8	Proj.	1.0	8	✓	1.07	1.82	3.96	9.07	99%
	1536	relu	✓	✗	5	✓	8	Proj.	1.0	8	✓	1.17	1.81	3.83	6.92	99%
Discriminator	1536	snake	✗	✗	✗	✓	8	Proj.	1.0	8	✓	1.13	1.92	4.12	1.07	62%
	1536	snake	✓	✗	1	✓	8	Proj.	1.0	8	✓	1.07	1.80	3.98	9.07	99%
	1536	snake	✗	✗	5	✓	8	Proj.	1.0	8	✓	1.07	1.81	3.97	9.04	99%
	1536	snake	✗	✓	5	✓	8	Proj.	1.0	8	✓	1.08	1.82	3.95	8.51	99%
Reconstruction loss	1536	snake	✓	✗	5	✗	8	Proj.	1.0	8	✓	1.10	1.87	4.01	7.68	99%
Latent dim	1536	snake	✓	✗	5	✓	2	Proj.	1.0	8	✓	1.44	2.08	3.65	2.22	84%
	1536	snake	✓	✗	5	✓	4	Proj.	1.0	8	✓	1.20	1.89	3.86	7.15	97%
	1536	snake	✓	✗	5	✓	32	Proj.	1.0	8	✓	1.10	1.84	3.95	9.05	98%
	1536	snake	✓	✗	5	✓	256	Proj.	1.0	8	✓	1.31	1.97	3.79	5.09	59%
Quantization setup	1536	snake	✓	✗	5	✓	8	EMA	1.0	8	✓	1.11	1.84	3.94	8.33	97%
	1536	snake	✓	✗	5	✓	8	Proj.	0.0	8	✓	0.98	1.70	4.09	10.14	99%
	1536	snake	✓	✗	5	✓	8	Proj.	0.25	8	✓	0.99	1.69	4.04	10.00	99%
	1536	snake	✓	✗	5	✓	8	Proj.	0.5	8	✓	1.01	1.75	4.03	9.74	99%
	1536	snake	✓	✗	5	✓	8	Proj.	1.0	24	✓	0.73	1.62	4.16	13.83	99%
Data	1536	snake	✓	✗	5	✓	8	Proj.	1.0	8	✗	1.09	1.94	3.89	8.89	99%

Descript Audio Codec (DAC)

https://github.com/descriptinc/descript-audio-codec

```
python3 -m dac download --model_type 44khz # downloads the 44kHz variant
python3 -m dac download --model_type 24khz # downloads the 24kHz variant
python3 -m dac download --model_type 16khz # downloads the 16kHz variant
```

```
# Load audio signal file
signal = AudioSignal('input.wav')

# Encode audio signal as one long file
# (may run out of GPU memory on long files)
signal.to(model.device)

x = model.preprocess(signal.audio_data, signal.sample_rate)
z, codes, latents, _, _ = model.encode(x)
```

DAC vs Encodec

Q: why 8 kbps?
A: 9*10*86

Codec	Sampling rate (kHz)	Target bitrate (kbps)	Striding factor	Frame rate (Hz)	# of 10-bit codebooks	Compression factor
Proposed	44.1	8	512	86	9	91.16
EnCodec	24	24	320	75	32	16
	48	24	320	150	16	32
SoundStream	24	6	320	75	8	64

Sampling rate (kHz)

Target bitrate (kbps)

Striding factor

Frame rate (Hz)

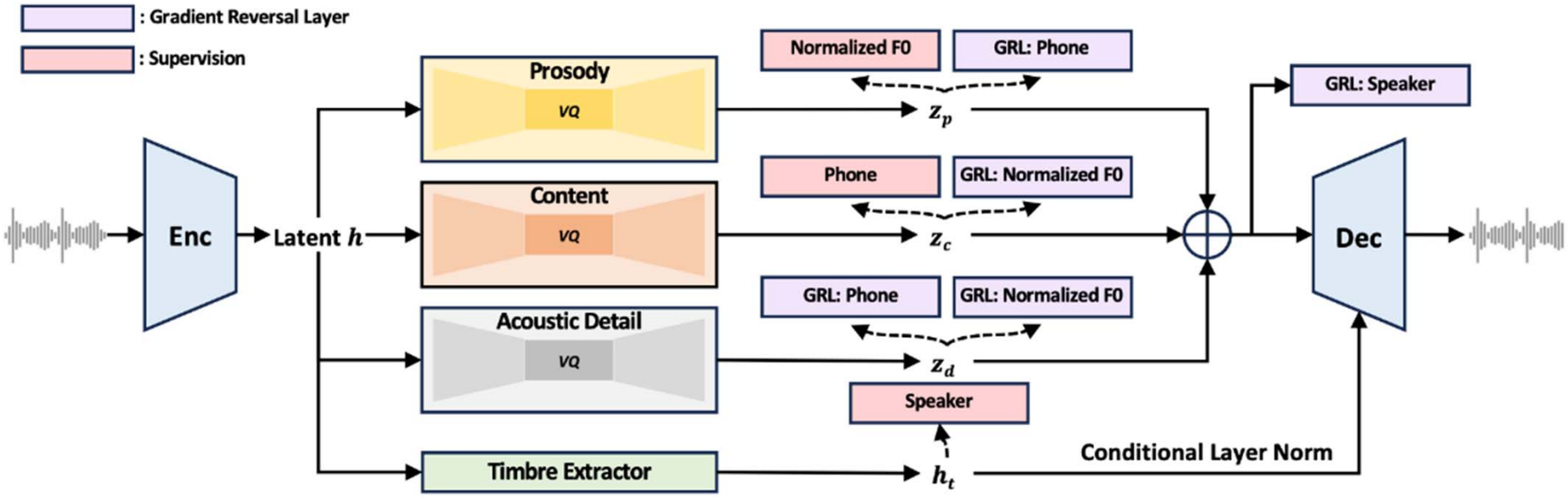
# of 10-bit codebooks

Compression factor

(Frame rate is related to the design of the encoder/decoder in VQVAE)

Many More Codec Models…

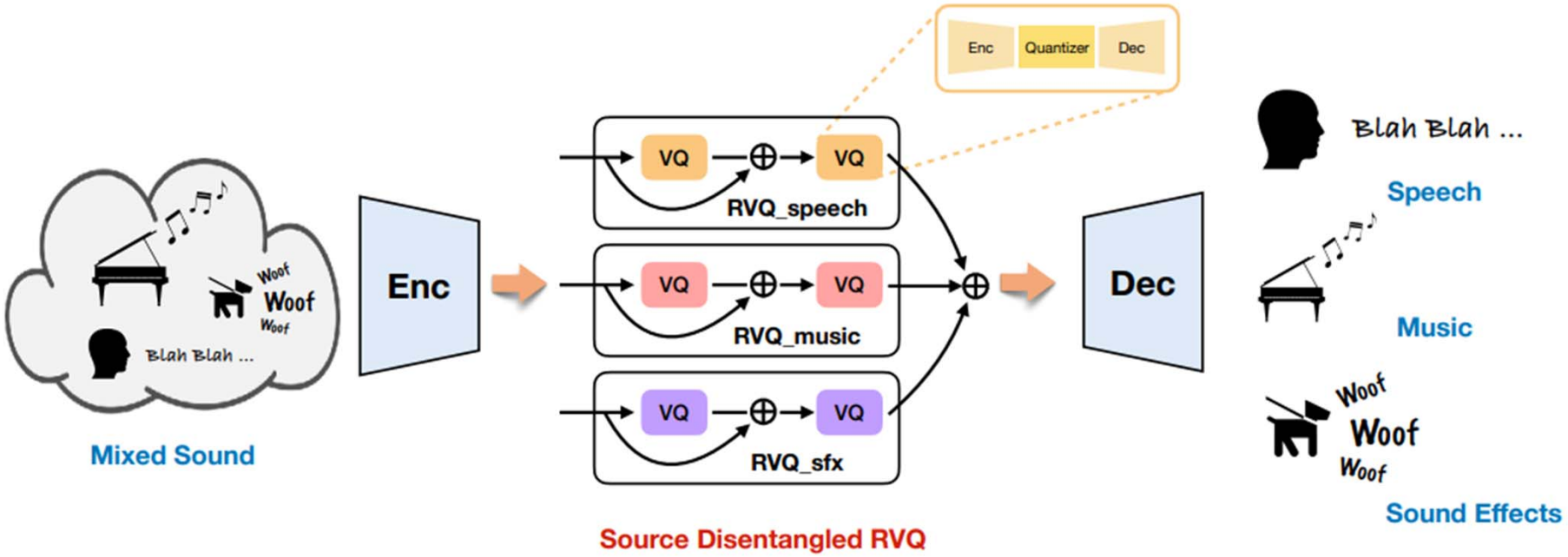
- **FACodec:** factorized neural speech codec (arxiv:2403.03100)



Ref: Ju et al, "NaturalSpeech 3: Zero-shot speech synthesis with factorized codec and diffusion models," arXiv 2024

Many More Codec Models…

- **SD-Codec:** source-disentangled neural audio codec (arxiv:2409.11228)



Ref: Bie et al, “Learning source disentanglement in neural audio codec,” arXiv 2024

Outline

- Image/audio tokenization and generation via VQVAE
- Audio codec models
- **Text-to-music: linking text and musical audio**
  - **Transformer-based approach**
  - Diffusion-based approach

Rapid Progress in “Text-to-Music”

- Given arbitrary text input, generate music
- **Google**’s MusicLM model (2023.01): https://google-research.github.io/seanet/musiclm/examples/
- **ByteDance**’s MeLoDy model (2023.05): https://Efficient-MeLoDy.github.io/
- **Facebook**’s MusicGen model (2023.06): https://github.com/facebookresearch/audiocraft

- Also great progress in “**text-to-sound**” but omitted here

TABLE 8: Large Music Models, TTM: Text-to-Music, VIM: Vocals to instrumental music, MTL: Melody to Lyric, MTM: Music to music, TSM: Text-to-symbolic music, PTM: Programming to Music

Model	Data	Tasks	Limitations	Code
MusciLDM [221]	Audiostock	TTM	The model is trained on a sample rate of 16 kHz while usually, music holds 44.1 kHz. Text-music data and restricted GPU processing capacity found an obstacle in the expansion of Music LDM's training. Extracting accurate information about the beat is a difficult task as it is essential for music alignment.	✓
TANGO [218]	AudioCaps	TTM	Cannot always perform when trained on a smaller dataset	✗
WavJourney [127]	AudioCaps	TTM	Inflexible to expand the functions. The process of remixing and deteriorating may push the synthetic audio away from the real. Model is time complex when generating the complex audio.	✓
SingSong [229]	1 million audio samples	VIM	The generated instrumentals often exhibit a disparity, with harmonic elements being notably weaker (both in volume and coherence) when compared to their percussive counterparts.	✓
LOAF-M2L [230]	Music Genaration	MTL	– –	✗
MeLoDy [232]	6.4 Million Samples based on MusicCaps	TTM MTM	Training data mostly contain non-vocal music only Training on LM and DPD on 10-second audio chunks can affect the long generation	✓
MuseCoco [233]	Million MIDI Dataset EMPOIA MetaMidi POP909 Symphony Emotion-gen	TSM	Model primarily focuses on producing symbolic music based on textual descriptions, with little consideration on long sequence modelling. The attribute set discussed in this work only represents a subset of all available music attributes.	✓
LaunchpadGPT [236]	music-frame pairs dataset	PTM	Although LaunchpadGPT partially captures colour similarities, it lacks the ability to effectively learn more structured patterns.	✓
Jukebox [241]	f 1.2 million songs	MTM	- -	✓

(Figure from Latif et al, "Sparks of large audio models: A survey and outlook," arXiv 2023)

Elements of a Text-to-Music Model

- **1. Audio encoder/decoder**
  - So that we can build an LM over the (discrete or continuous) decoder input
- **2. Music LM**
  - Can do unconditional generation
- **3. Text encoder** or **text-music joint embedding space**
  - Provides conditions for the music LM to realize text-to-music generation

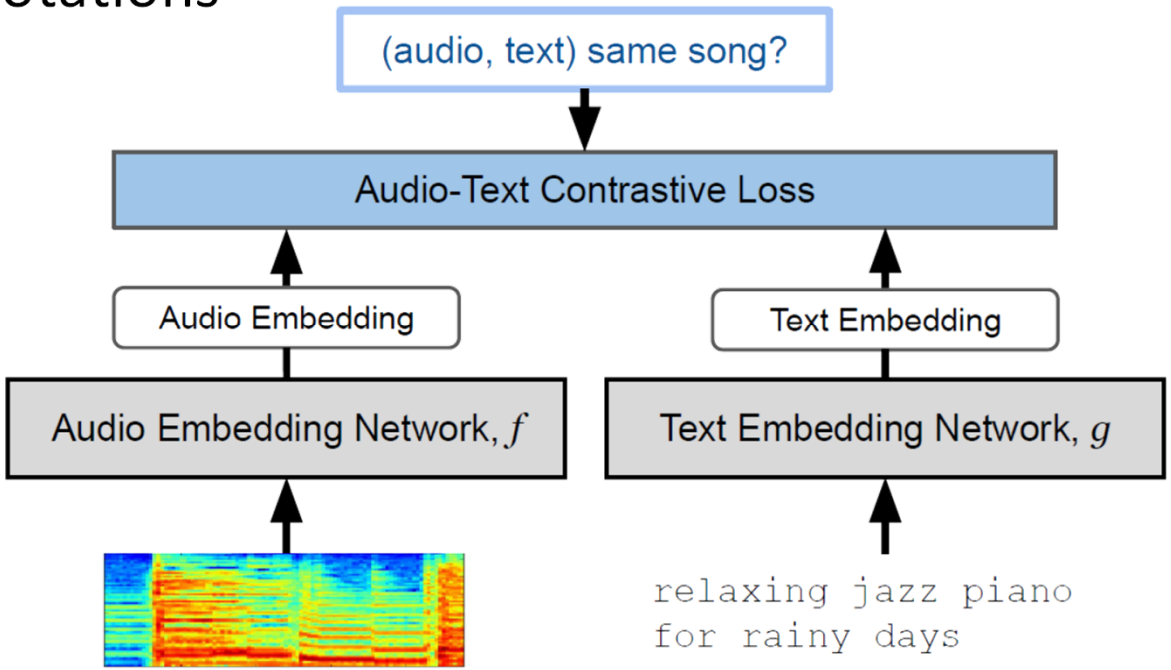
Key Technologies that Enable Text-to-Music Generation

- **Language model (LM) for music**: RNN, Transformers
  - Model long term dependency
  - Initially applied to MIDI music generation as it's easier to convert MIDI events into tokens
  - **Significance**: A few bars of MIDI music → full-length MIDI music
- **Audio waveform encoder/decoder**
  - Thanks to advances in Mel-vocoders, source separation, audio codec models, etc
  - Tokenize audio files (spectrograms or waveforms)
    - Enable us to build LM for musical audio
    - And learn the dependency between text tokens and audio tokens
  - **Significance:** LM for MIDI music → LM for musical audio

MuLan: Text-Music Joint Embedding Learning

- MuLan takes the form of a two-tower, joint audio-text embedding model trained using **44 million music recordings** (370K hours) and weakly-associated, free-form text annotations
  - **Audio encoder**: Resnet-50, or audio spectrogram Transformer
  - **Text encoder**: BERT

- However, **not** open source…



Ref: Huang et al, "MuLan: A joint embedding of music audio and natural language," ISMIR 2022

MuLan: Text-Music Joint Embedding Learning

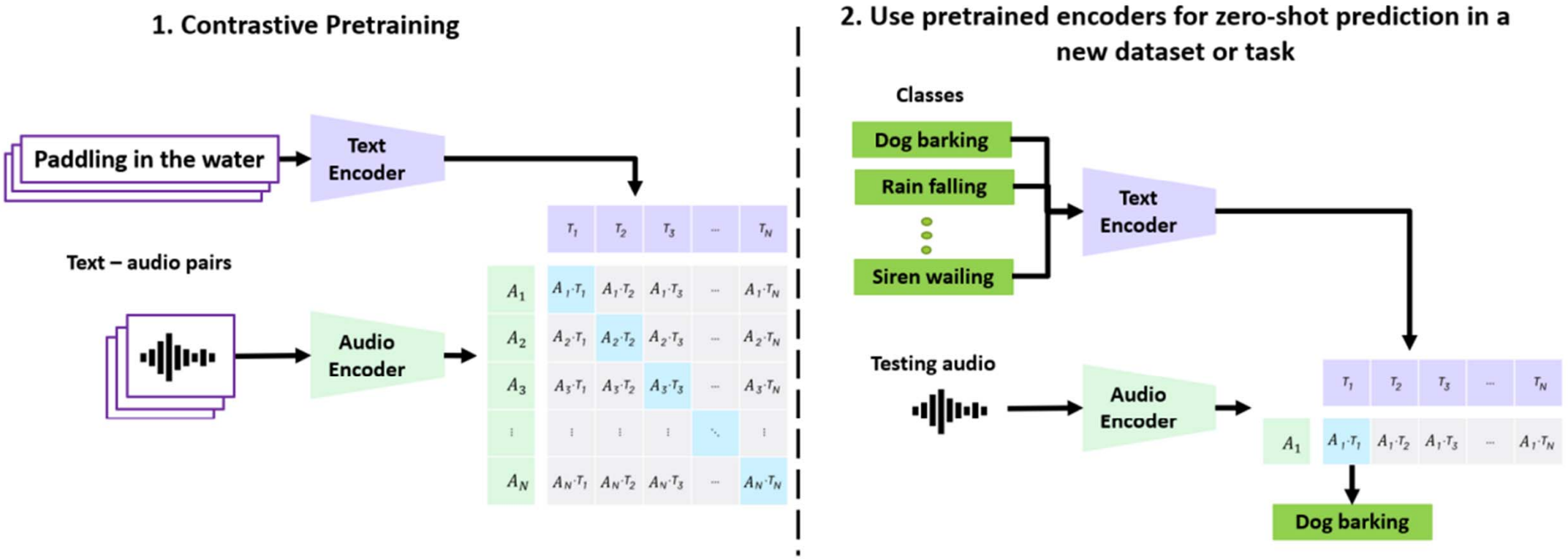
- MuLan takes the form of a two-tower, joint audio-text embedding model trained using **44 million music recordings** (370K hours) and weakly-associated, free-form text annotations
  - Data cleansing
    - Fine-tune a pre-trained BERT with a binary classification task on a small curated set of 700 sentences, which are manually labeled to be music-descriptive or not
    - However, found that training is surprisingly robust to annotation noise, achieving similar performance using *unfiltered* training text

Table 1. Text annotation examples.

Type	Examples
Short-form (SF)	tags like genre, mood, instrument, artist name, song title, album name
Long-form (LF)	'Hip-hop features rap with an electronic backing.' 'The melody is so nostalgic and unforgettable.'
Playlist (PL)	'Feel-good mandopop indie', 'Latin workout' 'Salsa for broken hearts', 'Piano for study'

Ref: Huang et al, "MuLan: A joint embedding of music audio and natural language," ISMIR 2022

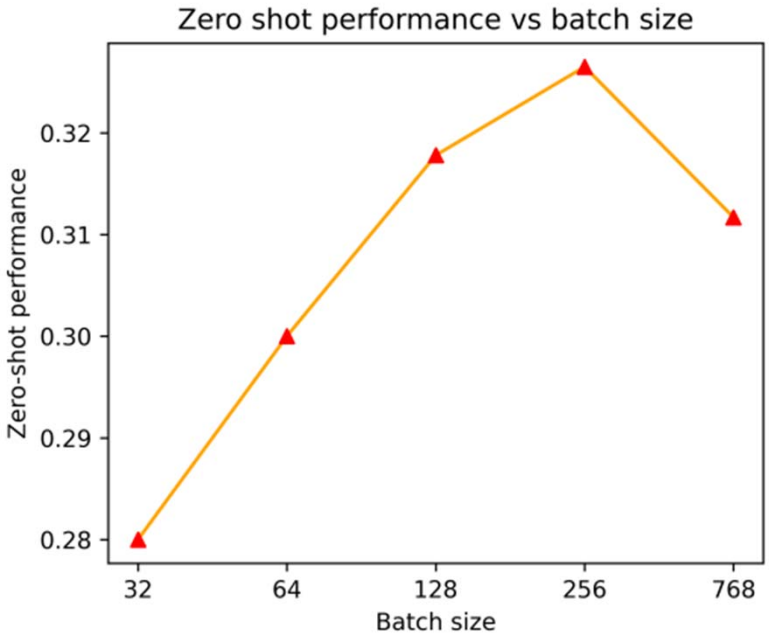
Microsoft's CLAP: Text-Audio Joint Embedding Learning



Ref: Elizalde et al, "CLAP: Learning audio concepts from natural language supervision," ICASSP 2023

Microsoft's CLAP: Text-Audio Joint Embedding Learning

- 128,010 audio/text pairs from 4 datasets (FSD50k, ClothoV2, AudioCaps, MACS)
  - Each audio clip is randomly truncated to 5 secs
- Audio encoder: **PANNs-CNN14**
  - 80.8 million parameters & an embedding size of 2048; pretrained on AudioSet
- Text encoder: **BERT**
  - 110 million parameters
- Use 8-24 V100 GPUs (16GB VRAM)
- **Batch size** is important (as large as 256)

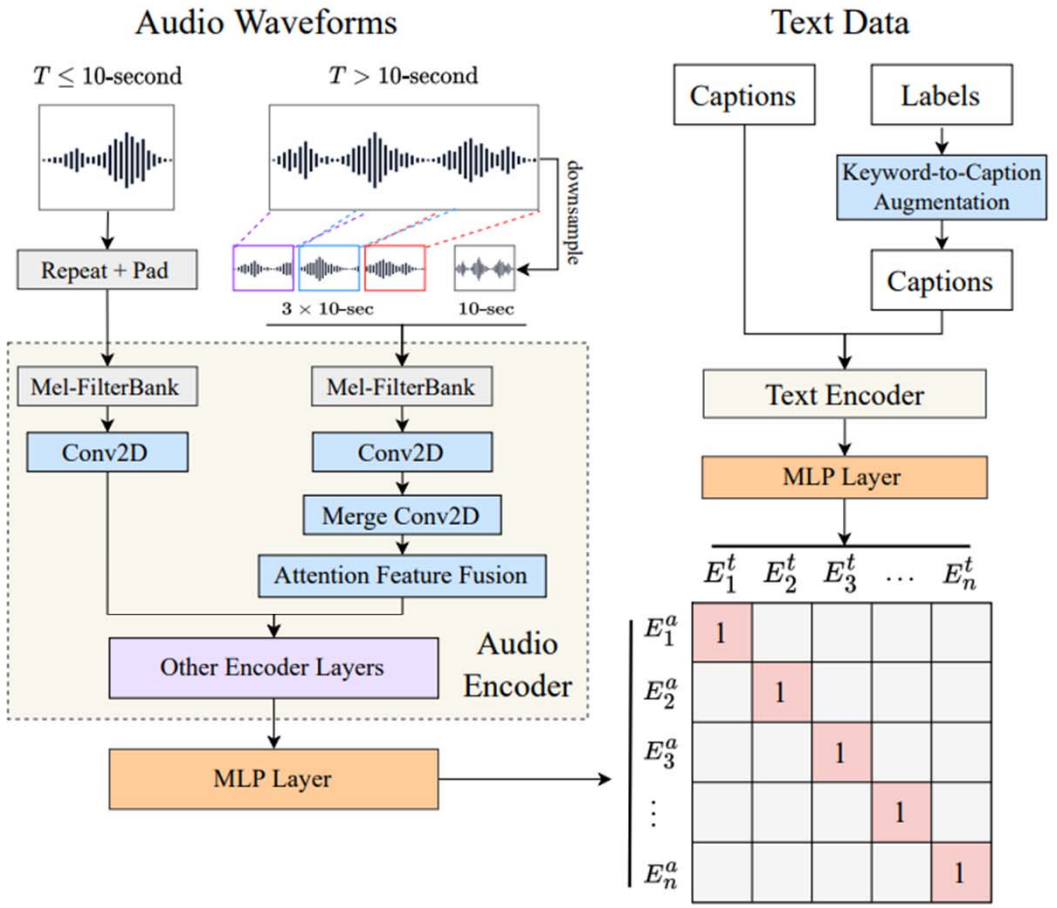


Ref: Elizalde et al, "CLAP: Learning audio concepts from natural language supervision," ICASSP 2023

MILA+UCSD+LAION's CLAP: Text-Audio Joint Embedding Learning

Dataset	Pairs	Audio Durations (hrs)
Clotho [15]	5,929	37.00
SoundDescs [16]	32,979	1060.40
AudioCaps [17]	52,904	144.94
LAION-Audio-630K	633,526	4325.39

Model	AudioCaps (mAP@10)	
	A→T	T→A
PANN+CLIP Trans.	4.7	11.7
PANN+BERT	34.3	44.3
PANN+RoBERTa	37.5	45.3
HTSAT+CLIP Trans.	2.4	6.0
HTSAT+BERT	43.7	49.2
HTSAT+RoBERTa	**45.7**	**51.3**



Ref: Wu et al, "Large-scale contrastive language-audio pretraining with feature fusion and keyword-to-caption augmentation," ICASSP 2023

MILA+UCSD+LAION's CLAP: Text-Audio Joint Embedding Learning

- More than 633,526 audio/text pairs
- Use 10-second audio segments
- Tokenize the text with a maximum token length of 77
- Very large **batch size**:
  - Train the model using a batch size of 768 on AudioCaps+Clotho dataset, 2304 on training dataset containing LAION-Audio-630K, and 4608 on training dataset containing AudioSet

Ref: Wu et al, "Large-scale contrastive language-audio pretraining with feature fusion and keyword-to-caption augmentation," ICASSP 2023

CLAP

https://github.com/microsoft/CLAP

CLAP weights are downloaded automatically (choose between versions *2022*, *2023*, and *clapcap*), but are also available at: Zenodo or HuggingFace

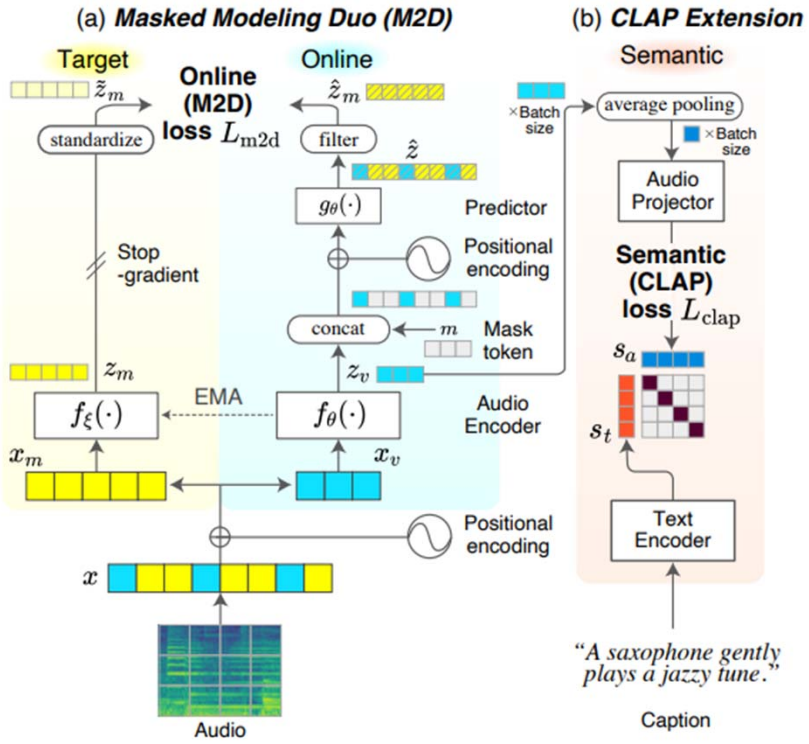
clapcap is the audio captioning model that uses the 2023 encoders.

https://github.com/LAION-AI/CLAP

- For general audio less than 10-sec: 630k-audioset-best.pt or 630k-best.pt
- For general audio with variable-length: 630k-audioset-fusion-best.pt or 630k-fusion-best.pt
- For music: music_audioset_epoch_15_esc_90.14.pt
- For music and speech: music_speech_epoch_15_esc_89.25.pt
- For speech, music and general audio: music_speech_audioset_epoch_15_esc_89.98.pt

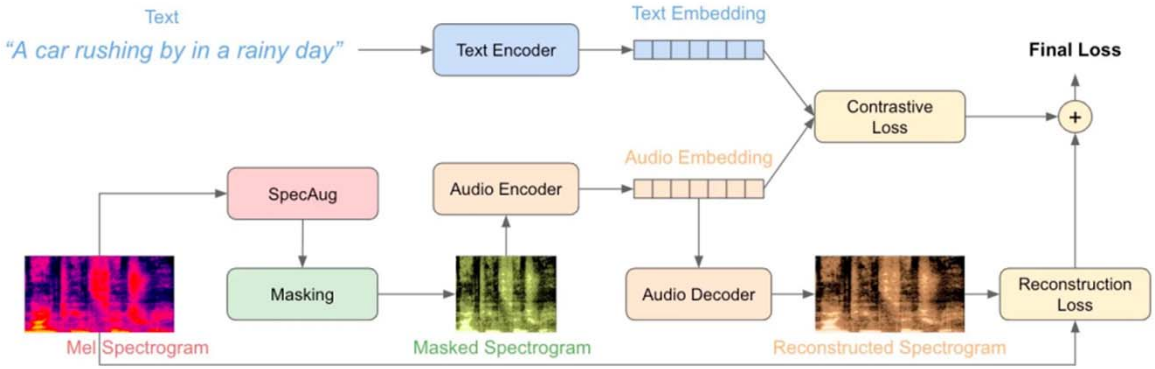
Variants of CLAP

- M2D-CLAP



Ref: Niizumi et al, "M2D-CLAP: Masked modeling duo meets clap for learning general-purpose audio-language representation," INTERSPEECH 2024

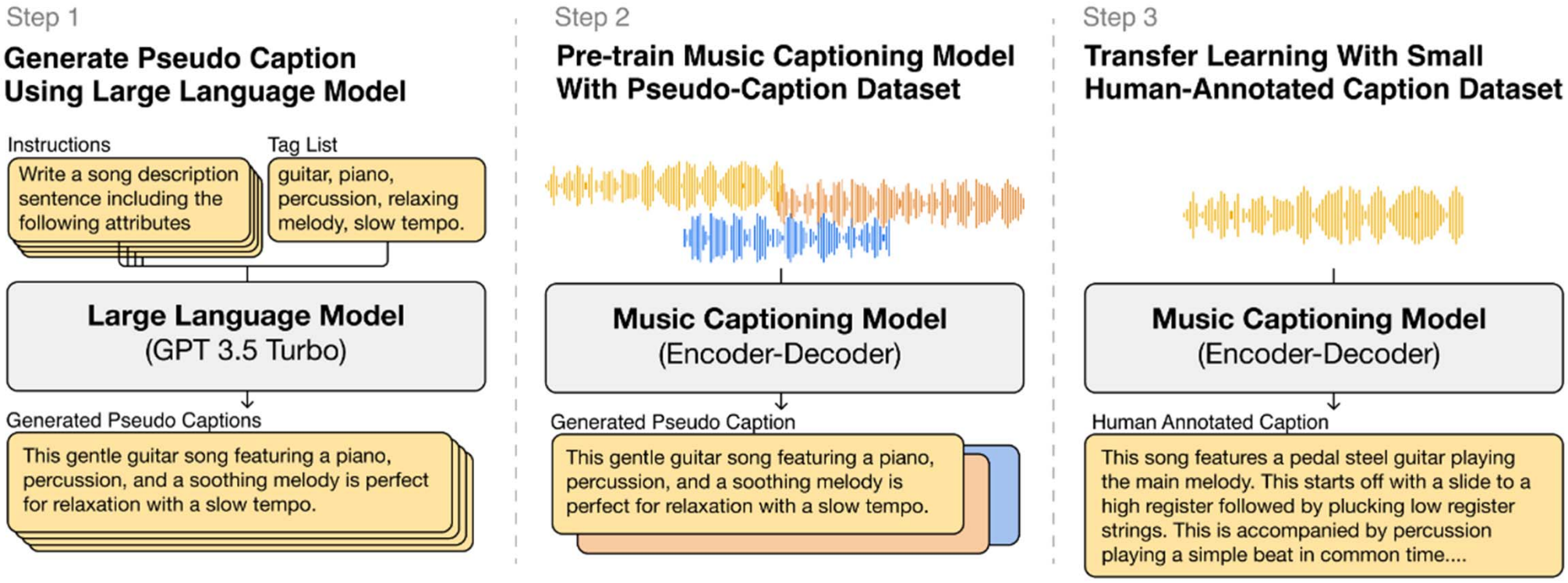
- FLAP



Ref: Yeh et al, "FLAP: Fast language-audio pre-training," ASRU 2023

LP-MusicCaps: LLM-Based Pseudo Music Captioning

https://github.com/seungheondoh/lp-music-caps



Ref: Doh et al, "LP-MusicCaps: LLM-based pseudo music captioning," ISMIR 2023

LP-MusicCaps: LLM-Based Pseudo Music Captioning

Dataset	# item	Duration (h)	C/A	Avg. Token
General Audio Domain				
AudioCaps [30]	51k	144.9	1	9.0±N/A
LAION-Audio [22]	630k	4325.4	1-2	N/A
WavCaps [18]	403k	7568.9	1	7.8±N/A
Music Domain				
MusicCaps [12]	6k	15.3	1	48.9±17.3
MuLaMCap* [19]	393k	1091.0	12	N/A
LP-MusicCaps-MC	6k	15.3	4	44.9±21.3
LP-MusicCaps-MTT	22k	180.3	4	24.8±13.6
LP-MusicCaps-MSD	514k	4283.1	4	37.3±26.8

Table 3. Comparison of audio-caption pair datasets. C/A stands for the number of caption per audio. *Although we include MuLaMCap in the table for comparison, it is not publicly accessible.

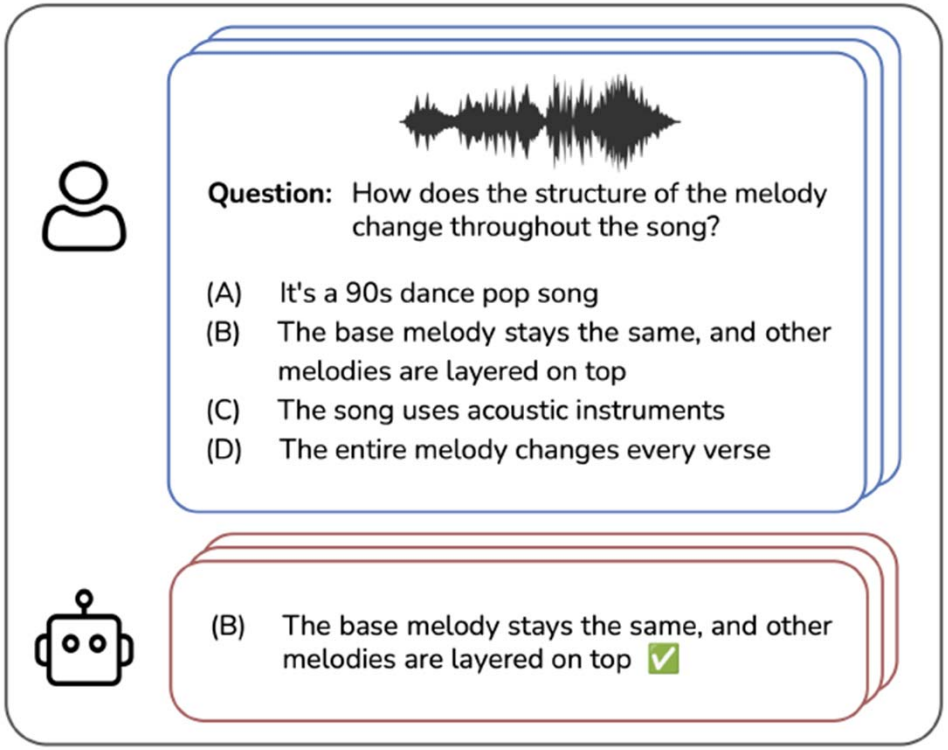
Ref: Doh et al, “LP-MusicCaps: LLM-based pseudo music captioning,” ISMIR 2023

More Datasets for Text-to-Audio in General

Dataset	Hours	Type	Source
Clotho	152	Caption	Drossos et al.
AudioCaps	109	Caption	Kim et al.
MACS	100	Caption	Martín-Morató & Mesaros
WavText5Ks	25	Caption	Deshmukh et al. (2022)
BBC sound effects	481	Caption	https://sound-effects.bbcrewind.co.uk/
Audiostock	43	Caption	https://audiostock.net/se
Filter AudioSet	2084	Label	Gemmeke et al.
ESC-50	3	Label	Piczak
FSD50K	108	Label	https://annotator.freesound.org/fsd/
Sonniss Game Effects	20	Label	https://sonniss.com/gameaudiogdc/
WeSoundEffects	11	Label	https://wesoundeffects.com/
Epidemic Sound	220	Label	https://www.epidemicsound.com/
UrbanSound8K	8	Label	Salamon et al.
LibriTTS	300	Language-free	Zen et al. (2019)
LP-MusicCaps-MSD	4283	Caption	Doh et al. (2023)
LP-MusicCaps-MC	15	Caption	Doh et al. (2023)

Ref: “HarmonyLM: Advancing unified large-scale language modeling for audio and music generation,” ICLR 2024 submission

Multimodal Audio-Language Models



Model	Audio encoder	LLM
MusiLingo [9]	MERT [40]	Vicuna 7B [41]
MuLLaMa [8]	MERT [40]	LLaMA-2 7B [42]
M2UGen [12]	MERT [40]	LLaMA-2 7B [42]
SALMONN [11]	BEATS [43] & $\text{Whisper}_{\text{large-v2}}$ [44]	Vicuna 7B [41]
Qwen-Audio [13]	$\text{Whisper}_{\text{large-v2}}$ [44]	Qwen 7B [45]

Table 2. Overview of models we evaluate in our study.

Ref: Weck et al, “MuChoMusic: Evaluating music understanding in multimodal audio-language models,” ISMIR 2024

MusicLM (from Google)

https://google-research.github.io/seanet/musiclm/examples/

- Given a **text description of music**, generate **waveforms** directly
  - "Piano for study" | "Hip-hop song with violin solo" | "Latin workout" | "Feel-good mandopop indie" | "Salsa for broken hearts"

- **Story mode**

Text prompts

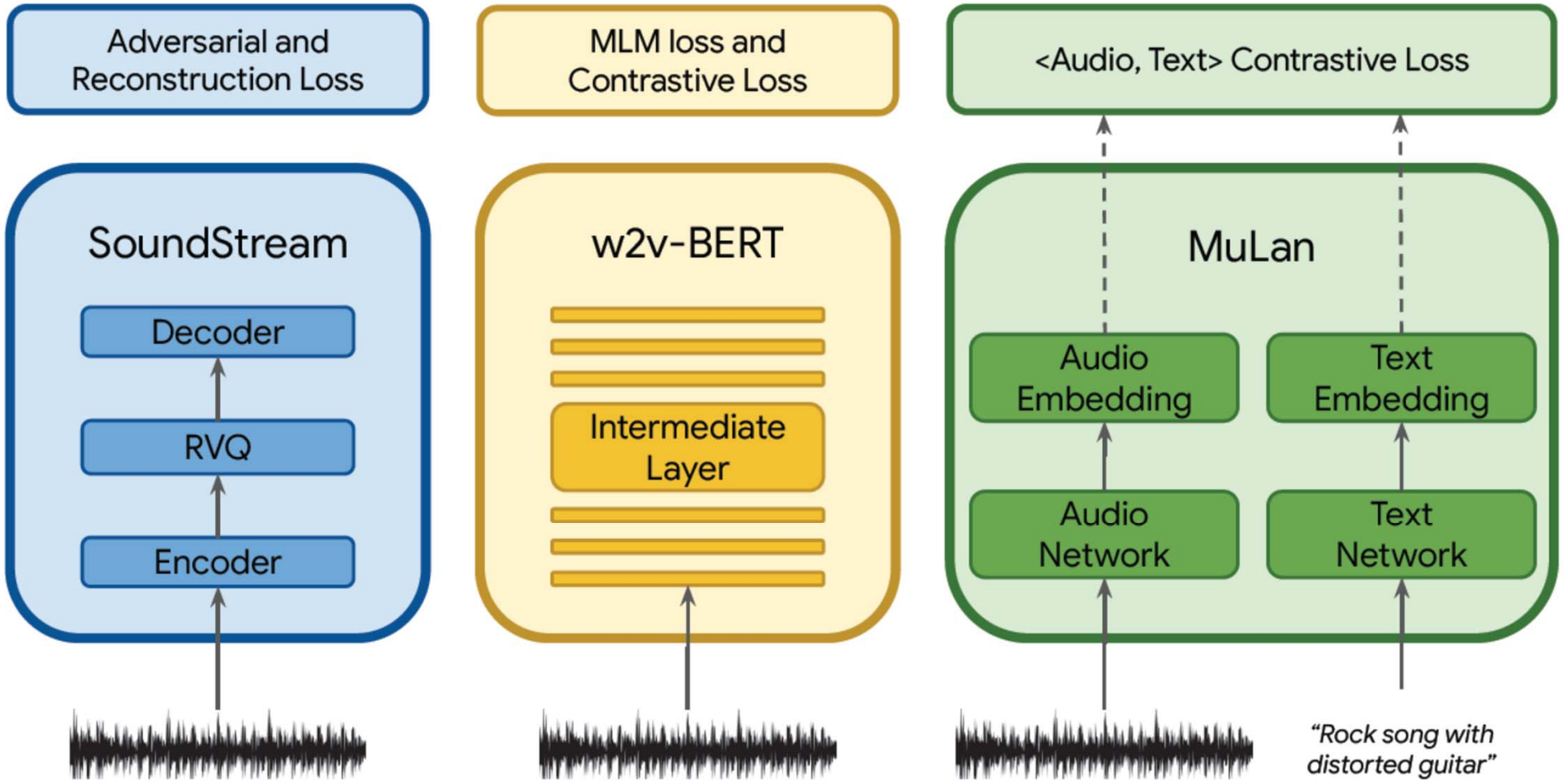
time to meditate (0:00-0:15)
time to wake up (0:15-0:30)
time to run (0:30-0:45)
time to give 100% (0:45-0:60)

- **Text and melody conditioning**
  - Text-conditioned continuation of the provided melody input

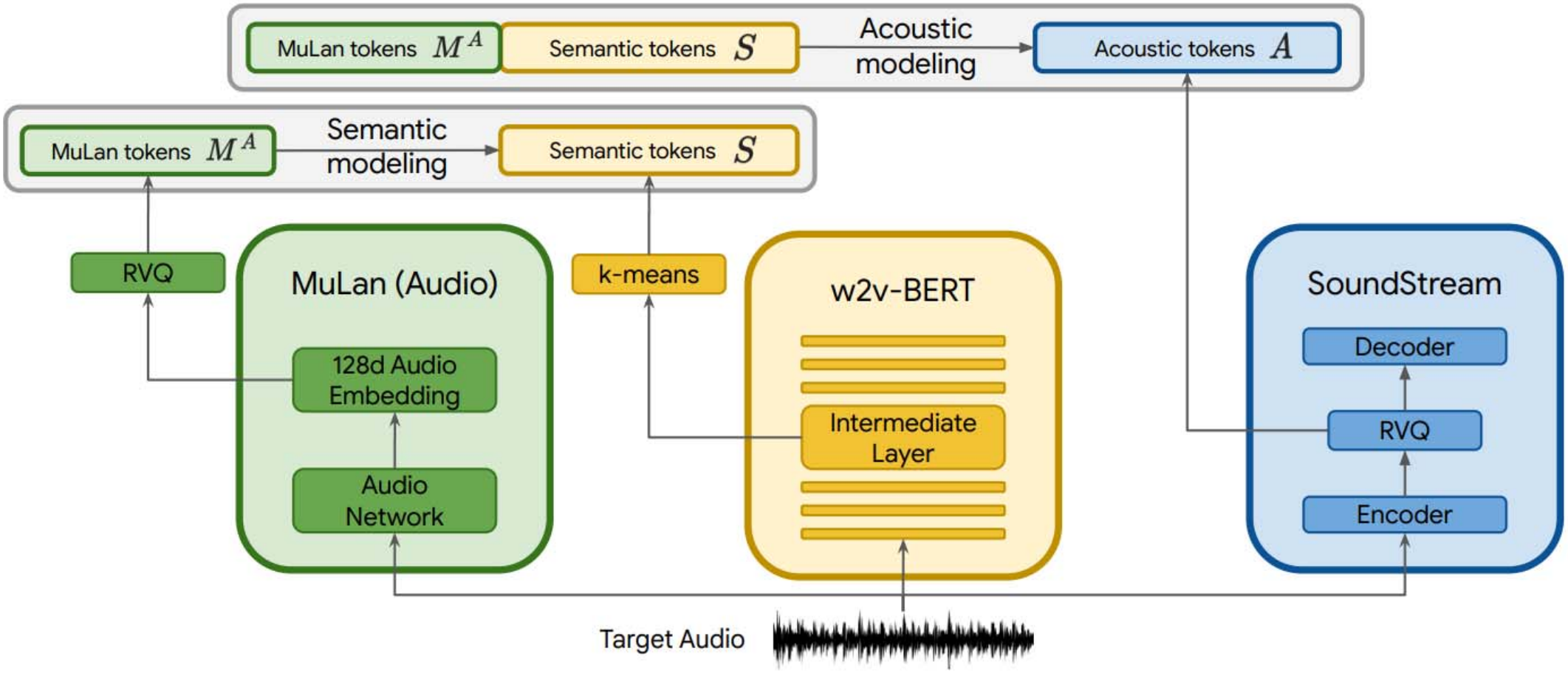
- **Image-to-music**
  - Painting caption conditioning

Ref: Agostinelli et al, "MusicLM: Generating music from text," arXiv 2023

MusicLM's Pretrained Networks



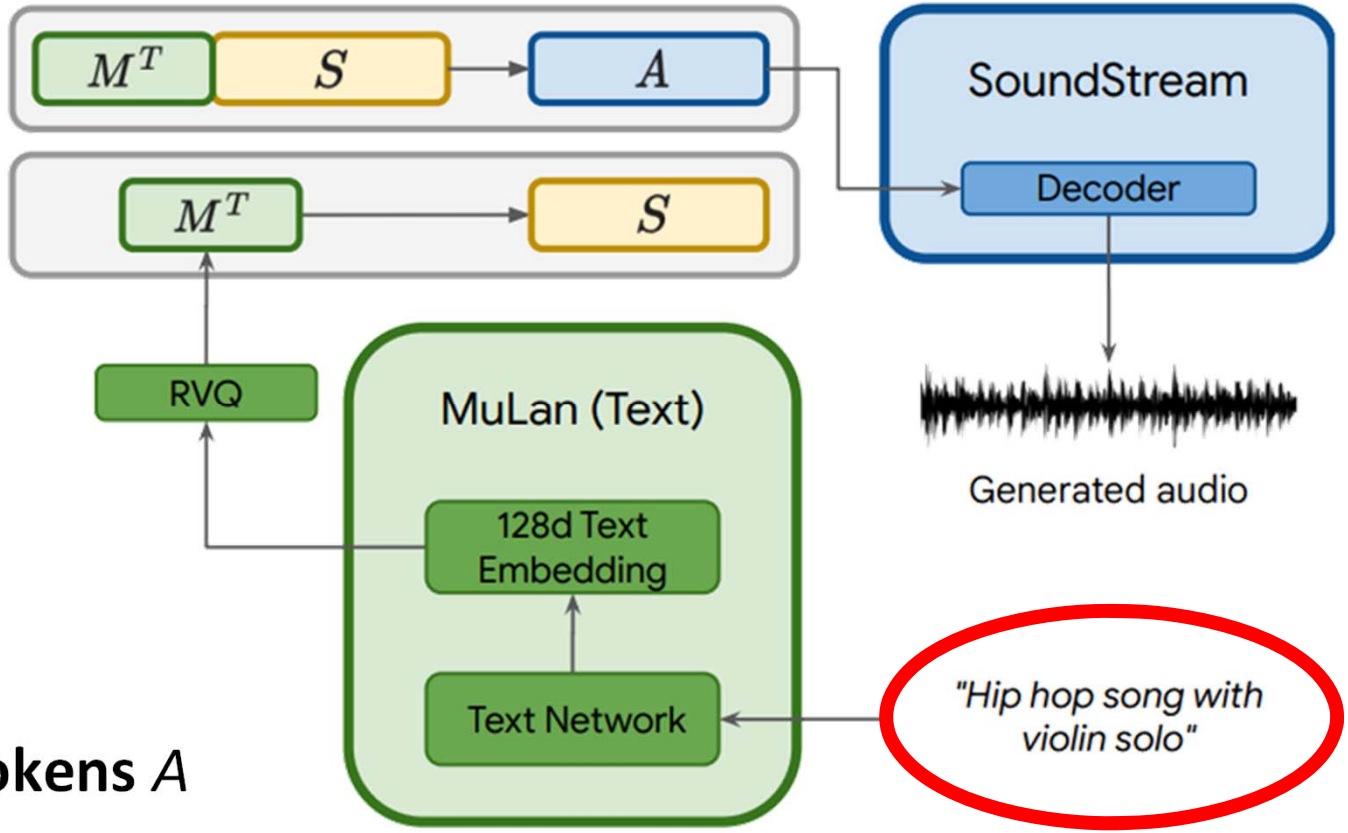
MusicLM Training Procedure



Ref: Agostinelli et al, "MusicLM: Generating music from text," arXiv 2023

MusicLM Inference Procedure

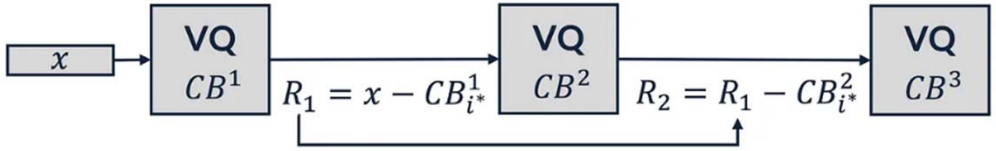
- Given **text tokens** M^T from the input text description
- Generate high-level **semantic tokens** *S* that model the long-term structure of the music to be generated
- Then generate **acoustic tokens** *A* that model the fine details



Ref: Agostinelli et al, "MusicLM: Generating music from text," arXiv 2023

Jukebox vs MusicLM

- **Jukebox**
  - 3 layers of **acoustic tokens**: high, mid, bottom
  - The three layers operate in **different** temporal resolution
  - About **7,234** tokens per second



- **MusicLM**
  - **600 acoustic tokens** per second
    - 12 layers of SoundStream RVQ tokens (each with a vocabulary size of 1024)
    - All the 12 layers operate in the **same** temporal resolution (50 Hz)
  - Plus **25 semantic tokens** per second
    - Semantic tokens from w2v-BERT (codebook size also 1024)

Issues of MusicLM

- **Not** open source; but there are unofficial implementations
  - https://github.com/lucidrains/musiclm-pytorch
  - https://github.com/zhvng/open-musiclm
- Slow (one second 625 tokens; i.e., **625** times of autoregressive sampling)
- Limited controllability
  - The main control signal is the text description (which is usually about the genre and instrumentation of music)
  - Advanced users may want to control, e.g., the **melody** of the singing vocals and the **grooving** (rhythm) of the backing instrumentals

Ref: Agostinelli et al, "MusicLM: Generating music from text," arXiv 2023

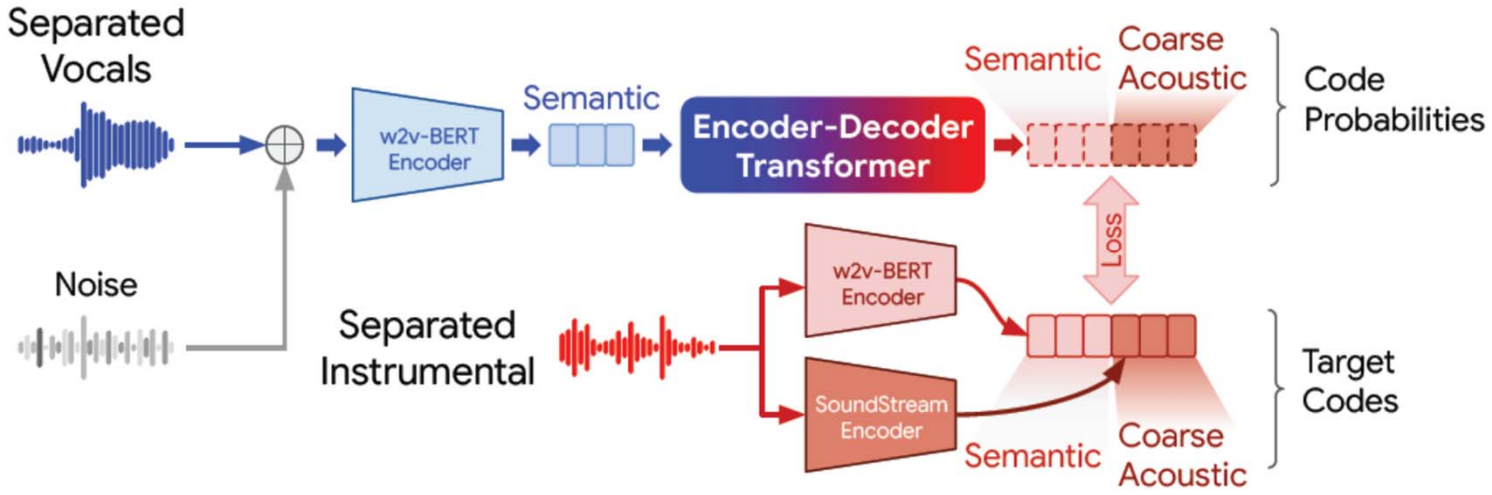
Issues of MusicLM

- Text-to-music models are in general costly
  - (Latif 2023 arXiv): “AudioGPT with 137 billion parameters requires approximately 1 million kilowatthours (kWh), which is approximately $137 million USD. Similarly, the training cost of the state-of-the-art AudioPaLM with 530 billion parameters is approximately $530 million USD.”

Ref: Latif et al, “Sparks of large audio models: A survey and outlook,” arXiv 2023

SingSong (from Google)

https://storage.googleapis.com/sing-song/index.html



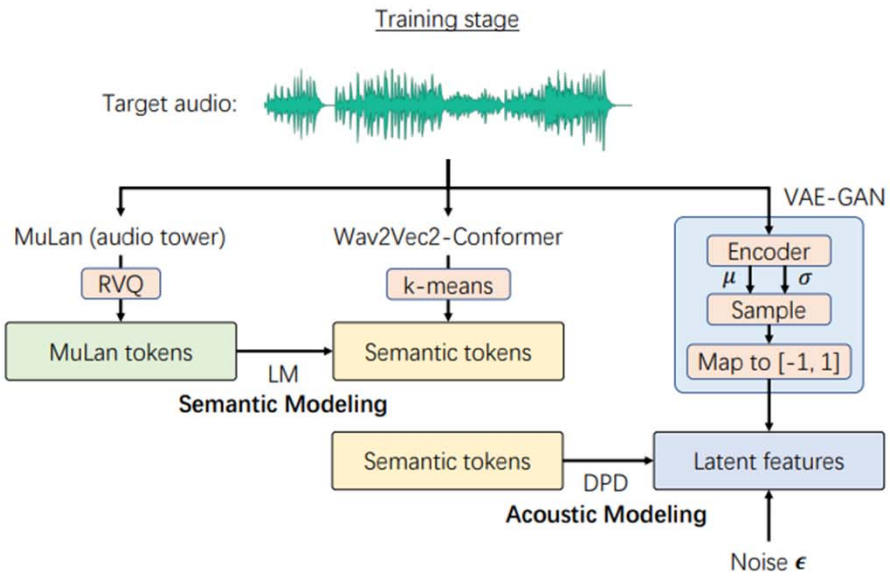
- **Given vocal, generate multi-instrument accompaniment**
  - Apply “blind source separation” to get pairs of vocal/backing tracks
  - Seq2seq: **vocal tokens** as the source, generate the backing tokens
- **Not** open source

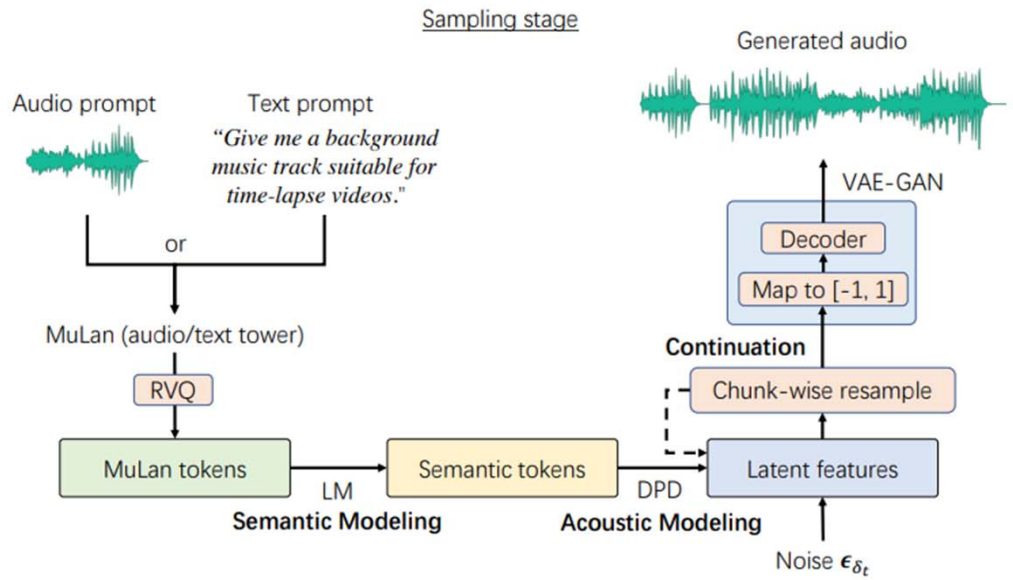
Ref: Donahue et al, “SingSong: Generating musical accompaniments from singing,” arXiv 2023

MeLoDy (from ByteDance)

https://Efficient-MeLoDy.github.io/

- Replace the LM for acoustic tokens in MusicLM by **latent diffusion**
- **Not** open source

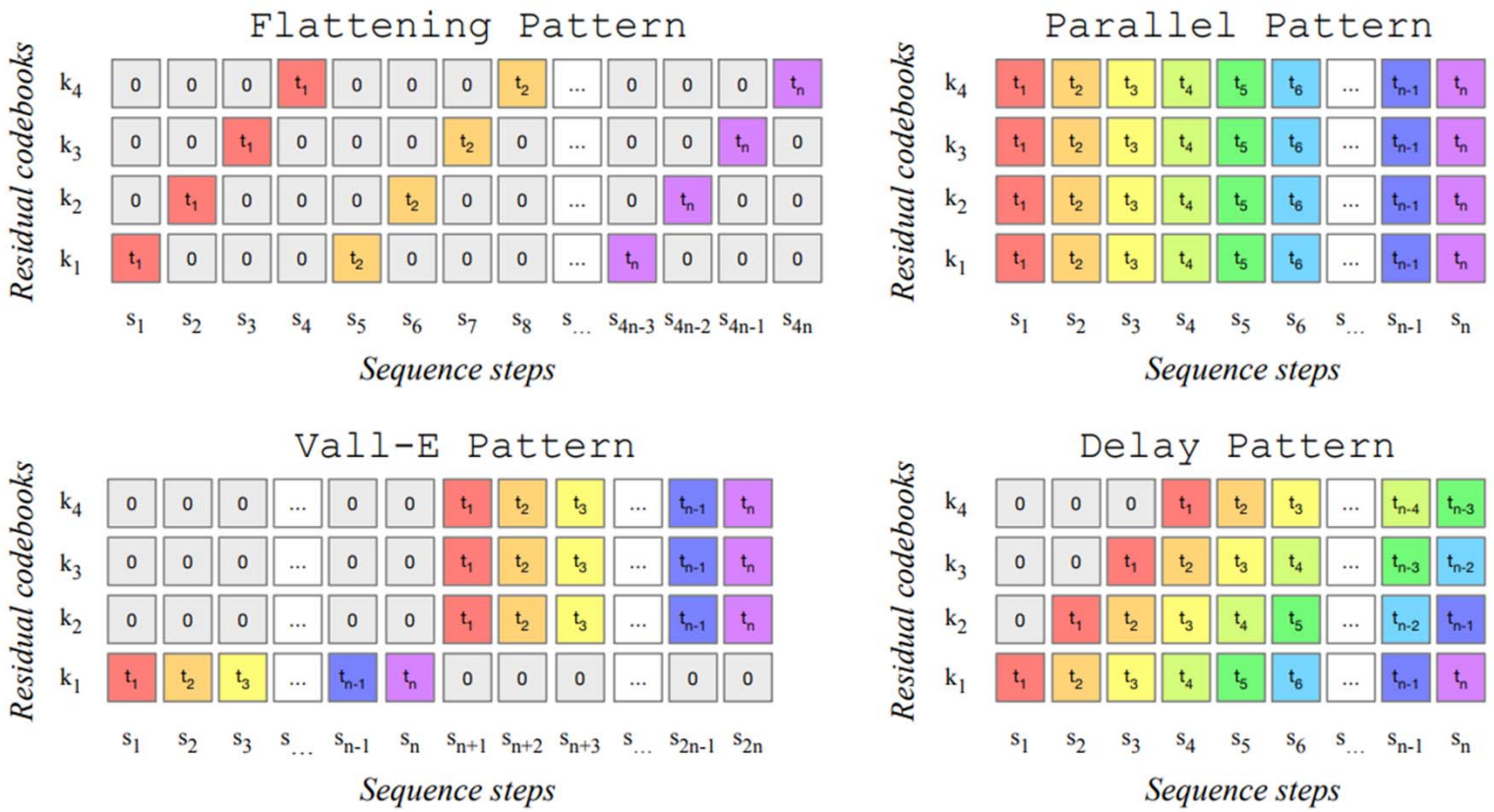




Ref: Lam et al, "Efficient neural music generation," arXiv 2023

MusicGen (from Meta)

- Compound word (CP)-like **parallel prediction** of the Encodec's RVQ tokens
- Open source!

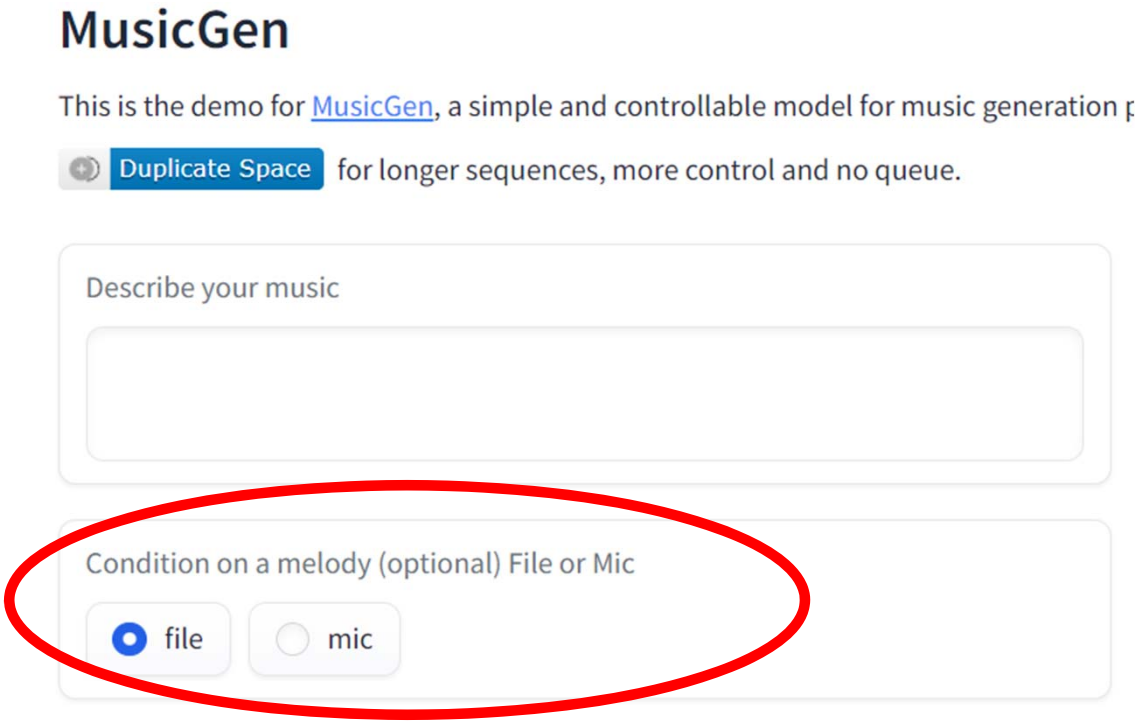


MusicGen (from Meta)

https://huggingface.co/spaces/facebook/MusicGen

https://github.com/facebookresearch/audiocraft

- **Melody conditioning:** Not just as a prompt
  - Tried using **chromagram** of the melody as input but this leads to overfitting
  - Introduce an **information bottleneck** by choosing the **dominant time-frequency bin** in each time step instead



Ref: Copet et al, "Simple and controllable music generation," arXiv 2023

MusicGen: Audio Encoder

- Audio encoder
  - We use a non-causal five layers **EnCodec** model for 32 kHz monophonic audio with a stride of 640, resulting in a frame rate of **50 Hz**
  - The embeddings are quantized with an RVQ with **4 quantizers**, each with a codebook size of **2048**
  - Train the model on one-second audio segments cropped at random
  - One second → **50 times** of autoregressive sampling with *Parallel* or *Delay* pattern
- Transformer model
  - Flash attention from the xFormers
  - Train on 30-sec clips sampled at random from the full track (batch 192), for 1M steps
  - Train 300M, 1.5B and 3.3B parameter models, using respectively 32, 64 and 96 GPUs
  - Top-k sampling with keeping the top 250 tokens and a temperature of 1.0

MusicGen

- While flattening improves generation, it comes at a high computational cost and similar performance can be reached for a fraction of this cost using a simple delay approach

		In Domain Test Set				
CONFIGURATION	Nb. steps	$\text{FAD}_{\text{vgg}} \downarrow$	KL $\downarrow$	$\text{CLAP}_{\text{scr}} \uparrow$	OVL. $\uparrow$	REL. $\uparrow$
Delay	1500	0.96	0.52	0.35	**79.69**$\pm$1.46	79.67$\pm$1.41
Partial Delay	1500	1.51	0.54	0.32	79.13$\pm$1.56	79.67$\pm$1.46
Parallel	1500	2.58	0.62	0.27	72.21$\pm$2.49	80.30$\pm$1.43
VALL-E	3000	1.98	0.56	0.30	74.42$\pm$2.28	76.55$\pm$1.67
Partial Flattening	3000	1.32	0.54	0.34	78.56$\pm$1.86	79.18$\pm$1.49
Flattening	6000	**0.86**	**0.51**	**0.37**	**79.71**$\pm$1.58	**82.03**$\pm$1.1

				In Domain Test Set					
Dim.	Heads	Depth	# Param.	PPL$\downarrow$	$\text{FAD}_{\text{vgg}} \downarrow$	KL $\downarrow$	$\text{CLAP}_{\text{scr}} \uparrow$	OVL. $\uparrow$	REL. $\uparrow$
1024	16	24	300M	56.1	0.96	0.52	0.35	78.3$\pm$1.4	82.5 $\pm$1.6
1536	24	48	1.5B	48.4	0.86	**0.50**	0.35	**81.9**$\pm$1.4	82.9$\pm$1.5
2048	32	48	3.3B	**46.1**	**0.82**	**0.50**	**0.36**	79.2$\pm$1.3	**83.5**$\pm$1.3

MusicGen: Text Encoder

- **No text-audio joint embedding**; simply use a **pure text encoder** such as T5 or Flan-T5
- And **no semantic tokens**; just RVQ acoustic tokens → simple architecture
- No diffusion

Table A.1: Text encoder results. We report results for T5, Flan-T5, and CLAP as text encoders. We observe similar results for T5 and Flan-T5 on all the objective metrics. CLAP encoder performs consistently worse on all the metrics but CLAP score.

	MusicCaps Test Set				
Model	$\text{FAD}_{vgg}\downarrow$	KL ↓	$\text{CLAP}_{scr}\uparrow$	Ovl. ↑	Rel. ↑
T5	**3.12**	**1.29**	0.31	84.89±1.78	**82.52±1.31**
Flan-T5	3.36	1.30	**0.32**	**86.25±1.75**	80.83±1.88
CLAP	4.23	1.53	**0.32**	79.79±1.76	77.28±1.54

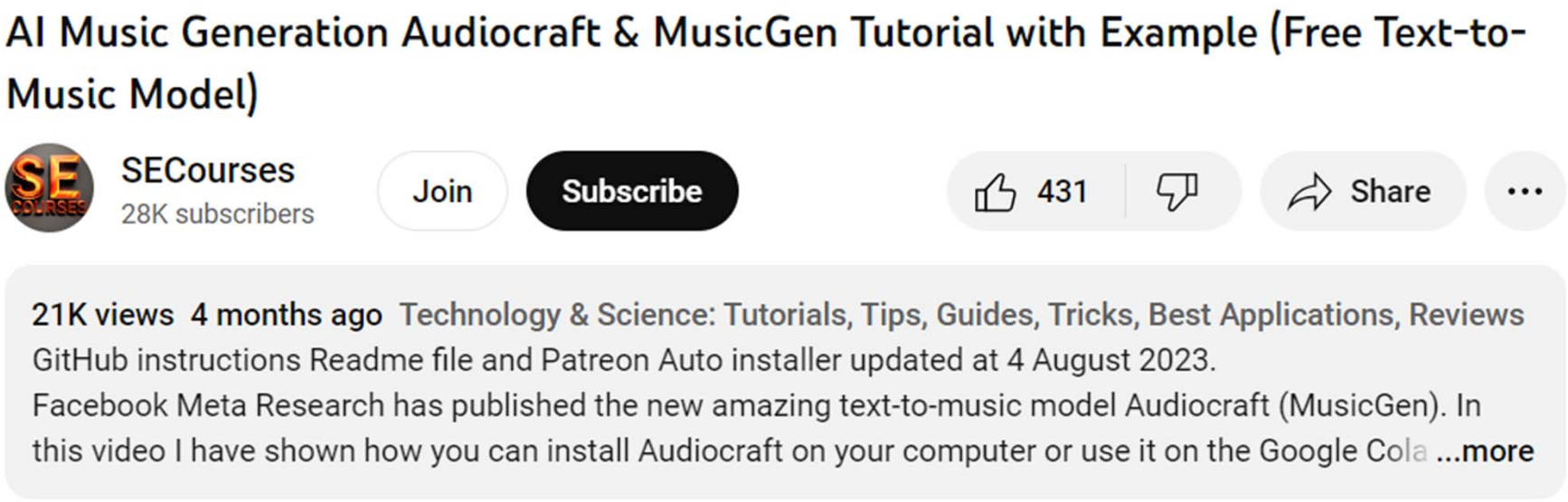
Ref: Copet et al, "Simple and controllable music generation," arXiv 2023

Jukebox vs. MusicLM vs. MusicGen

	Jukebox (2020)	MusicLM (2023.01)	MusicGen (2023.06)
Audio tokens	**7,234** *acoustic tokens* (3-layer hierarchical VQVAE: high, mid, bottom)	**600** *acoustic tokens* (12-layer SoundStream codec) + **25** *semantic tokens* (w2v-BERT) per second	**200** *acoustic tokens* (4-layer EnCodec codec)
Text tokens	No text tokens	**Text tokens representing the user input** (via VQed MuLan: contrastive learning based joint text-audio embedding)	**Text tokens representing the user input** (via T5 or FLAN-T5)
LM	72-layer Transformer	24-layer Transformer	24- or 48- layer Transformer
#Param.	>6B	N/A	300M, 1.5B, or 3.3B

MusicGen Tutorial

https://github.com/FurkanGozukara/Stable-Diffusion/blob/main/Tutorials/AI-Music-Generation-Audiocraft-Tutorial.md



https://www.youtube.com/watch?v=v-YpvPkhdO4

UniAudio: Unified Model for Audio Generation

- UniAudio supports 11 audio generation tasks
  - **TTS**, **VC**, **SE** (speech enhancement), **TSE** (target speech extraction), **SVS**, **TT-Sound** (text-to-sound generation), **TT-Music** (text-to-music generation), **A-Edit** (audio edit), **SD** (speech dereverberation), **I-TTS** (instructed TTS), **S-Edit** (speech edit)

Model	TTS	VC	SE	TSE	SVS	TT-Sound	TT-Music	A-Edit	SD	I-TTS	S-Edit
YourTTS (Casanova et al., 2022)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
VALL-E (Wang et al., 2023a)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
MusicLM (Wang et al., 2023a)	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗
SPEARTTS (Kharitonov et al., 2023)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
NaturalSpeech2 (Shen et al., 2023)	✓	✓	✓	✗	✓	✗	✗	✗	✗	✗	✗
Make-A-Voice (Huang et al., 2023b)	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗
Maga-TTS (Jiang et al., 2023)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
VoiceBox (Le et al., 2023)	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓
AudioLDM2 (Liu et al., 2023b)	✓	✗	✗	✗	✗	✓	✓	✗	✗	✗	✗
SpeechX (Wang et al., 2023c)	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗	✓
UniAudio (ours)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Ref: Yang et al, "UniAudio: An audio foundation model toward universal audio generation," ICLR 2024 submission

UniAudio

- Training of UniAudio is scaled up to 165K hours of audio and **1B** parameters

Table 6: Data Statistics

Dataset	Type	Annotation	Volume (hrs)
Training			
LibriLight (Kahn et al., 2020)	speech	-	60k
LibriTTS Zen et al. (2019)	speech	text	1k
MLS (Pratap et al., 2020)	speech	-	20k
AudioSet (Gemmeke et al., 2017)	sounds	-	5.8k
AudioCaps Kim et al. (2019)	sounds	text description	500
WavCaps Mei et al. (2023)	sounds	text description	7k
Million Song Dataset McFee et al. (2012)	music	text description	7k
OpenCPOP Wang et al. (2022)	singing	text, MIDI	5.2h
OpenSinger Huang et al. (2021a)	singing	text, MIDI	50h
AISHELL3 Shi et al. (2020)	speech	text	85h
PromptSpeech Guo et al. (2023)	speech	text, instruction	200h
openSLR26,openSLR28 Ko et al. (2017)	Room Impulse Response	-	100h
Test Only			
LibriSpeech-test clean Panayotov et al. (2015)	speech	text	8h
VCTK Veaux et al. (2017)	speech	text	50h
TUT2017 Task1 Mesaros et al. (2017)	Noise	-	10h
Cloth Drossos et al. (2020)	Sounds	text description	3h
MusicCaps Agostinelli et al. (2023)	Music	text description	15h
M4SingerZhang et al. (2022)	singing	text, MIDI	1h

Ref: Yang et al, “UniAudio: An audio foundation model toward universal audio generation,” ICLR 2024 submission

Outline

- Image/audio tokenization and generation via VQVAE
- Audio codec models
- **Text-to-music: linking text and musical audio**
  - Transformer-based approach
  - **Diffusion-based approach**

Denoising Diffusion Probabilistic Models (DDPM)

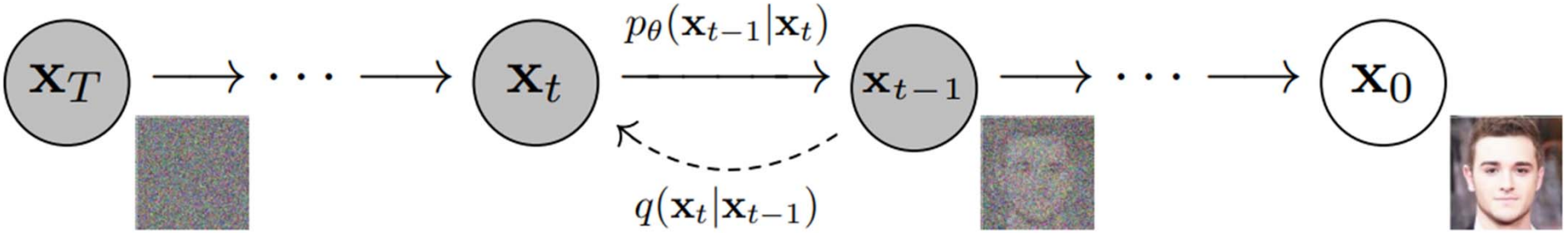


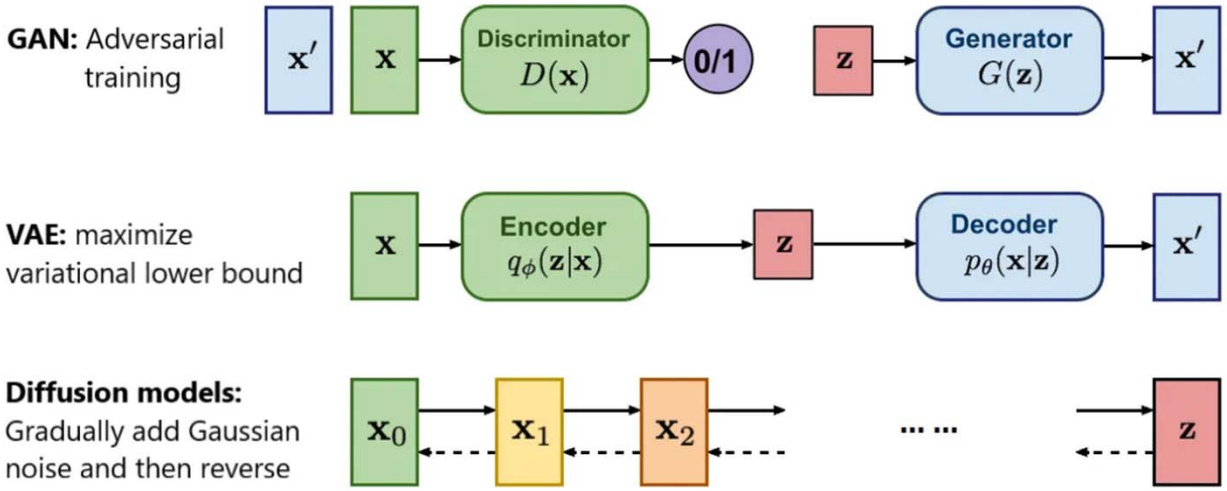
Figure 2: The directed graphical model considered in this work.

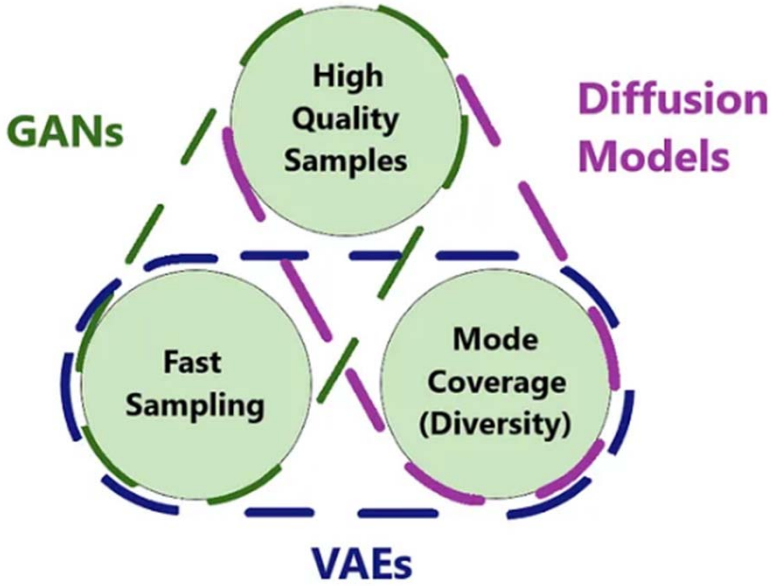
- **Forward** (or diffusion) process: $\boldsymbol{x}_0$ (real data) → $\boldsymbol{x}_T$ (Gaussian noise)
- **Reverse** process: $\boldsymbol{x}_T \rightarrow \boldsymbol{x}_0$ [denoise]
- The intermediate noisy data serve as latent codes ($\boldsymbol{z}$) and have the same size as the training data

Ref: Ho et al, "Denoising diffusion probabilistic models," NeurIPS 2020

Diffusion Models

https://pub.towardsai.net/diffusion-models-vs-gans-vs-vaes-comparison-of-deep-generative-models-67ab93e0d9ae





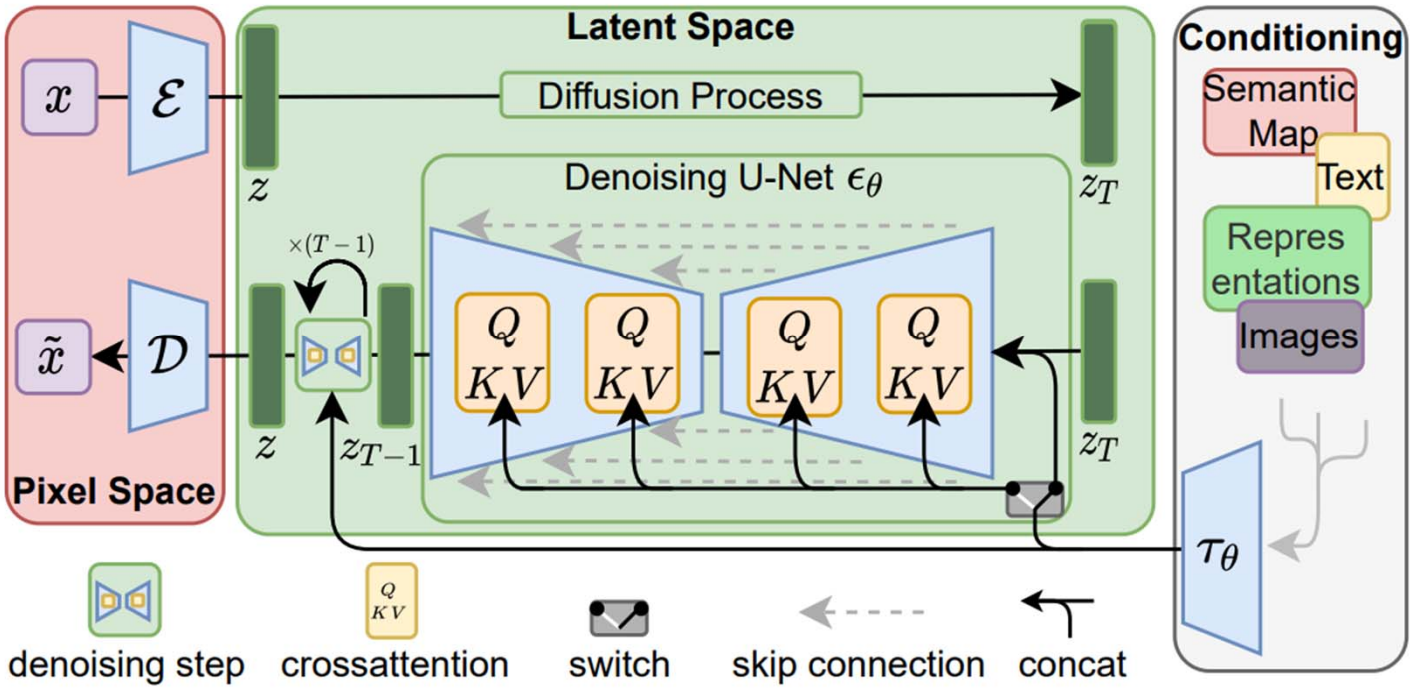
- **High-fidelity samples:** due to the nature of gradually removing noise
- **High diversity samples**: likelihood maximization covers all data modes
- **Slow sample generation**: requires multiple runs to gradually generate samples

Latent Diffusion Models

- Work on a **latent** space instead of pixel space
  - focus on the important, semantic bits of data
  - computational efficiency
- Latent space regularization
  - KL-reg
  - VQ-reg
- Adding condition
  - cross-attention

$$x \in \mathbb{R}^{H \times W \times 3}$$

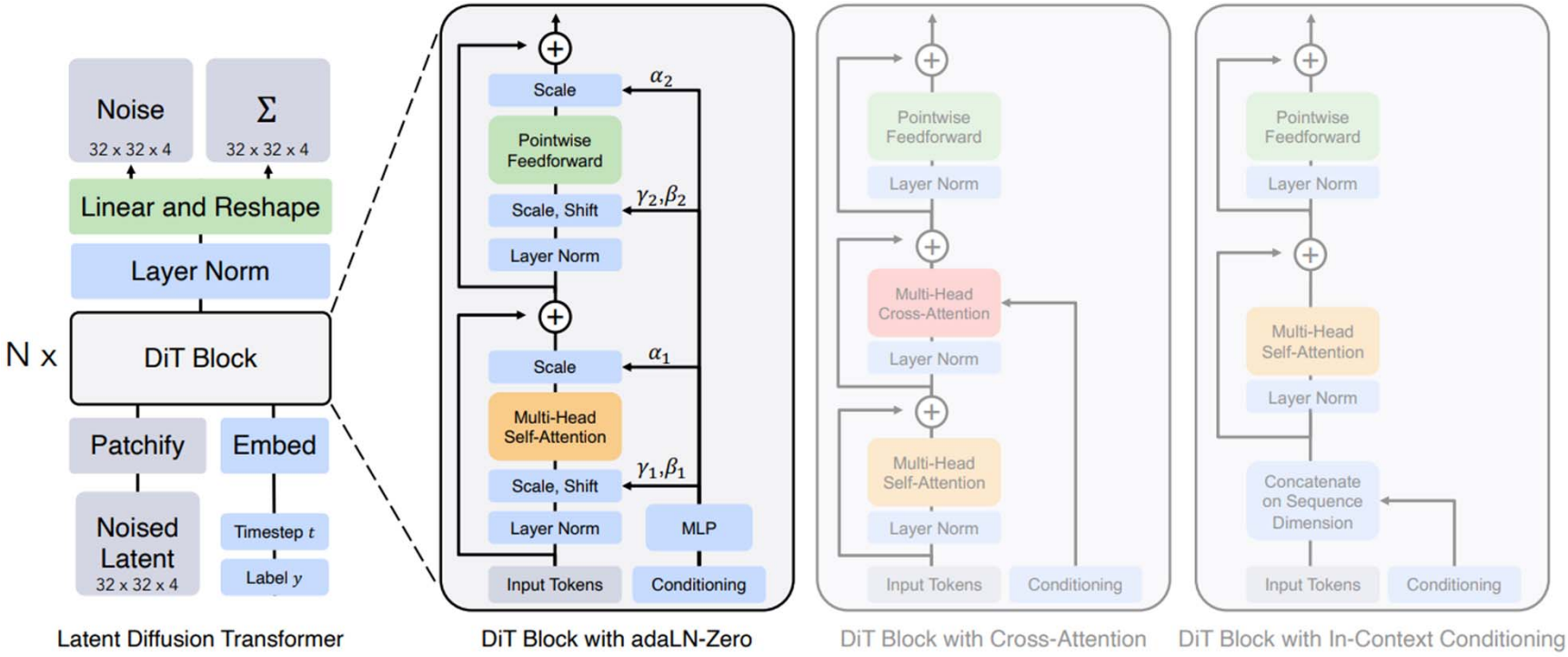
$$z \in \mathbb{R}^{h \times w \times c}$$



Ref: Rombach et al, "High-resolution image synthesis with latent diffusion models," CVPR 2022

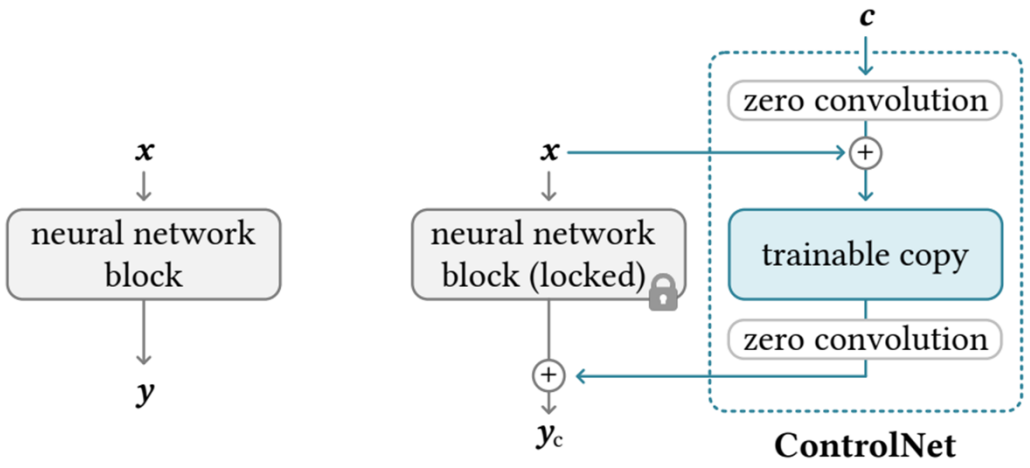
Diffusion Transformer (DiT)

- Self-attention layers instead of convolution layers
- Use adaptive layer norm to incorporate conditioning

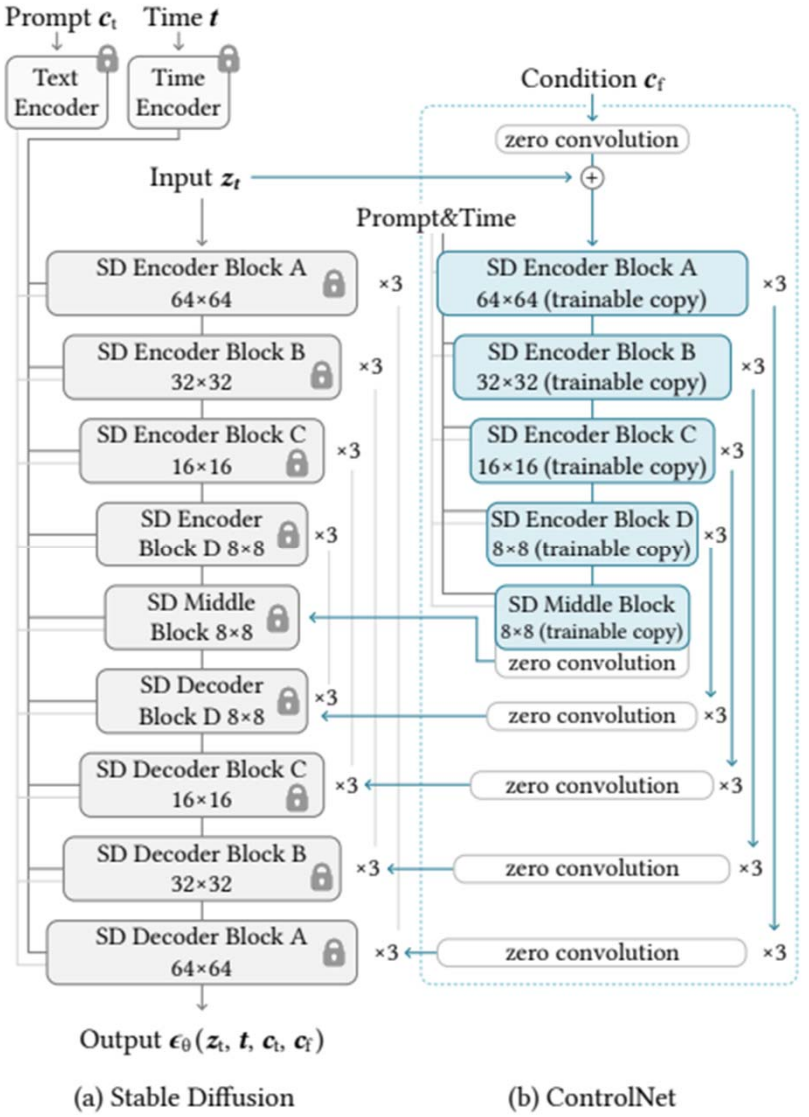


Ref: Peebles & Xie, "Scalable diffusion models with Transformers," CVPR 2023

ControlNet



(a) Before (b) After



(a) Stable Diffusion (b) ControlNet

Ref: Zhang et al, "Adding conditional control to text-to-image diffusion models," CVPR 2023

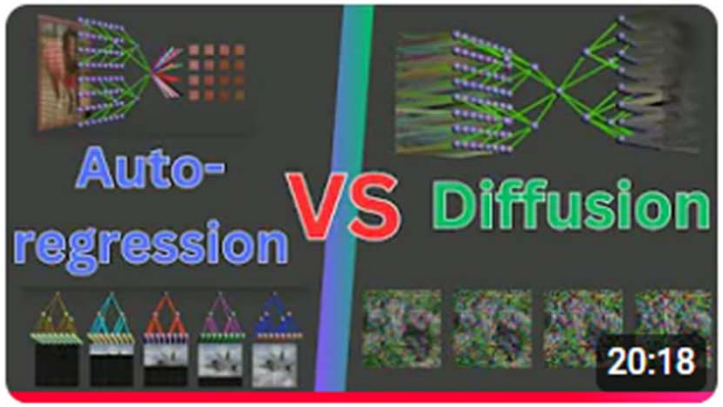
References for Diffusion Models

- References
  - Diffusion model tutorial @ ISMIR 2024 (https://sites.google.com/view/diffusion-tutorial-ismir24/materials)

  - Prof. Hung-Yi Lee's videos (https://www.youtube.com/watch?v=ifCDXFdeaaM)

References for Diffusion Models

https://www.youtube.com/watch?v=zc5NTeJbk-k



Why Does Diffusion Work Better than Auto-Regression?

Algorithmic Simplicity • 374K views

Have you ever wondered how generative AI actually works? Well the short answer is, in exactly the same as way as regular AI! In this...

Diffusers

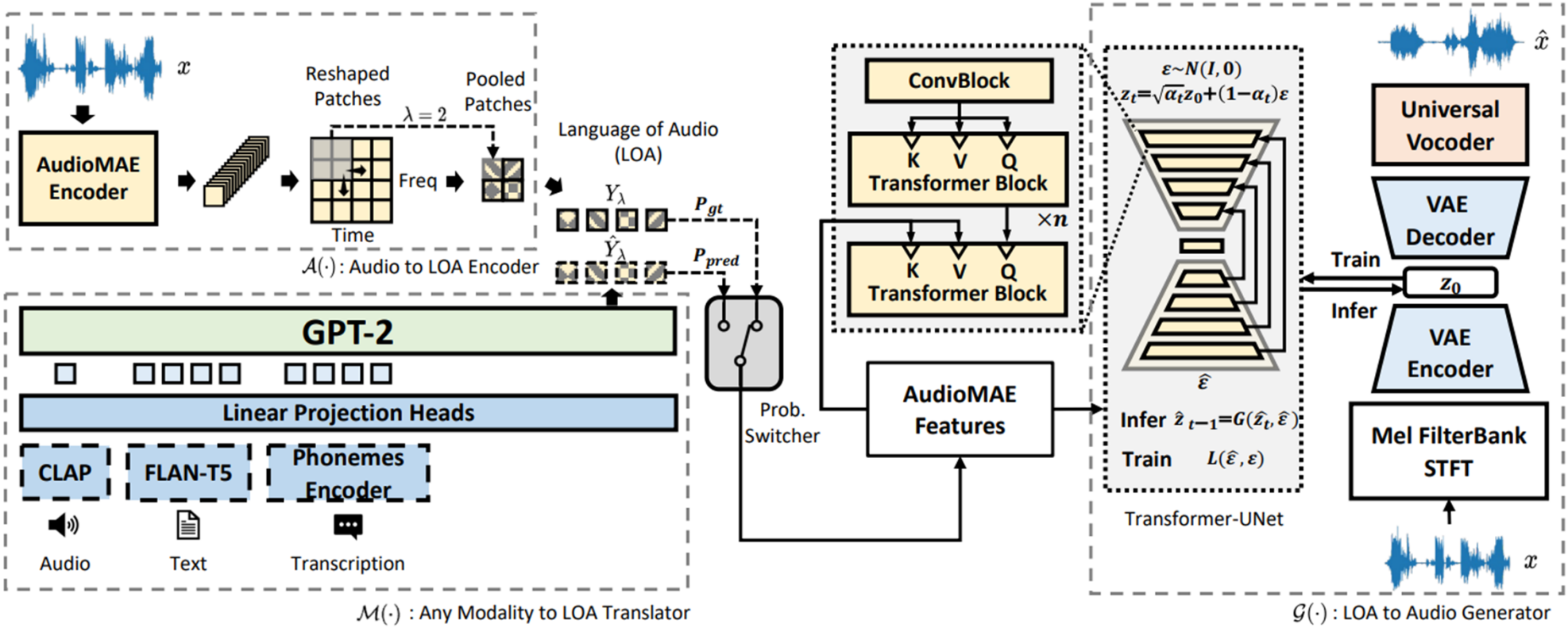
https://github.com/huggingface/diffusers

Task	Pipeline	🤗 Hub
Unconditional Image Generation	DDPM	google/ddpm-ema-church-256
Text-to-Image	Stable Diffusion Text-to-Image	stable-diffusion-v1-5/stable-diffusion-v1-5
Text-to-Image	unCLIP	kakaobrain/karlo-v1-alpha
Text-to-Image	DeepFloyd IF	DeepFloyd/IF-I-XL-v1.0
Text-to-Image	Kandinsky	kandinsky-community/kandinsky-2-2-decoder
Text-guided Image-to-Image	ControlNet	lllyasviel/sd-controlnet-canny
Text-guided Image-to-Image	InstructPix2Pix	timbrooks/instruct-pix2pix
Text-guided Image-to-Image	Stable Diffusion Image-to-Image	stable-diffusion-v1-5/stable-diffusion-v1-5
Text-guided Image Inpainting	Stable Diffusion Inpainting	runwayml/stable-diffusion-inpainting
Image Variation	Stable Diffusion Image Variation	lambdalabs/sd-image-variations-diffusers
Super Resolution	Stable Diffusion Upscale	stabilityai/stable-diffusion-x4-upscaler
Super Resolution	Stable Diffusion Latent Upscale	stabilityai/sd-x2-latent-upscaler

AudioLDM2

https://github.com/haoheliu/AudioLDM2

- Open source!
- Latent diffusion

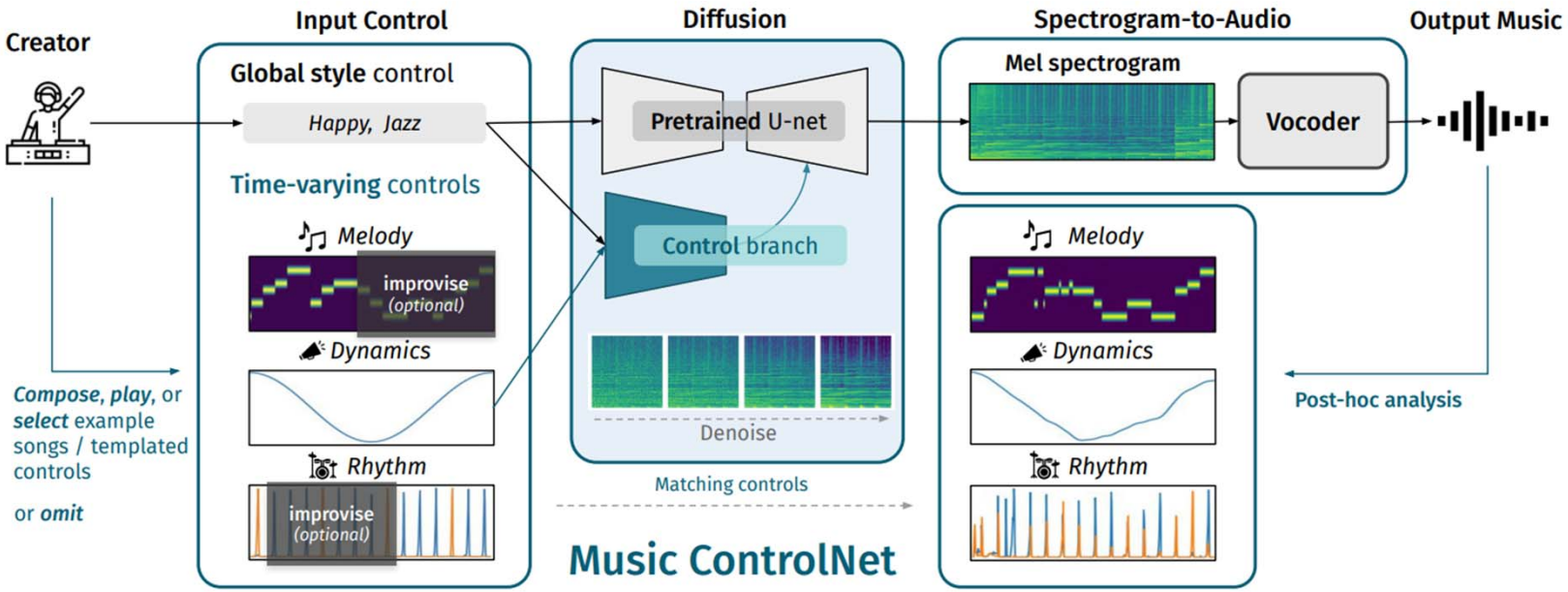


Ref: Liu et al, "AudioLDM 2: Learning holistic audio generation with self-supervised pretraining," TASLP 2024

Music ControlNet

https://musiccontrolnet.github.io/web/

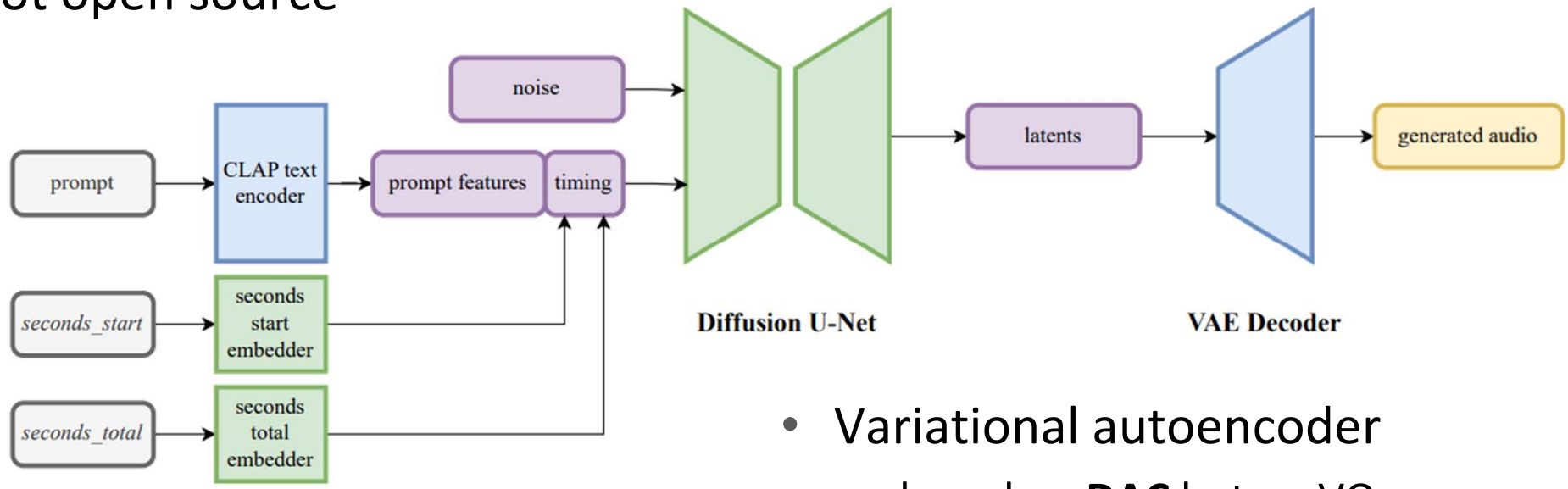
- Work in the “pixel” domain
- Not open source

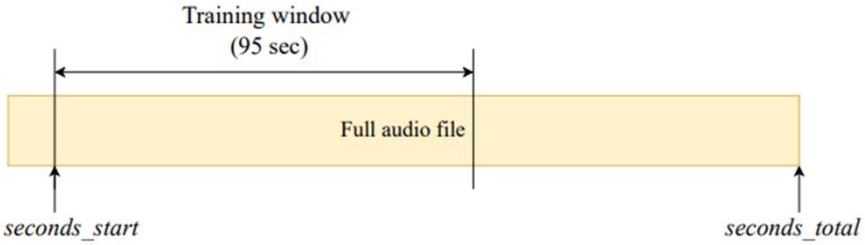


Ref: Wu et al, “Music ControlNet: Multiple time-varying controls for music generation,” TASLP 2024

Stable Audio

- Not open source





- Variational autoencoder
  - based on **DAC** but no VQ
  - **sequence of latents**: maps a 2×L input into 64×L/1024 latents
- Use **DiT** with Flash Attention

Ref: Evans et al, "Fast timing-conditioned latent audio diffusion," ICML 2024

Stable Audio 2

- Not open source

	DiT	AE	CLAP	Total
Parameters	1.1B	157M	125M	1.3B

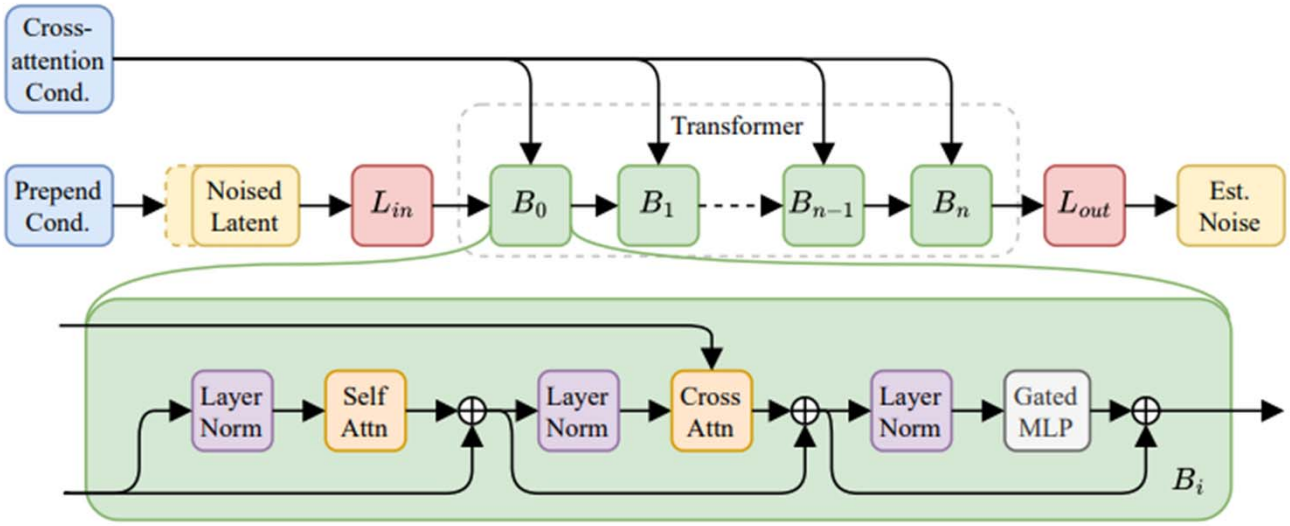
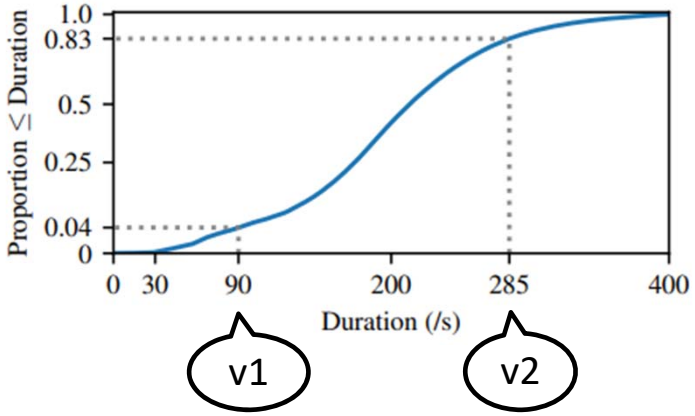


Figure 2: Architecture of the diffusion-transformer (DiT).



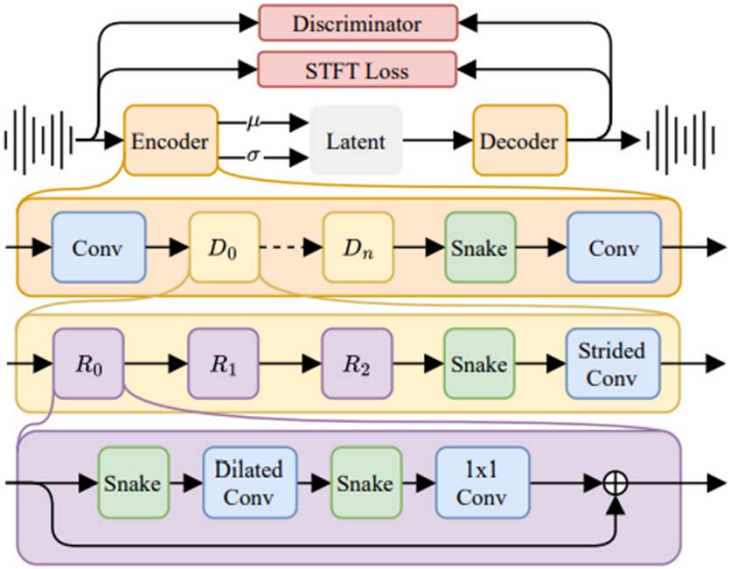


Figure 3: Architecture of the autoencoder.

Ref: Evans et al, "Long-form music generation with latent diffusion," ISMIR 2024

Stable Audio 2 vs MusicGen-large

	channels/sr	output length	$FD_{openl3} \downarrow$	$KL_{passt} \downarrow$	$CLAP_{score} \uparrow$	inference time
MusicGen-large-stereo [8]	2/32kHz	2m	204.03	0.49	0.28	6m 38s
Ours (fully-trained)	2/44.1kHz	2m†	79.09	0.35	0.40	13s
MusicGen-large-stereo [8]	2/32kHz	4m 45s	218.02	0.50	0.27	12m 53s
Ours (fully-trained)	2/44.1kHz	4m 45s	81.96	0.34	0.39	13s

Results with the fully-trained model:	2m long			4m 45s long	
	Stable Audio 2	MusicGen-large-stereo	ground truth	Stable Audio 2	MusicGen-large-stereo
Audio Quality	4.0±0.6	2.8±0.8	4.6±0.4	4.5±0.4	2.8±0.8
Text Alignment	4.3±0.7	3.1±0.8	4.6±0.5	4.6±0.4	2.9±1.0
Structure	3.5±1.3	2.4±0.7	4.3±0.8	4.0±1.0	2.1±0.7
Musicality	4.0±0.8	2.7±0.9	4.6±0.5	4.3±0.7	2.6±0.7
Stereo correctness	96%	61%	96%	100%	57%

Stable Audio Open

- Open source!
  - trained on data from Freesound and FMA (about 500K recordings; or 7,300 h)
  - all licensed under CC-0, CC-BY, or CC-Sampling+

	channels/sr	output length	$FD_{openl3} \downarrow$	$KL_{passt} \downarrow$	$CLAP_{score} \uparrow$
MusicGen-large-stereo [8]	2/32kHz	47	190.47	0.52	0.31
Stable Audio 1.0 [5]	2/44.1kHz	95 sec †	142.50	0.40	0.38
Stable Audio 2.0 [6]	2/44.1kHz	190 sec †	**71.25**	**0.37**	**0.42**
Stable Audio 2.0 [6]	2/44.1kHz	285 sec †	81.05	0.39	0.42
Stable Audio Open	2/44.1kHz	47	96.51	0.55	0.41

Table 2. *Song Desciber Dataset (instrumental music, not sounds).*

Ref: Evans et al, "Stable Audio Open," arXiv 2024

Recap: Elements of a Text-to-Music Model

- **1. Music LM/generator**
  - Transformer-based: operating on discrete tokens
  - Diffusion-based: operating on continuous latents
- **2a. Text encoder** that provides conditions for the music LM/generator
- **2b.** (Optional) **text-music joint embedding space**
  - Not needed if there is a strong text encoder
- **3. Audio encoder/decoder**
  - VQVAE-based (in particular **audio codec** models) if it's for Transformer-based LMs
  - Not necessarily VQVAE-based if it's for diffusion based generator
  - Audio encoder/decoder is not needed if it's for MIDI generation