

PAT 464/564 (Winter 2026)

# Generative AI for Music & Audio Creation

## **Lecture 12: Variational Autoencoders**

Instructor: Hao-Wen Dong

# Representative Types of Deep Generative Models

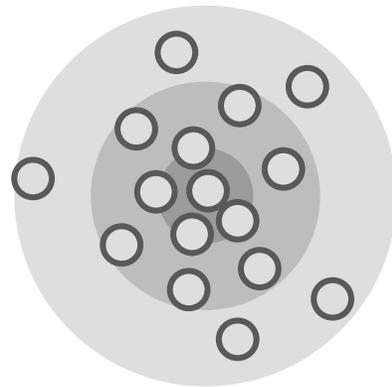
- **Deep autoregressive models**
  - Recurrent neural network (RNN)
  - Long short-term memory (LSTM)
  - Transformer model
- **Deep latent variable models**
  - Variational autoencoder (VAE) **Today's topic!**
  - Generative adversarial network (GAN)
  - Diffusion model
  - Flow-based model
- *And many others...*

# Deep Latent Variable Models

# Deep Latent Variable Models

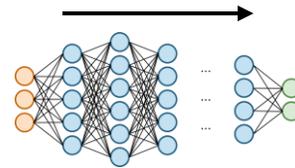
- **Intuition:** Learn to map a known distribution to the data distribution

Known distribution

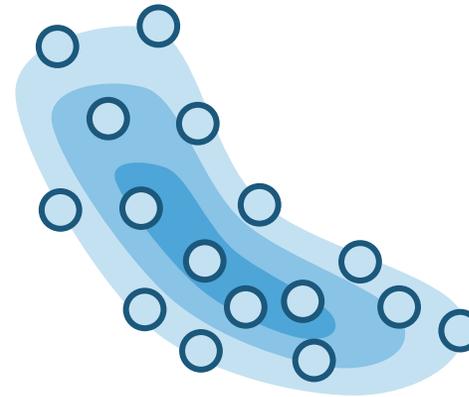


$P(z)$

$P(x | z)$



Data distribution

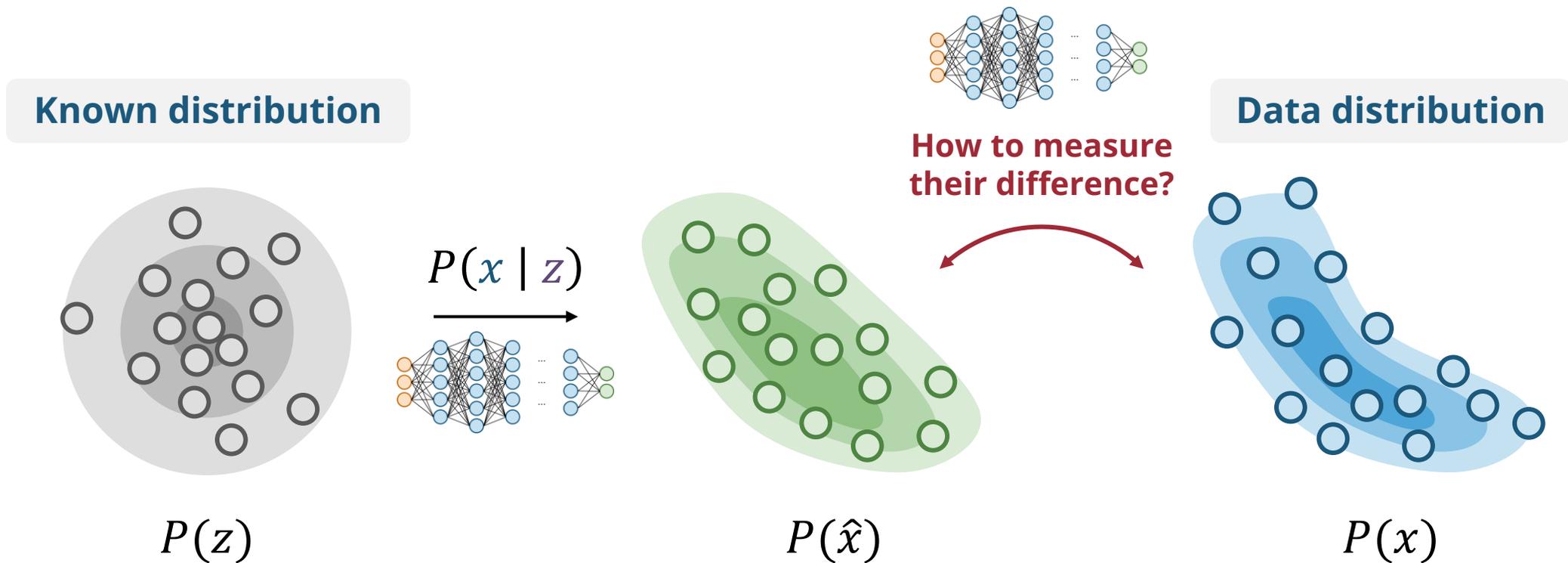


$P(x)$

$$P(x) = P(z) P(x | z)$$

# Deep Latent Variable Models

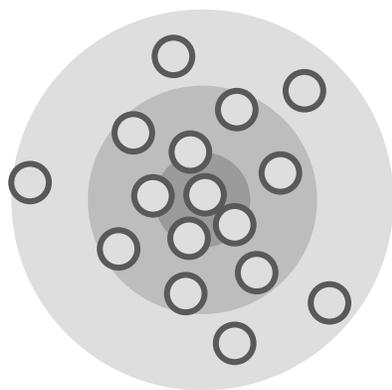
- **Intuition:** Learn to map a known distribution to the data distribution



# Deep Latent Variable Models

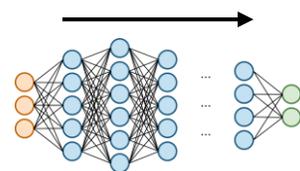
- **Intuition:** Learn to map a known distribution to the data distribution

Known distribution

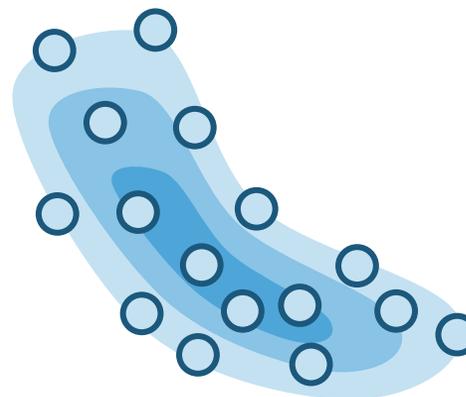


$P(z)$

$P(x | z)$



Data distribution



$P(x)$

$$P(x) = P(z) P(x | z)$$

# Deep Latent Variable Models

- **Intuition:** Learn to map a known distribution to the data distribution

What we want the model to learn!

$$P(x) = P(z) P(x | z)$$

Diagram illustrating the decomposition of the data distribution  $P(x)$  into the latent distribution  $P(z)$  and the conditional distribution  $P(x | z)$ .

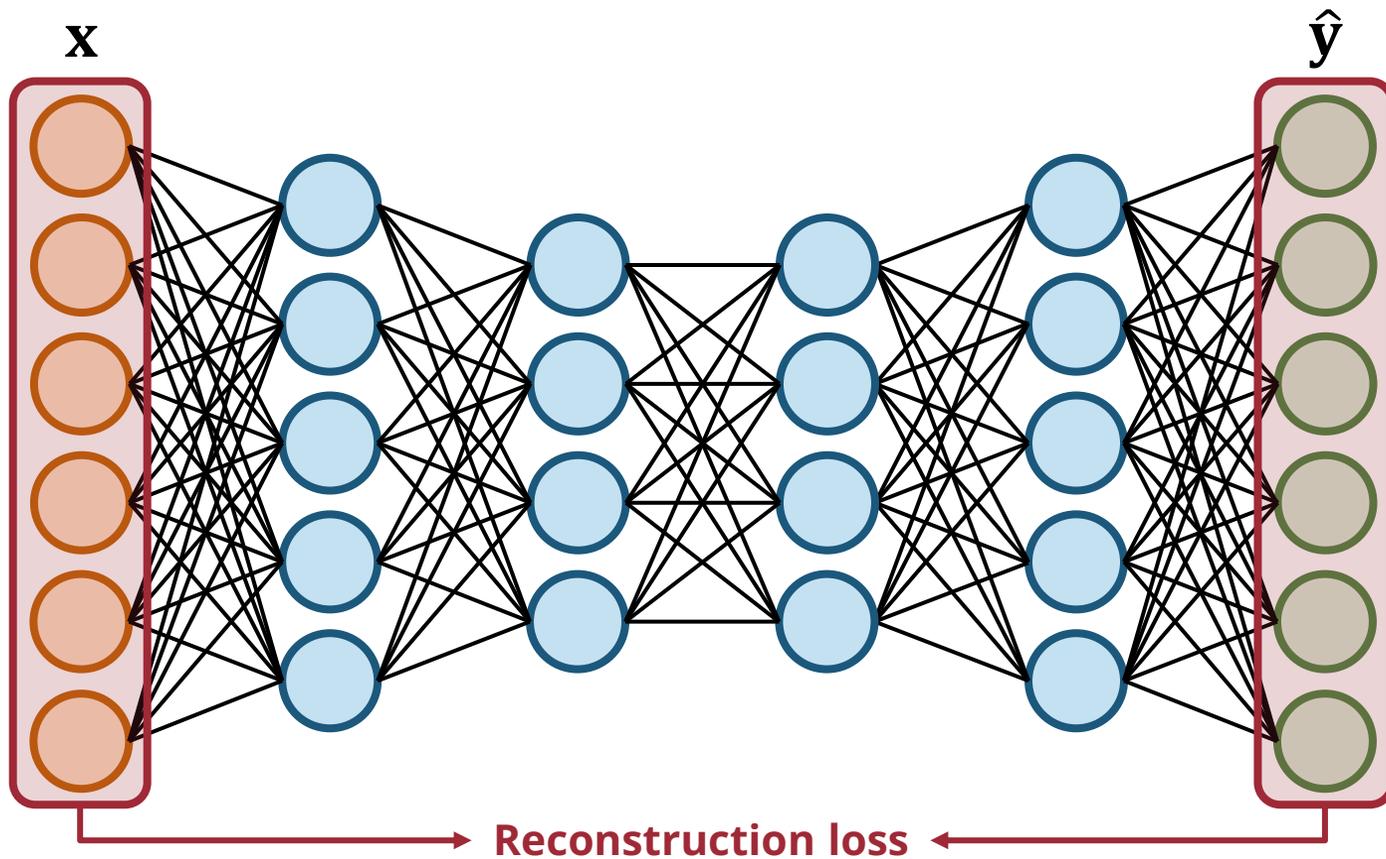
The equation  $P(x) = P(z) P(x | z)$  is shown, with  $P(x | z)$  highlighted in a red box. An upward arrow points from the red box to the text "What we want the model to learn!".

Arrows point from  $P(x)$  to "Data distribution" and from  $P(z)$  to "Latent distribution".

# Autoencoders

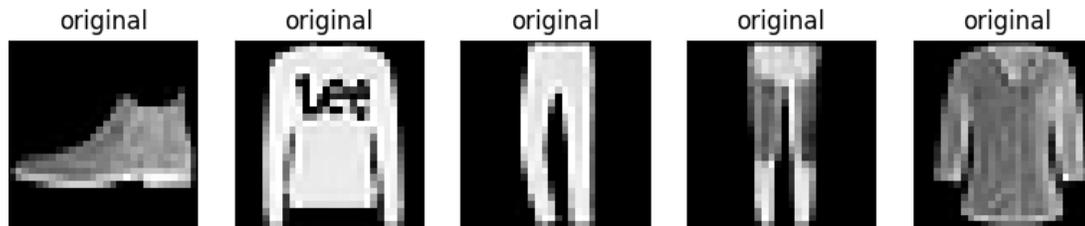
# Autoencoders

- A neural network where the **input and output are the same**

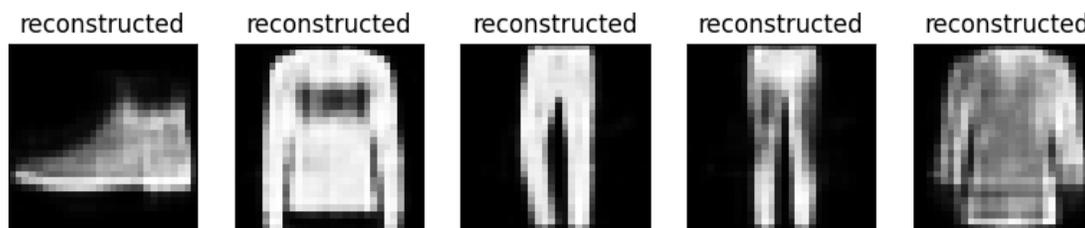


# Autoencoders: Reconstruction Examples

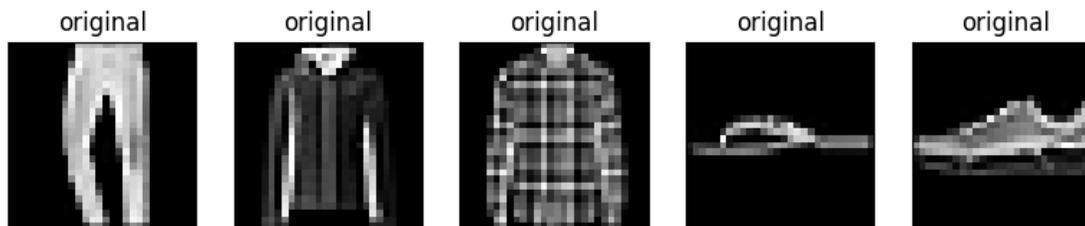
Original



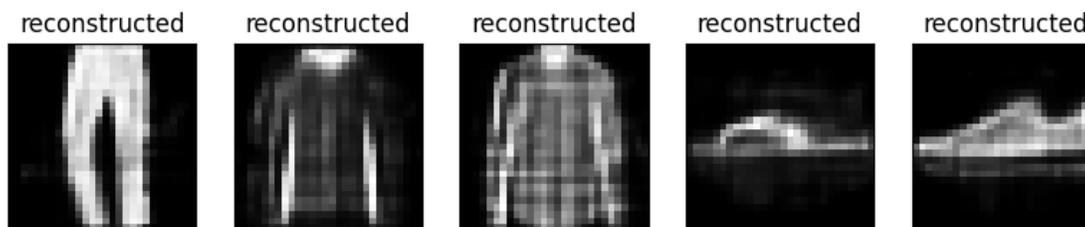
Reconstructed



Original



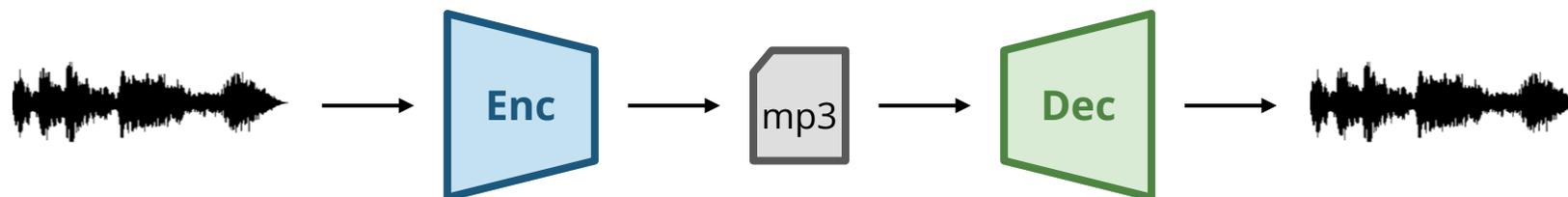
Reconstructed



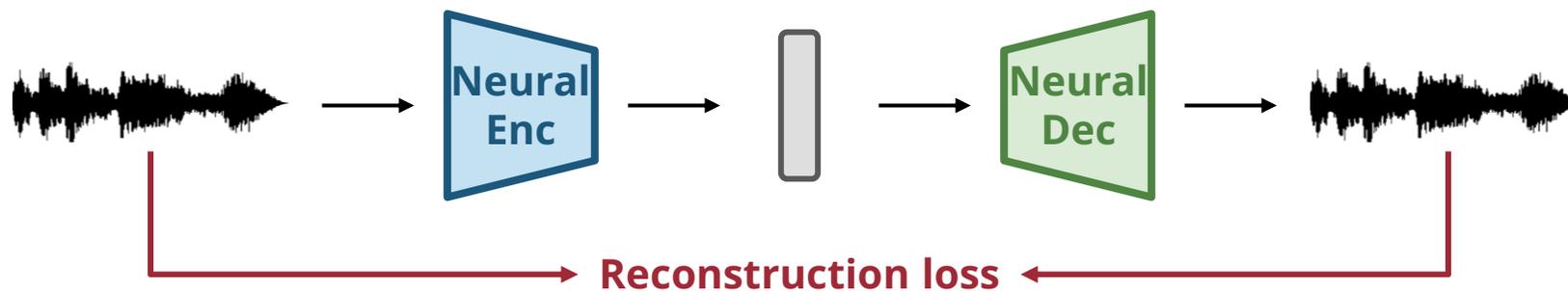
(Source: tensorflow.org)

# Codec is an Autoencoder

## Traditional Codec

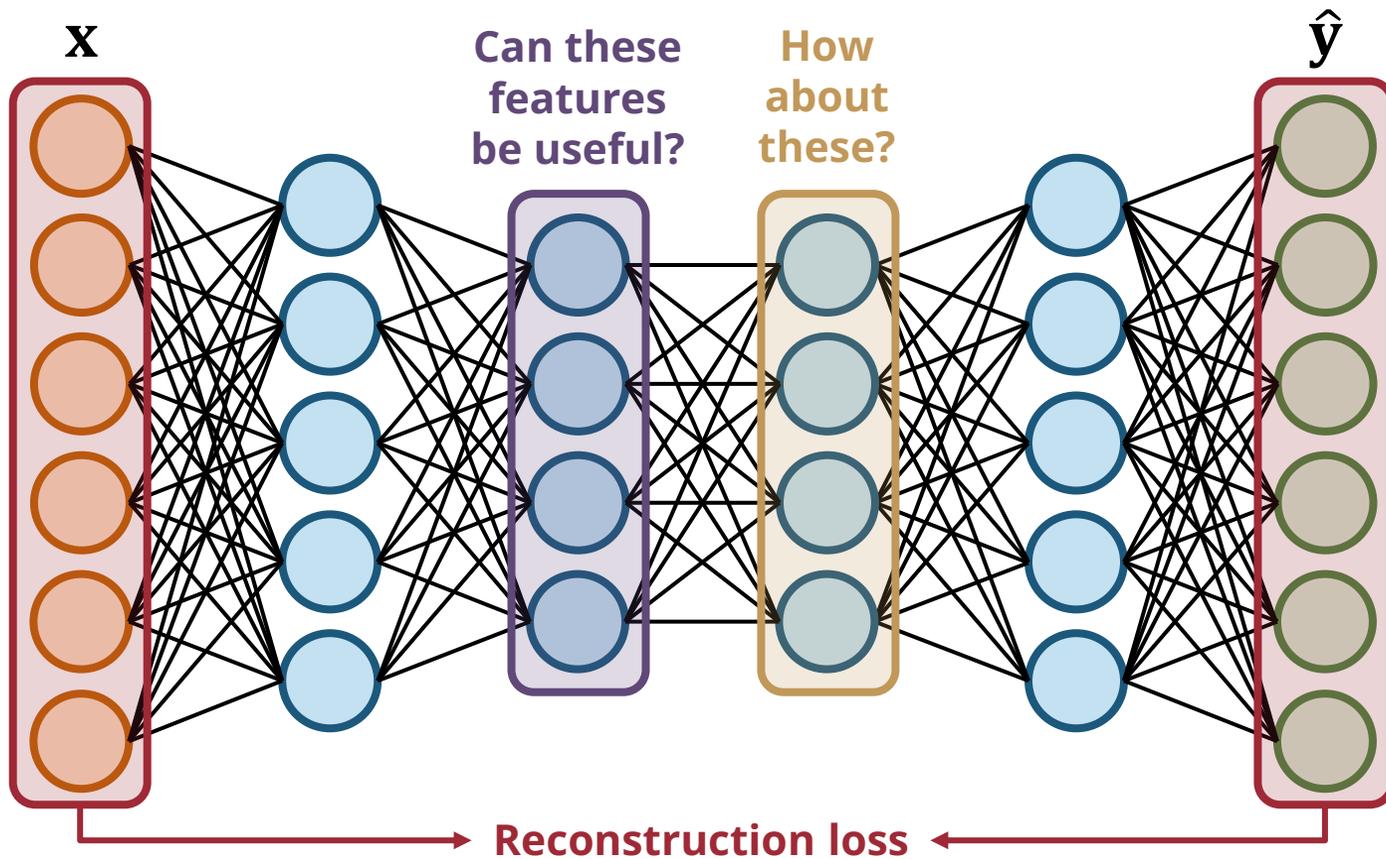


## Neural Codec

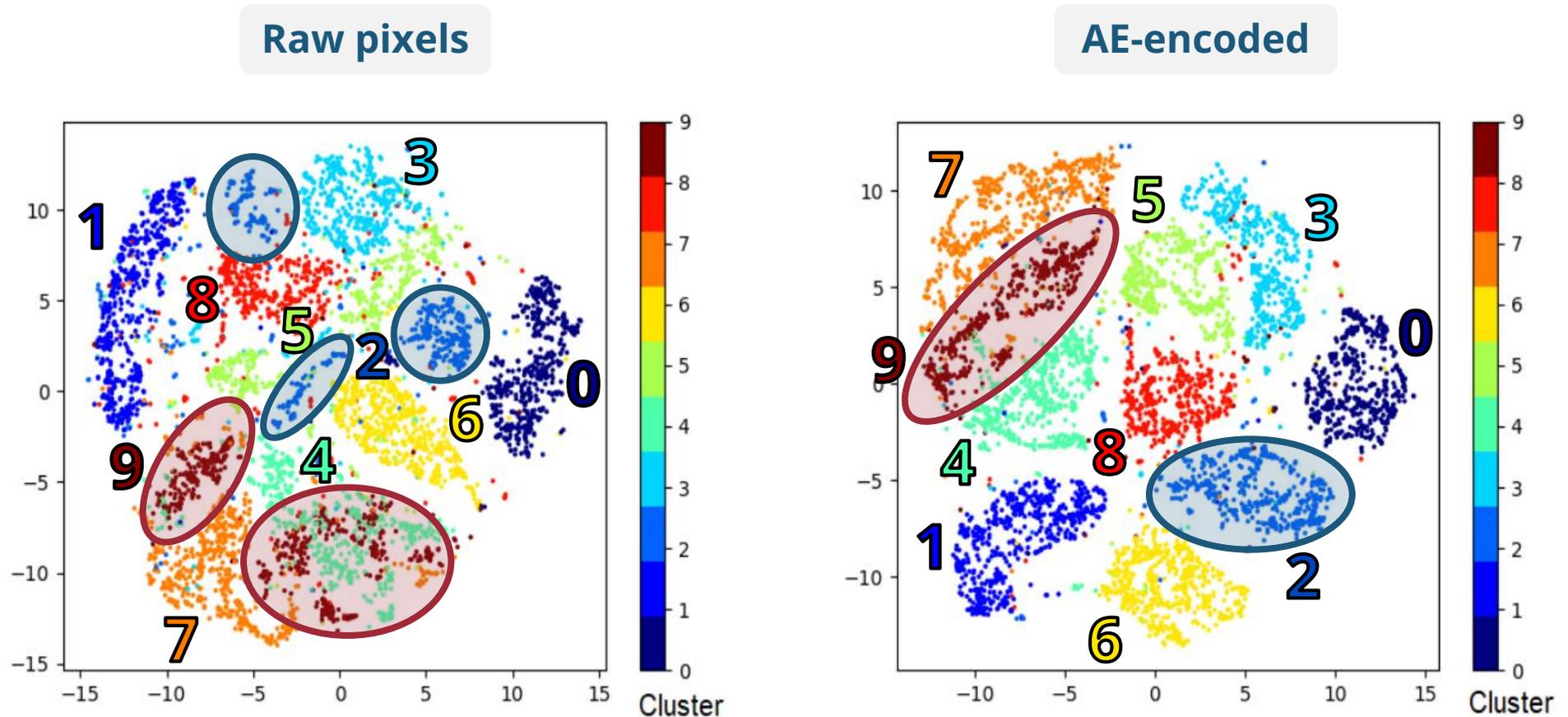


# Autoencoders

- A neural network where the **input and output are the same**

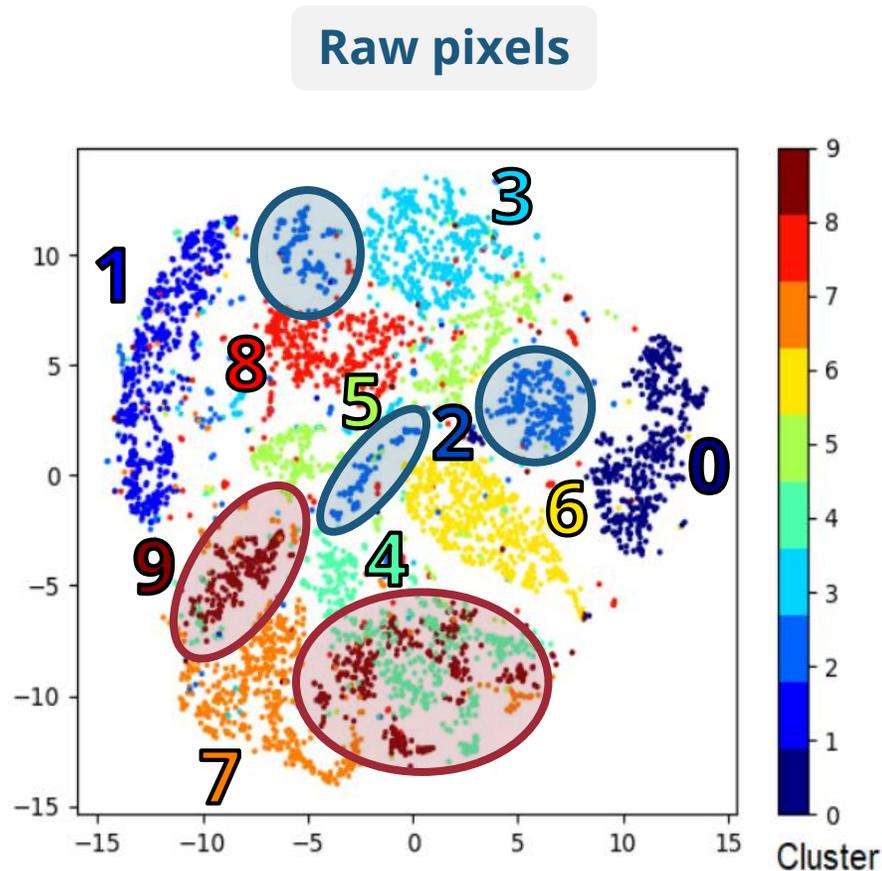


# Unsupervised Clustering with an Autoencoder

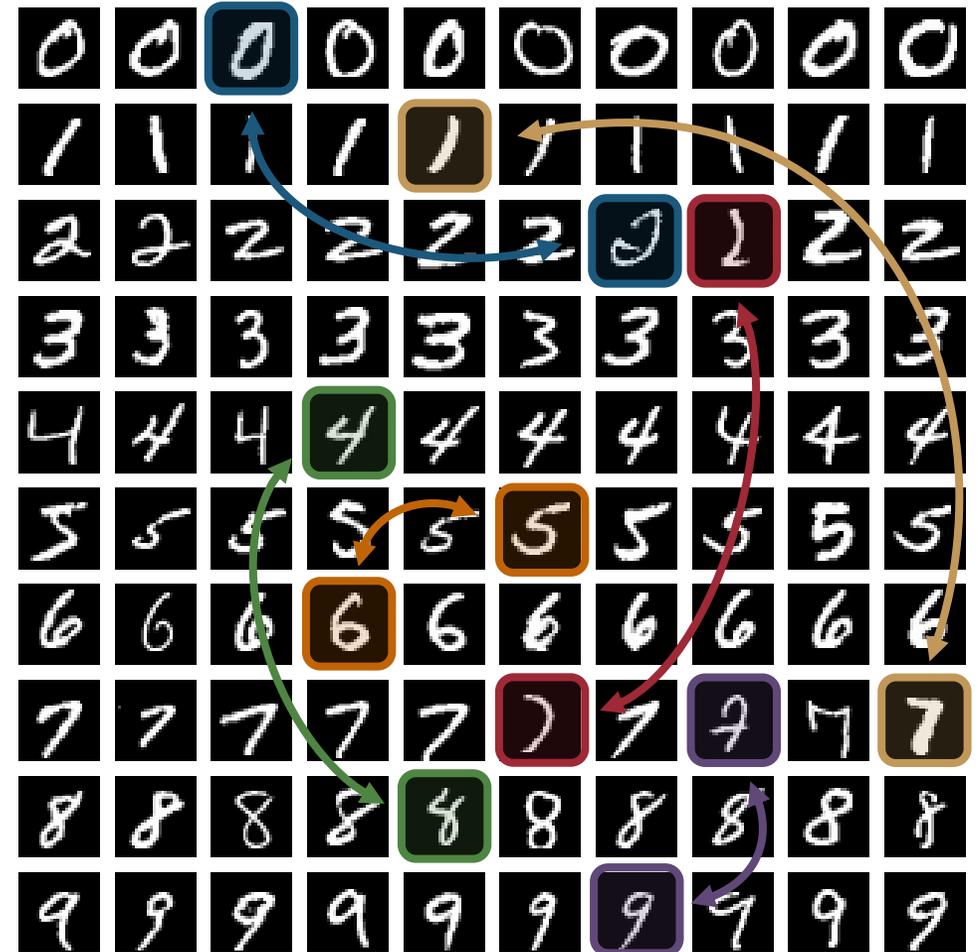


(Source: Aljalbout et al., 2020)

# Unsupervised Clustering with an Autoencoder



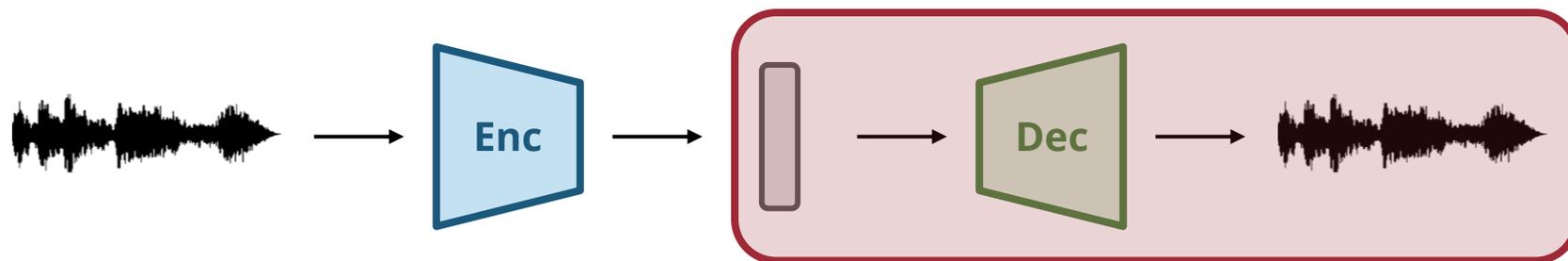
(Source: Aljalbout et al., 2020)





# Variational Autoencoder (VAE)

# Autoencoder

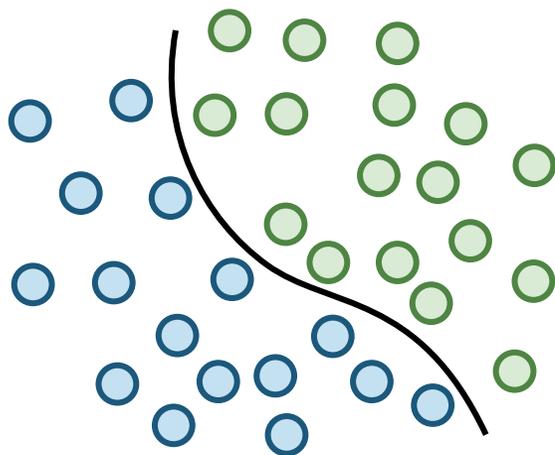


**Isn't this like a generative model?**

**What exactly is a generative model?**

# Discriminative vs Generative Models

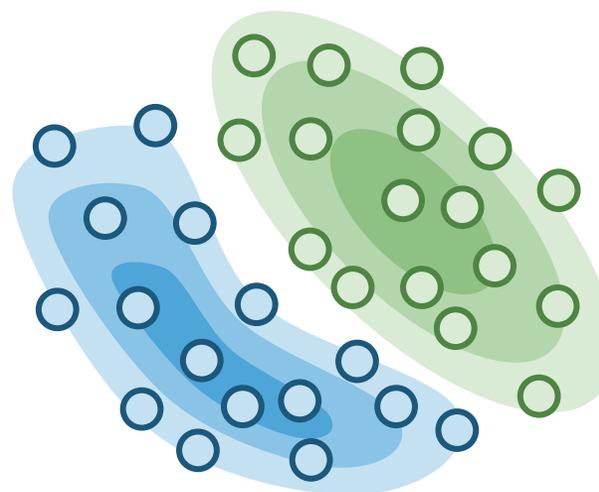
Discriminative



Discriminative models learn the decision boundary

$$P(y|x)$$

Generative



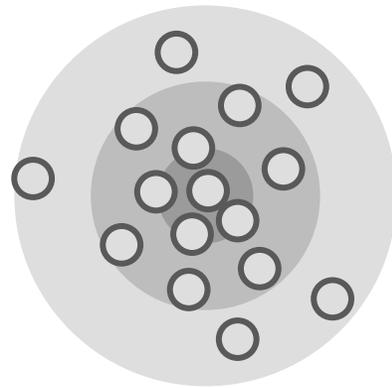
Generative models learn the underlying distribution

$$P(x) \text{ or } P(x|y)$$

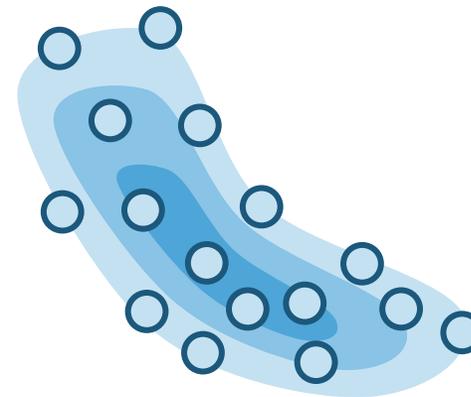
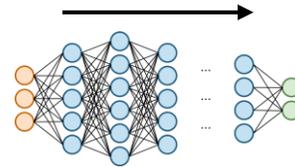
# Generating Data from a Random Distribution

Random distribution

Data distribution



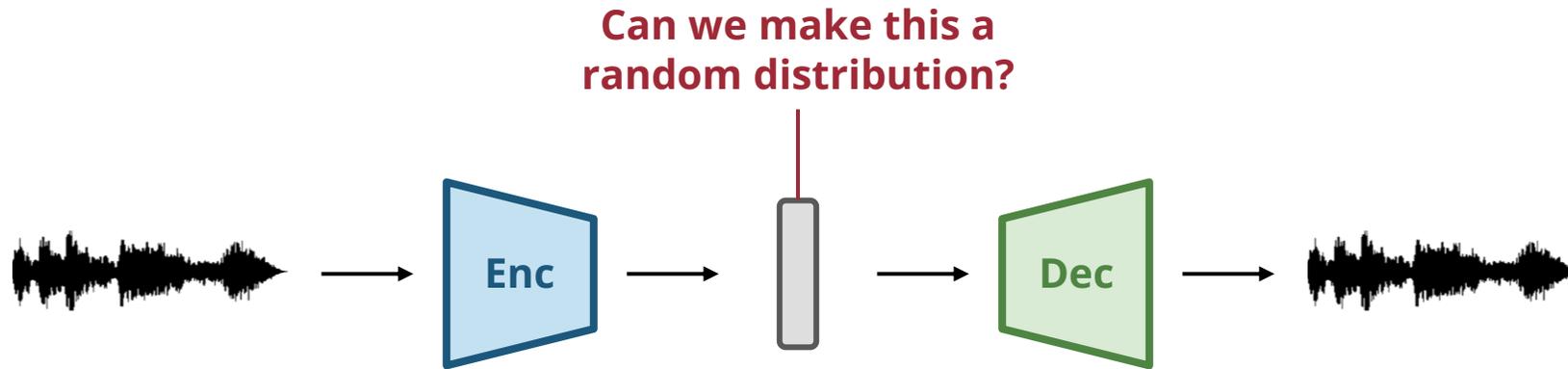
$P(z)$



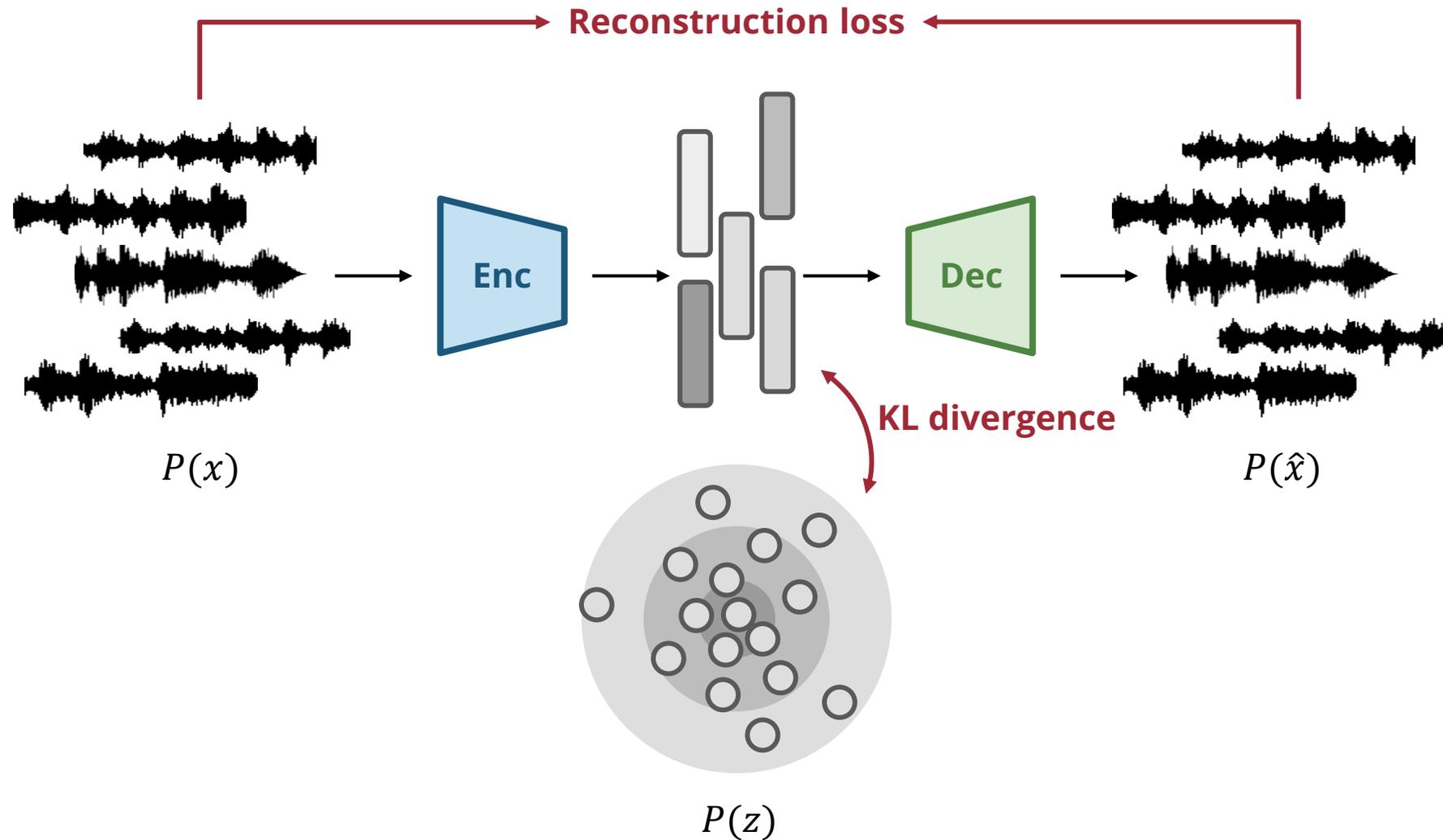
$P(x)$

If we can learn this mapping, we can then generate new samples from the data distribution

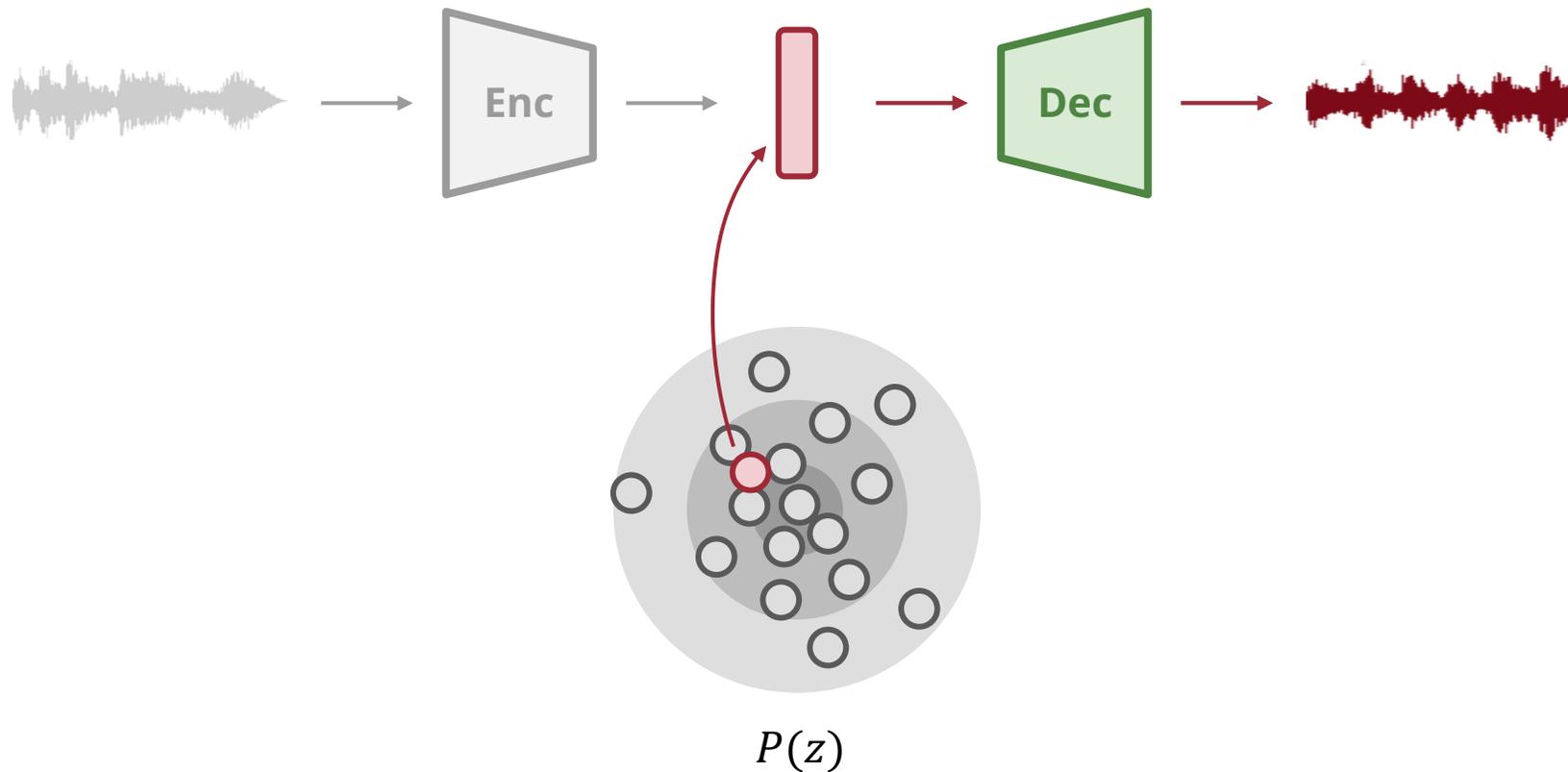
# Variational Autoencoder (VAE)



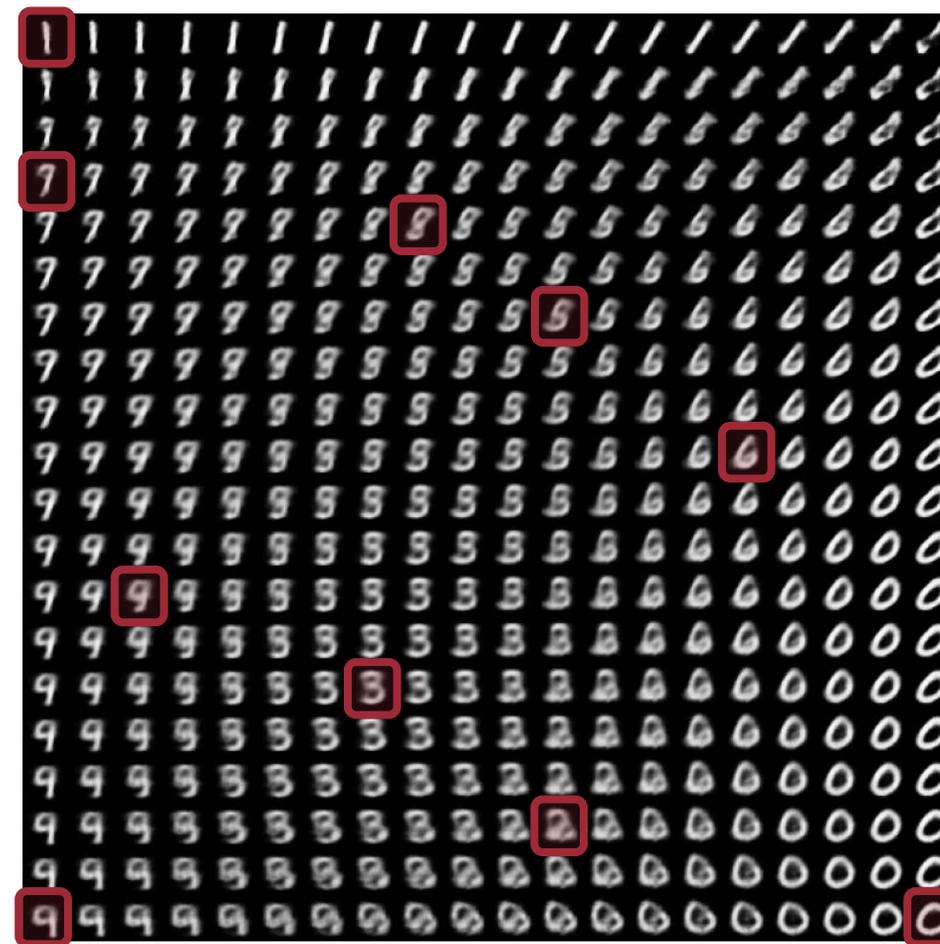
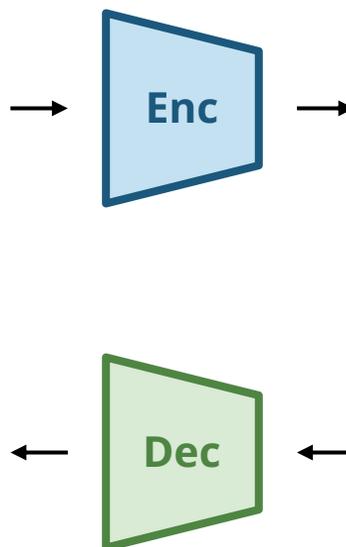
# Variational Autoencoder (VAE): Training



# Variational Autoencoder (VAE): Generation



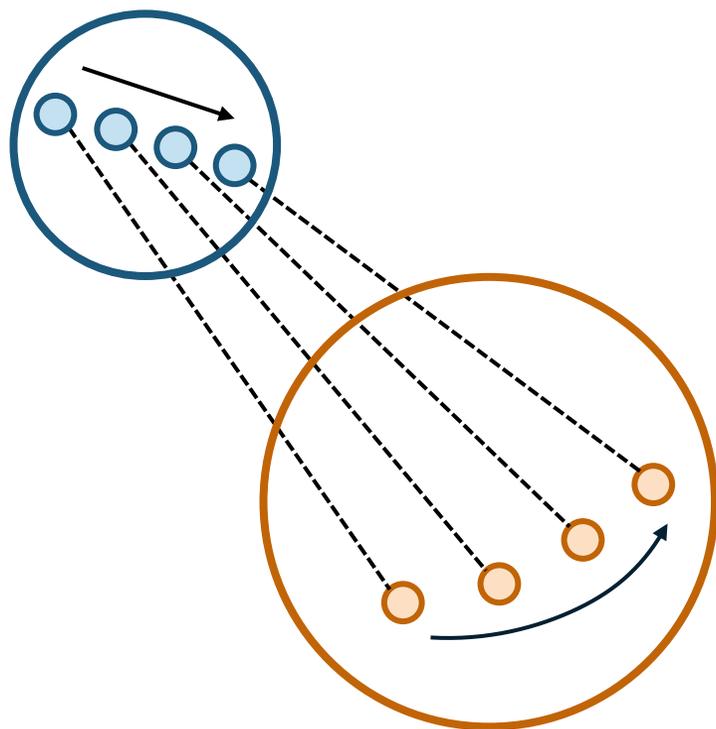
# What does a VAE learn?



(Source: tensorflow.org)

# Latent Space Interpolation of a VAE

Latent space



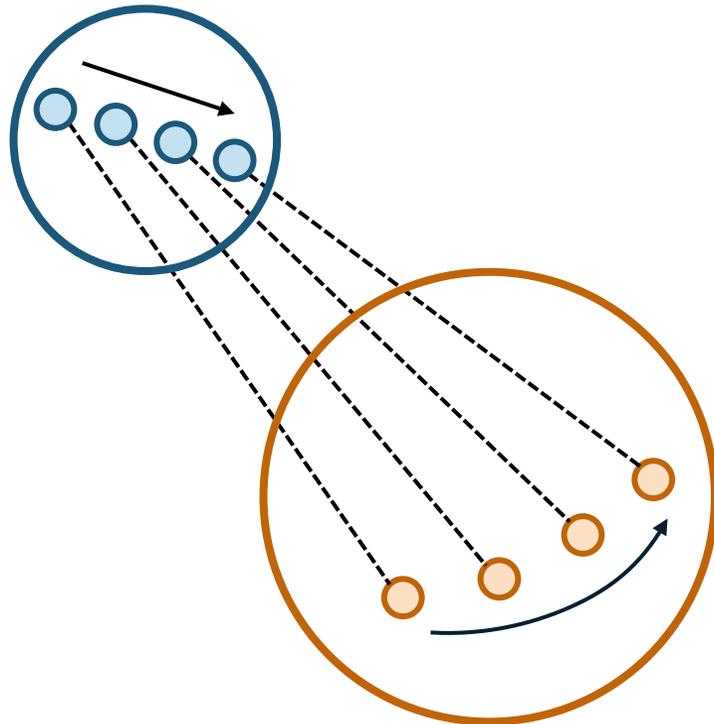
Data space



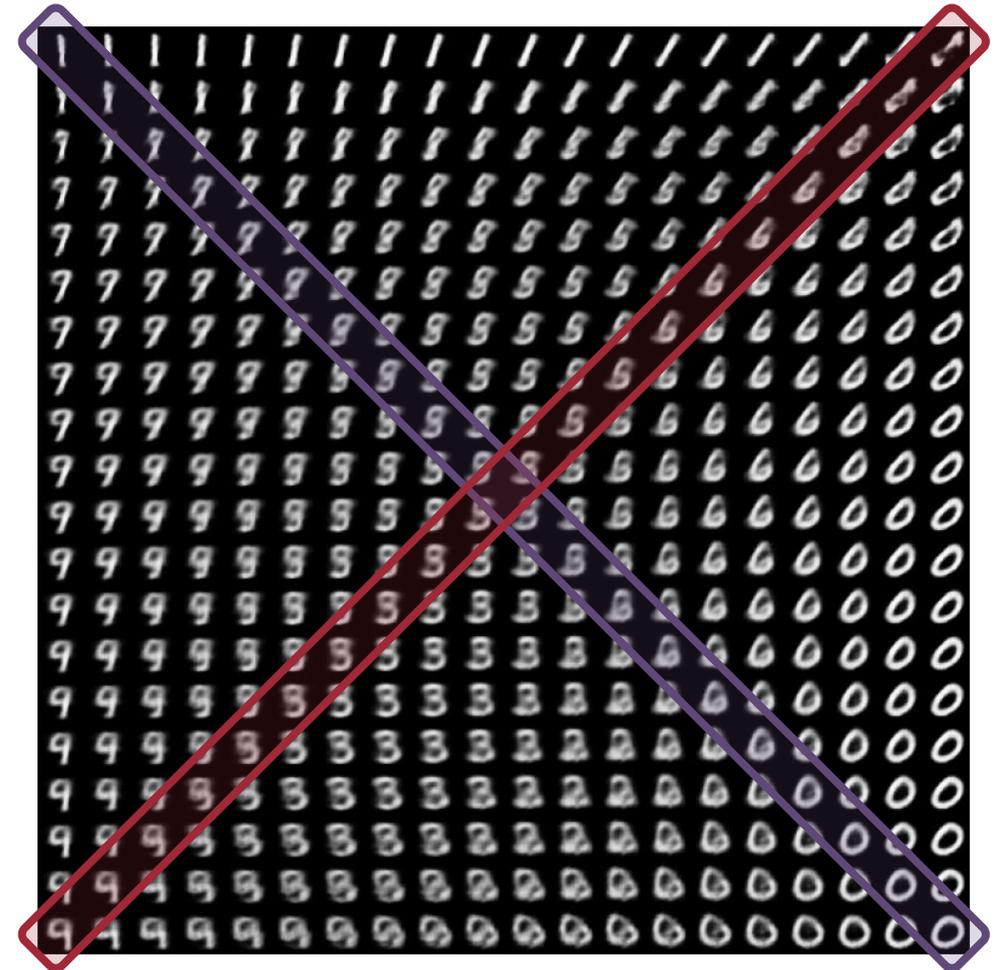
(Source: tensorflow.org)

# Latent Space Interpolation of a VAE

Latent space

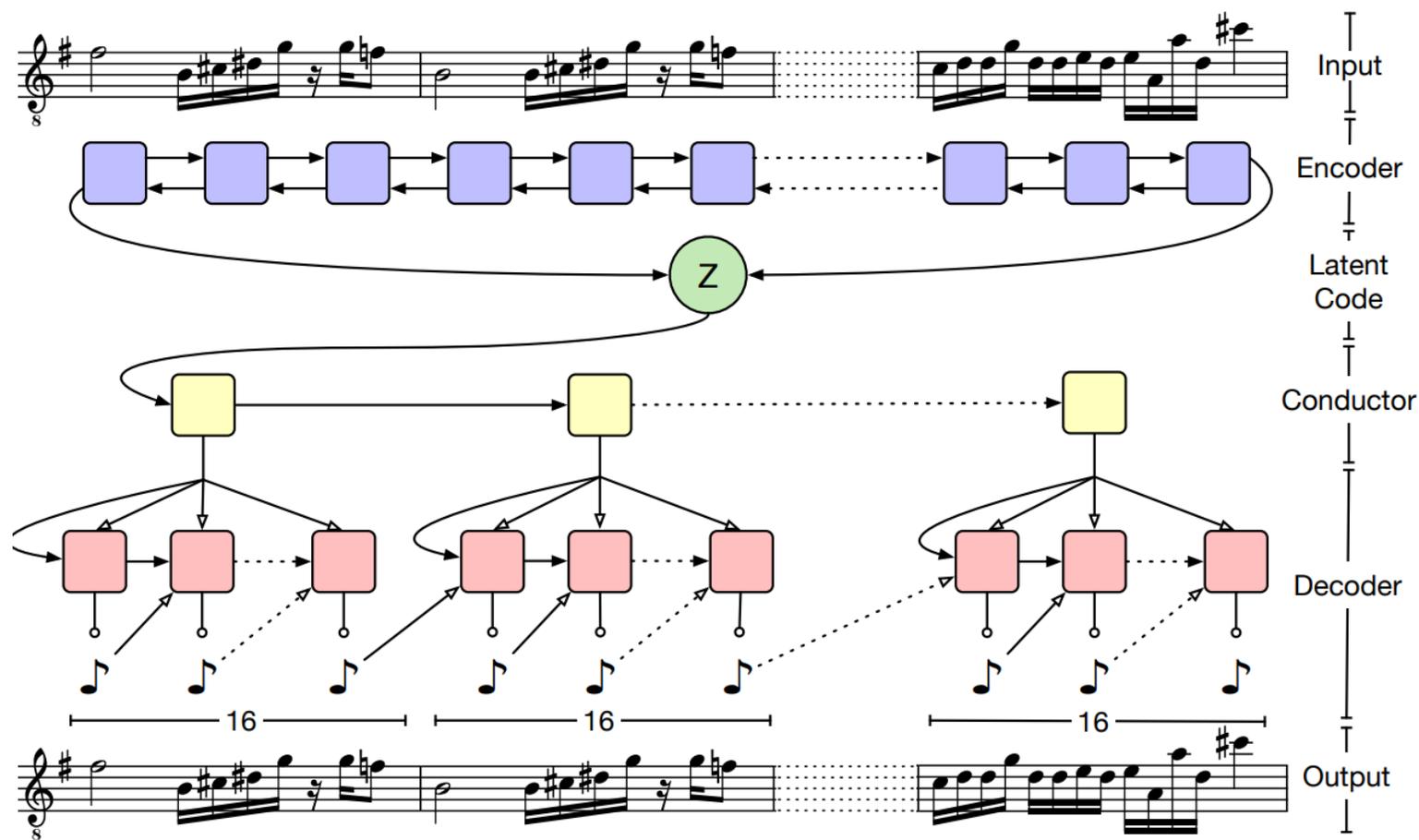


Data space



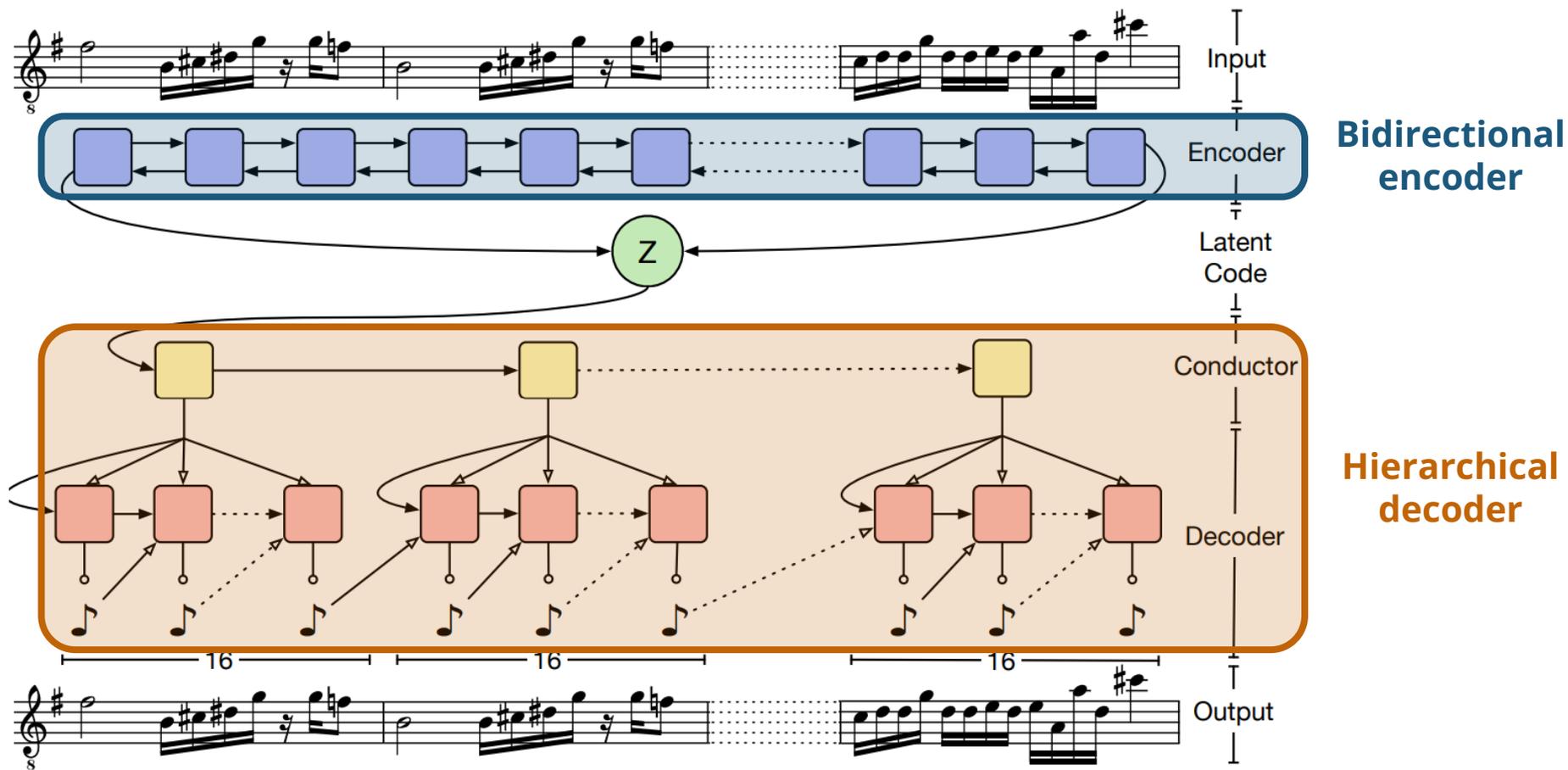
(Source: tensorflow.org)

# MusicVAE: A VAE for Symbolic Music (Roberts et al., 2018)



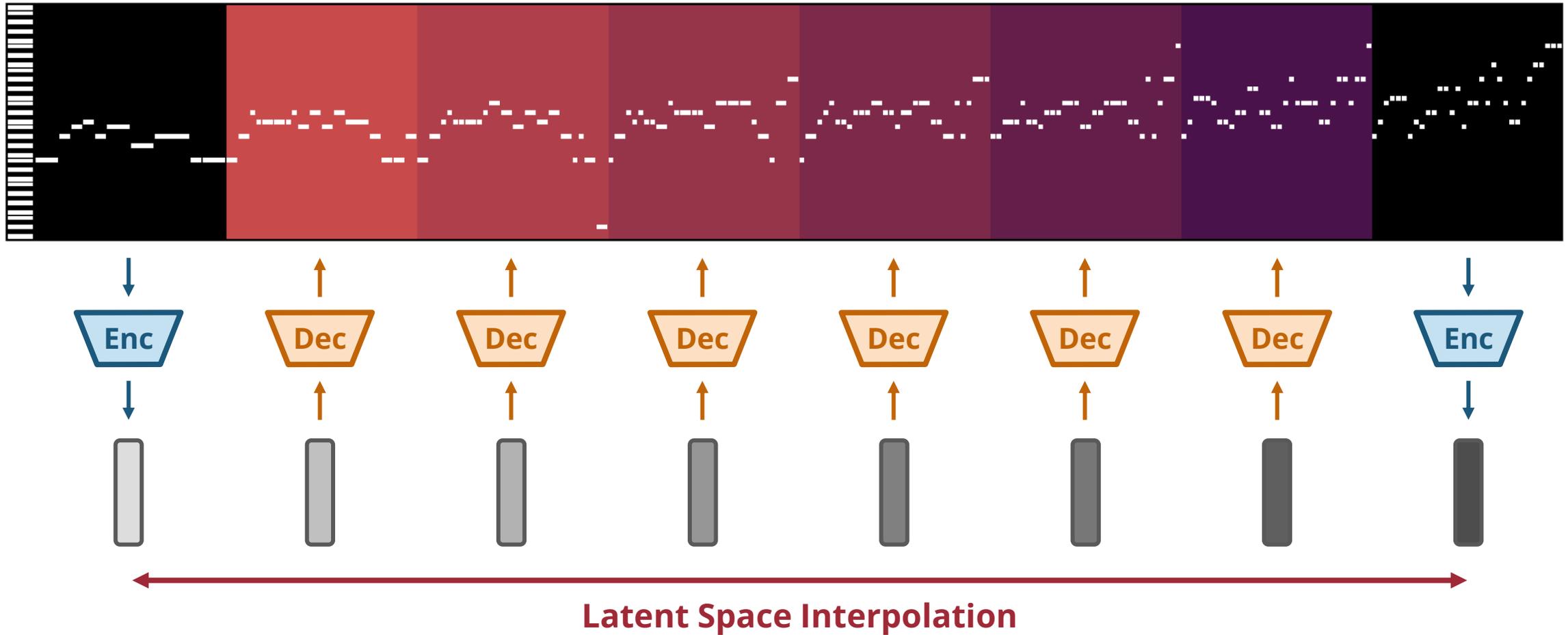
(Source: Roberts et al., 2018)

# MusicVAE: A VAE for Symbolic Music (Roberts et al., 2018)



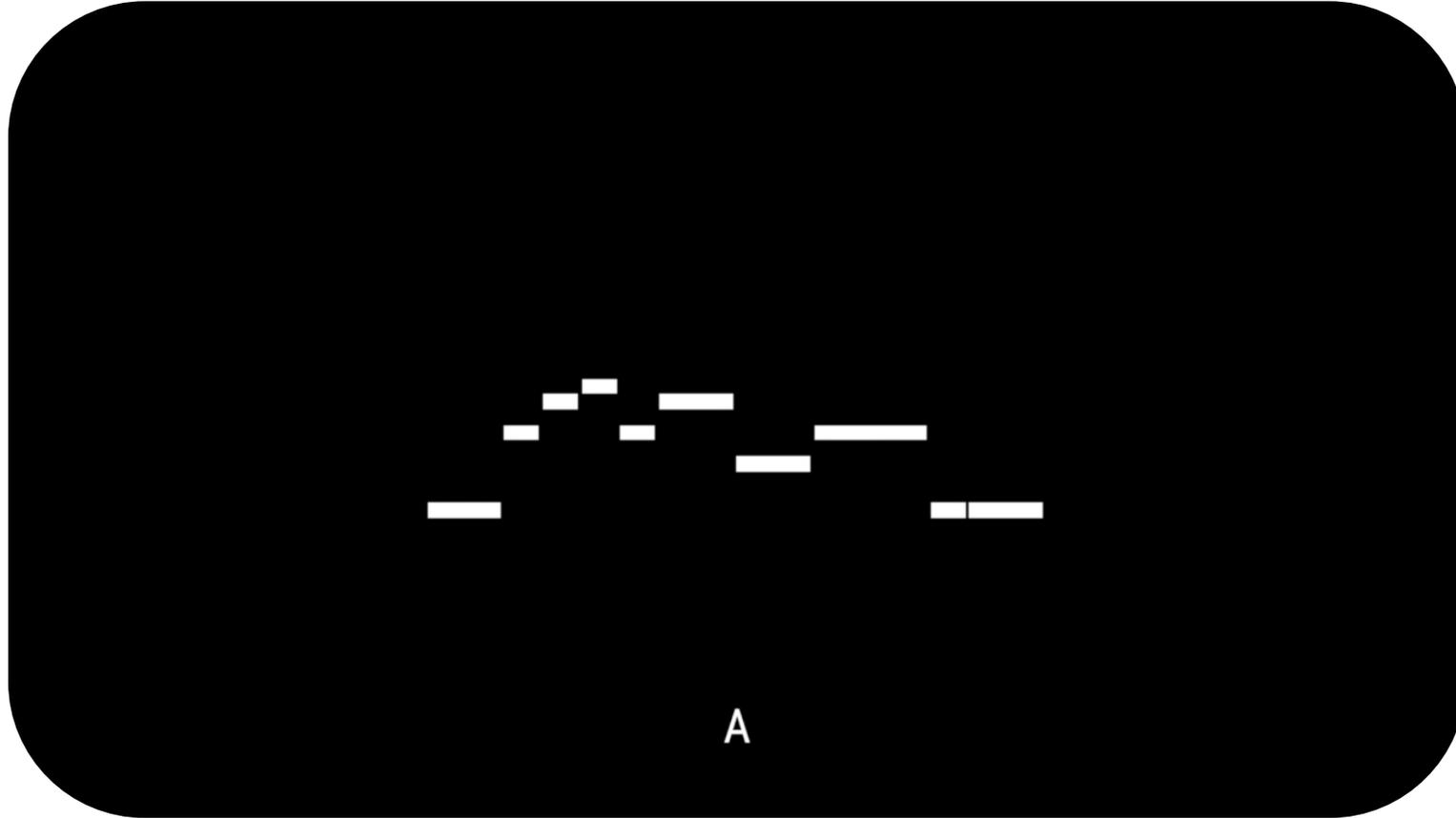
(Source: Roberts et al., 2018)

# Latent Space Interpolation for MusicVAE (Roberts et al., 2018)



(Source: Roberts et al., 2018)

# Latent Space Interpolation for MusicVAE (Roberts et al., 2018)

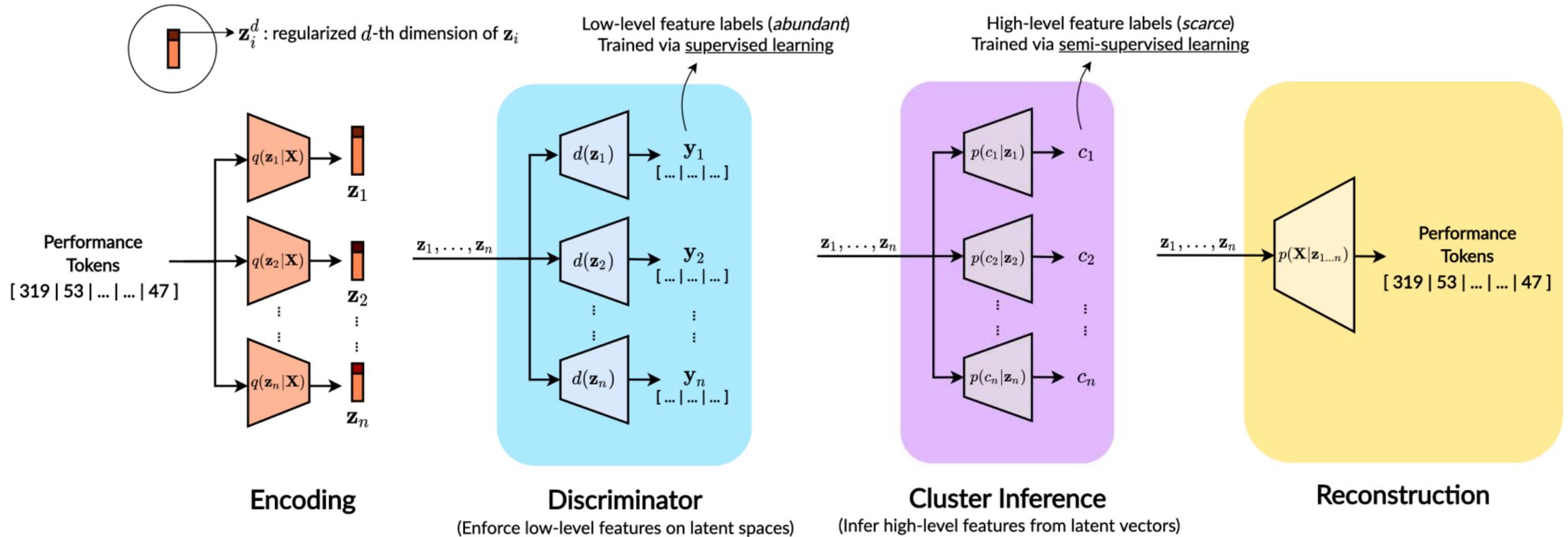


(Source: Roberts et al., 2018)

[goo.gl/magenta/musicvae-examples](https://goo.gl/magenta/musicvae-examples)

# Disentangling the Latent Variables

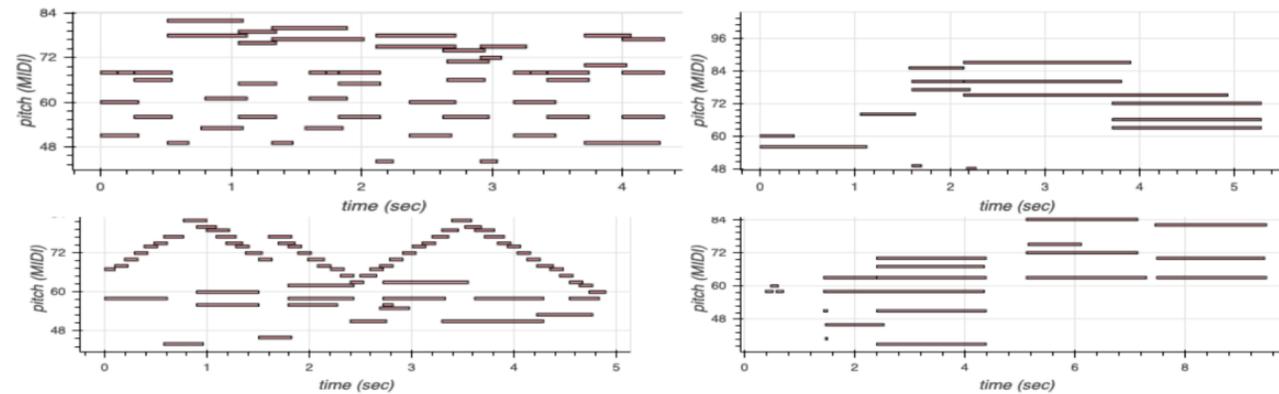
# Music FaderNet (Tan & Herremans, 2020)



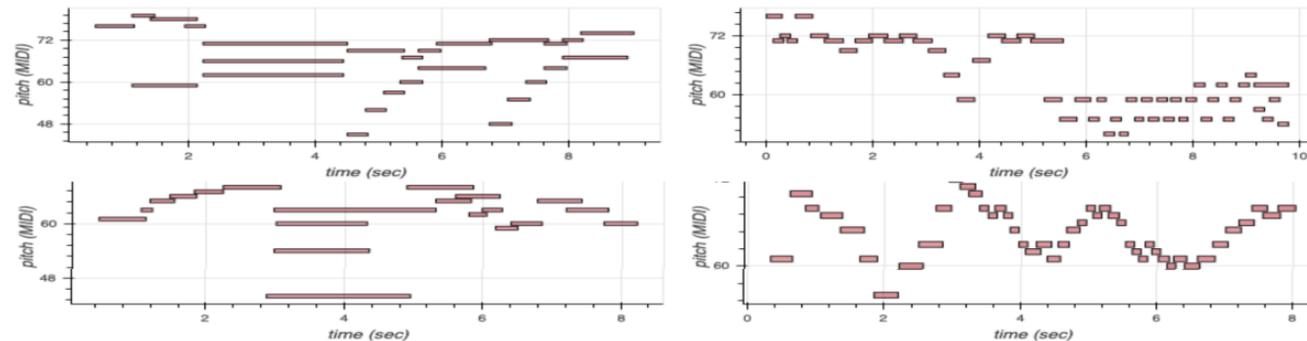
(Source: Tan & Herremans, 2020)

# Music FaderNet (Tan & Herremans, 2020)

## High Arousal → Low Arousal



## Low Arousal → High Arousal

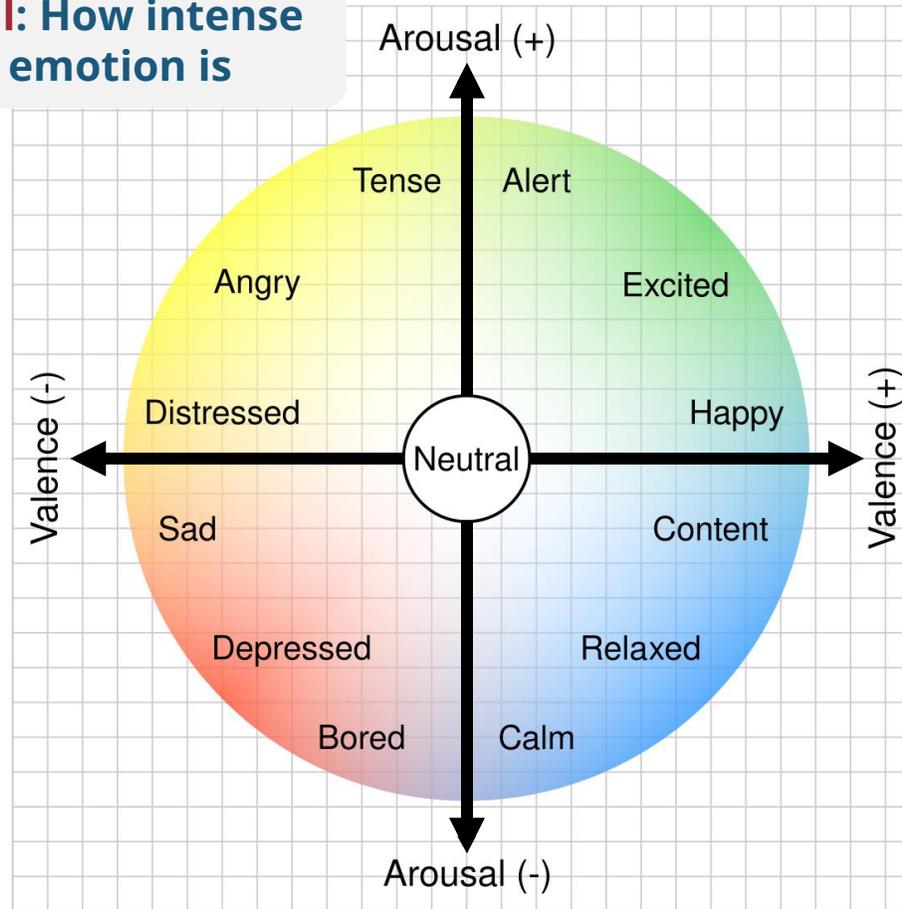


(Source: Tan & Herremans, 2020)

[music-fadernets.github.io](https://music-fadernets.github.io)

# Valence-Arousal Model for Emotion

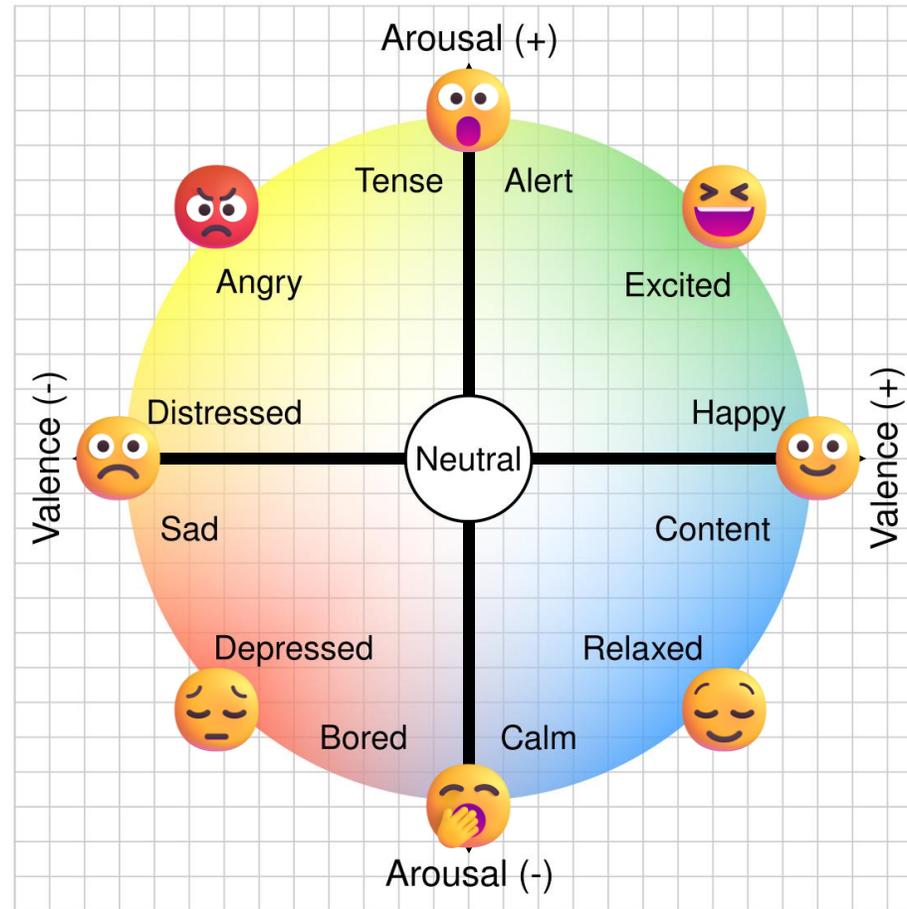
**Arousal:** How intense the emotion is



**Valence:** How pleasant the emotion is

(Source: mrAnmol)

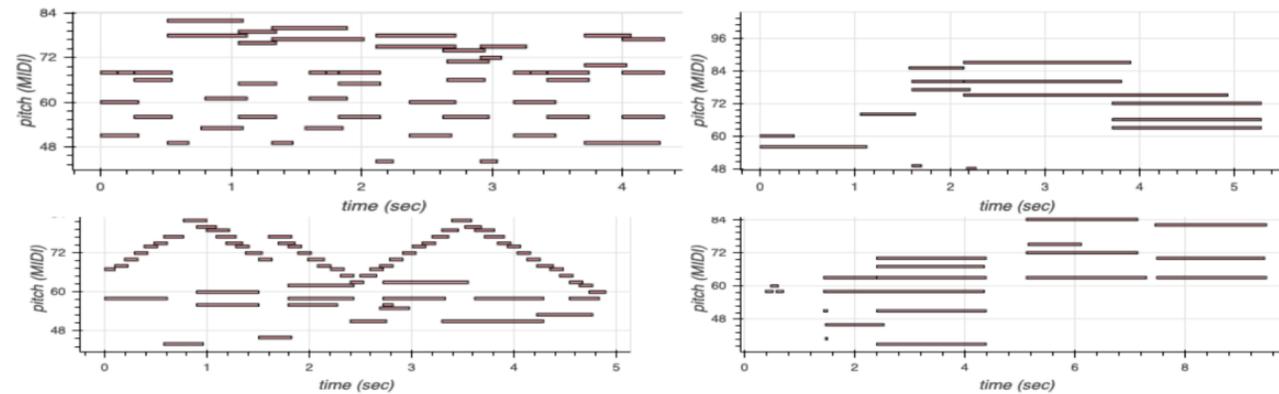
# Valence-Arousal Model for Emotion



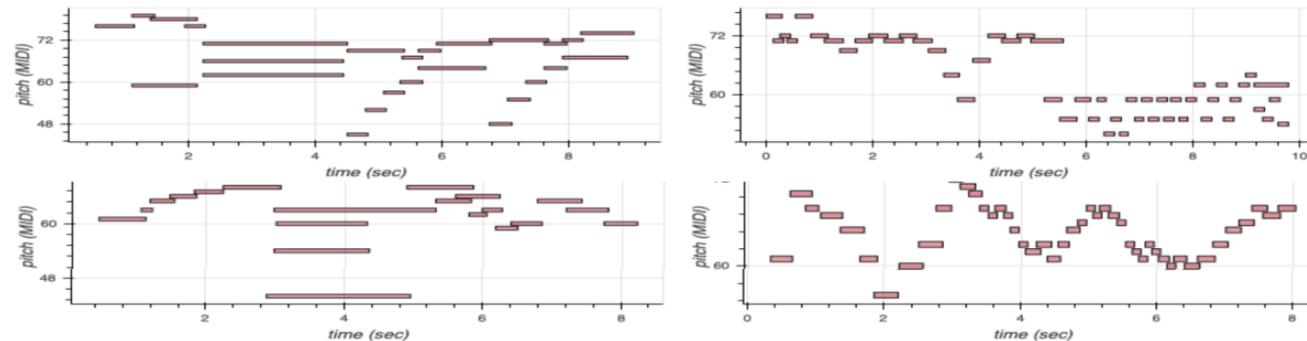
(Source: mrAnmol)

# Music FaderNet (Tan & Herremans, 2020)

## High Arousal → Low Arousal



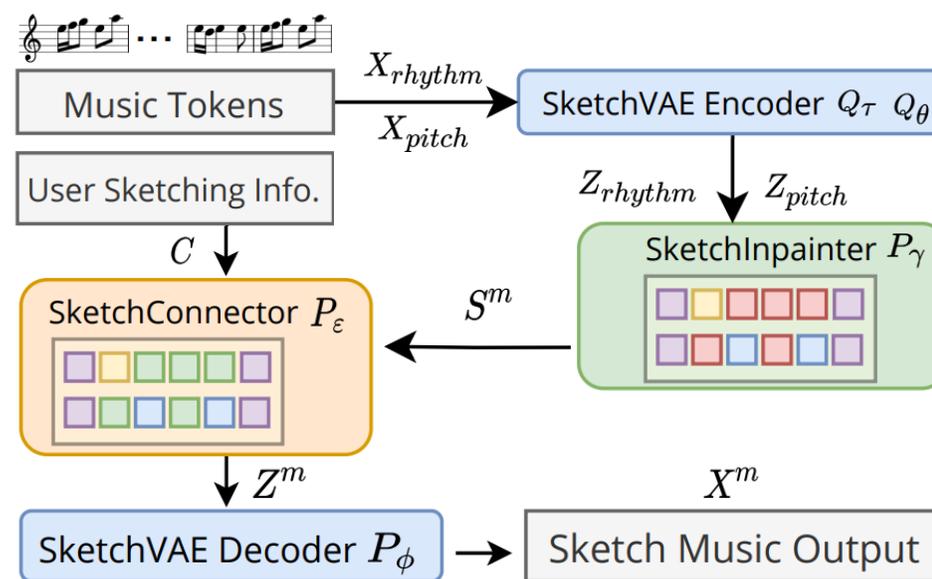
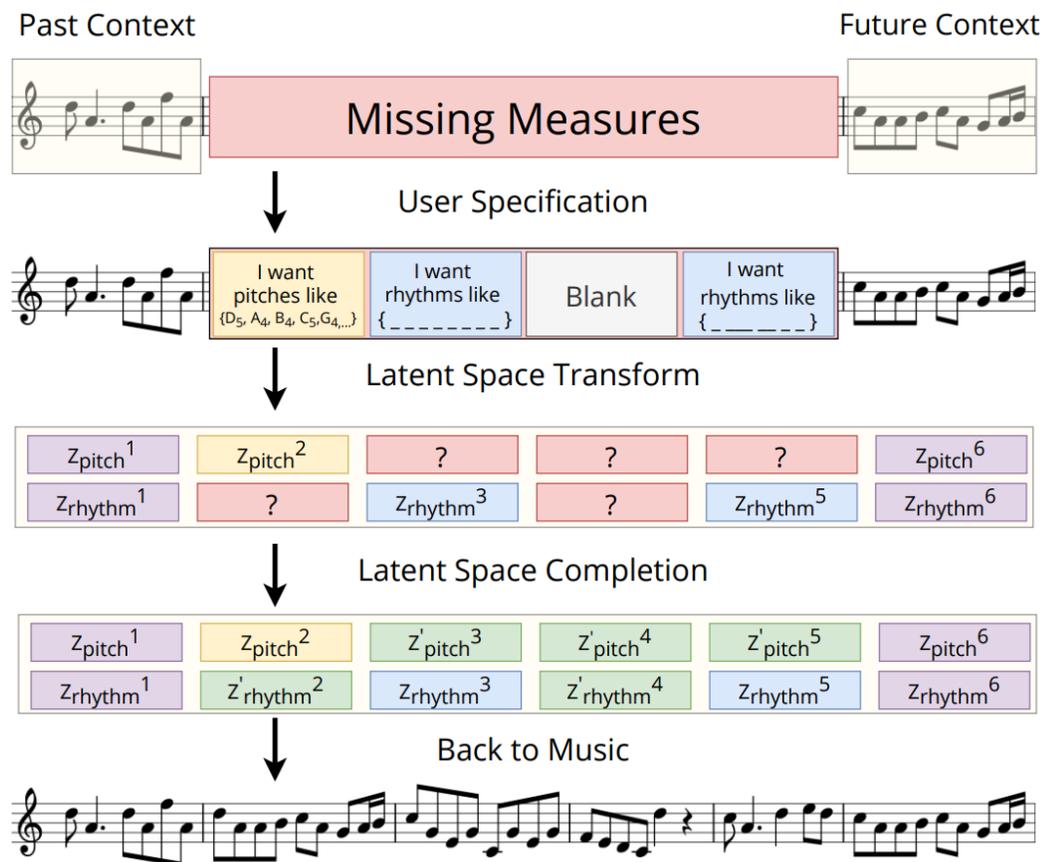
## Low Arousal → High Arousal



(Source: Tan & Herremans, 2020)

[music-fadernets.github.io](https://music-fadernets.github.io)

# Music SketchNet (Chen et al., 2020)



(Source: Chen et al., 2020)

# Music SketchNet (Chen et al., 2020)

The diagram illustrates the Music SketchNet architecture across three stages: Past Context, Generation, and Future Context. It features four staves:

- Original:** The target musical piece.
- Control Pitch:** A sequence of chords and triplets that guide the pitch of the generated music. Chords are labeled as  $\{Ab5, Db6, Eb6, Gb6\}$ ,  $\{C6, Eb6, Db6, F6, Db6\}$ ,  $\{F6, Gb6, Ab6, Ab6, F6\}$ , and  $\{Db6, F6, Ab6, Bb6, Db6\}$ .
- Control Rhythm:** A sequence of rhythmic patterns, represented by pink bars, that guide the rhythm of the generated music.
- Control Both:** A sequence of chords and triplets that guide both pitch and rhythm. A grey bar labeled "No Sketch" indicates a period where no sketch is provided.

Timeline labels: Past Context, Generation, Future Context.

(Source: Chen et al., 2020)

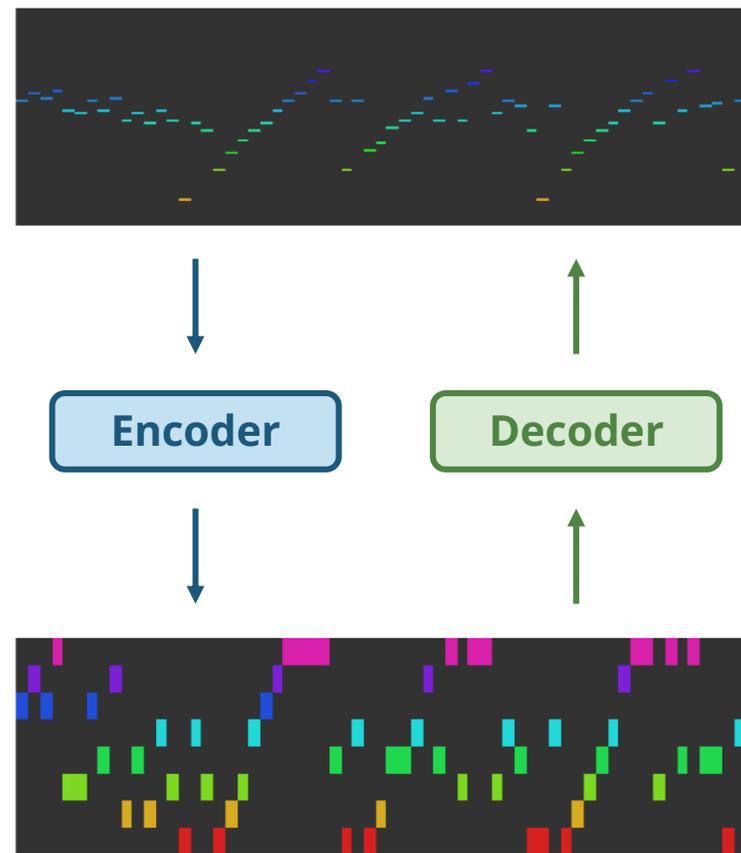
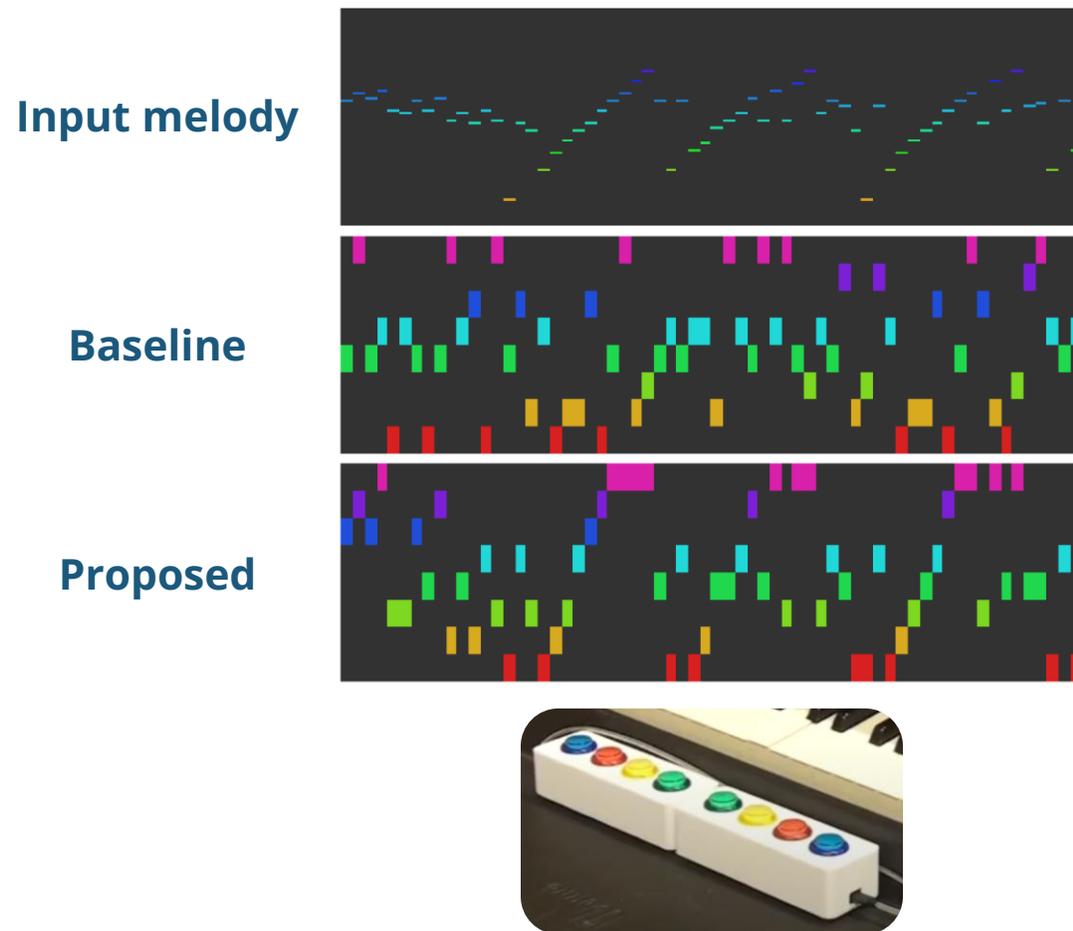
# Piano Genie

# Piano Genie (Donahue et al., 2019)



[youtu.be/YRb0XAnUpIk](https://youtu.be/YRb0XAnUpIk) & [magenta.tensorflow.org/pianogenie](https://magenta.tensorflow.org/pianogenie)

# Piano Genie (Donahue et al., 2019)



(Source: Donahue et al., 2019)

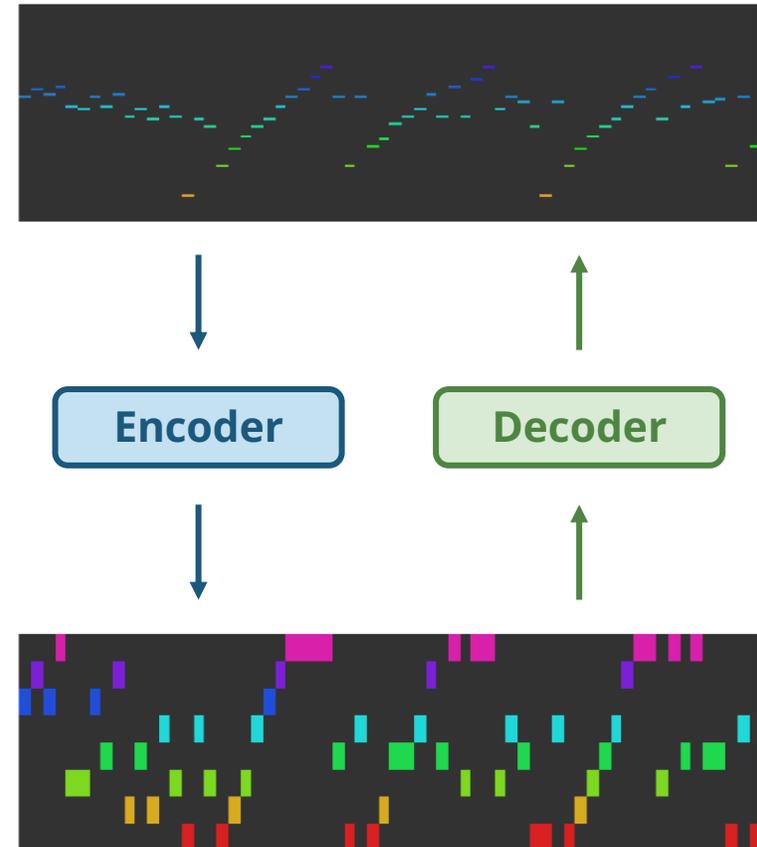
# Piano Genie (Donahue et al., 2019)

$$L = L_{\text{recons}} + L_{\text{margin}} + L_{\text{contour}}$$

$$L_{\text{recons}} = -\sum \log P_{\text{dec}}(\mathbf{x}|\text{enc}(\mathbf{x}))$$

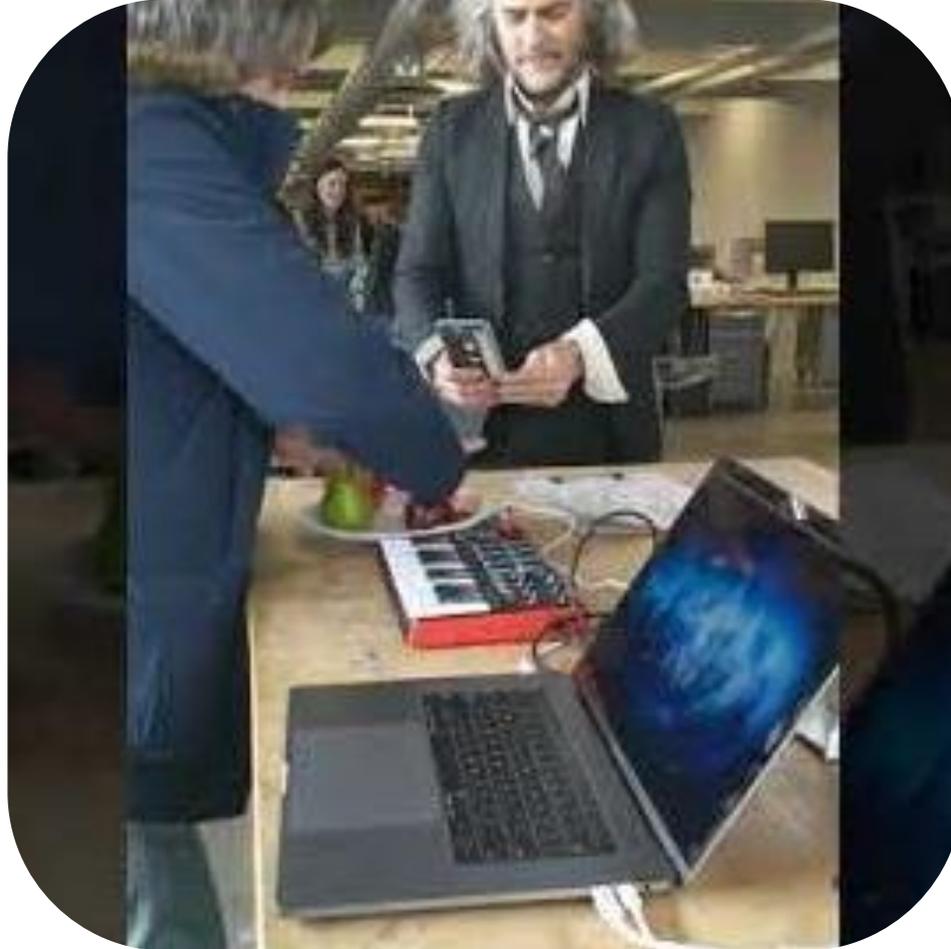
$$L_{\text{margin}} = \sum \max(|\text{enc}_s(\mathbf{x})| - 1, 0)^2$$

$$L_{\text{contour}} = \sum \max(1 - \Delta\mathbf{x}\Delta\text{enc}_s(\mathbf{x}), 0)^2$$



(Source: Donahue et al., 2019)

# Fruit Genie (2019)



[youtu.be/HoVs4kC68no](https://youtu.be/HoVs4kC68no)

# Fruit Genie Live (2019)



[youtu.be/L4wvXrPmIkU](https://youtu.be/L4wvXrPmIkU)

# Variational Autoencoders for Audio

# Four Paradigms of Music Generation



## Symbolic music generation

### Text-based

```
Program_change_0,  
Note_on_60, Time_shift_2, Note_off_60,  
Note_on_60, Time_shift_2, Note_off_60,  
Note_on_76, Time_shift_2, Note_off_67,  
Note_on_67, Time_shift_2, Note_off_67,  
...
```

### MIDI

### Image-based



### Piano roll



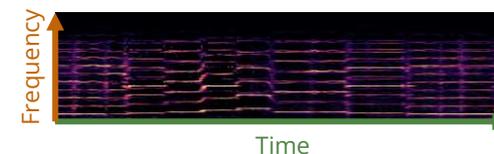
## Audio-domain music generation

### Time series-based



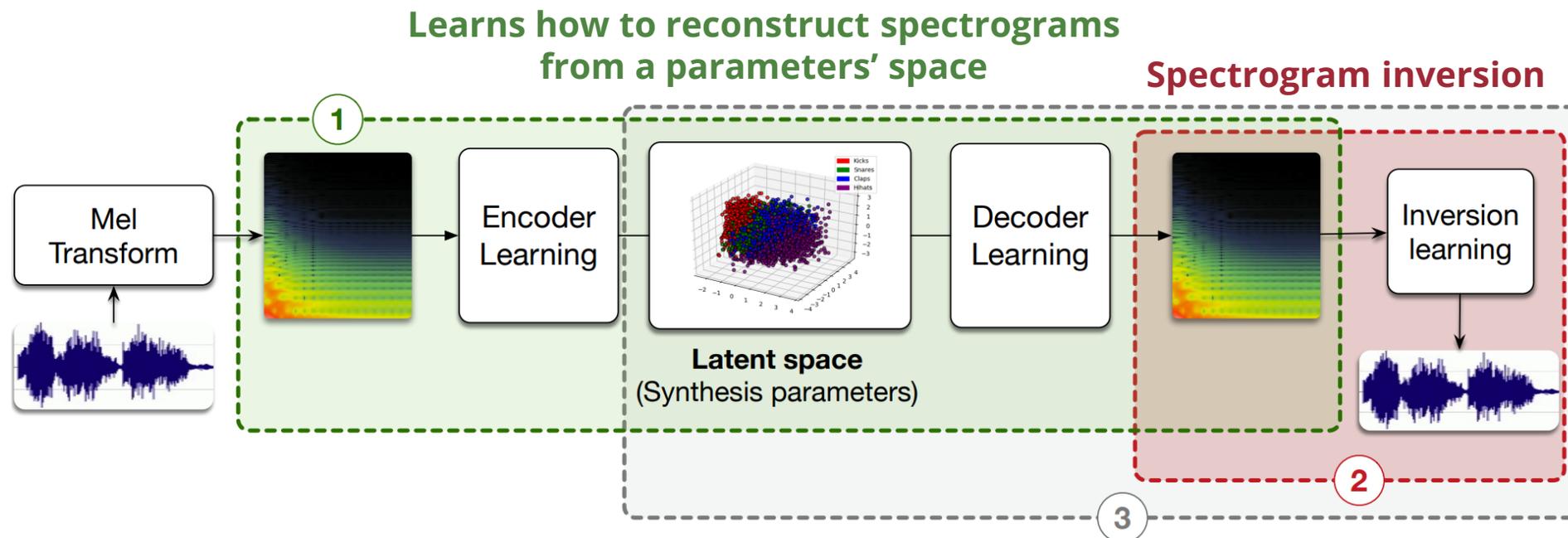
### Waveform

### Image-based



### Spectrogram

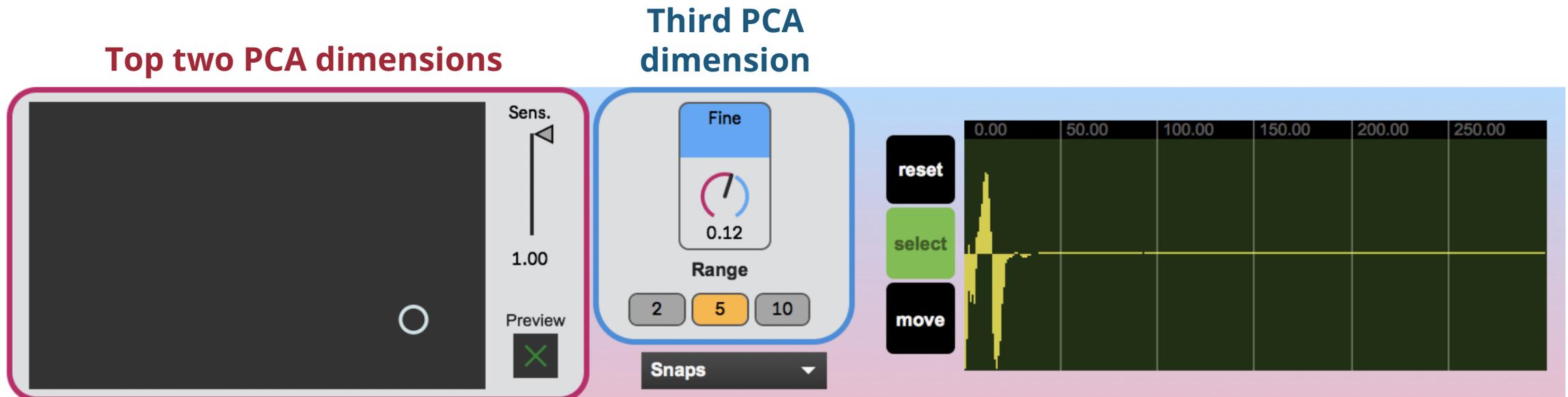
# Neural Drum Machine (Aouameur et al., 2019)



**Allows a user to interact with the model and to generate sound from the parameters' space**

(Source: Aouameur et al., 2019)

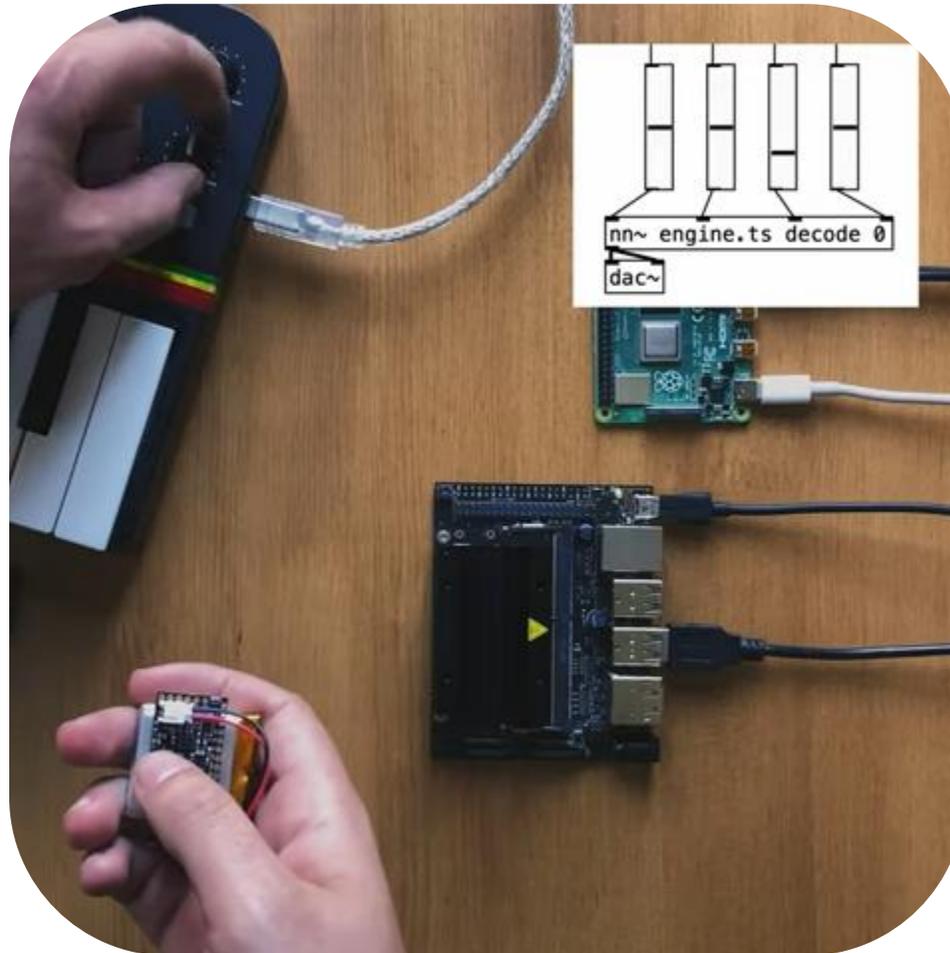
# Neural Drum Machine (Aouameur et al., 2019)



(Source: Aouameur et al., 2019)

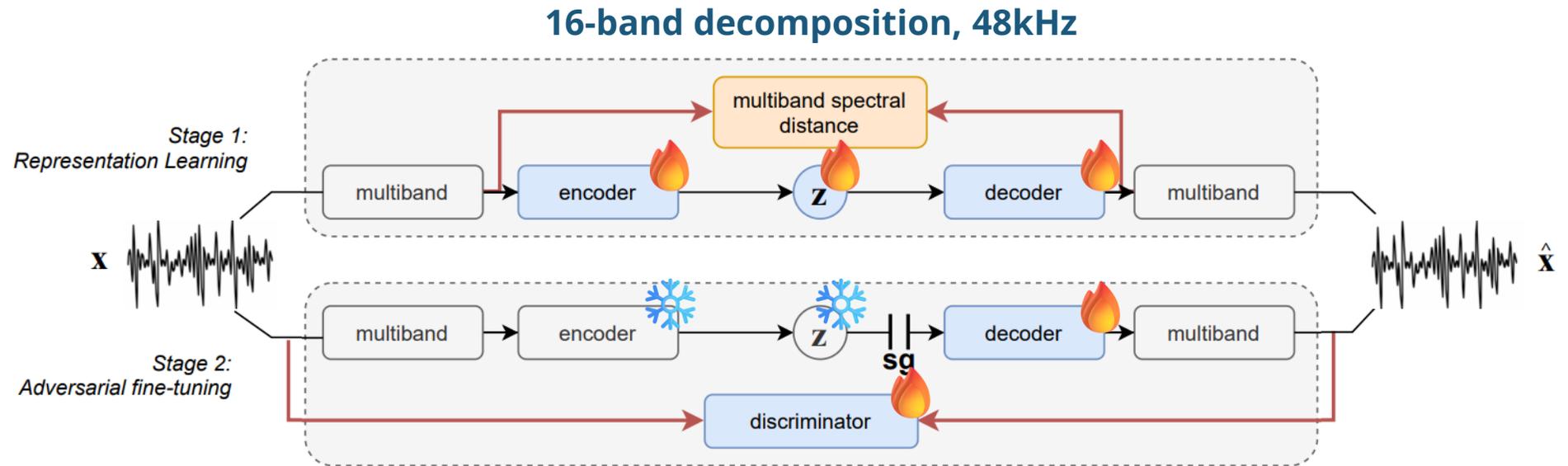
[drive.google.com/file/d/1DDo0\\_KnwkWirCM4t0PT8cp6uotsfuufj/view](https://drive.google.com/file/d/1DDo0_KnwkWirCM4t0PT8cp6uotsfuufj/view)

# RAVE: Real-time Audio Synthesis (Caillon & Esling, 2022)



[youtu.be/jAIRf4nGgYI](https://youtu.be/jAIRf4nGgYI)

# RAVE: Real-time Audio Synthesis (Caillon & Esling, 2022)



(Source: Caillon & Esling, 2021)

[github.com/acids-ircam/RAVE](https://github.com/acids-ircam/RAVE)

# RAVE: Real-time Audio Synthesis (Caillon & Esling, 2022)

Model	CPU synthesis	GPU synthesis
NSynth	18 Hz	57 Hz
SING	304 kHz	9.8 MHz
RAVE (Ours) w/o multiband	38 kHz	3.7 MHz
<b>RAVE (Ours)</b>	<b>985 kHz</b>	<b>11.7 MHz</b>

**Realtime capable on CPUs & GPUs**

(Source: Caillon & Esling, 2021)

[anonymous84654.github.io/RAVE\\_anonymous](https://anonymous84654.github.io/RAVE_anonymous)

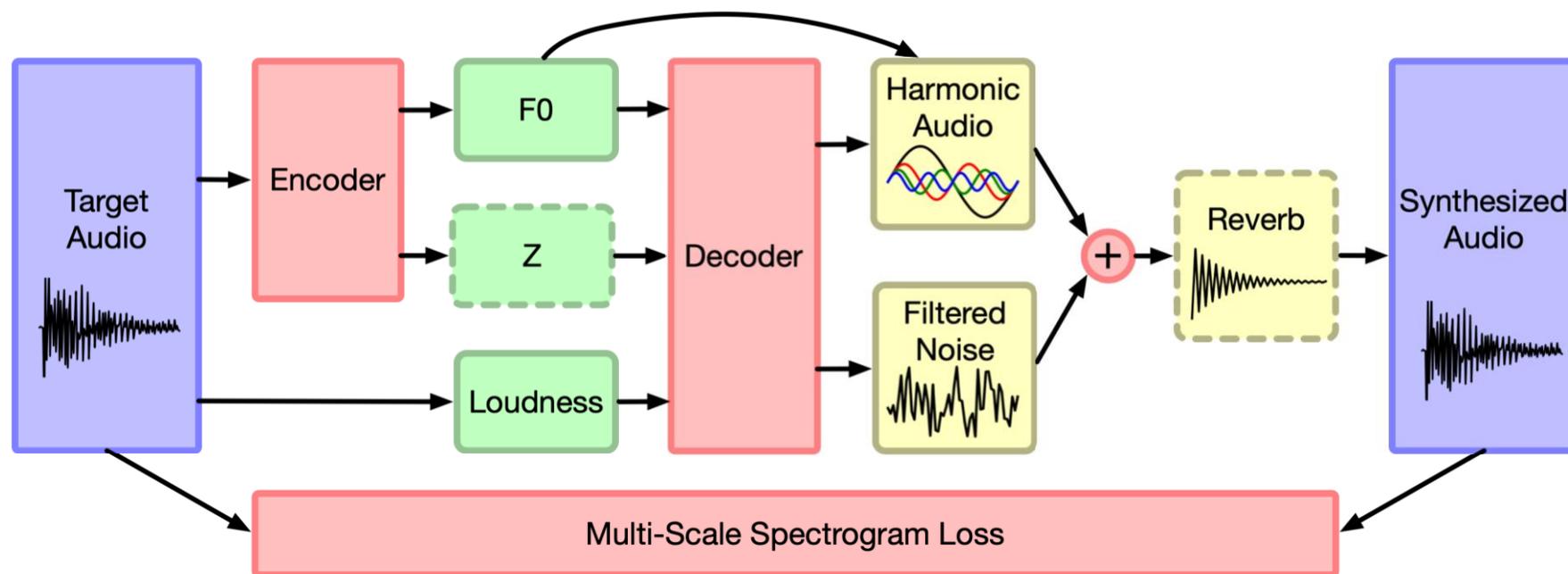
# RAVE: Real-time Audio Synthesis (Caillon & Esling, 2022)



[youtu.be/dMZs04TzxUI](https://youtu.be/dMZs04TzxUI)

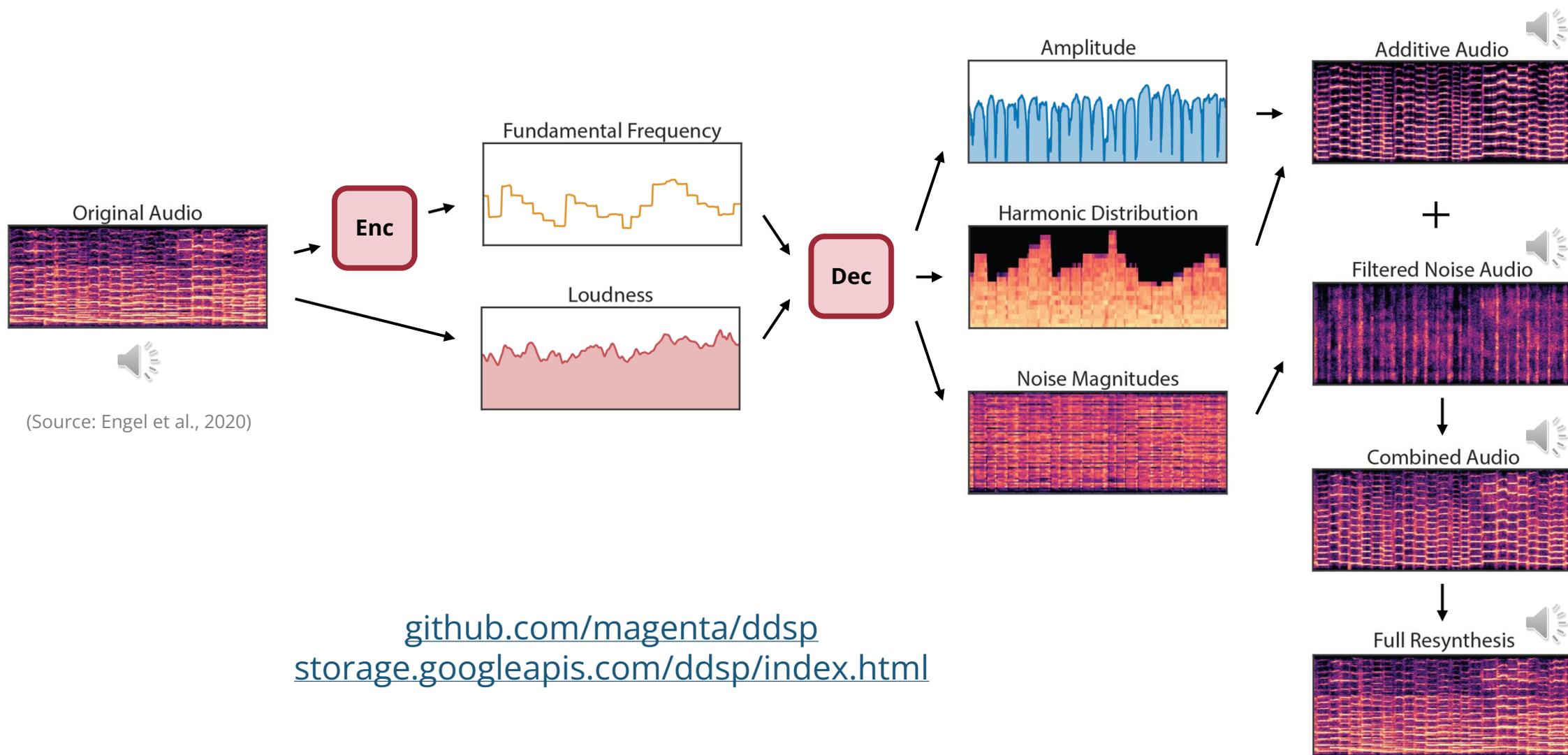
# Differentiable DSP

# Differentiable DSP (DDSP) (Engel et al., 2020)



(Source: Engel et al., 2020)

# Differentiable DSP (DDSP) (Engel et al., 2020)



# Entering Demons & Gods by Yaboi Hanoi (2022)



[youtu.be/PbrRoR3nEVw](https://youtu.be/PbrRoR3nEVw)

[soundcloud.com/yaboihanoi/enter-demons-and-gods](https://soundcloud.com/yaboihanoi/enter-demons-and-gods)

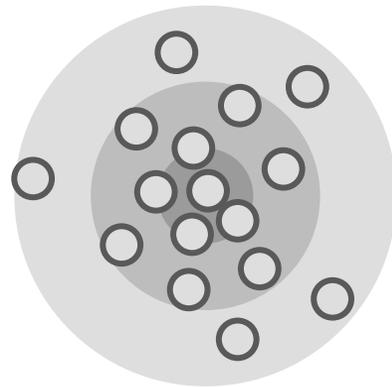


# Recap

# Deep Latent Variable Models

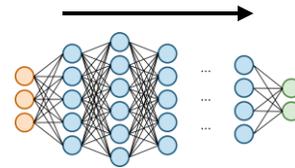
- **Intuition:** Learn to map a known distribution to the data distribution

Known distribution

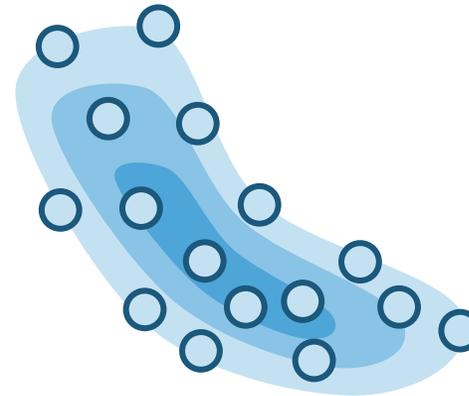


$P(z)$

$P(x | z)$



Data distribution

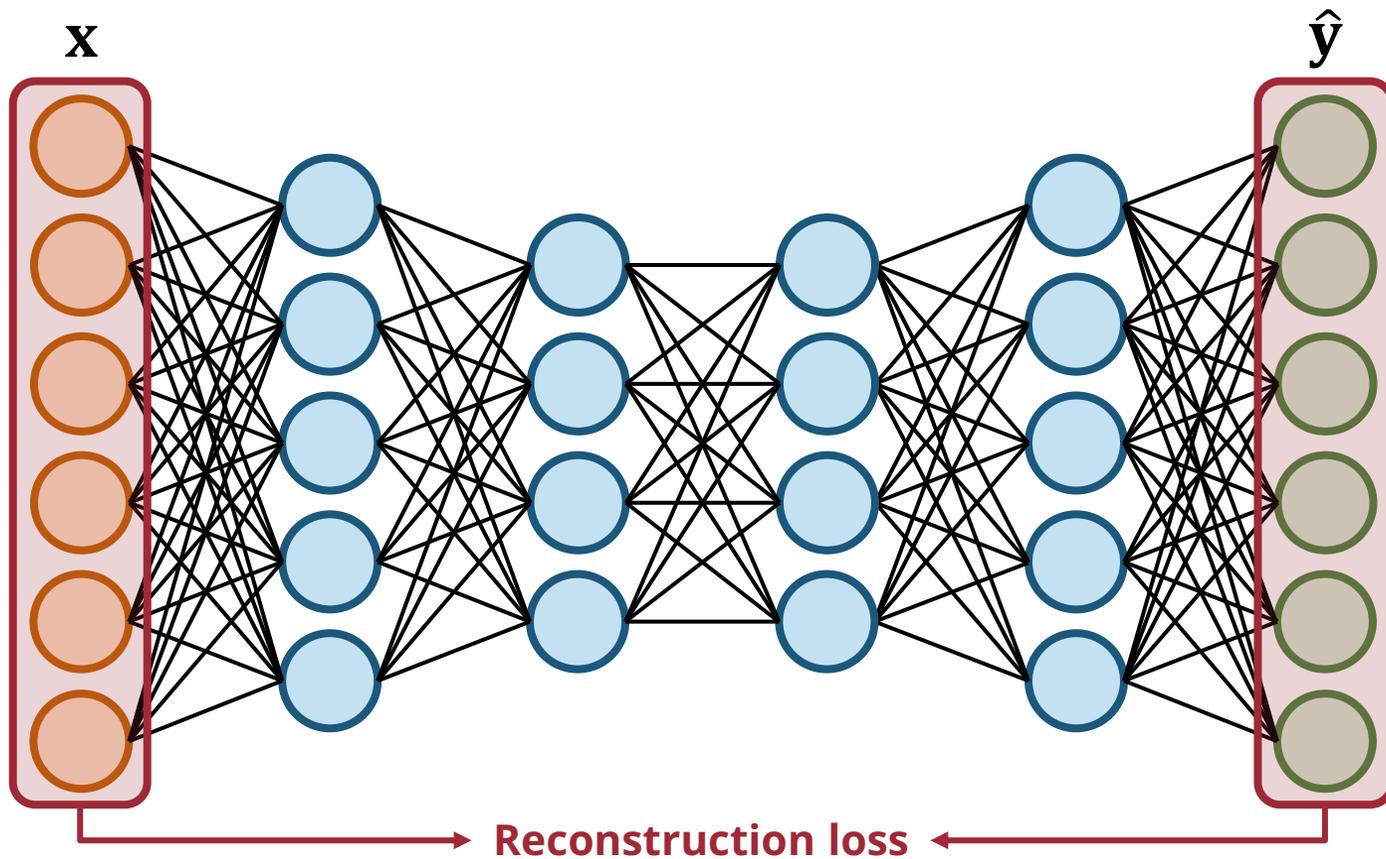


$P(x)$

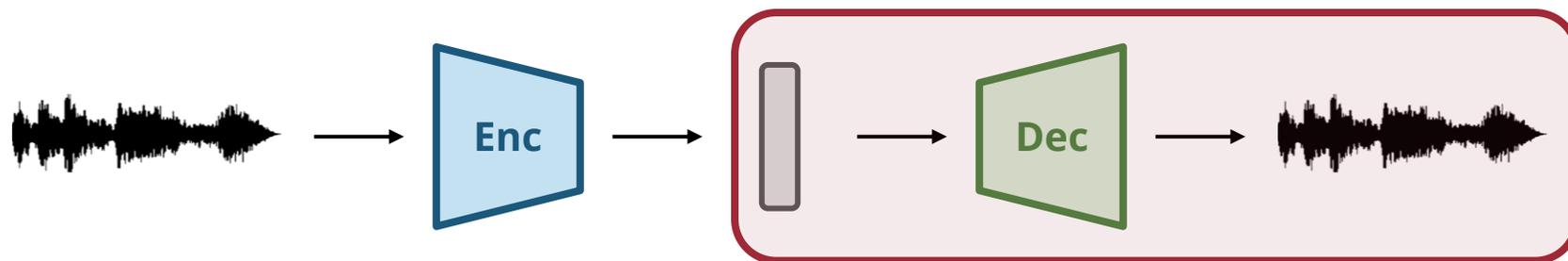
$$P(x) = P(z) P(x | z)$$

# Autoencoders

- A neural network where the **input and output are the same**



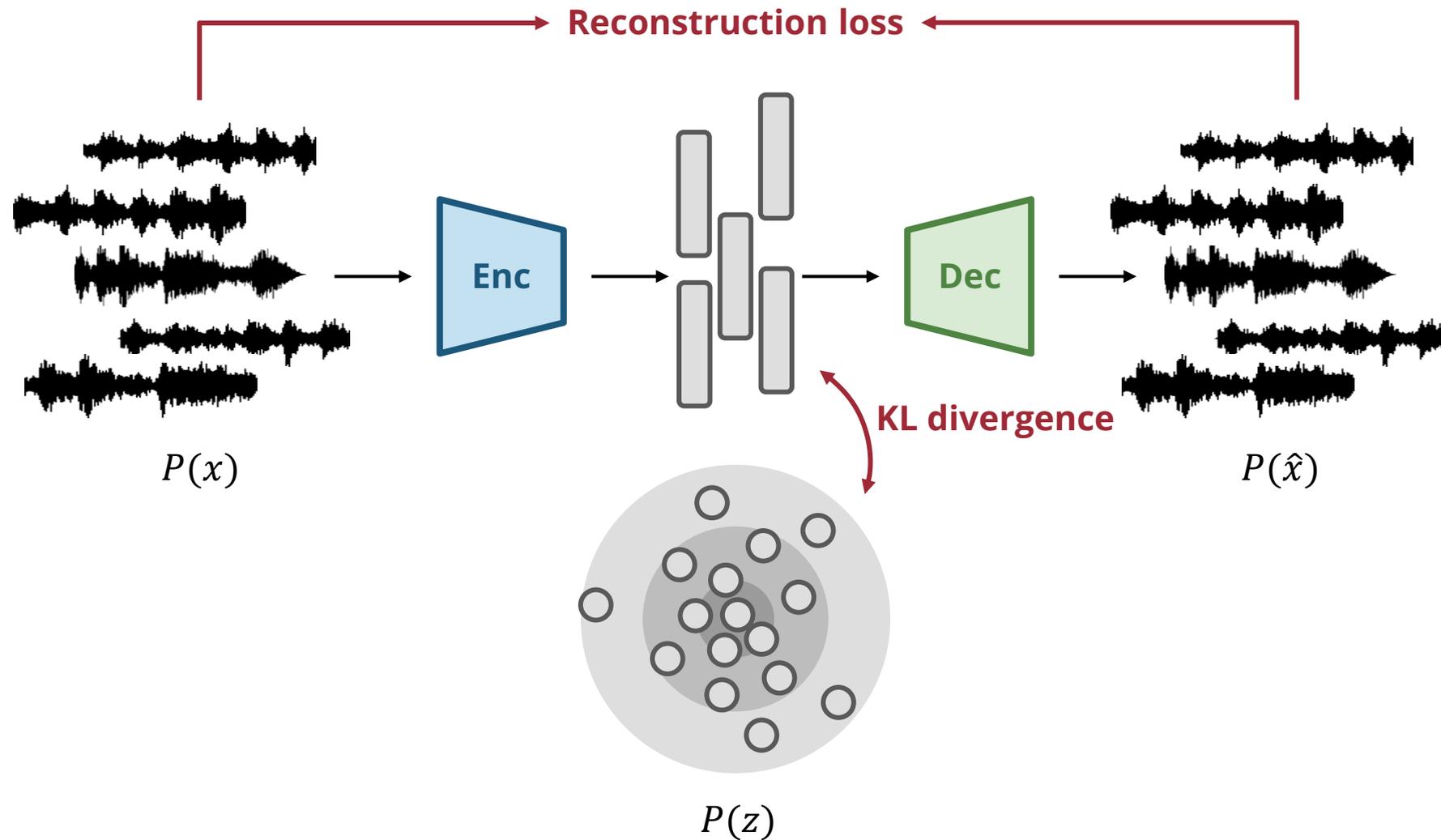
# Autoencoder



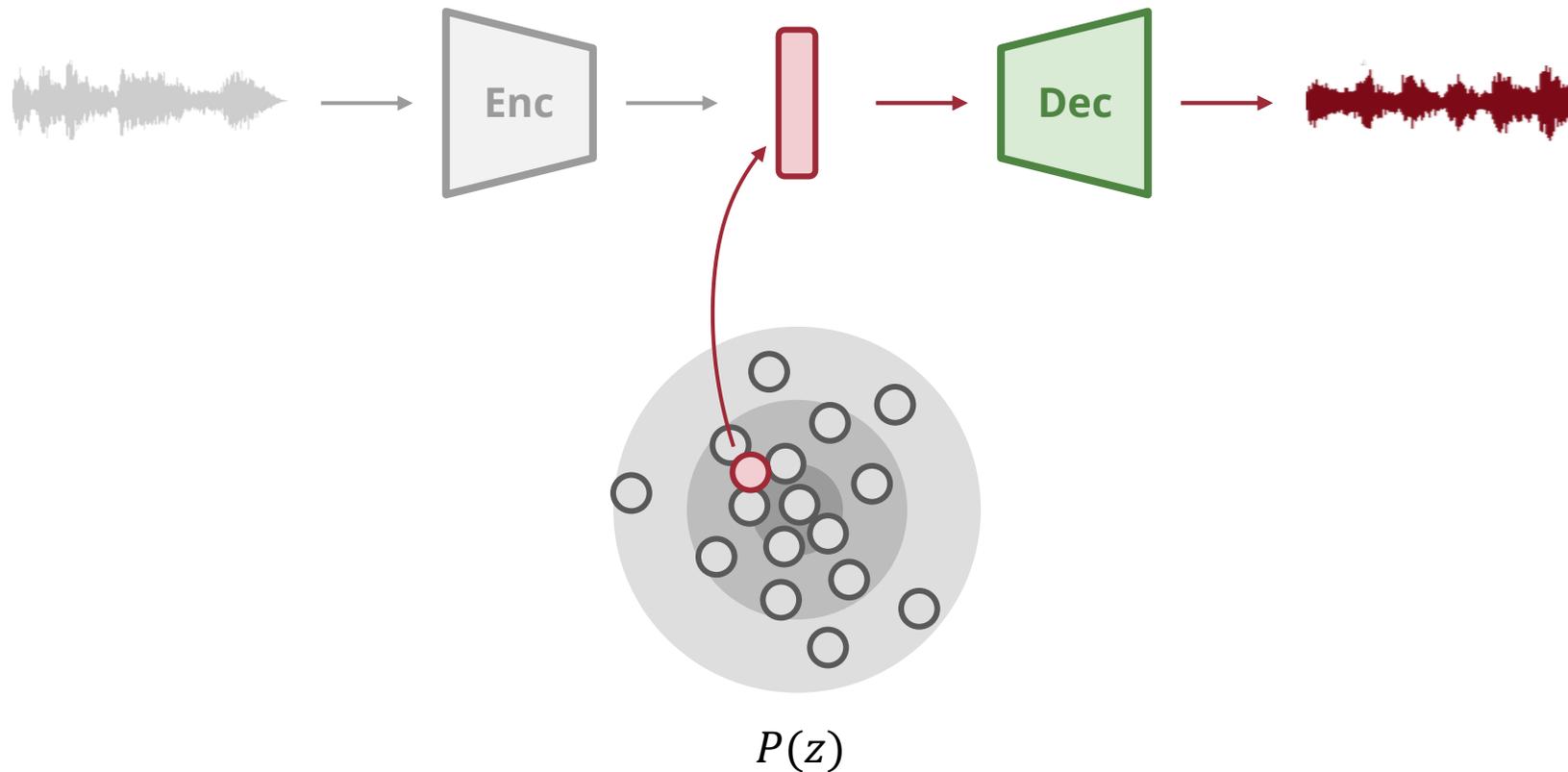
**Isn't this like a generative model?**

**What exactly is a generative model?**

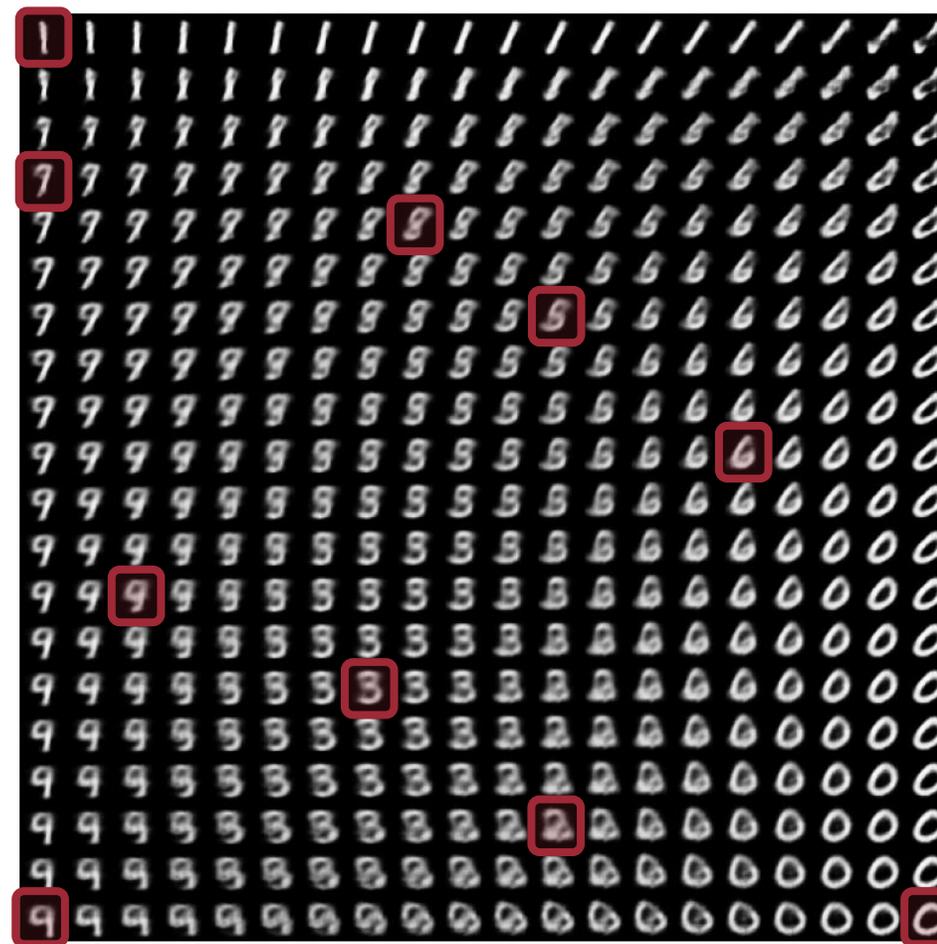
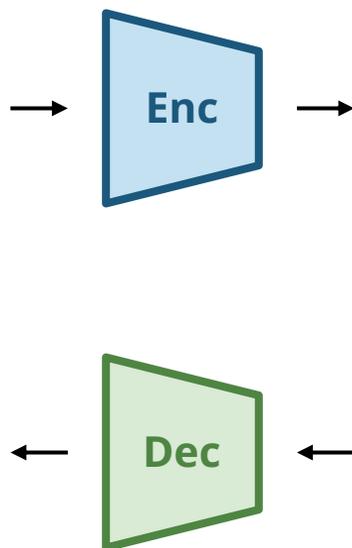
# Variational Autoencoder (VAE): Training



# Variational Autoencoder (VAE): Generation



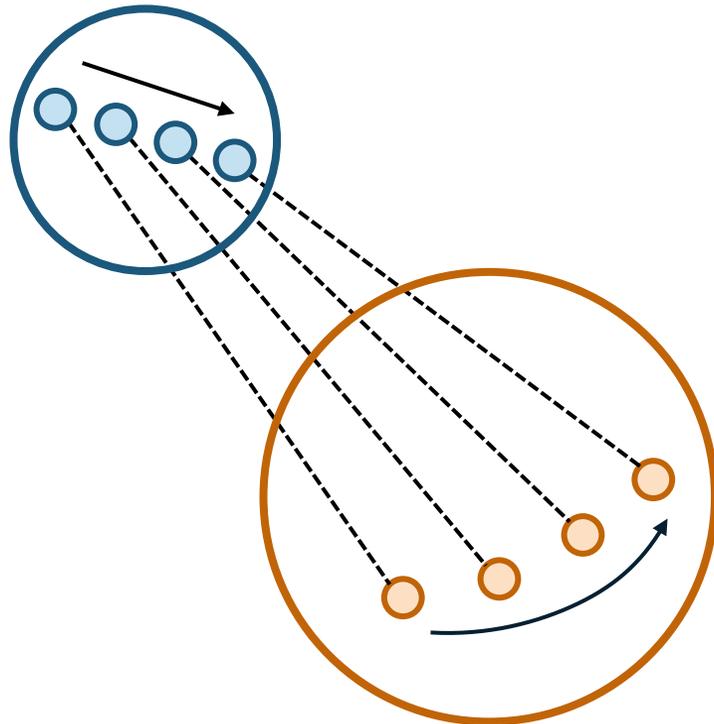
# What does a VAE learn?



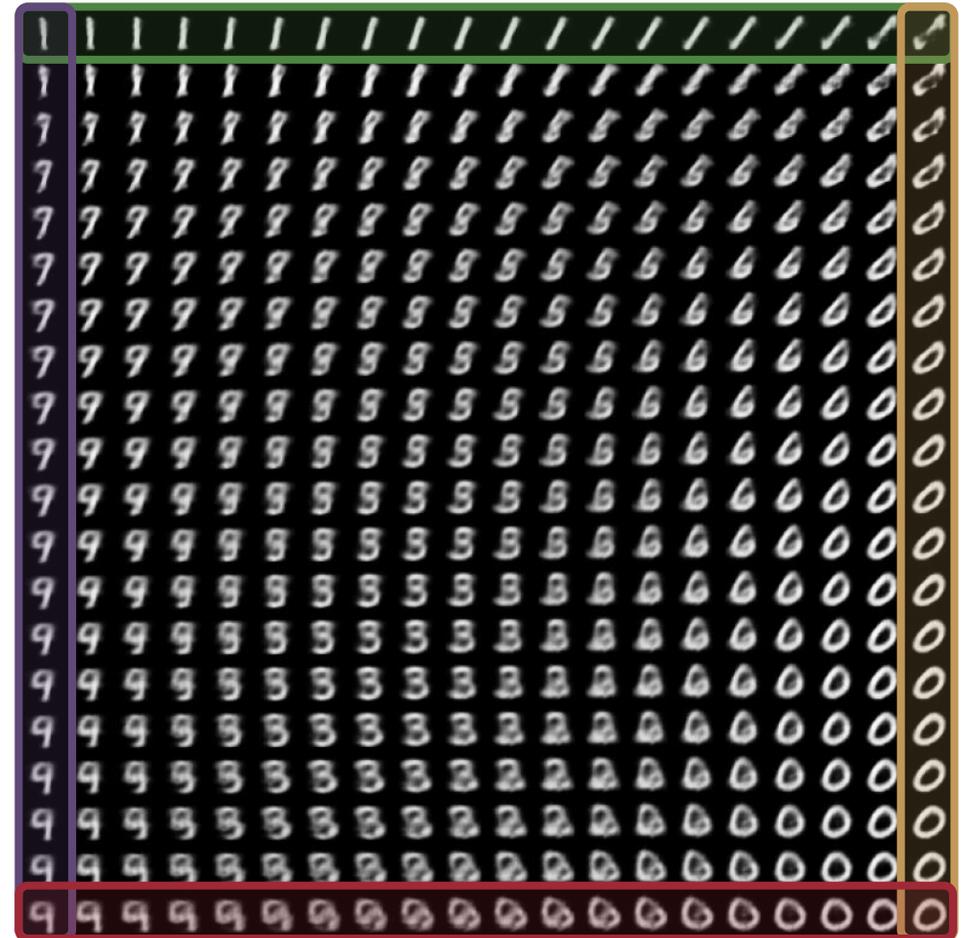
(Source: tensorflow.org)

# Latent Space Interpolation of a VAE

Latent space

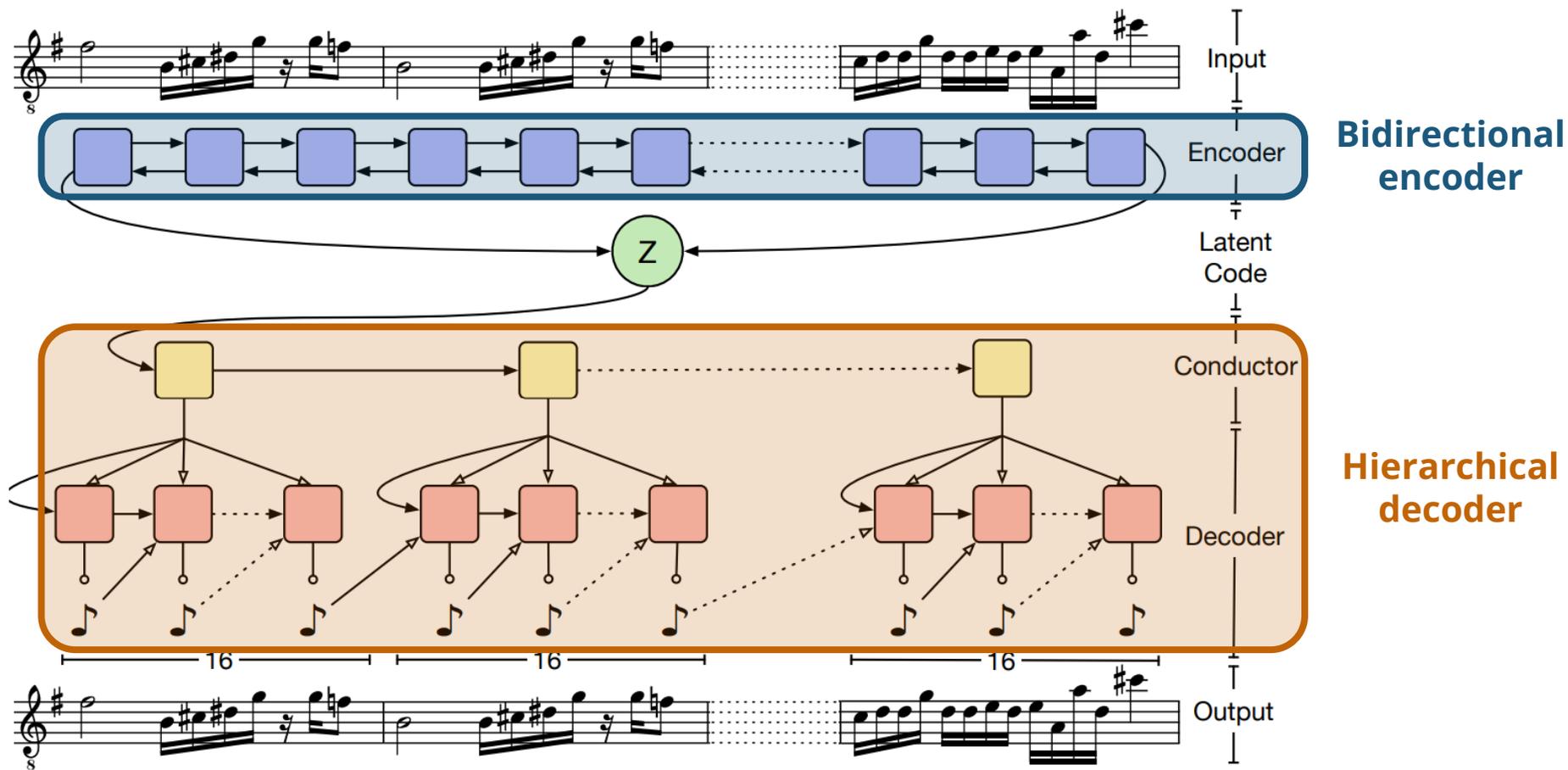


Data space



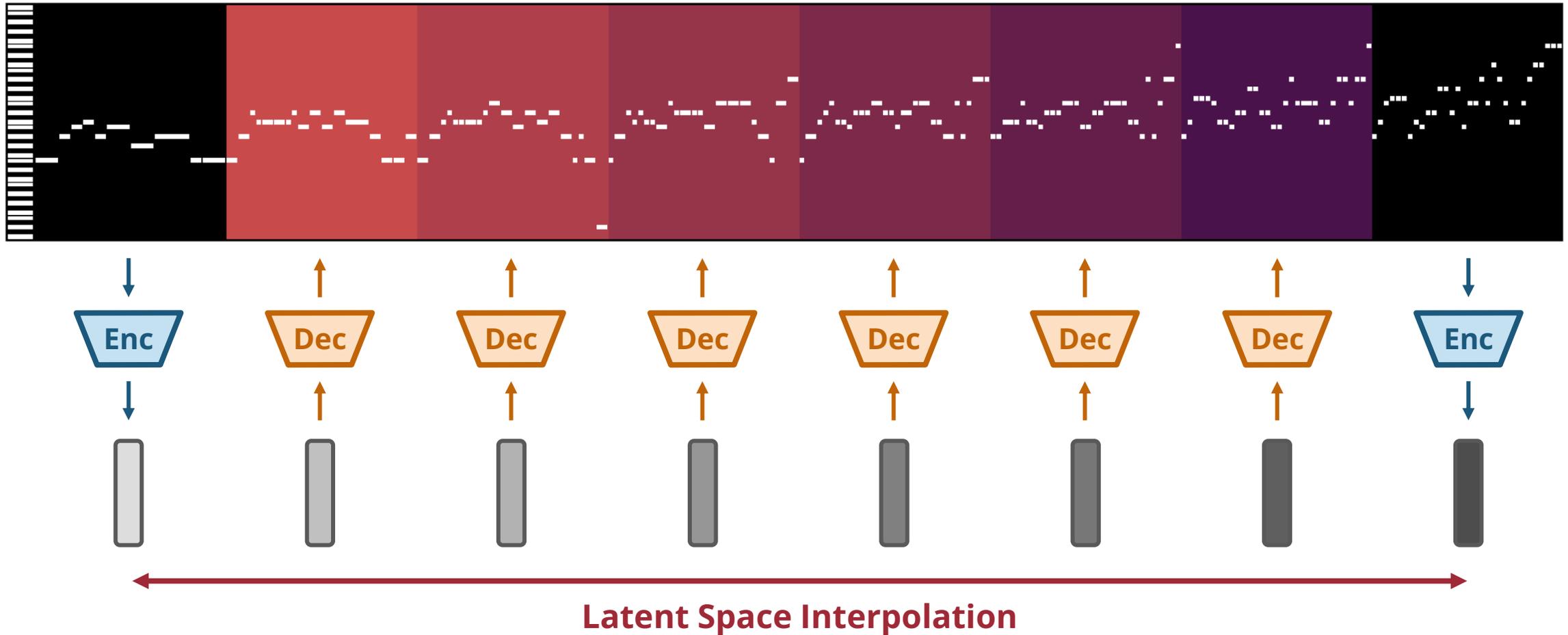
(Source: tensorflow.org)

# MusicVAE: A VAE for Symbolic Music (Roberts et al., 2018)



(Source: Roberts et al., 2018)

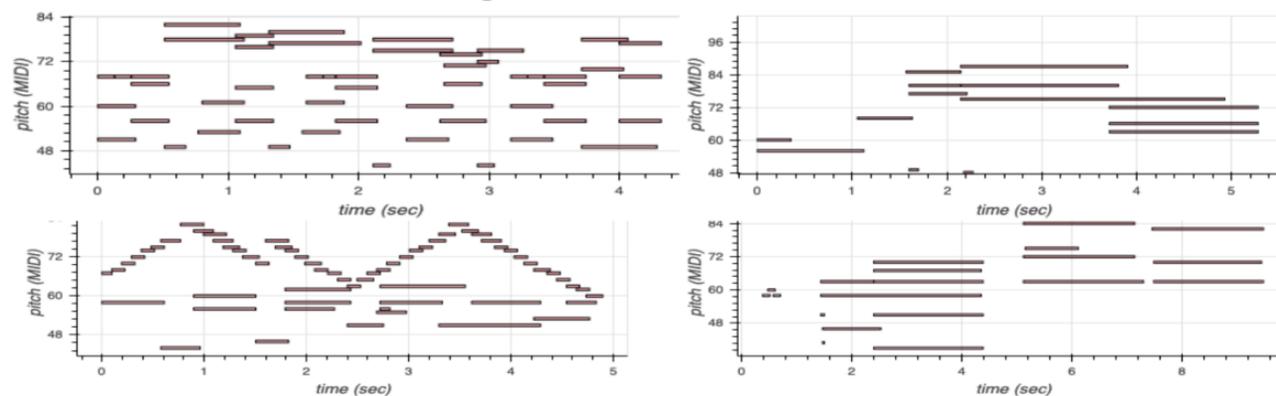
# Latent Space Interpolation for MusicVAE (Roberts et al., 2018)



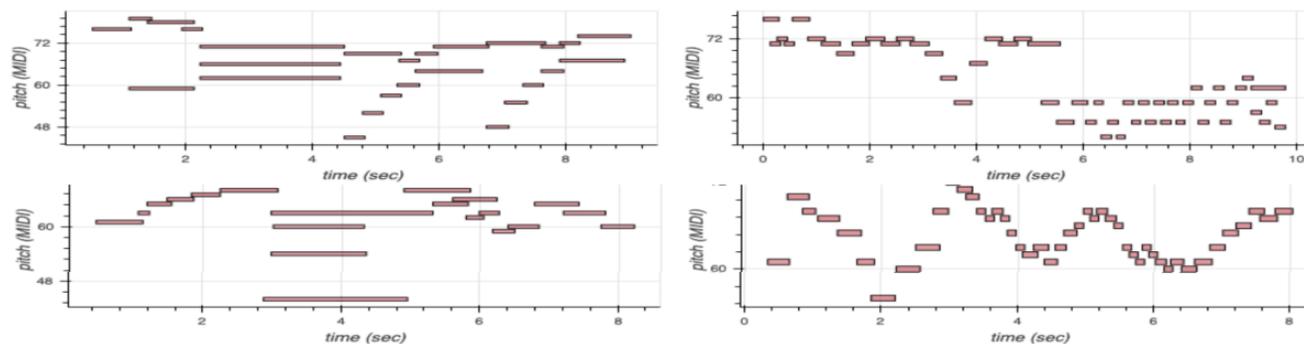
(Source: Roberts et al., 2018)

# Music FaderNet (Tan & Herremans, 2020)

## High Arousal → Low Arousal



## Low Arousal → High Arousal



(Source: Tan & Herremans, 2020)

[music-fadernets.github.io](https://music-fadernets.github.io)

# Music SketchNet (Chen et al., 2020)

The diagram illustrates the Music SketchNet architecture across three stages: Past Context, Generation, and Future Context. It features four tracks:

- Original:** The target musical piece.
- Control Pitch:** A track where pitch is controlled by a sequence of chords:  $\{Ab5, Db6, Eb6, Gb6\}$ ,  $\{C6, Eb6, Db6, F6, Db6\}$ ,  $\{F6, Gb6, Ab6, Ab6, F6\}$ , and  $\{Db6, F6, Ab6, Bb6, Db6\}$ . Triplet markings (3) are present under the first four measures of the Generation section.
- Control Rhythm:** A track where rhythm is controlled by pink rectangular blocks. Triplet markings (3) are present under the first four measures of the Generation section.
- Control Both:** A track where both pitch and rhythm are controlled. It includes a grey box labeled "No Sketch" covering the latter part of the Generation section.

Timeline labels: Past Context, Generation, Future Context.

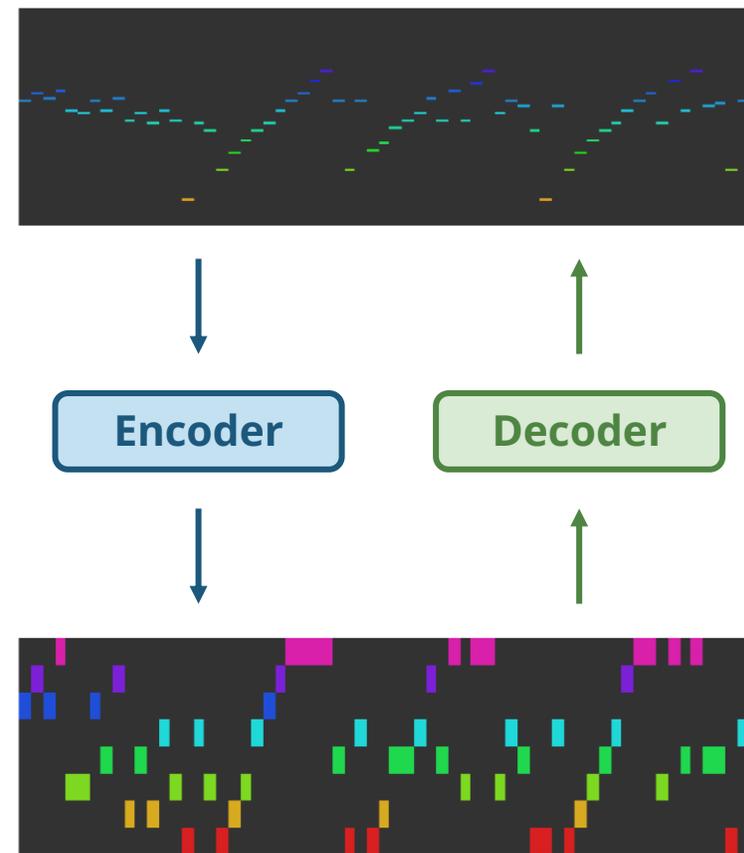
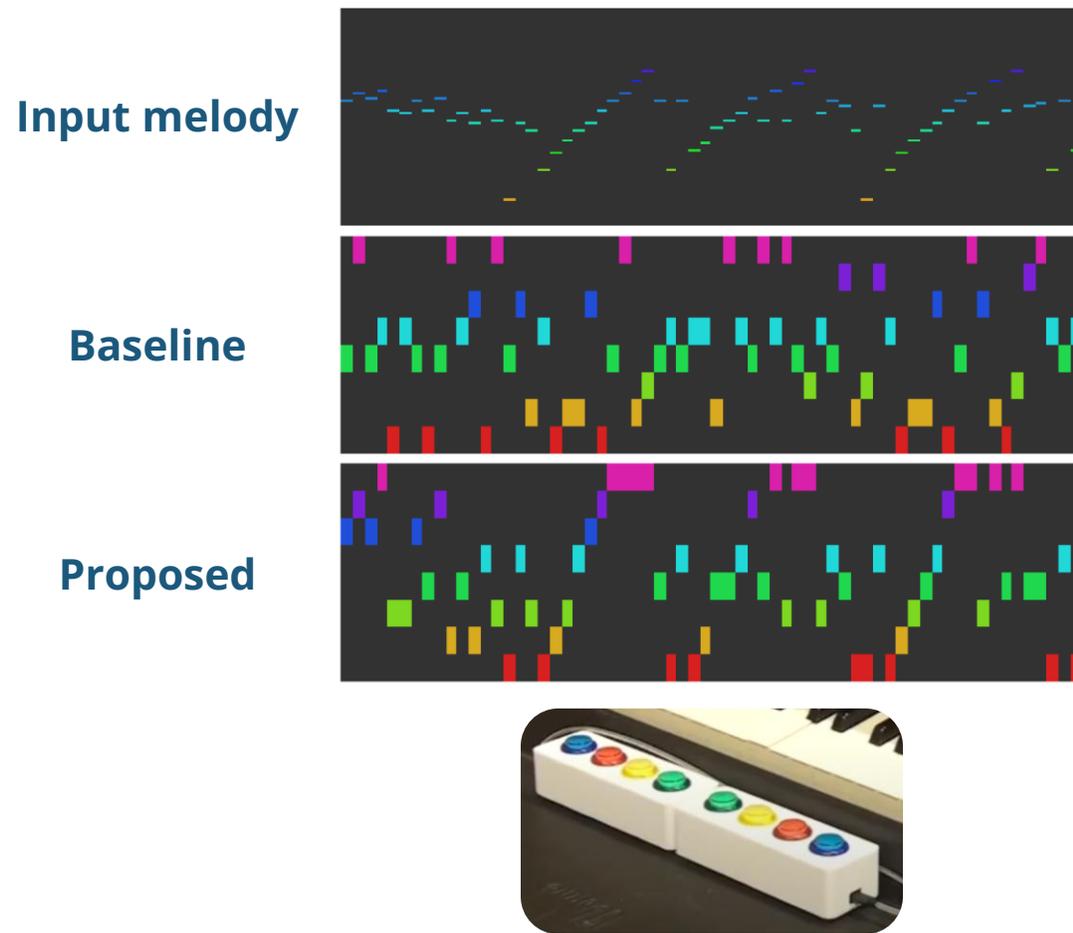
(Source: Chen et al., 2020)

# Piano Genie (Donahue et al., 2019)



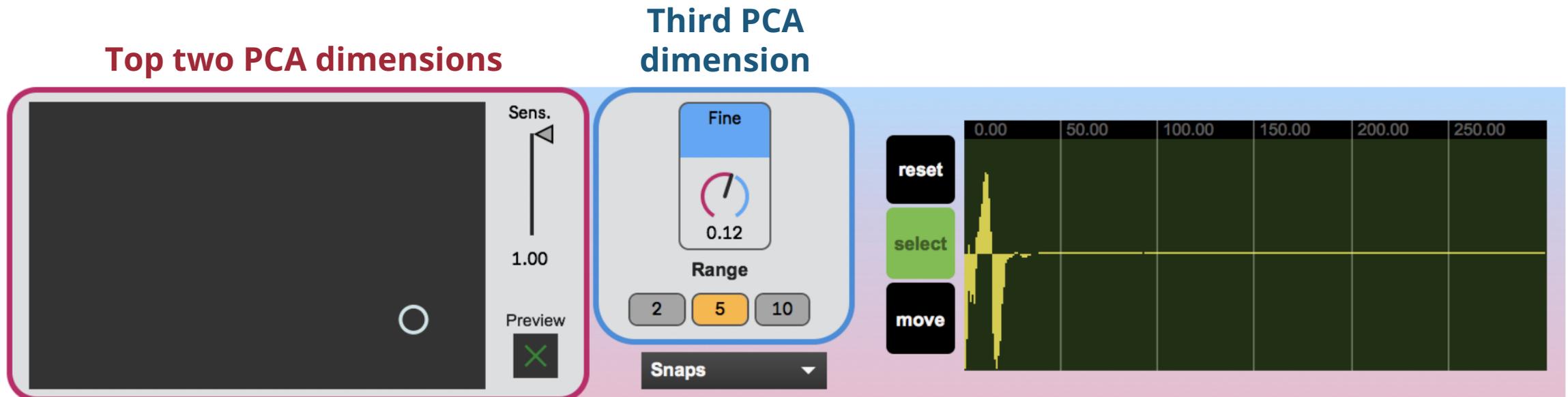
[youtu.be/YRb0XAnUpIk](https://youtu.be/YRb0XAnUpIk) & [magenta.tensorflow.org/pianogenie](https://magenta.tensorflow.org/pianogenie)

# Piano Genie (Donahue et al., 2019)



(Source: Donahue et al., 2019)

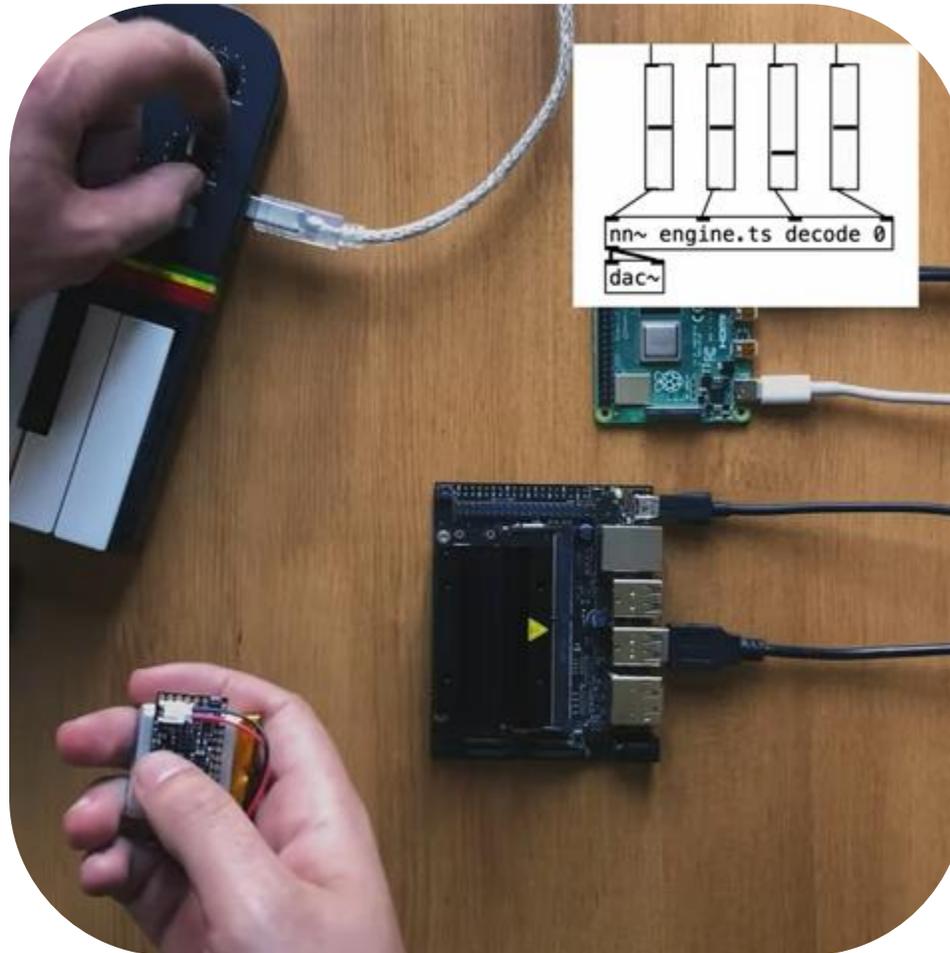
# Neural Drum Machine (Aouameur et al., 2019)



(Source: Aouameur et al., 2019)

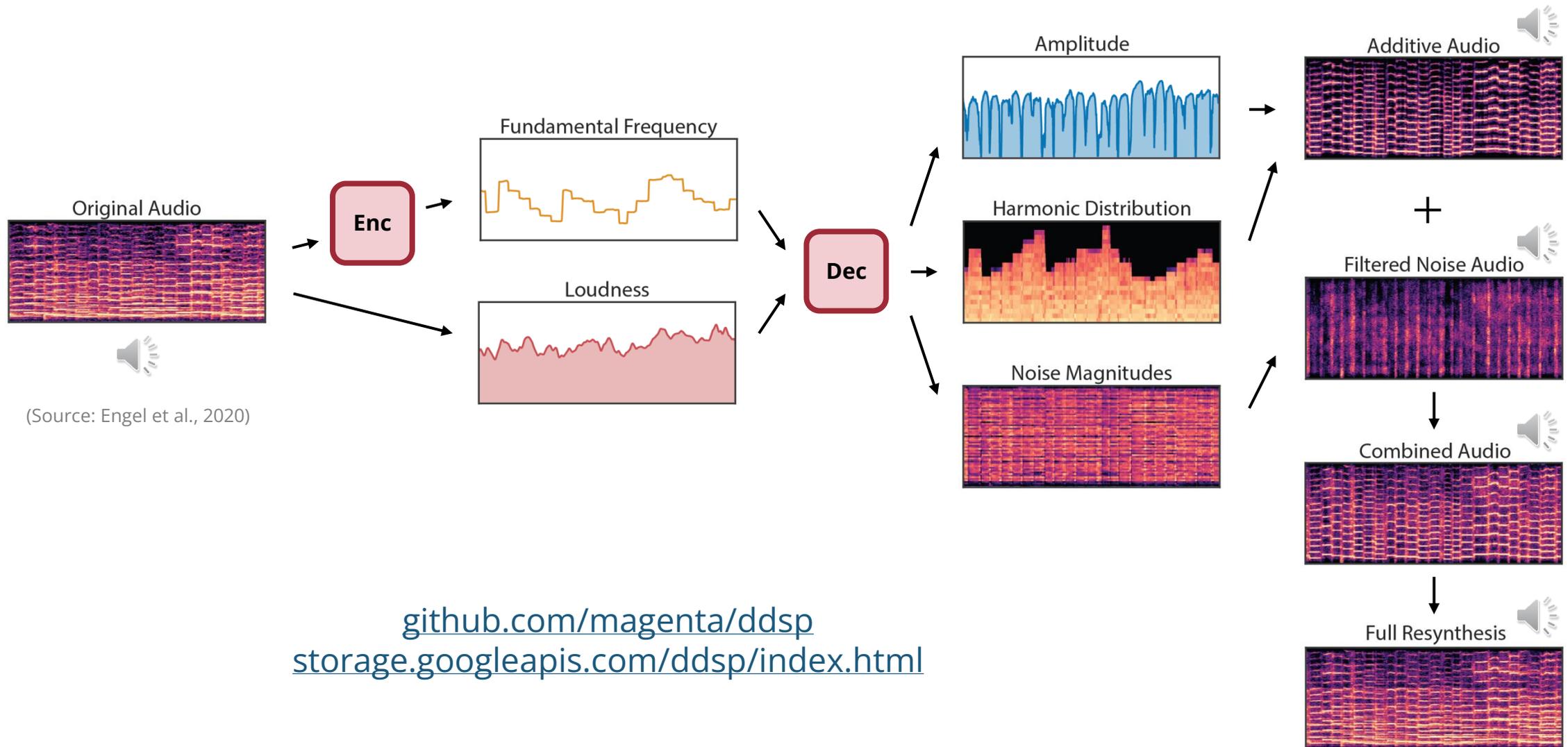
[drive.google.com/file/d/1DDo0\\_KnwkWirCM4t0PT8cp6uotsfuufj/view](https://drive.google.com/file/d/1DDo0_KnwkWirCM4t0PT8cp6uotsfuufj/view)

# RAVE: Real-time Audio Synthesis (Caillon & Esling, 2022)



[youtu.be/jAIRf4nGgYI](https://youtu.be/jAIRf4nGgYI)

# Differentiable DSP (DDSP) (Engel et al., 2020)



# Entering Demons & Gods by Yaboi Hanoi (2022)



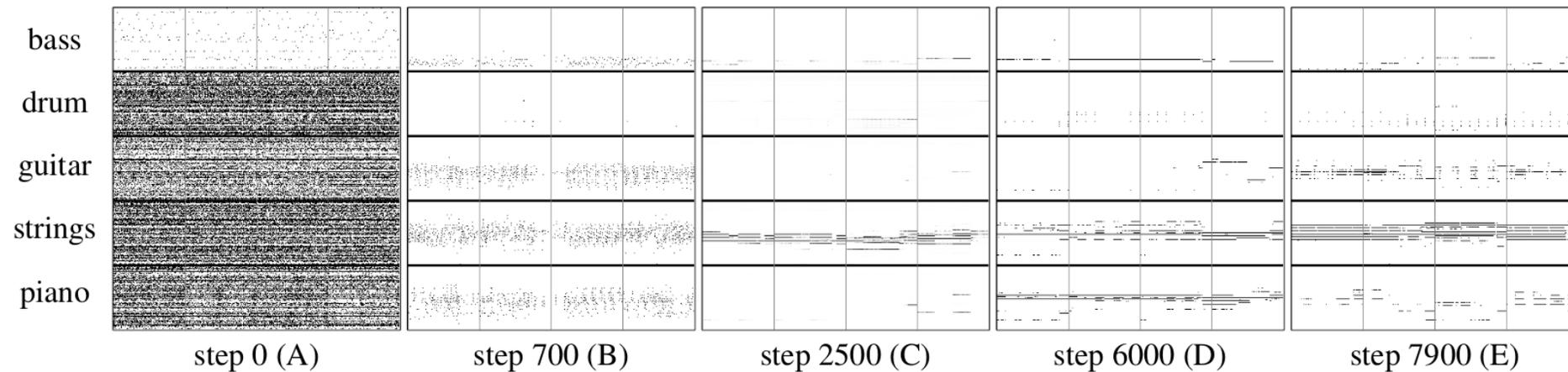
[youtu.be/PbrRoR3nEVw](https://youtu.be/PbrRoR3nEVw)

[soundcloud.com/yaboihanoi/enter-demons-and-gods](https://soundcloud.com/yaboihanoi/enter-demons-and-gods)



# Next Lecture

## Generative Adversarial Nets



(Source: Dong et al., 2018)