

# A PRACTICAL GUIDE TO GENERATIVE MUSIC AI FOR DEVELOPERS

Session I: An Introduction to AI Music

# ABOUT ME



- PhD student & Presidential Fellow at the MIT Media Lab
- MEng and MRes in *Artificial Intelligence & Machine Learning* at Imperial College London
- Classically-trained Jazz pianist

# MY WORK

- Working with multiple GRAMMY-winning artists to develop Generative AI-powered musical instruments for live performances.
- Generally interested in exploring the field of real-time Artist-AI musical interaction.

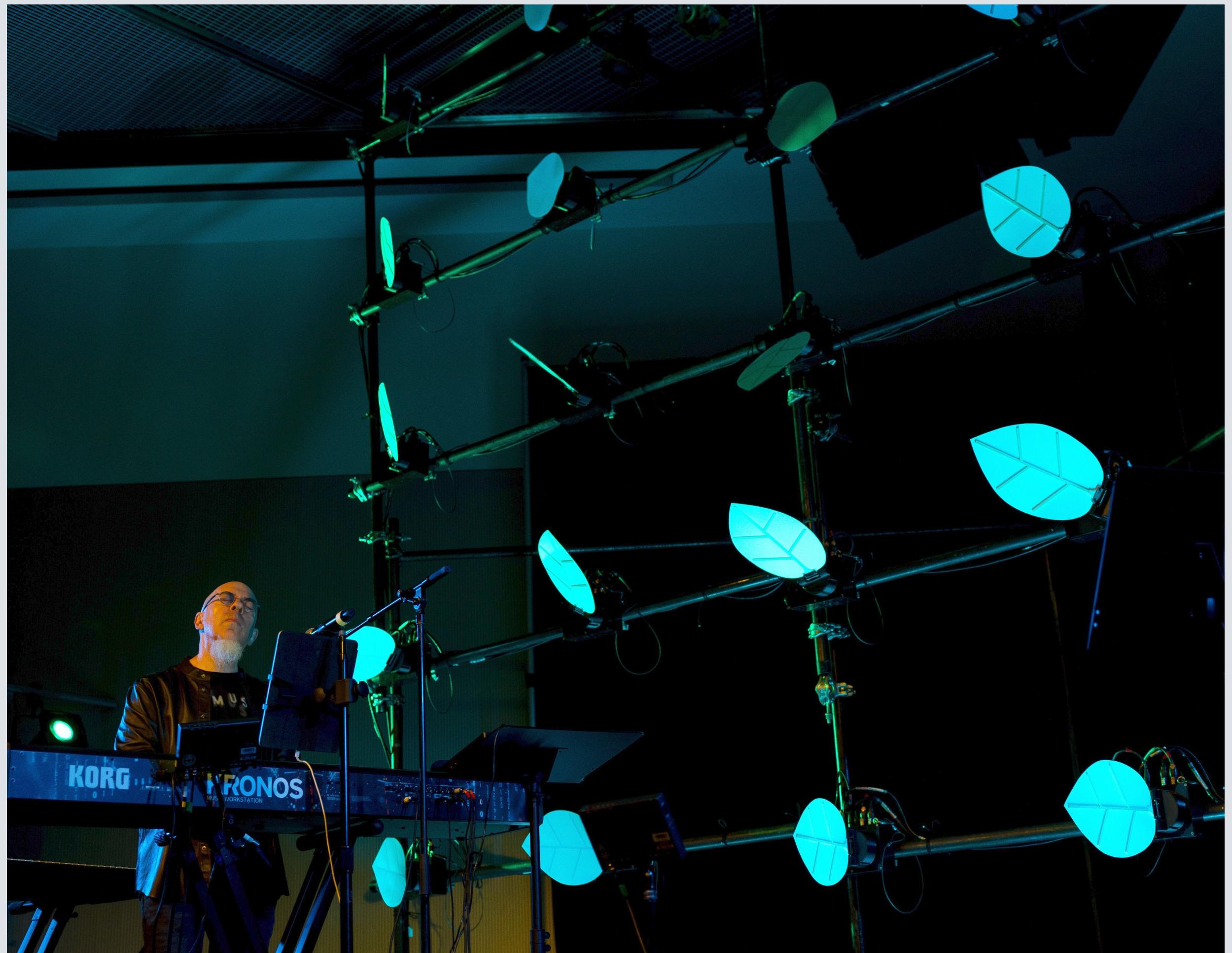


Photo Credit: Caroline Alden

# A BRIEF HISTORY OF AI AND MUSIC

Before AI, "*generative music*" (a term popularized by Brian Eno) referred to music that was created by a **system** and that **changed over time**.

Diverse systems have been used to create music.

- Randomness and chance
- Algorithms and computers
- Deep Learning methods

# ALEATORIC MUSIC

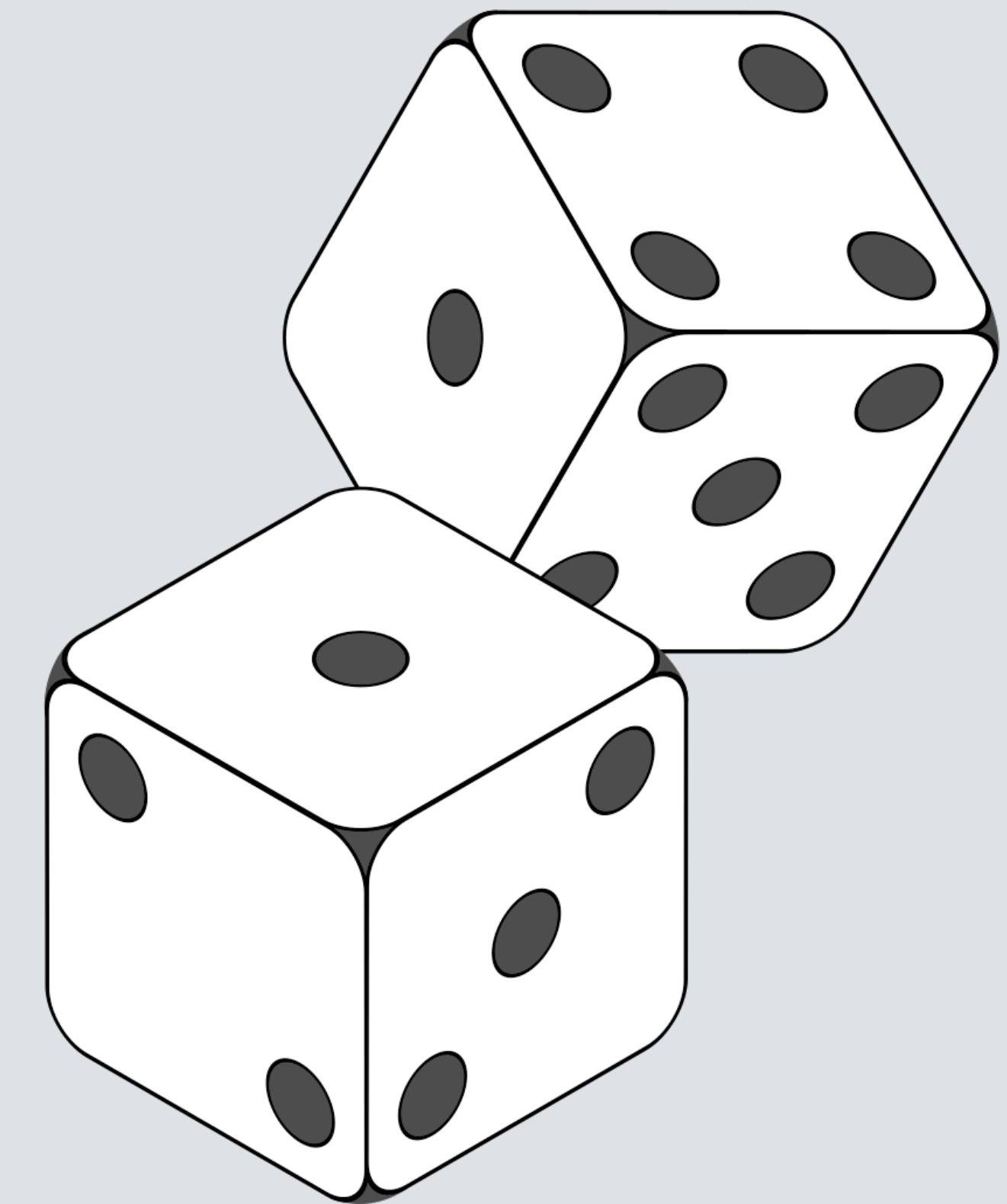
## THROUGH RANDOMNESS AND CHANCE

### **Musikalisches Würfelspiel**

- Attributed to Mozart, Haydn, and Bach.
- A number of pre-computed bars, randomly selected by dice roll.

Mozart's Anleitung zum Componieren von Walzern so viele man will vermittelst zweier Würfel, ohne etwas von der Musik oder Composition zu verstehen

("Instructions for the composition of as many waltzes as one desires with two dice, without understanding anything about music or composition")



# ALGORITHMIC MUSIC

## THROUGH ALGORITHMS AND COMPUTERS

### Illiac Suite (1957)

Composed by Lejaren Hiller & Leonard Isaacson at the University of Illinois, Urbana-Champaign.

- First computer-generated piece
- Four movements



# ALGORITHMIC MUSIC

## THROUGH ALGORITHMS AND COMPUTERS

### **Project One & Project Two (1964-1966)**

Composed by Gottfried Michael Koenig at the *Institute of Sonology* in Utrecht.

- Probabilistic rule-based system that defined musical parameters such as pitch, duration, dynamics, and timbre.



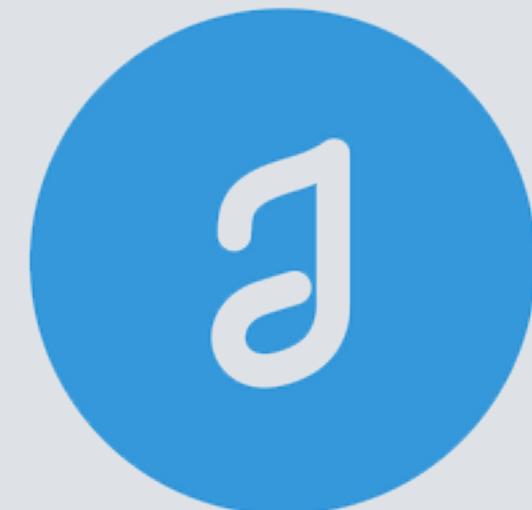
# ALGORITHMIC MUSIC

## THROUGH ALGORITHMS AND COMPUTERS

### **Jukedeck (2012)**

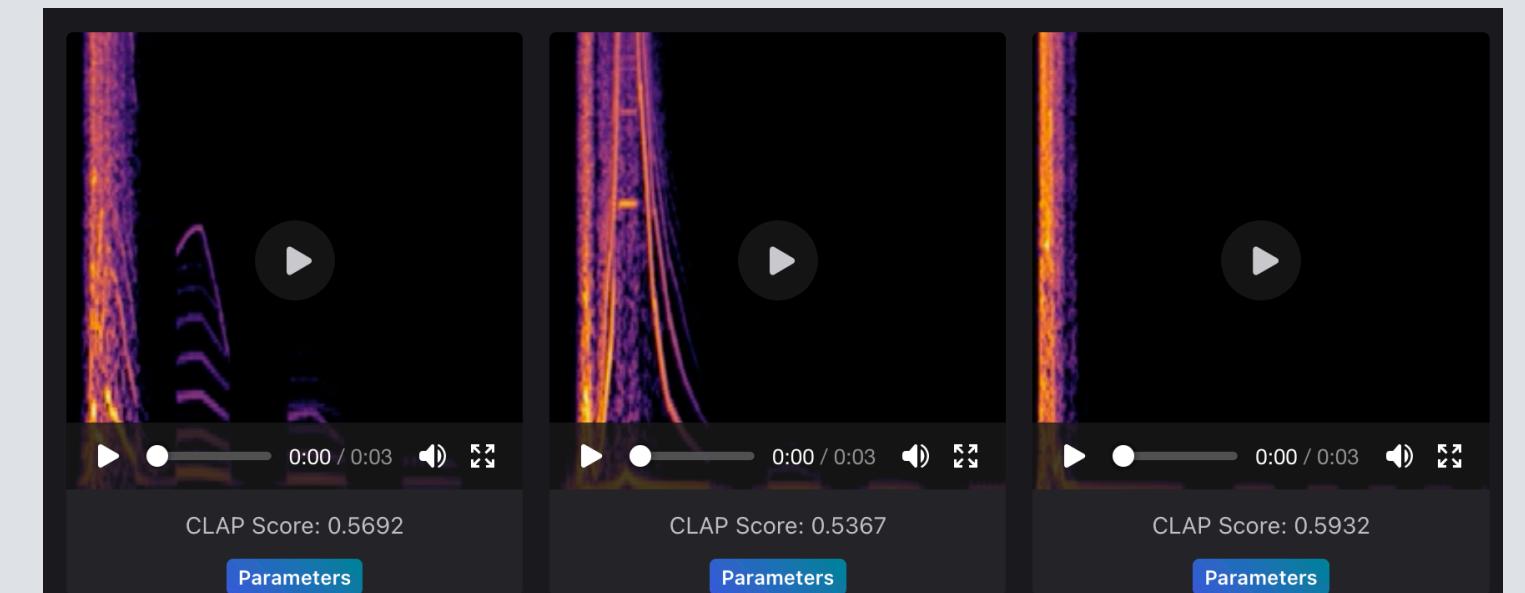
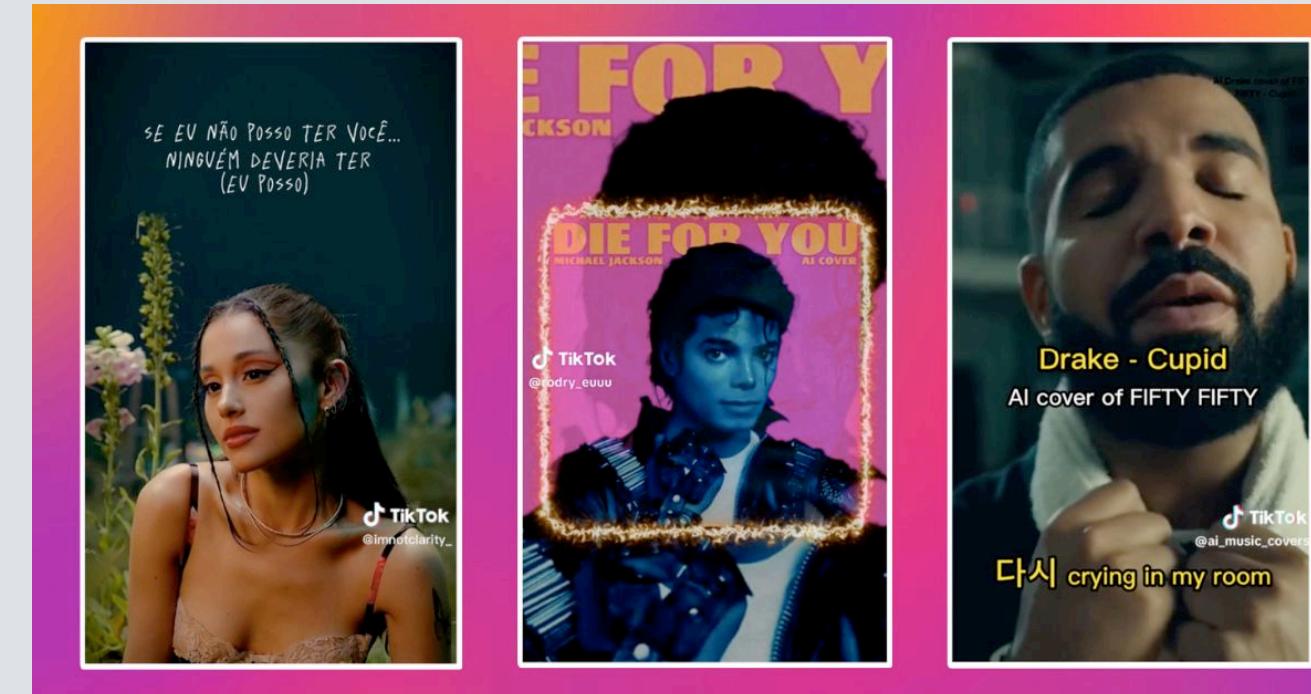
Founded by Ed-Newton Rex and Patrick Stobbs

- Royalty-free music generation through retrieval and samples and loops.
- Acquired by ByteDance.



Jukedeck

# CURRENT STATE OF AI AND MUSIC



udio

A large, stylized word "udio" with a downward-pointing arrow on the left side.

# SYMBOLIC VS AUDIO

JOHANN SEBASTIAN BACH

371 Harmonized Chorales

Revised, corrected, edited, and annotated by  
Albert Riemenschneider\*

1.

Aus meines Herzens Grunde

2.

Ich dank' dir, lieber Herre

3.

Ach Gott, vom Himmel sieh' darin

\*The previous publications of the 371—even the latest of them—contain numerous inaccuracies, which have been corrected in this edition. Those chorales in which corrections have been made (beyond the mere removal of meaningless slurs) are marked with asterisks.

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## Control over

- Harmony
- Melody
- Rhythms
- Expression & Articulation
- Orchestration & Arrangement

# SYMBOLIC MUSIC

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2.

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3.

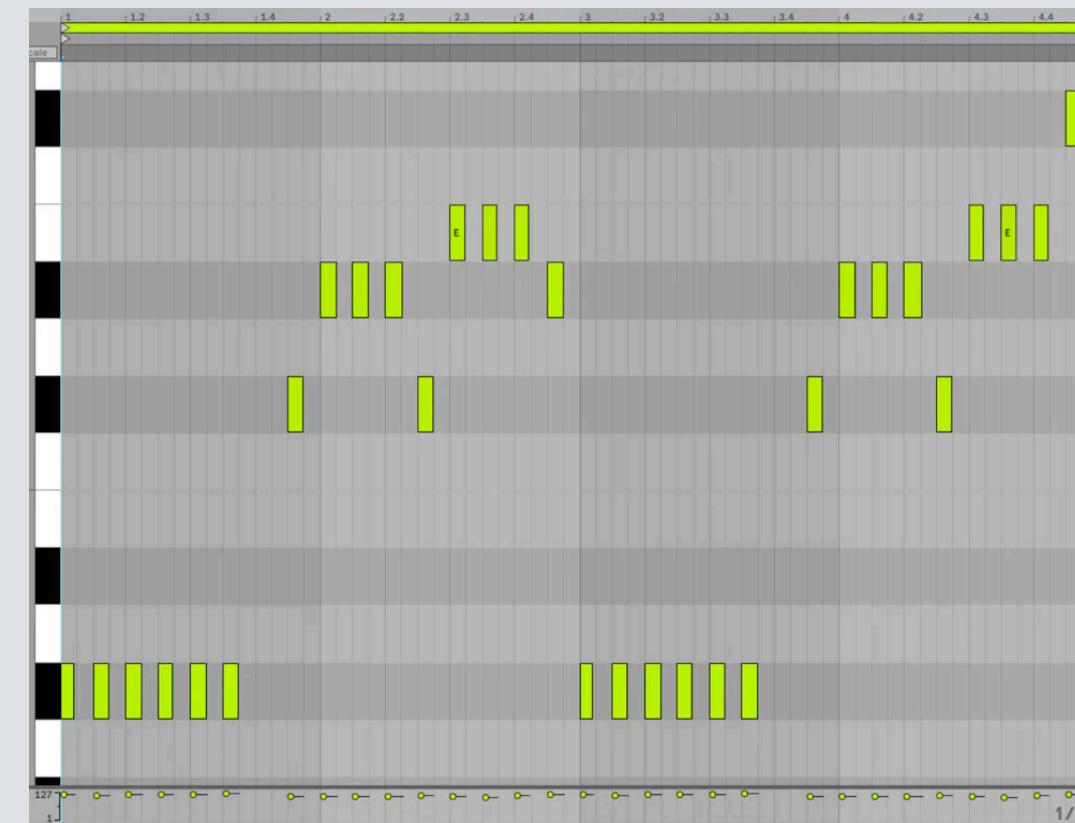
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Can be represented by



```

<note>
  <pitch>
    <step>E</step>
    <alter>-1</alter>
    <octave>4</octave>
  </pitch>
  <duration>2</duration>
  <type>half</type>
</note>

```

X: 0

T: My Tune

M: 4/4

L: 1/4

K: C

C,D,E,F | G,A,B,C | DEFG | ABcd | efga | bc'd'e' | f'g'a'b' |

# AUDIO

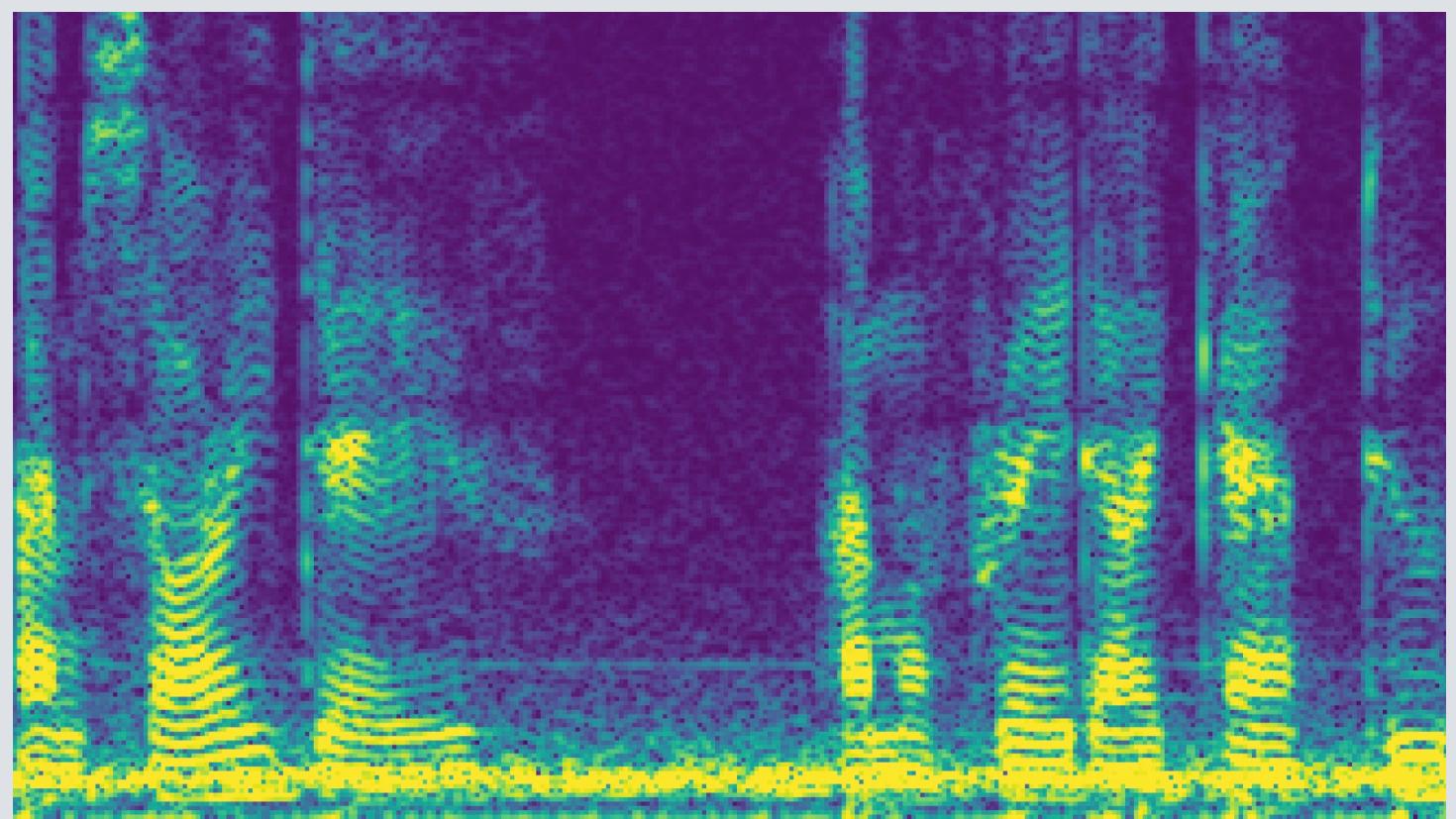
Control over

- Timbre
- Sonic details
- Phrasing
- Mixing & Mastering

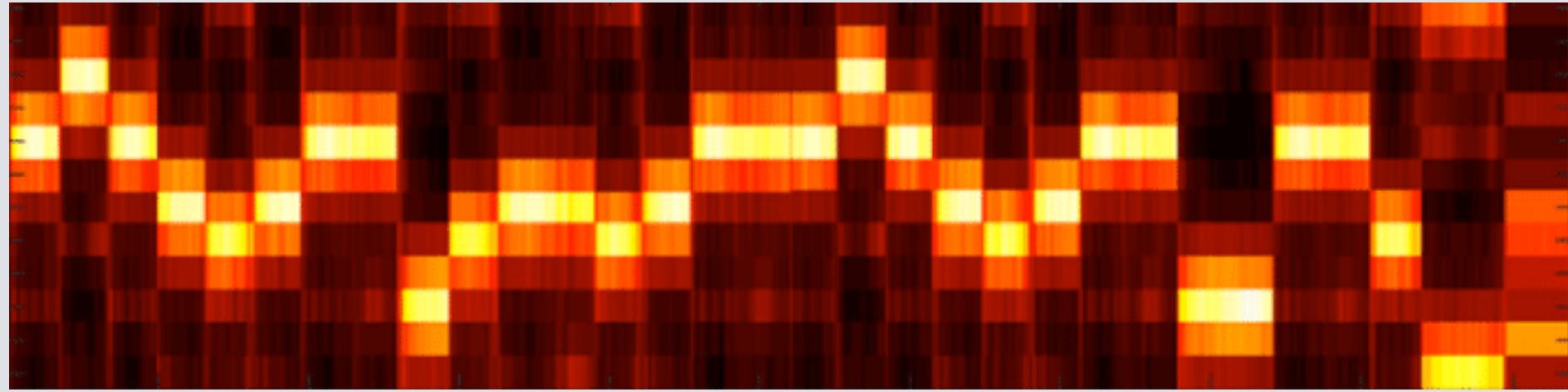


# AUDIO

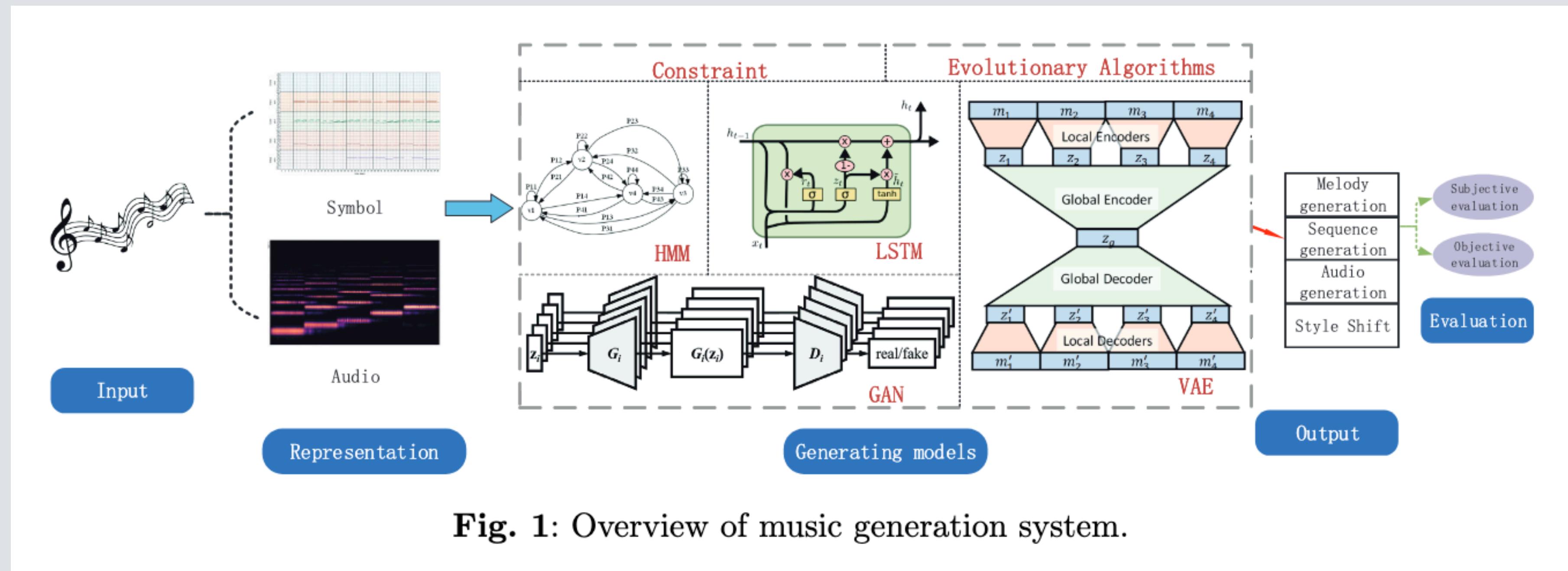
Can be represented by



```
[[[[0.1561, ..., 0.2555],  
...  
[[[0.8834, ..., 0.5366],  
...  
[0.9060, ..., 0.2069]]]]]
```



# AVAILABLE TECHNOLOGIES



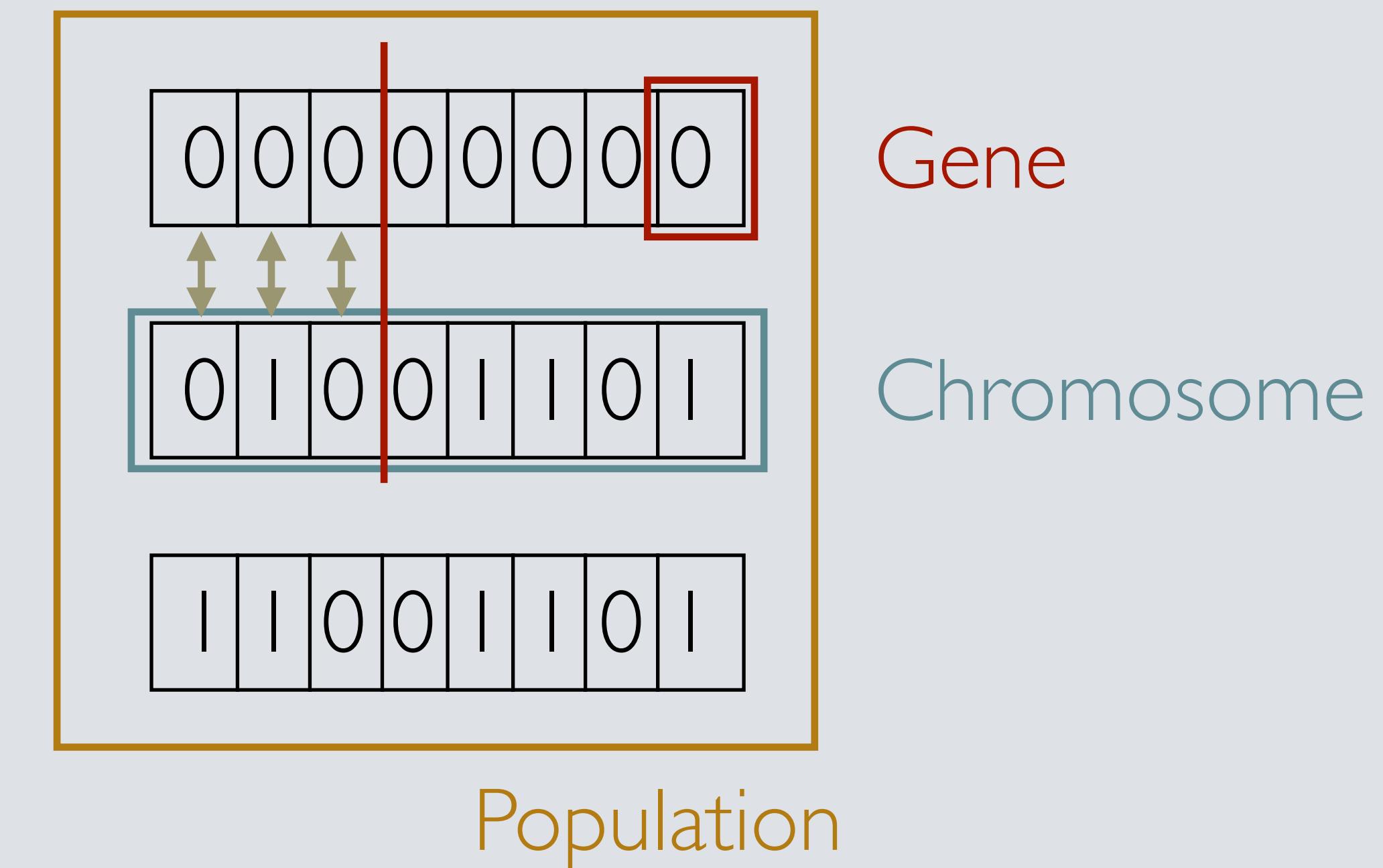
from (Wang et al., 2022)

# AVAILABLE TECHNOLOGIES

## PRE DEEP LEARNING

### Genetic Algorithms

- Evolutionary search over populations of musical sequences
- Mutation, crossover, and selection optimize fitness (e.g., harmony, melody)
- Good at exploration but slow convergence
- e.g., John A. Bile's GenJam

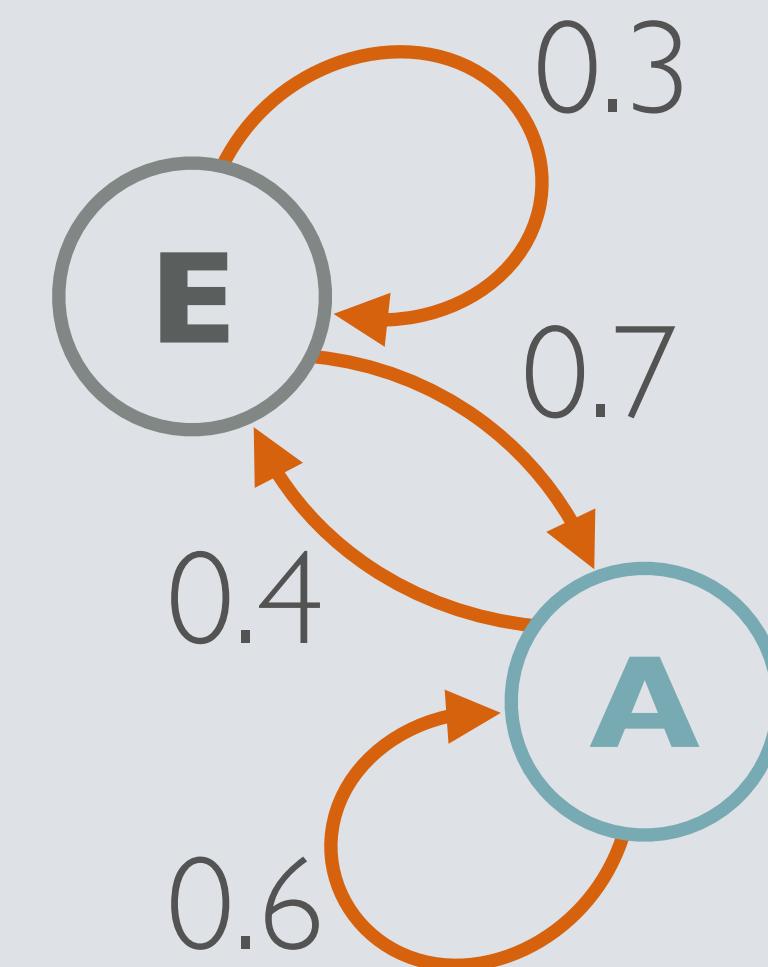


# AVAILABLE TECHNOLOGIES

## PRE DEEP LEARNING

### Hidden Markov Models (HMMs)

- State-based system with transition probabilities.
- e.g. François Pachet's *Continuator*

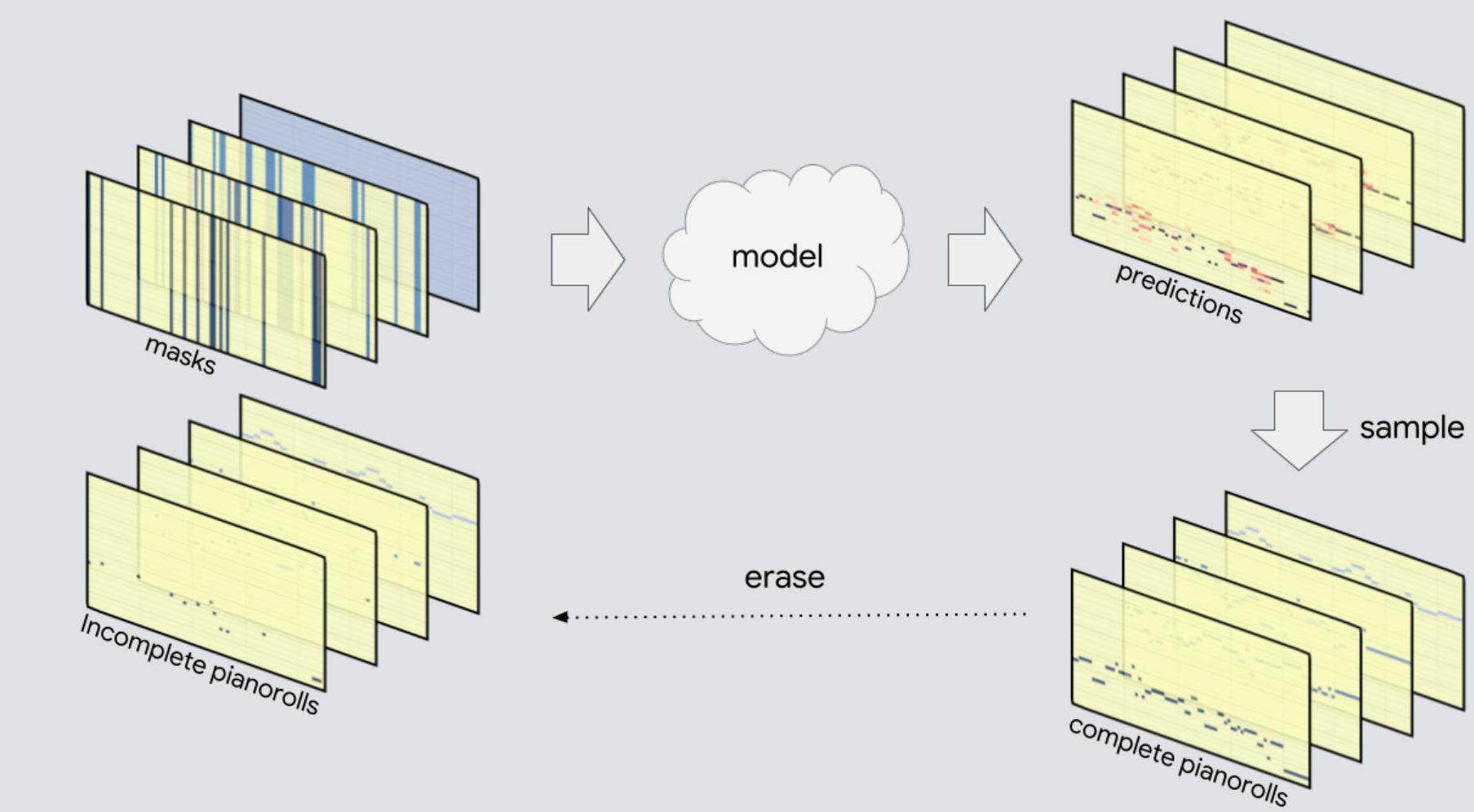


# AVAILABLE TECHNOLOGIES

## DEEP LEARNING - EARLY ERA

### Convolutional Neural Networks (CNNs)

- Learn local patterns (e.g., rhythms, timbres) in audio or pianoroll formats
- Limited at modeling long-term structure
- Strong at capturing spatial or short-time structure
- e.g. Google Magenta's Coconet

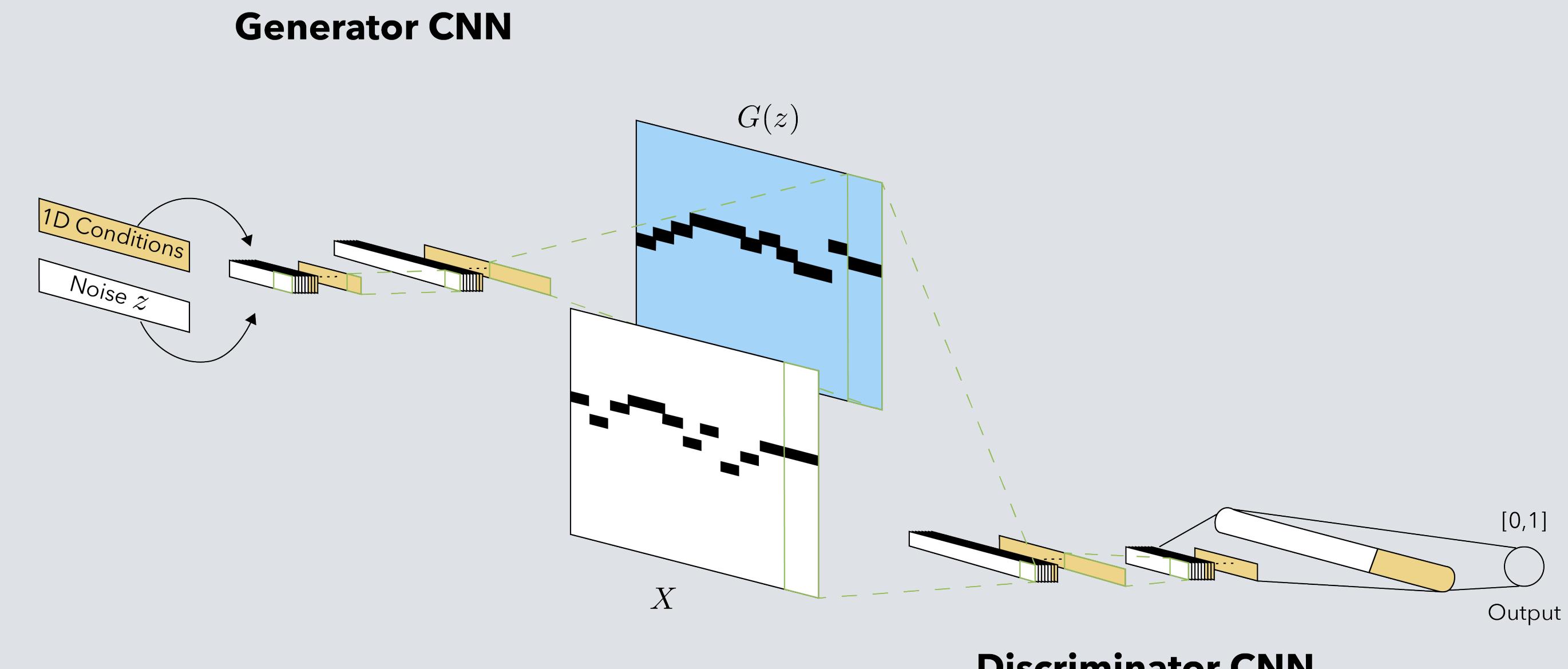


# AVAILABLE TECHNOLOGIES

## DEEP LEARNING - EARLY ERA

### Generative Adversarial Networks (GANs)

- Generator creates music; discriminator evaluates realism.
- Adversarial training improves quality and diversity.
- Often used for symbolic generation (piano rolls) or spectrograms.
- e.g. Yang et al.'s *MidiNET*

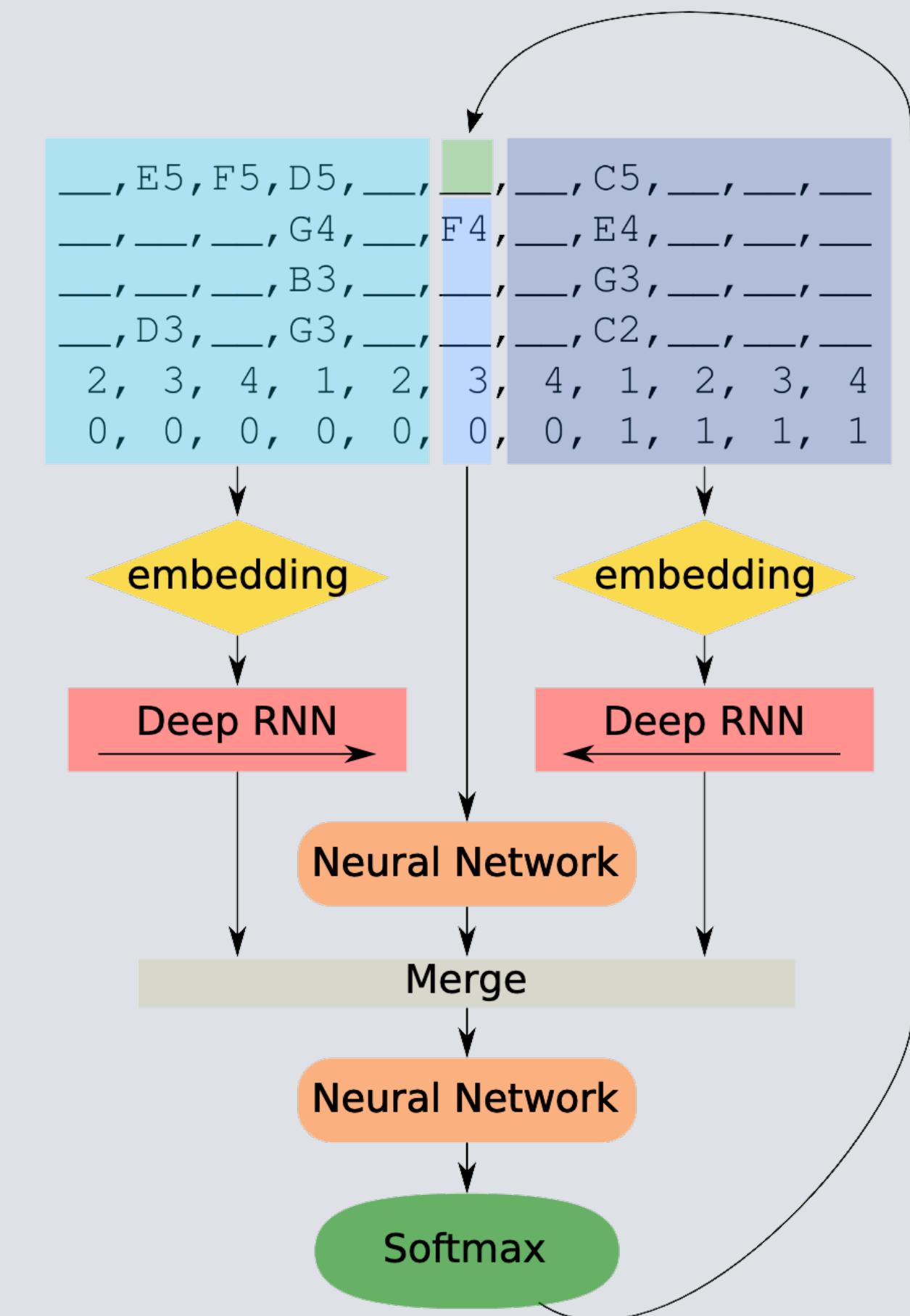


# AVAILABLE TECHNOLOGIES

## DEEP LEARNING - EARLY ERA

### Recurrent Neural Networks (RNNs)

- Model sequences step-by-step with internal memory (hidden states)
- Good at short-term dependencies; struggle with very long-term coherence
- Variants like LSTM and GRU mitigate vanishing gradients
- e.g. Sony CSL's *DeepBach*

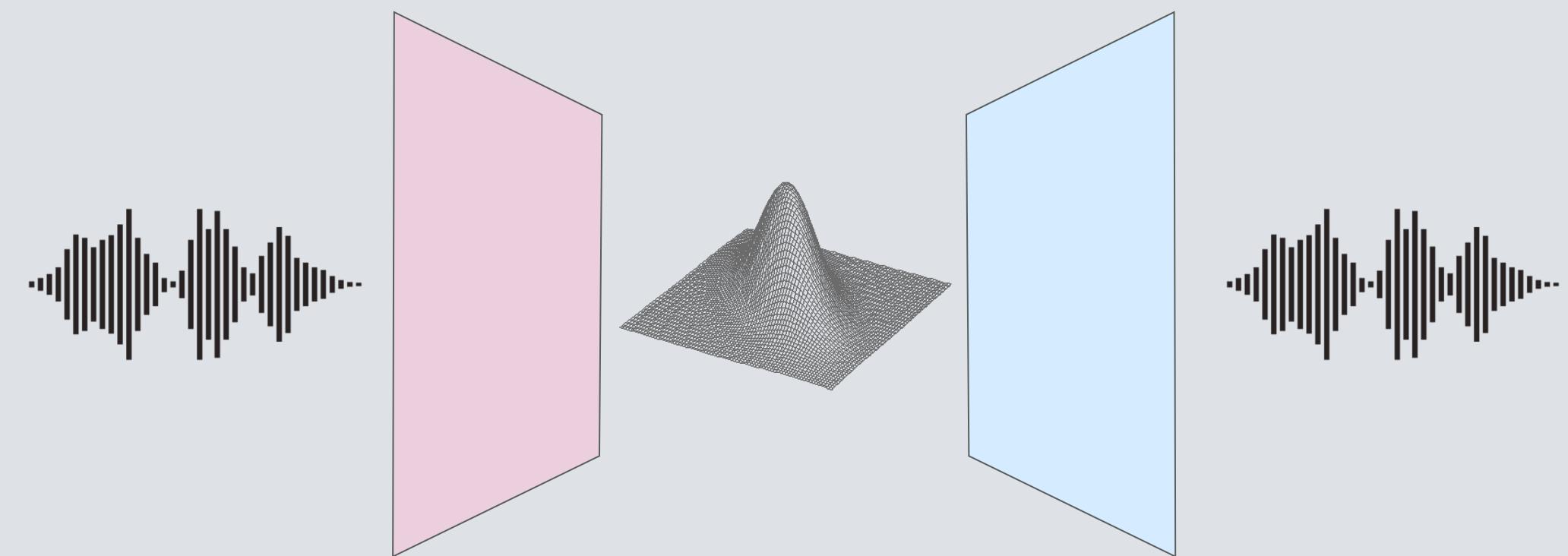


# AVAILABLE TECHNOLOGIES

## DEEP LEARNING - CURRENT ERA

### Variational AutoEncoders (VAEs)

- Learn to create a latent representation that allows accurate reconstruction.
- Varying encoding levels
- Limited long-term dependencies
- e.g. OpenAI's *Jukebox*

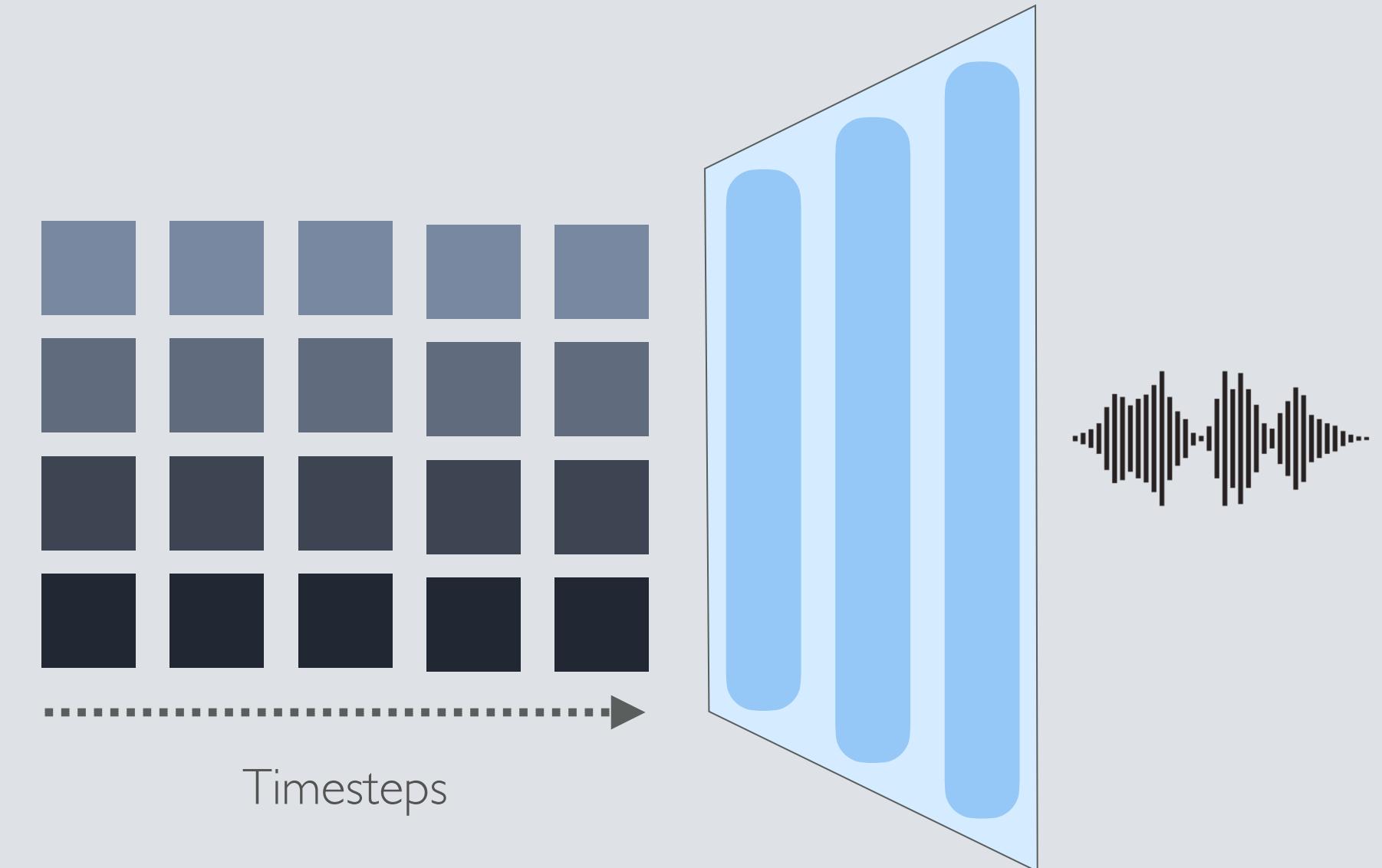


# AVAILABLE TECHNOLOGIES

## DEEP LEARNING - CURRENT ERA

### Transformers

- Learn to model and auto-regressively complete a sequence of music tokens
- Better long-term dependencies
- e.g. Meta's MusicGen

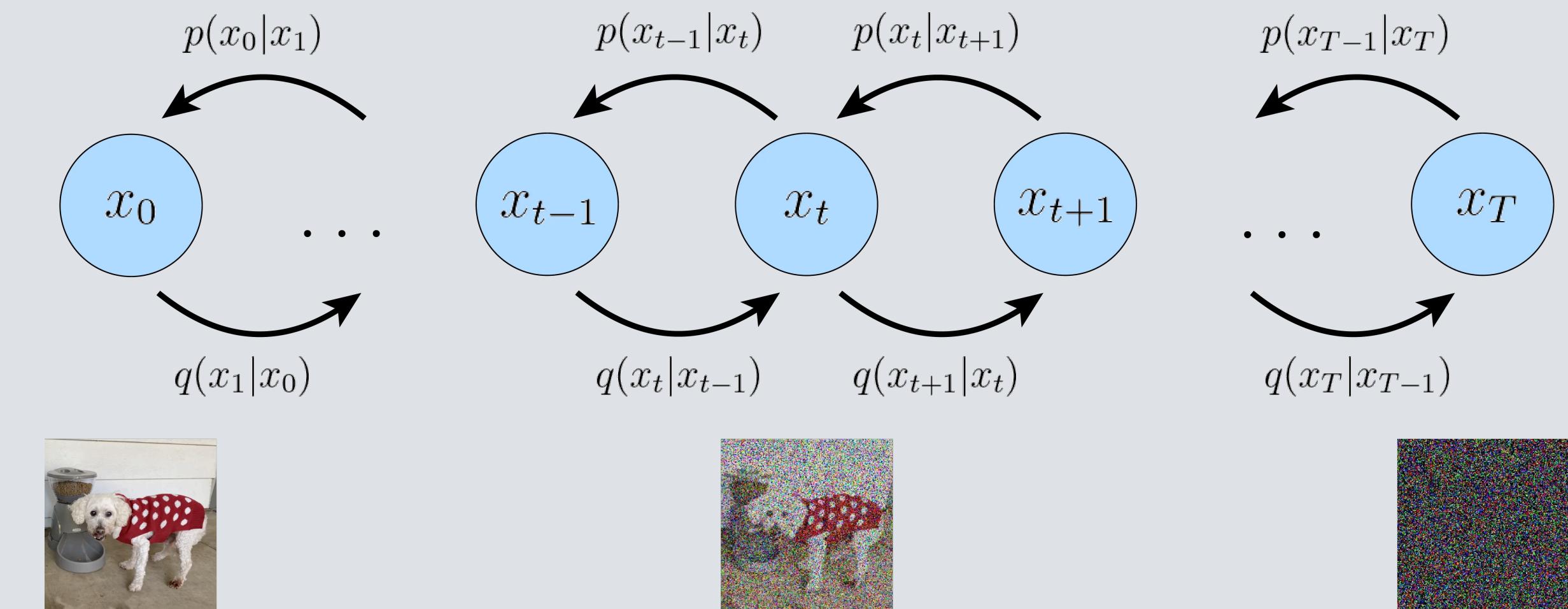


# AVAILABLE TECHNOLOGIES

## DEEP LEARNING - CURRENT ERA

### Diffusion Models

- Learn a denoising process over a (latent) audio representation
- Great overall cohesion
- Limited long-term dependencies
- e.g. ByteDance's AudioLDM2



# IN THIS COURSE

- Week 1: Introduction & Foundational Skills
- Week 2: ML Fundamentals applied to Music
- Week 3: (Re)using State-Of-The-Art Generative AI Models for Musical Creation
- Week 4: Real-Time Music Generation
- Week 5: Commercial Applications & Final Project Preparation
- Week 6: Final Projects

THANK YOU!

# REFERENCES

- Hiller, L. 1981. Composing with computers: A progress report. Computer Music Journal, 5(4):7-21.
- Laske, O. 1981. Composition theory in Koenig's Project One and Project Two. Computer Music Journal, 5(4):54-65.
- Wang, L. et al. 2022. A Review of Intelligent Music Generation Systems.