

Generative AI for Music: Challenges & Opportunities


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Can you? (I, Robot, 2004)



Can a robot write a Symphony?



Can a robot take a blank canvas
and turn it into a masterpiece?



Can you?

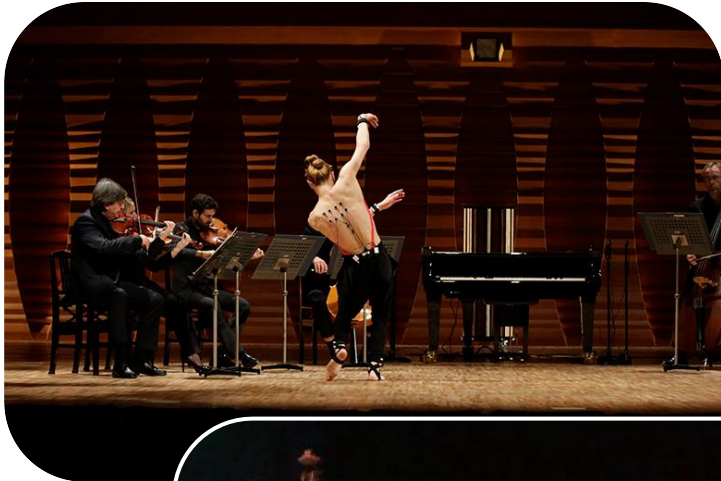
Music & Technology Co-evolves



Hildegard Dodel, Public domain, via Wikimedia Commons.
Taken at Hamamatsu Museum of Musical Instruments, August 2019.
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Music & AI

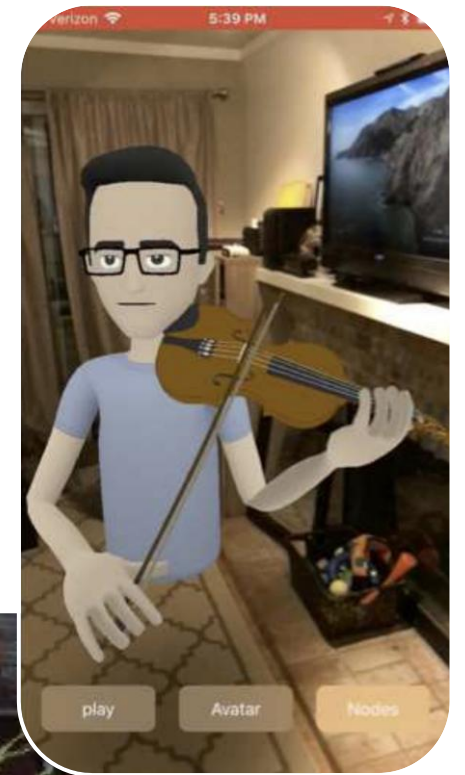
(Source: Yamaha)



(Source: Sankei Shimbun)



(Shlizerman et al., 2019)



(Source: Robot Gizmos)



(Source: NBC DFW)

yamaha.com/en/news_release/2018/18013101/
sankei.com/article/20240113-CQCOSQHJWFIYPJJKZDCITRTRVI/
roboticgizmos.com/shimon-musical-robot-deep-learning/
nbcdfw.com/entertainment/the-scene/how-verdigris-ensemble-is-using-ai-to-create-a-new-concert-experience/3366031/
Shlizerman et al., "Audio to Body Dynamics," *Proc. CVPR*, 2018.

Generative AI for Content Creation



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descript.com/blog/article/what-is-the-best-audio-interface-for-recording-a-podcast
denverpost.com/2019/08/02/colorado-symphony-movie-scores-harry-potter-star-wars/
dailybruin.com/2023/08/04/theater-review-the-musical-les-misrables-offers-stellar-displays-and-impassioned-vocals

Art challenges Technology



Music

**Augmenting Human Creativity
with AI**



AI



Technology inspires the Art

| My Research on AI for Music

- **Multitrack music generation** (AAAI 2018, ISMIR 2018, ISMIR 2020, ICASSP 2023, ISMIR 2024, AIMG 2024)
- **Text-to-symbolic music generation** (ISMIR LBD 2024, arXiv 2024)
- **Expressive violin performance synthesis** (ICASSP 2022, ICASSP 2025)
- **Music instrumentation** (ISMIR 2021)
- **Music harmonization** (JNMR 2020)
- **Music LLM** (NLP4MusA 2024, ICASSP 2025)
- **Choral music separation** (ISMIR 2022)
- **Optical music recognition** (ISMIR 2021)



Multitrack Music Transformer

Hao-Wen Dong Ke Chen Shlomo Dubnov Julian McAuley Taylor Berg-Kirkpatrick

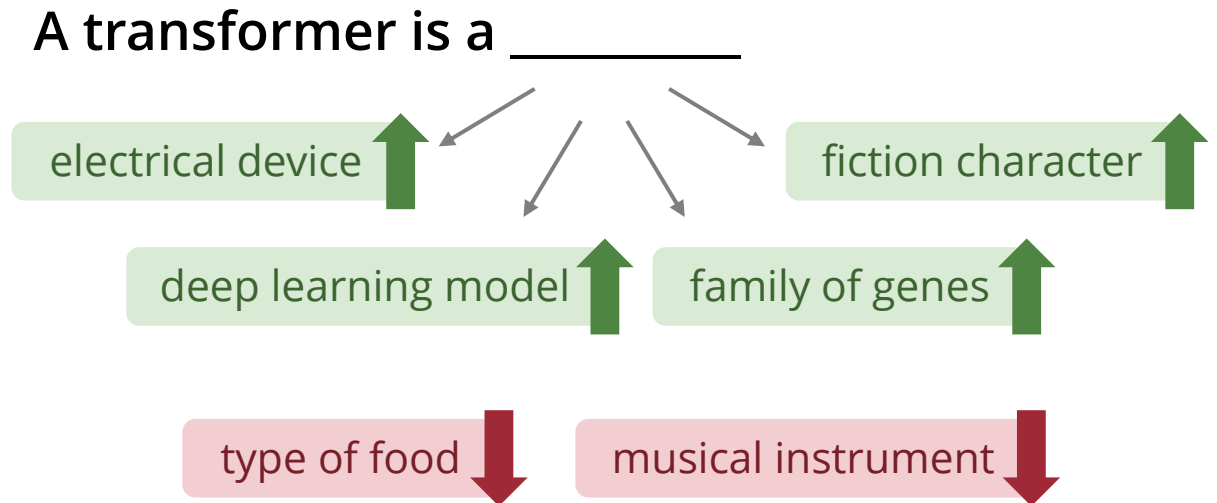
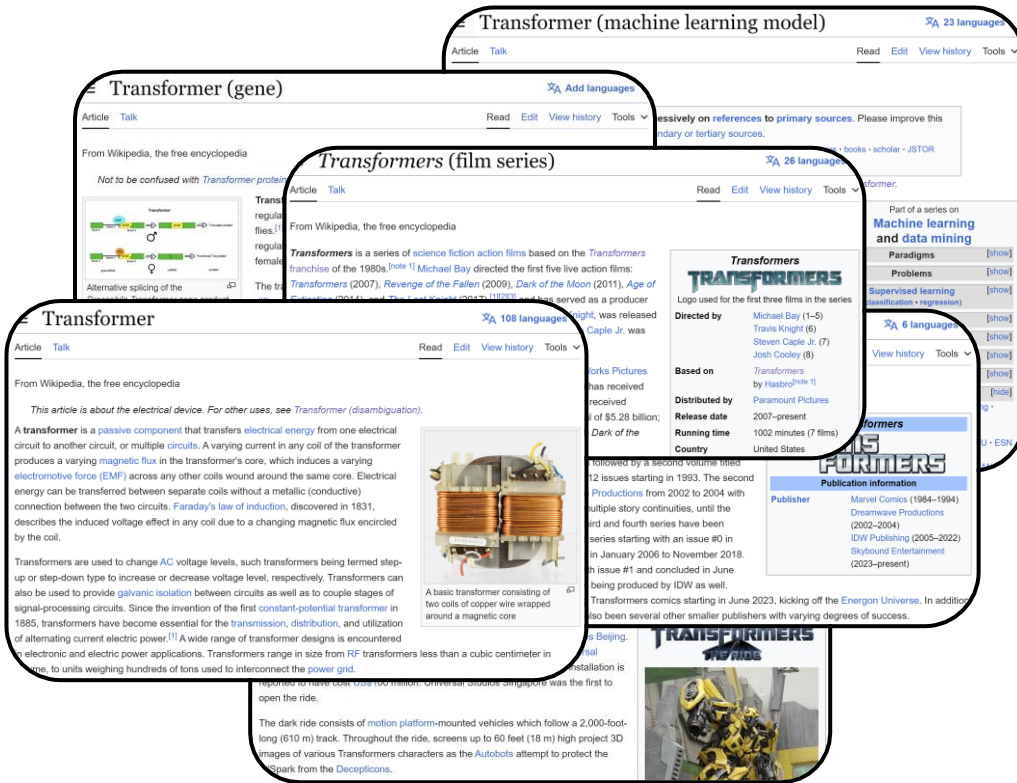
University of California San Diego



UC San Diego

Generating Text using Language Models

- Predicting the next word given the past sequence of words



Generating Text using Language Models

- How do we generate a new sentence with a language model?

A transformer is a

→ Model → deep

A transformer is a deep

→ Model → learning

A transformer is a deep learning

→ Model → model

A transformer is a deep learning model

→ Model → introduced

A transformer is a deep learning model introduced

→ Model → in

A transformer is a deep learning model introduced in

→ Model → 2017

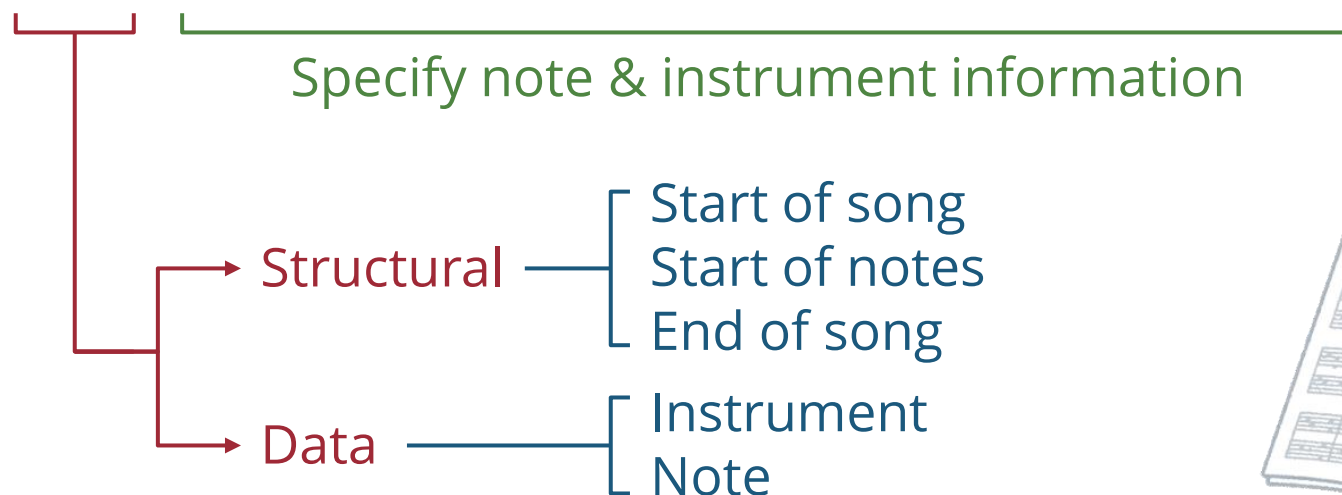
Designing a Machine-readable Music Language

- We represent a music piece as a sequence of “**super words**”

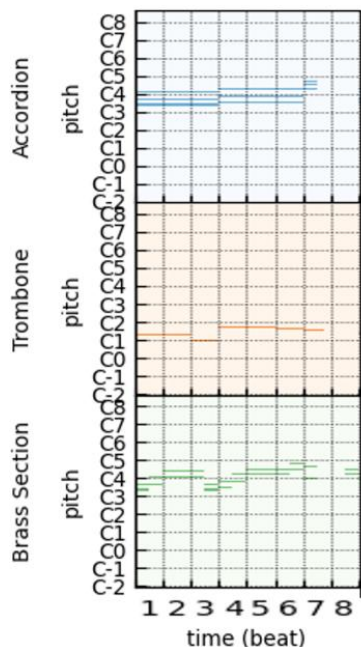
$$\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_n)$$

- Each super word \mathbf{x}_i encodes:

$$\mathbf{x}_i = (x_i^{\text{type}}, x_i^{\text{beat}}, x_i^{\text{position}}, x_i^{\text{pitch}}, x_i^{\text{duration}}, x_i^{\text{instrument}})$$



An Example of the Proposed Representation



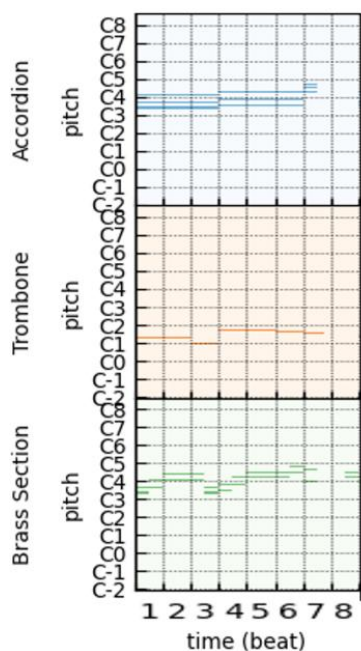
Structural events

(0, 0, 0, 0, 0, 0)	Start of song
(1, 0, 0, 0, 0, 15)	Instrument: accordion
(1, 0, 0, 0, 0, 36)	Instrument: trombone
(1, 0, 0, 0, 0, 39)	Instrument: brasses
(2, 0, 0, 0, 0, 0)	Start of notes
(3, 1, 1, 41, 15, 36)	Note: beat=1, position=1, pitch=E2, duration=48, instrument=trombone
(3, 1, 1, 65, 4, 39)	Note: beat=1, position=1, pitch=E4, duration=12, instrument=brasses
(3, 1, 1, 65, 17, 15)	Note: beat=1, position=1, pitch=E4, duration=72, instrument=accordion
(3, 1, 1, 68, 4, 39)	Note: beat=1, position=1, pitch=G4, duration=12, instrument=brasses
(3, 1, 1, 68, 17, 15)	Note: beat=1, position=1, pitch=G4, duration=72, instrument=accordion
(3, 1, 1, 73, 17, 15)	Note: beat=1, position=1, pitch=C5, duration=72, instrument=accordion
(3, 1, 13, 68, 4, 39)	Note: beat=1, position=13, pitch=G4, duration=12, instrument=brasses
(3, 1, 13, 73, 4, 39)	Note: beat=1, position=13, pitch=C5, duration=12, instrument=brasses
(3, 2, 1, 73, 12, 39)	Note: beat=2, position=1, pitch=C5, duration=36, instrument=brasses
(3, 2, 1, 77, 12, 39)	Note: beat=2, position=1, pitch=E5, duration=36, instrument=brasses
...	...
(4, 0, 0, 0, 0, 0)	End of song

Instrument events

Note events

An Example of the Proposed Representation



(0, 0, 0, 0, 0, 0)
(1, 0, 0, 0, 0, 15)
(1, 0, 0, 0, 0, 36)
(1, 0, 0, 0, 0, 39)
(2, 0, 0, 0, 0, 0)
(3, 1, 1, 1, 15, 36)
(3, 1, 1, 5, 4, 39)
(3, 1, 1, 5, 17, 15)
(3, 1, 1, 8, 4, 39)
(3, 1, 1, 8, 17, 15)
(3, 1, 1, 7, 17, 15)
(3, 1, 13, 8, 4, 39)
(3, 1, 13, 7, 4, 39)
(3, 2, 1, 7, 12, 39)
(3, 2, 1, 7, 12, 39)
(4, 0, 0, 0, 0, 0)

Start of song

Instrument: accordion

Instrument: trombone

Instrument: brasses

Start of notes

Note: beat=1, position=1, pitch=E2, duration=48, instrument=trombone

Note: beat=1, position=1, pitch=E4, duration=12, instrument=brasses

Note: beat=1, position=1, pitch=E4, duration=72, instrument=accordion

Note: beat=1, position=1, pitch=G4, duration=12, instrument=brasses

Note: beat=1, position=1, pitch=G4, duration=72, instrument=accordion

Note: beat=1, position=1, pitch=C5, duration=72, instrument=accordion

Note: beat=1, position=13, pitch=G4, duration=12, instrument=brasses

Note: beat=1, position=13, pitch=C5, duration=12, instrument=brasses

Note: beat=2, position=1, pitch=C5, duration=36, instrument=brasses

Note: beat=2, position=1, pitch=E5, duration=36, instrument=brasses

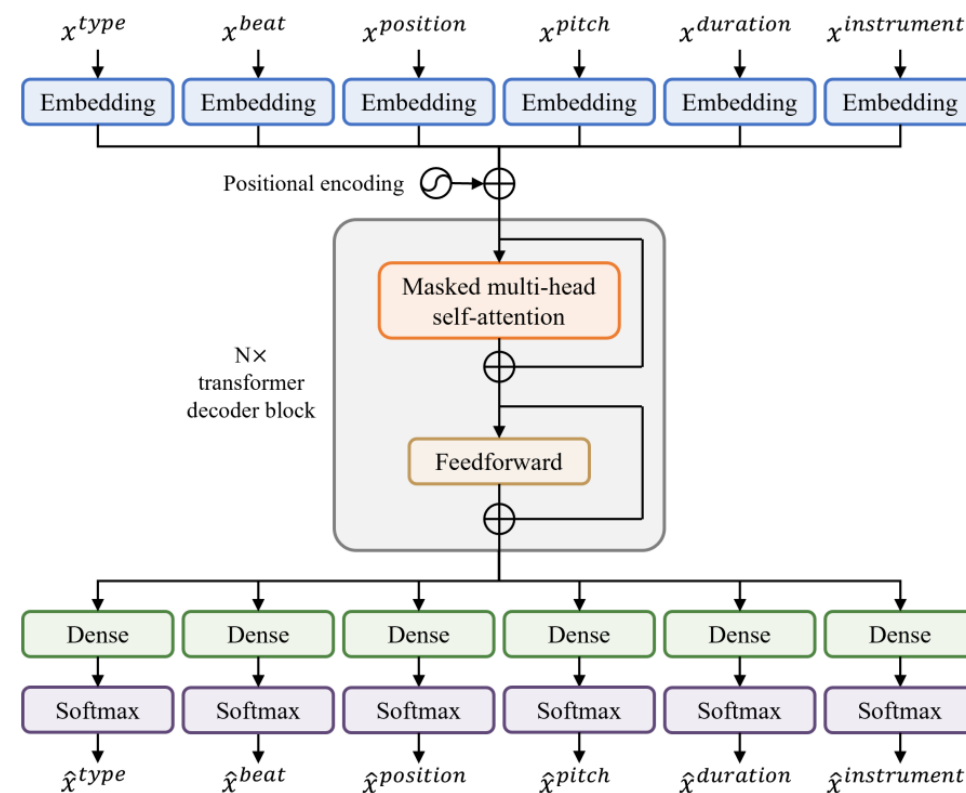
...

End of song

Multitrack Music Transformer (MMT)

- A decoder-only transformer model
- Predicts six fields at the same time
- Trained autoregressively

Note-by-note



Symbolic Orchestral Database (SOD)

- 5,743 orchestral pieces (**357 hours** in total)
- Contains various ensembles: choir, string quartet, symphony, etc.



Example Results

Unconditional
generation



Three Sampling Modes

Unconditional generation

Input

(0, 0, 0, 0, 0, 0)	Start of song
(1, 0, 0, 0, 0, 15)	Instrument: accordion
(1, 0, 0, 0, 0, 36)	Instrument: trombone
(1, 0, 0, 0, 0, 39)	Instrument: brasses
(2, 0, 0, 0, 0, 0)	Start of notes
(3, 1, 1, 41, 15, 36)	Note: beat=1, position=1, pitch=E2, duration=48, instrument=trombone
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(3, 1, 1, 68, 4, 39)	Note: beat=1, position=1, pitch=G4, duration=12, instrument=brasses
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(3, 1, 13, 73, 4, 39)	Note: beat=1, position=13, pitch=C5, duration=12, instrument=brasses
(3, 2, 1, 73, 12, 39)	Note: beat=2, position=1, pitch=C5, duration=36, instrument=brasses
(3, 2, 1, 77, 12, 39)	Note: beat=2, position=1, pitch=E5, duration=36, instrument=brasses
...	...
(4, 0, 0, 0, 0, 0)	End of song

Instrument-informed generation

Input

(0, 0, 0, 0, 0, 0)	Start of song
(1, 0, 0, 0, 0, 15)	Instrument: accordion
(1, 0, 0, 0, 0, 36)	Instrument: trombone
(1, 0, 0, 0, 0, 39)	Instrument: brasses
(2, 0, 0, 0, 0, 0)	Start of notes
(3, 1, 1, 41, 15, 36)	Note: beat=1, position=1, pitch=E2, duration=48, instrument=trombone
(3, 1, 1, 65, 4, 39)	Note: beat=1, position=1, pitch=E4, duration=12, instrument=brasses
(3, 1, 1, 65, 17, 15)	Note: beat=1, position=1, pitch=E4, duration=72, instrument=accordion
(3, 1, 1, 68, 4, 39)	Note: beat=1, position=1, pitch=G4, duration=12, instrument=brasses
(3, 1, 1, 68, 17, 15)	Note: beat=1, position=1, pitch=G4, duration=72, instrument=accordion
(3, 1, 1, 73, 17, 15)	Note: beat=1, position=1, pitch=C5, duration=72, instrument=accordion
(3, 1, 13, 68, 4, 39)	Note: beat=1, position=13, pitch=G4, duration=12, instrument=brasses
(3, 1, 13, 73, 4, 39)	Note: beat=1, position=13, pitch=C5, duration=12, instrument=brasses
(3, 2, 1, 73, 12, 39)	Note: beat=2, position=1, pitch=C5, duration=36, instrument=brasses
(3, 2, 1, 77, 12, 39)	Note: beat=2, position=1, pitch=E5, duration=36, instrument=brasses
...	...
(4, 0, 0, 0, 0, 0)	End of song

N-beat continuation

Input

(0, 0, 0, 0, 0, 0)	Start of song
(1, 0, 0, 0, 0, 15)	Instrument: accordion
(1, 0, 0, 0, 0, 36)	Instrument: trombone
(1, 0, 0, 0, 0, 39)	Instrument: brasses
(2, 0, 0, 0, 0, 0)	Start of notes
(3, 1, 1, 41, 15, 36)	Note: beat=1, position=1, pitch=E2, duration=48, instrument=trombone
(3, 1, 1, 65, 4, 39)	Note: beat=1, position=1, pitch=E4, duration=12, instrument=brasses
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(3, 1, 1, 73, 17, 15)	Note: beat=1, position=1, pitch=C5, duration=72, instrument=accordion
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(3, 1, 13, 73, 4, 39)	Note: beat=1, position=13, pitch=C5, duration=12, instrument=brasses
(3, 2, 1, 73, 12, 39)	Note: beat=2, position=1, pitch=C5, duration=36, instrument=brasses
(3, 2, 1, 77, 12, 39)	Note: beat=2, position=1, pitch=E5, duration=36, instrument=brasses
...	...
(4, 0, 0, 0, 0, 0)	End of song

Only needs to train ONE model!

Example Results

Unconditional
generation



Instrument-
informed generation



church-organ, viola,
contrabass, strings,
voices, horn, oboe

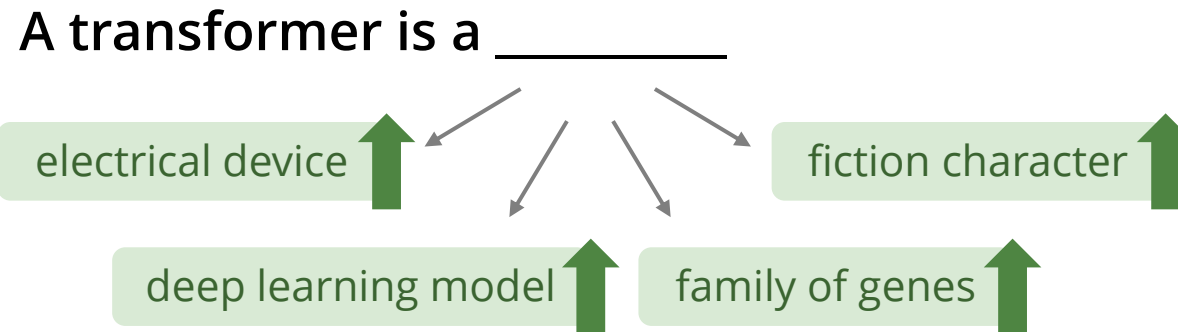
4-beat continuation



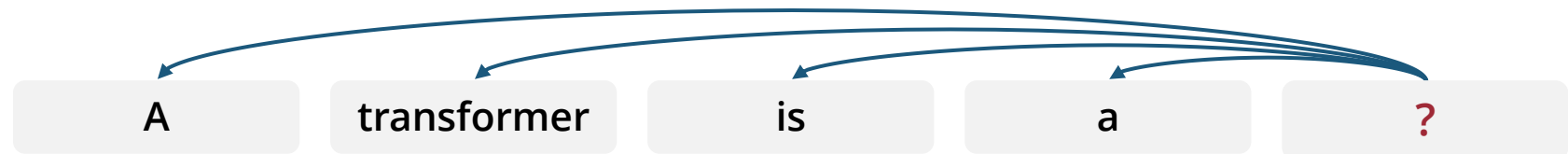
Mozart's
Eine kleine Nachtmusik



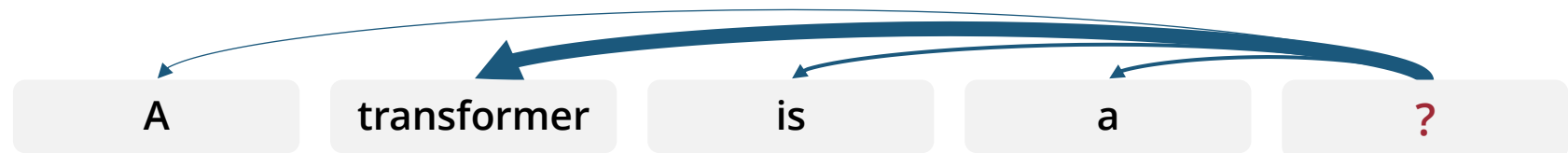
The Magic of Transformers – Self-attention Mechanism



Uniform attention



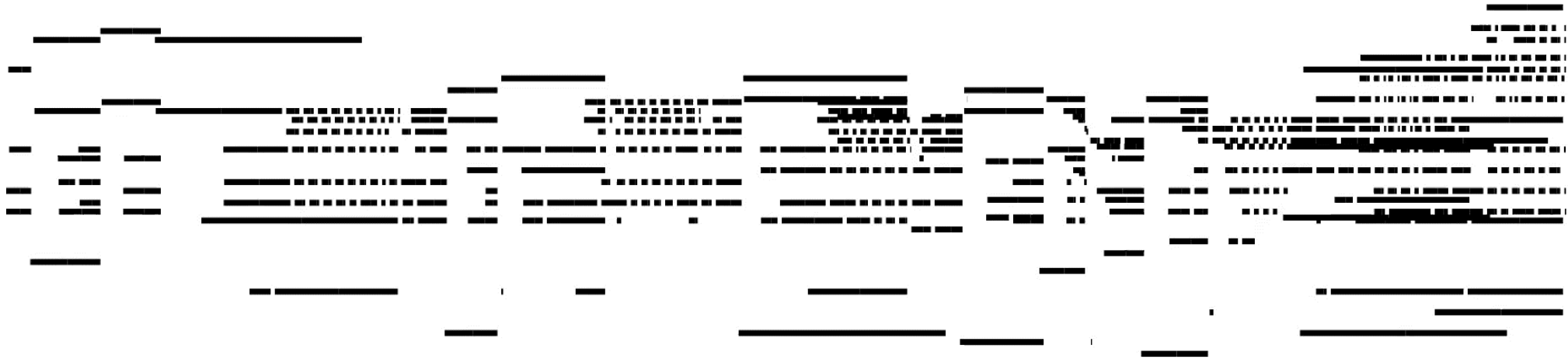
Variable attention



Transformers learn what to attend to from big data!

Visualizing Musical Self-attention (Huang et al., 2018)

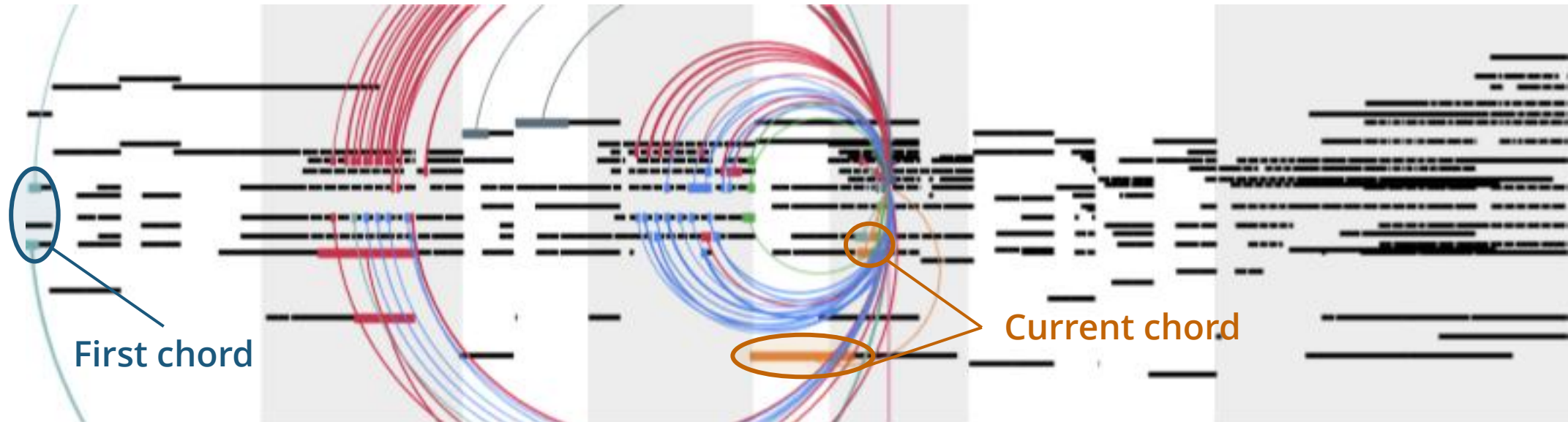
(Each color represents an attention head)



(Source: Huang et al., 2018)

Visualizing Musical Self-attention (Huang et al., 2018)

(Each color represents an attention head)



(Source: Huang et al., 2018)

Can we go beyond case studies?

Systematically Analyzing Musical Self-attention

- We proposed two new quantities for measuring **mean relative attention**

$$\gamma_k^{(d)} = \frac{\sum_{\mathbf{x} \in \mathcal{D}} \sum_{s > t} a_{s,t}(\mathbf{x}) \mathbb{1}_{x_t^{(d)} - x_s^{(d)} = k}}{\sum_{\mathbf{x} \in \mathcal{D}} \sum_{s > t} a_{s,t}(\mathbf{x})}$$

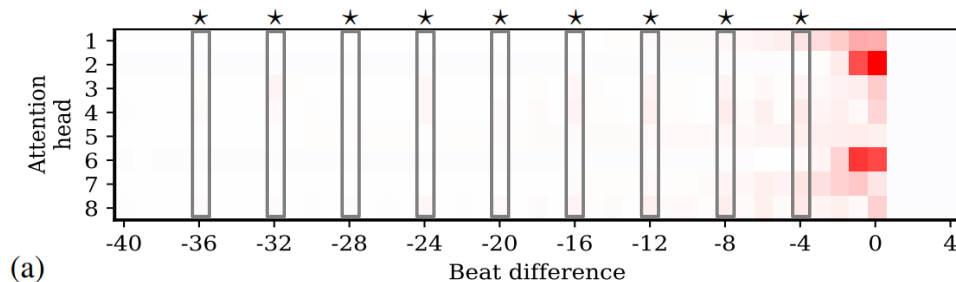
$$\tilde{\gamma}_k^{(d)} = \gamma_k^{(d)} - \frac{\sum_{\mathbf{x} \in \mathcal{D}} \sum_{s > t} \mathbb{1}_{x_t^{(d)} - x_s^{(d)} = k}}{\sum_{\mathbf{x} \in \mathcal{D}} \sum_{s > t} 1}$$

- The MMT model attends more to notes

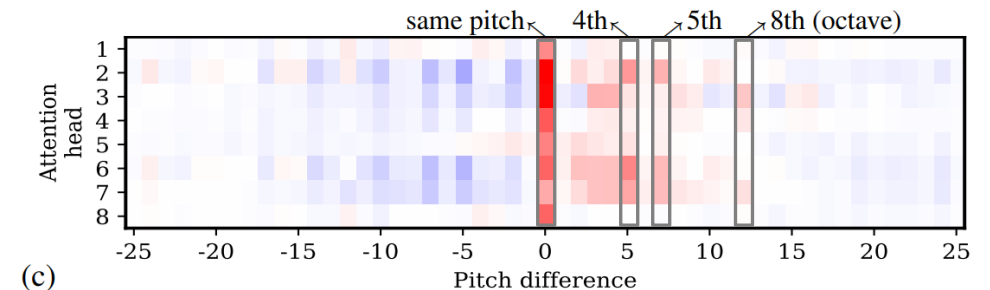
that are $4N$ beats away in the past

that has a pitch in an octave above which forms a consonant interval

Positive and negative mean relative attention gain



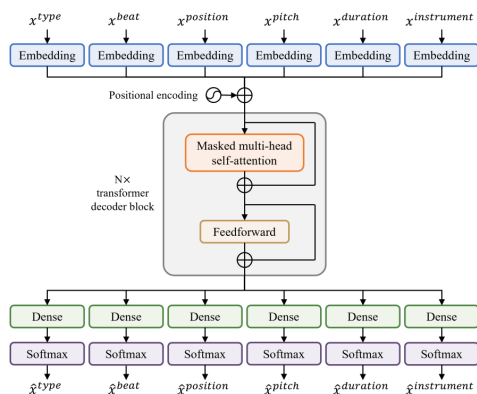
Positive and negative mean relative attention gain



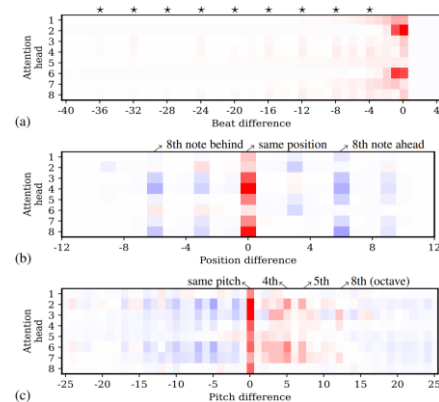
Summary

- **State-of-the-art orchestral music generation model**
- Presented the **first systematic analysis** of **musical self-attention**
- Showed that MMT learns a **relative self-attention for beat and pitch**

Multitrack Music Transformer



Musical Self-attention



Paper: arxiv.org/abs/2207.06983
Demo: salu133445.github.io/mmt/
Code: github.com/salu133445/mmt



UC San Diego



Towards Automatic Instrumentation by Learning to Separate Parts in Multitrack Music

Hao-Wen Dong¹ Chris Donahue² Taylor Berg-Kirkpatrick¹ Julian McAuley¹

¹ University of California San Diego ² Stanford University



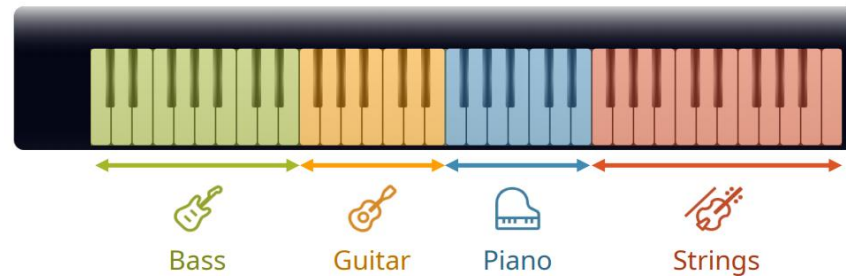
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Automatic Instrumentation

- **Goal:** Dynamically **assign instruments** to notes in solo music

Intelligent musical instruments



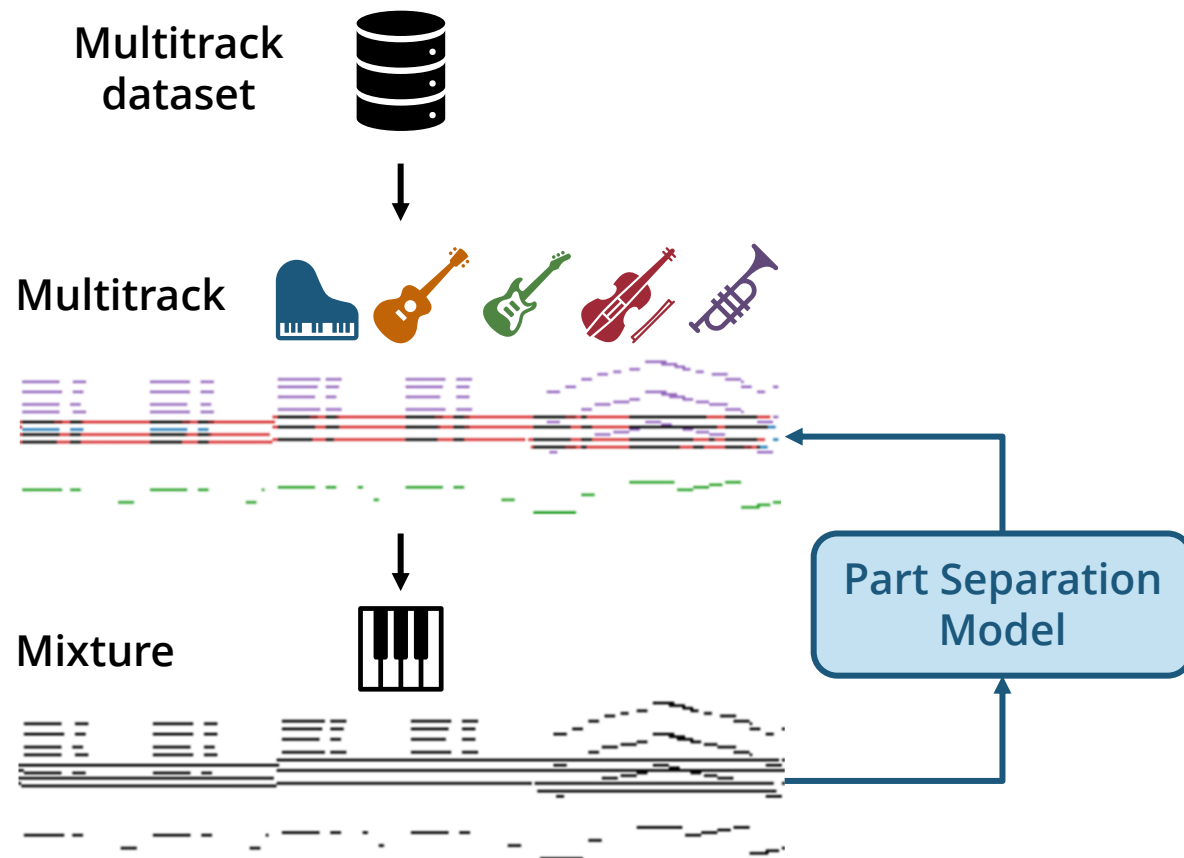
Assistive composing tools



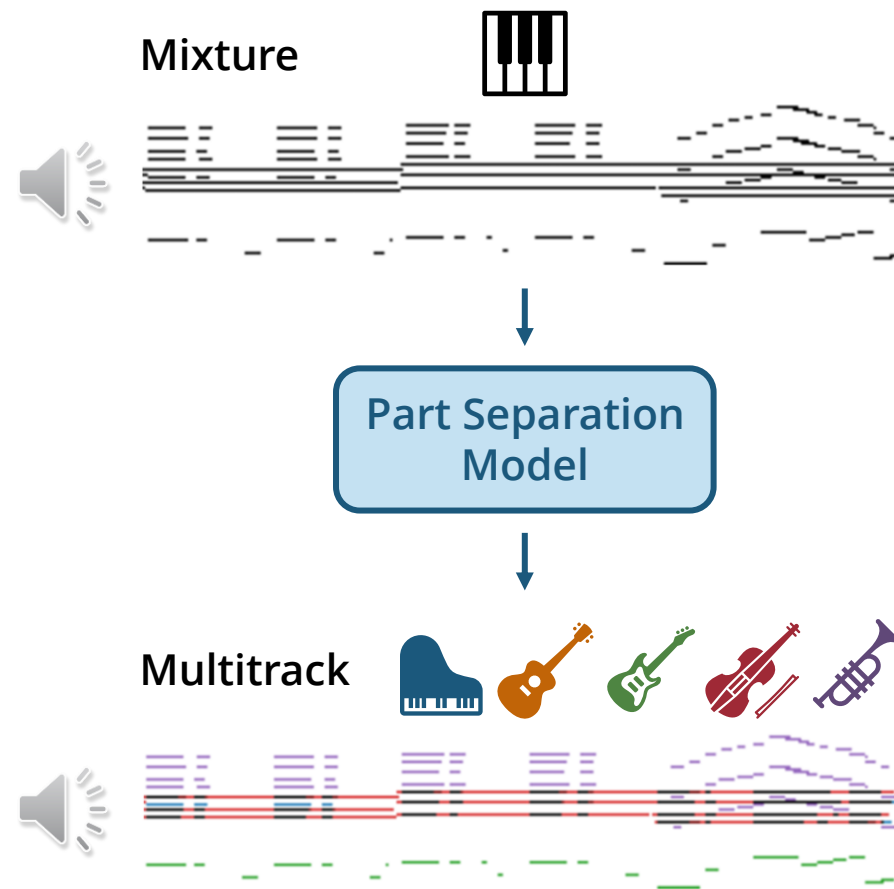
How can we acquire paired data?

Learning Automatic Instrumentation **without Paired Data**

Training



Inference

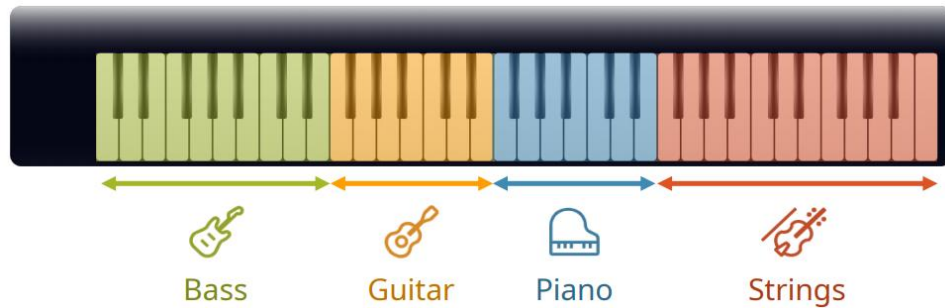


Online vs Offline Models

Online models

Can only look at the **past**

- LSTMs
- Transformer decoders



Offline models

Can look at both the **future** and the **past**

- BiLSTMs
- Transformer encoders



Representation & Datasets

A **sequence of notes** specified by

- **Time** Onset time (in time step)
- **Pitch** Pitch as a MIDI note number
- **Duration** Note length (in time step)
- **Frequency** Frequency of the pitch (in Hz)
- **Beat** Onset time (in beat)
- **Position** Position within a beat (in time step)

Representing music in a
machine-readable format

Dataset	Hours	Files	Notes	Parts	Ensemble	Most common label
Bach chorales [31]	3.23	409	96.6K	4	soprano, alto, tenor, bass	bass (27.05%)
String quartets [32]	6.31	57	226K	4	first violin, second violin, viola, cello	first violin (38.72%)
Game music [33]	45.05	4.61K	2.46M	3	pulse wave I, pulse wave II, triangle wave	pulse wave II (39.35%)
Pop music [34]	1.02K	16.2K	63.6M	5	piano, guitar, bass, strings, brass	guitar (42.50%)

Example Results

- Produce alternative convincing instrumentations for an existing arrangement

piano, guitar, bass, strings, brass

Original



LSTM
(w/o entry hints)



BiLSTM
(w/ entry hints)



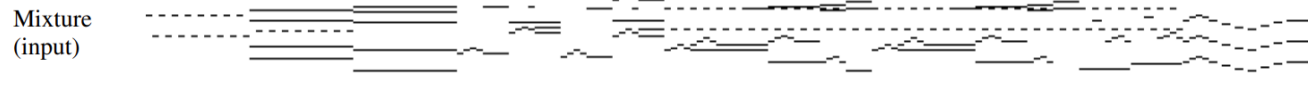
More Results

Bach chorales



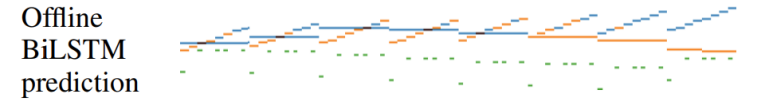
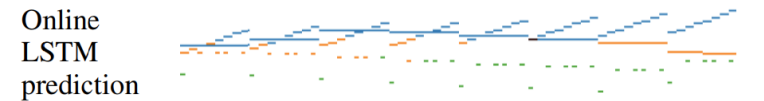
(Audio available. ¹ Colors: soprano, alto, tenor, bass.)

String quartets



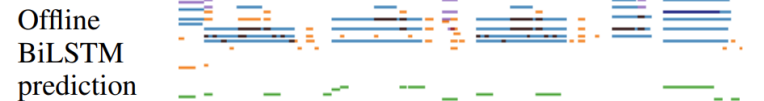
(Audio available. ¹ Colors: first violin, second violin, viola, cello.)

Game music



(Audio available. ¹ Colors: pulse wave I, pulse wave II, triangle wave.)

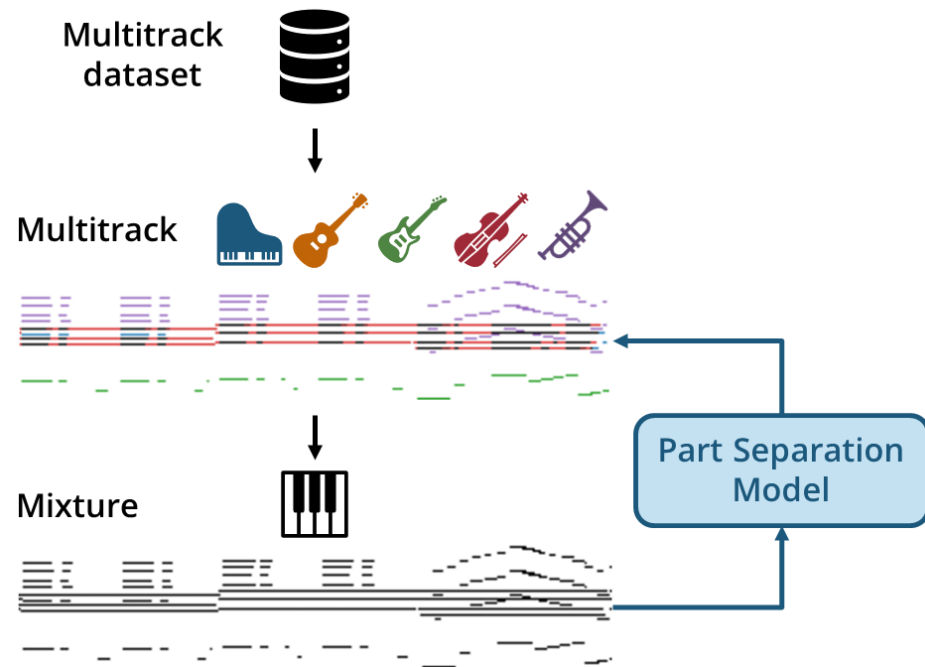
Pop music



(Audio available. ¹ Colors: piano, guitar, bass, strings, brass.)

Summary

- First ever machine learning model for **automatic instrumentation**
- Potential applications in **assistive creation tools** and **intelligent keyboards**



Paper: arxiv.org/abs/2107.05916
Demo: salu133445.github.io/arranger
Code: github.com/salu133445/arranger

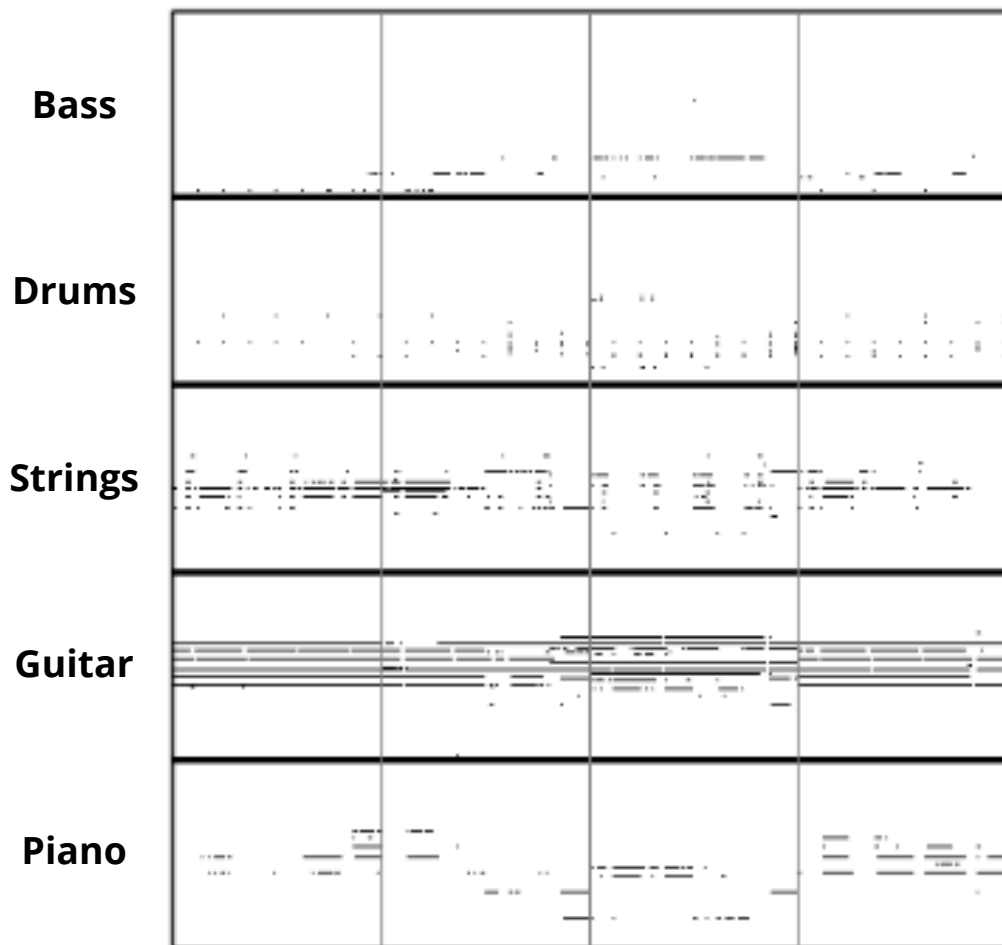


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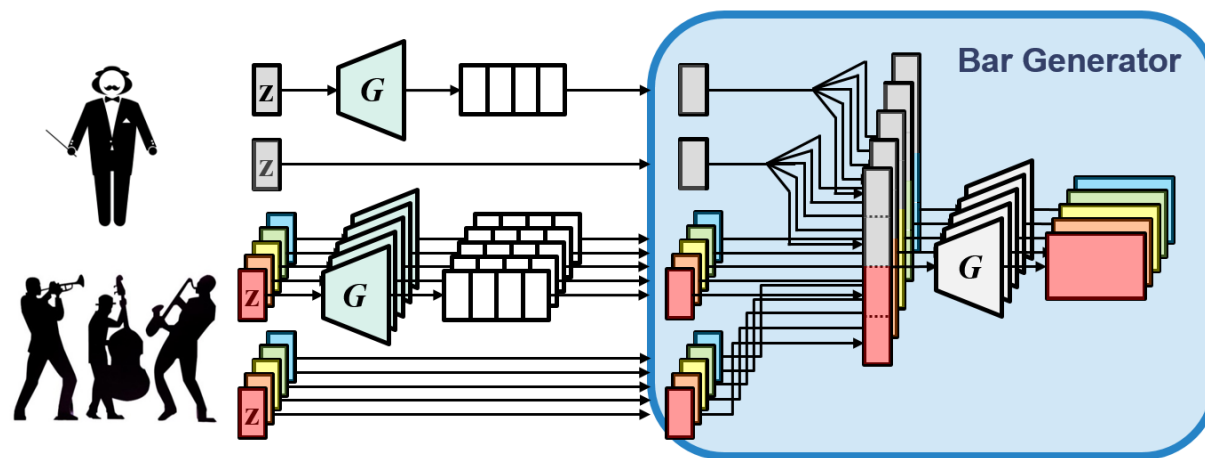
Stanford

Generating Multi-instrument Music using GANs (AAAI 2018)

Multitrack Piano Roll



MuseGAN Generator



MuseGAN Features in AWS DeepComposer (2020)

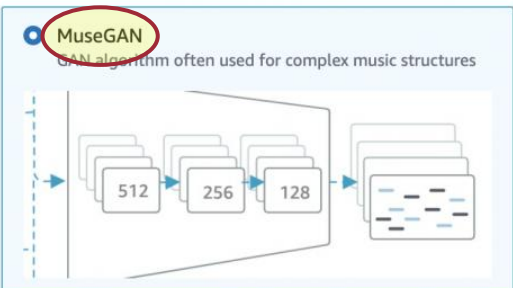
AWS DeepComposer > Models > Train a model

Train a model

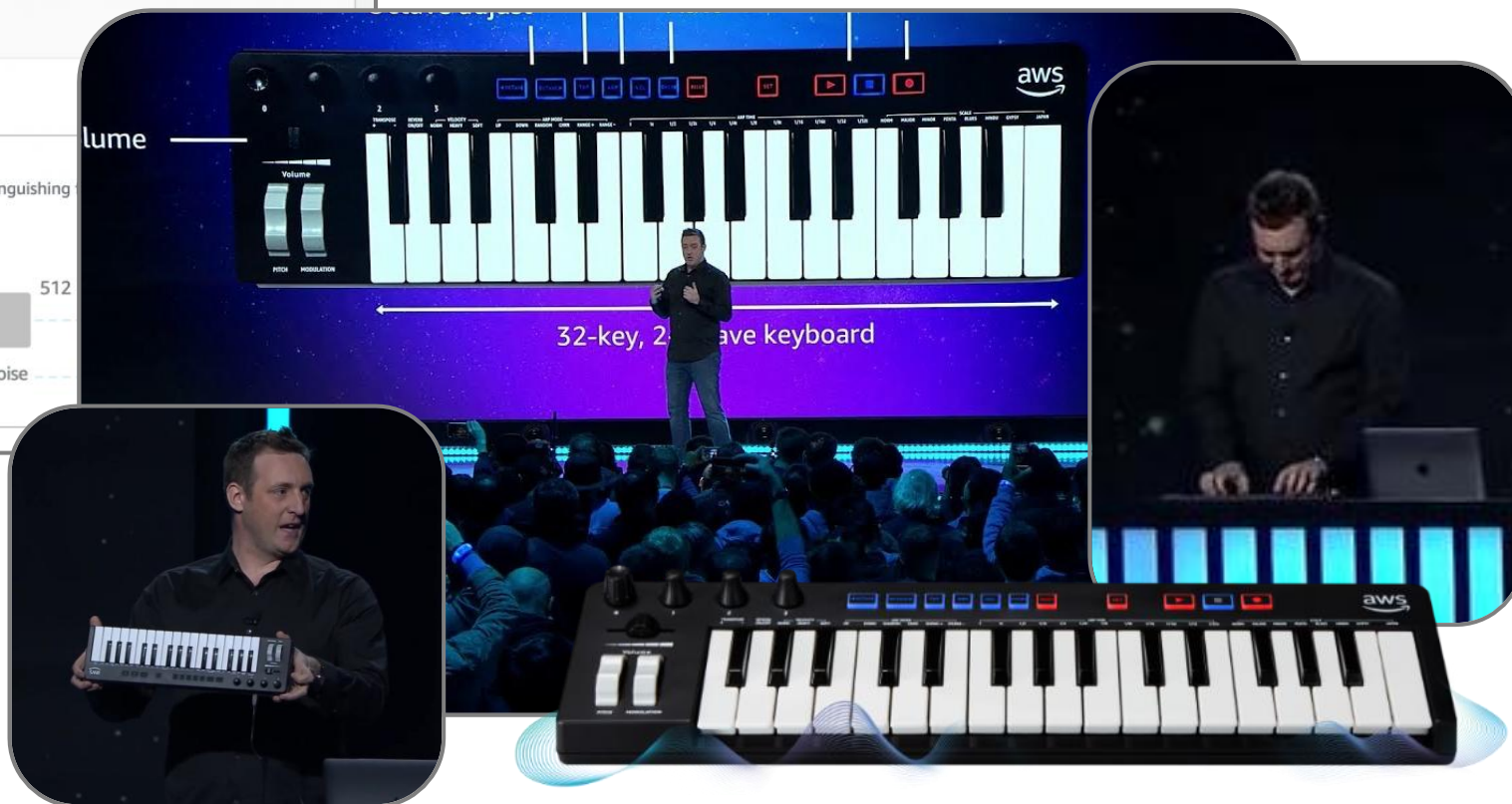
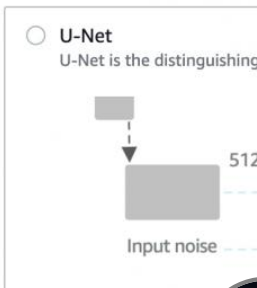
Generative algorithm [Info](#)

Choose a generative algorithm to train a model

MuseGAN
GAN algorithm often used for complex music structures



U-Net
U-Net is the distinguishing

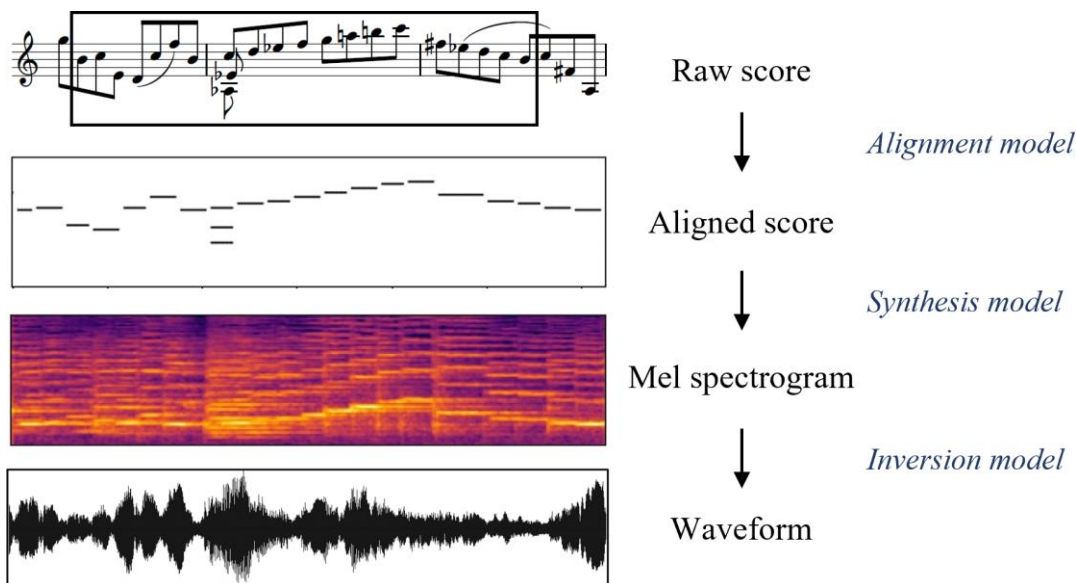


amazon.com/dp/B07YGZ4V5B/

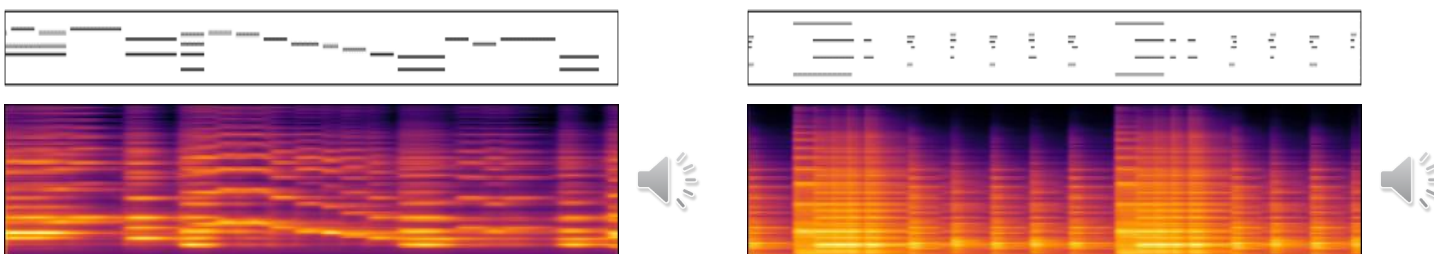
Julien Simon, "AWS DeepComposer – Now Generally Available With New Features," *AWS News Blog*, April 2, 2020.

Synthesizing Expressive Violin Performance (ICASSP 2022)

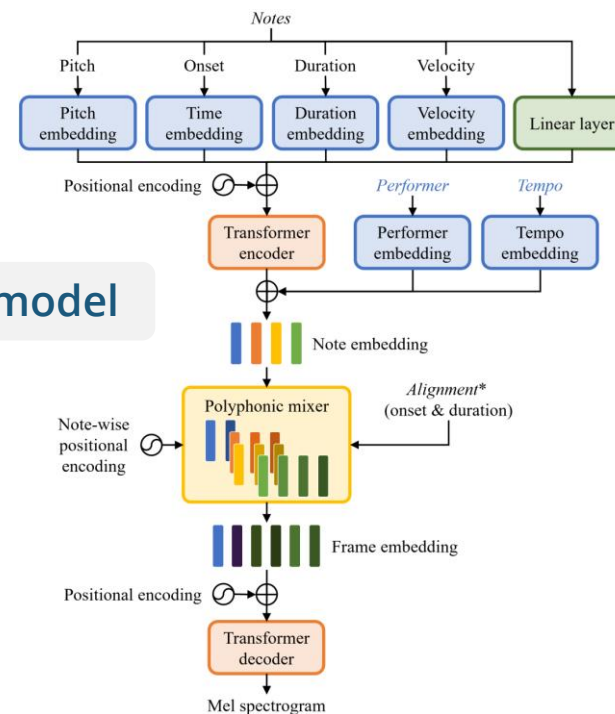
Performance synthesis



Example results



TTS-based model



Challenges & Opportunities

| The Five Challenges

Representations

Usability

Creativity

Multimodality

Personalization

Challenge 1: Representations

How can we best represent music for machine learning?

Music Generation – Four Paradigms



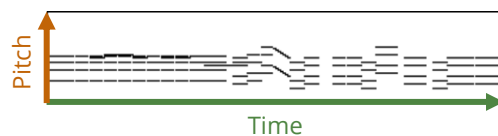
Symbolic music generation

Text-based

Image-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



Piano roll



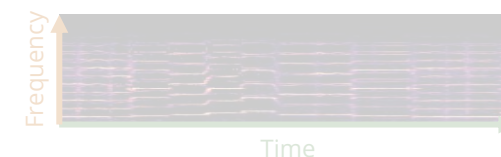
Audio-domain music generation

Time series-based

Image-based

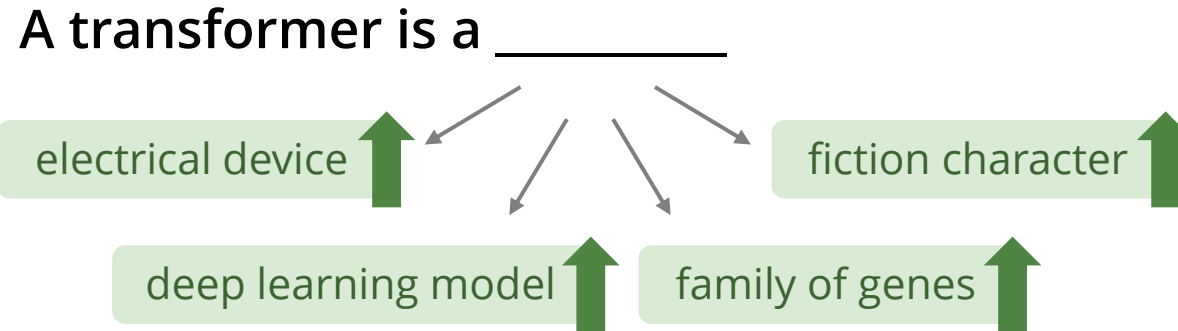


Waveform

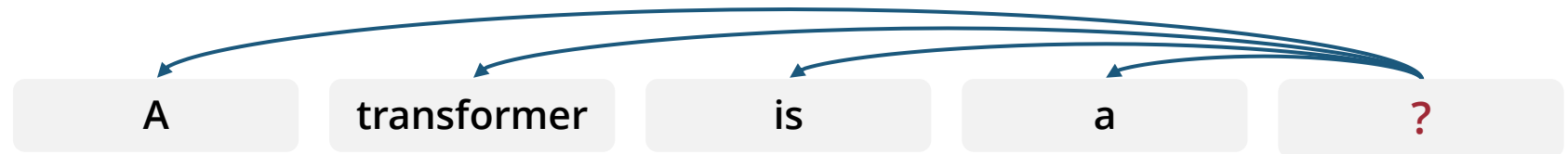


Spectrogram

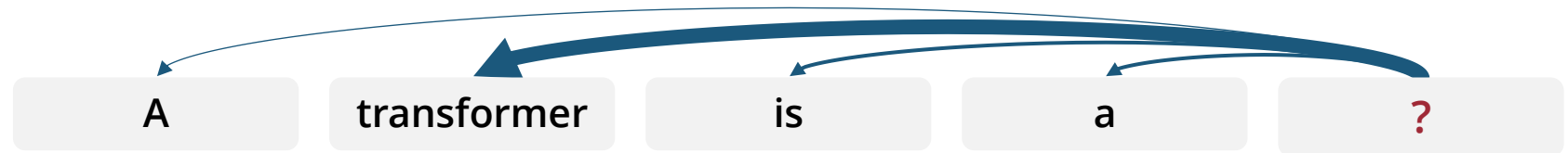
The Magic of Transformers – Self-attention Mechanism



Uniform attention



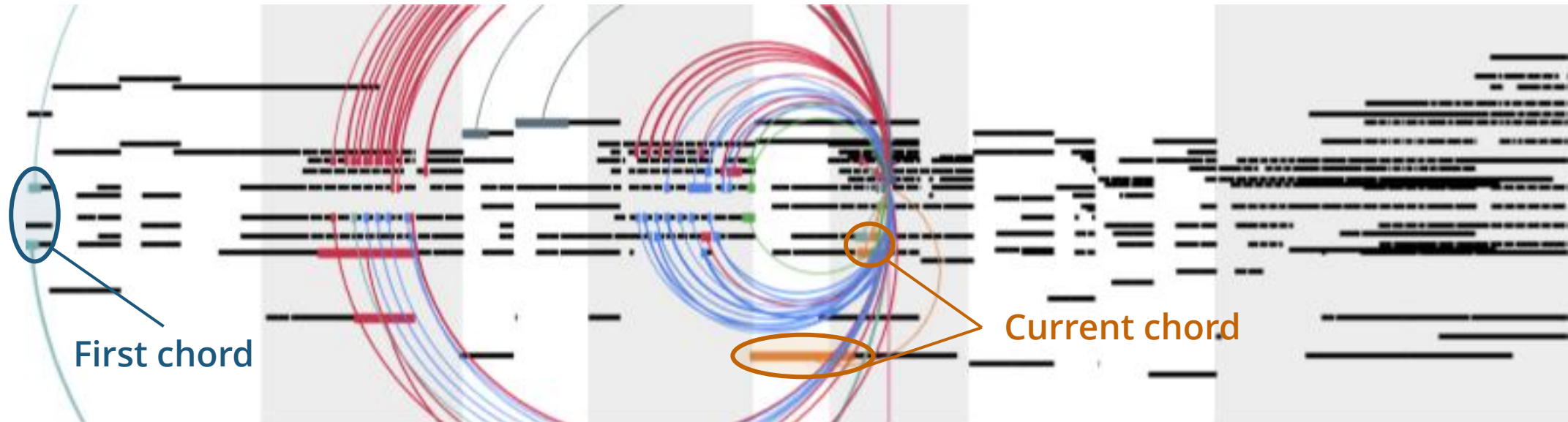
Variable attention



Transformers learn what to attend to from big data!

Visualizing Musical Self-attention (Huang et al., 2018)

(Each color represents an attention head)



(Source: Huang et al., 2018)

Systematically Analyzing Musical Self-attention

- We proposed two new quantities for measuring **mean relative attention**

$$\gamma_k^{(d)} = \frac{\sum_{\mathbf{x} \in \mathcal{D}} \sum_{s > t} a_{s,t}(\mathbf{x}) \mathbb{1}_{x_t^{(d)} - x_s^{(d)} = k}}{\sum_{\mathbf{x} \in \mathcal{D}} \sum_{s > t} a_{s,t}(\mathbf{x})}$$

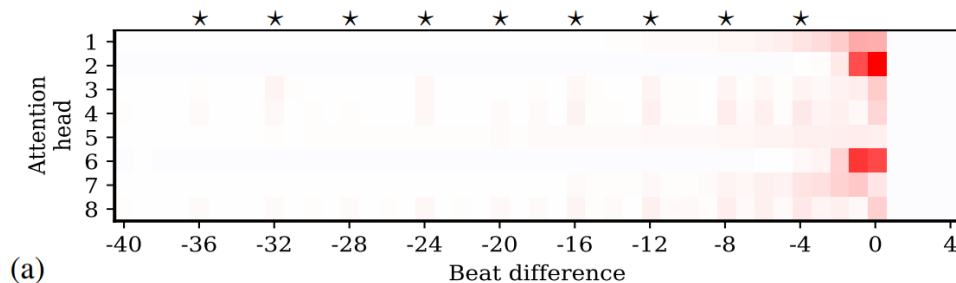
$$\tilde{\gamma}_k^{(d)} = \gamma_k^{(d)} - \frac{\sum_{\mathbf{x} \in \mathcal{D}} \sum_{s > t} \mathbb{1}_{x_t^{(d)} - x_s^{(d)} = k}}{\sum_{\mathbf{x} \in \mathcal{D}} \sum_{s > t} 1}$$

- The MMT model attends more to notes

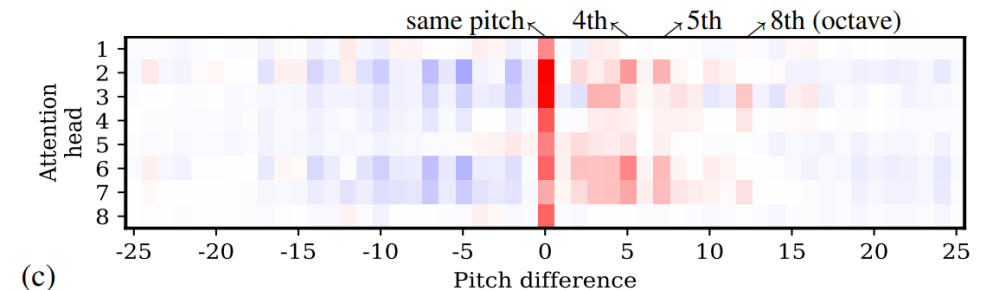
that are $4N$ beats away in the past

that has a pitch in an octave above which forms a consonant interval

Positive and negative mean relative attention gain



Positive and negative mean relative attention gain



Music Generation – Four Paradigms



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



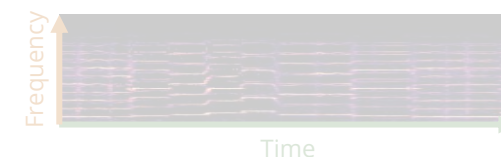
Audio-domain music generation

Time series-based



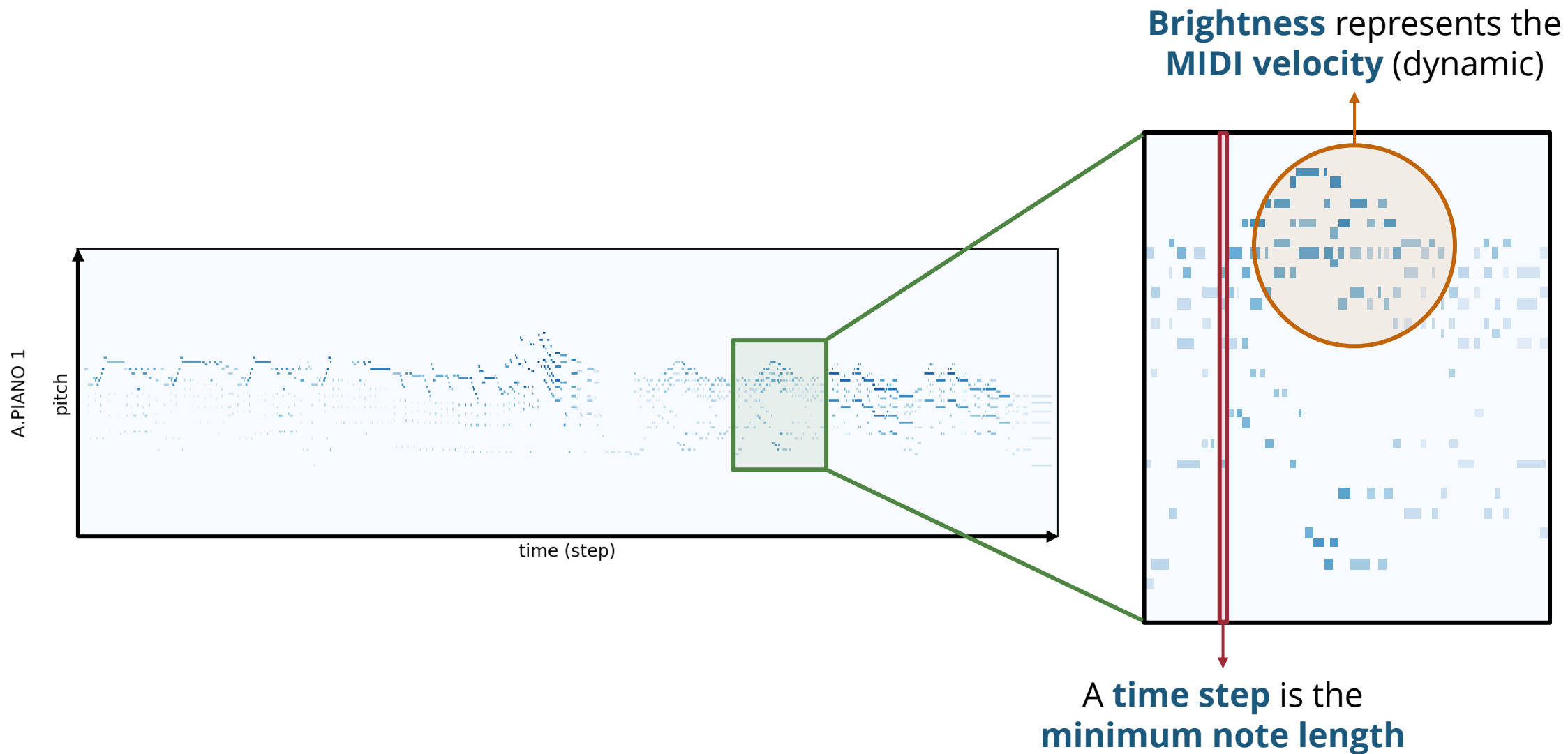
Waveform

Image-based

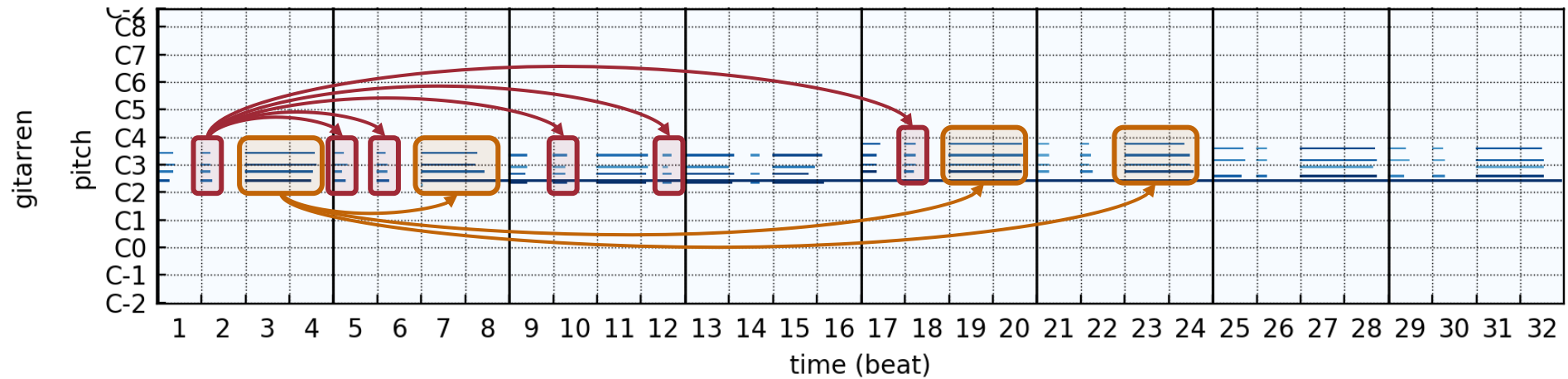


Spectrogram

Piano Roll Representation



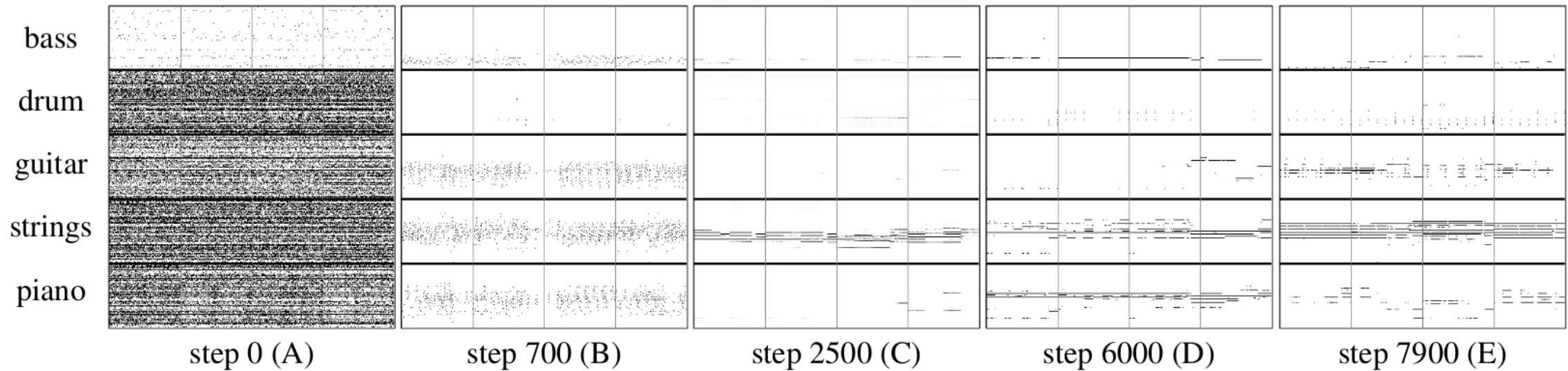
Why Piano Rolls?



Many musical patterns like melodies, chords, scales and arpeggios are **translational invariant** in the temporal and pitch axes

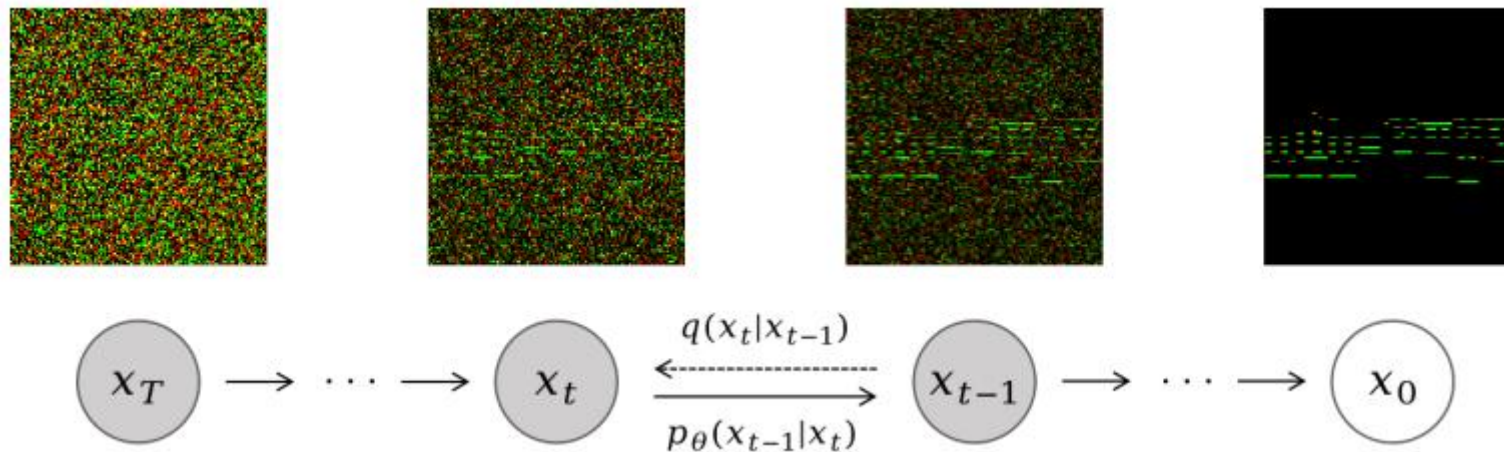
MuseGAN (Dong et al., 2018)

Examples of generated music



(Source: Dong et al., 2018)

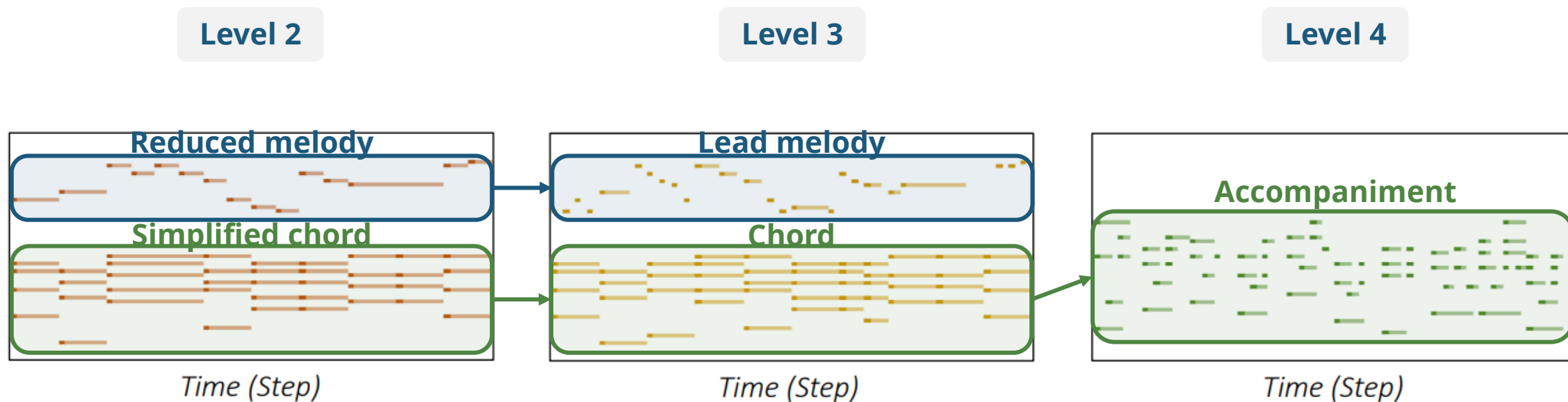
Polyffusion (Min et al., 2023)



(Source: Min et al., 2023)

polyffusion.github.io

Example: Cascaded Diffusion Models (Wang et al., 2024)



(Source: Wang et al., 2024)

wholesonggen.github.io

Music Generation – Four Paradigms



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



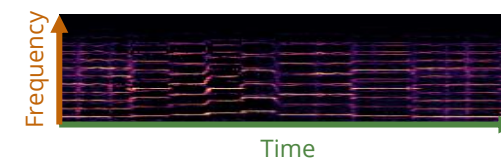
Audio-domain music generation

Time series-based



Waveform

Image-based



Spectrogram

Challenge 1: Representations

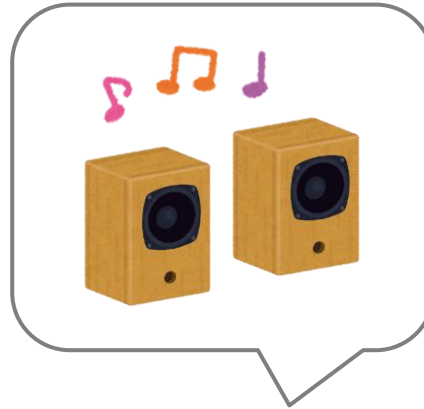
How can we best represent music for machine learning?

Challenge 2: Multimodality

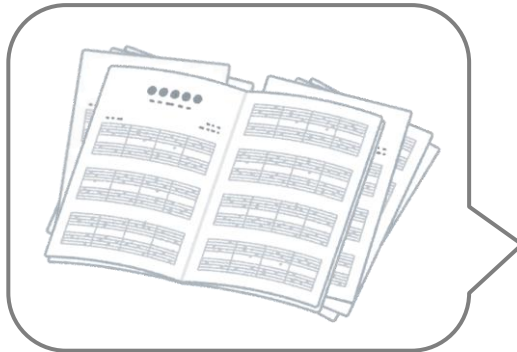
Can AI learn to create music by “listening to” music rather than “reading” music?

Human-inspired Machine Learning for Music & Audio

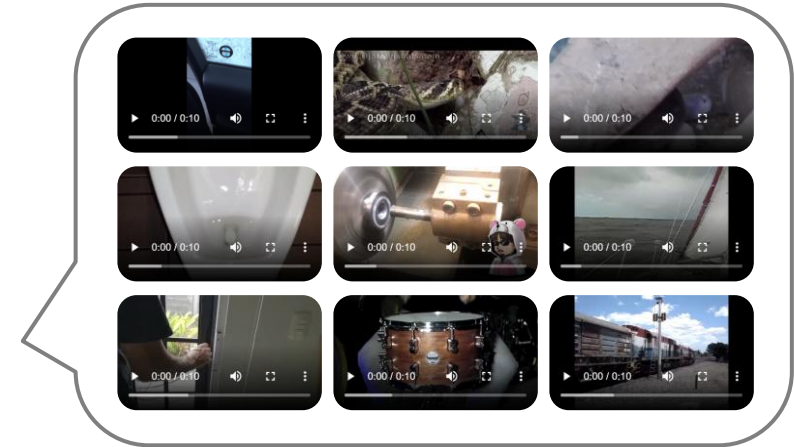
Learning from listening



Learning from reading



Learning from watching



A Baseline through Music Transcription

- Apply a music transcript model to acquire symbolic music data from audio
- But can we directly **learn to compose symbolic music through “listening to music” and “practicing music,”** just like how humans do?

Multimodal Inputs for Generative Music AI



Text



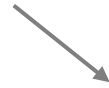
Image



Video



Emotion



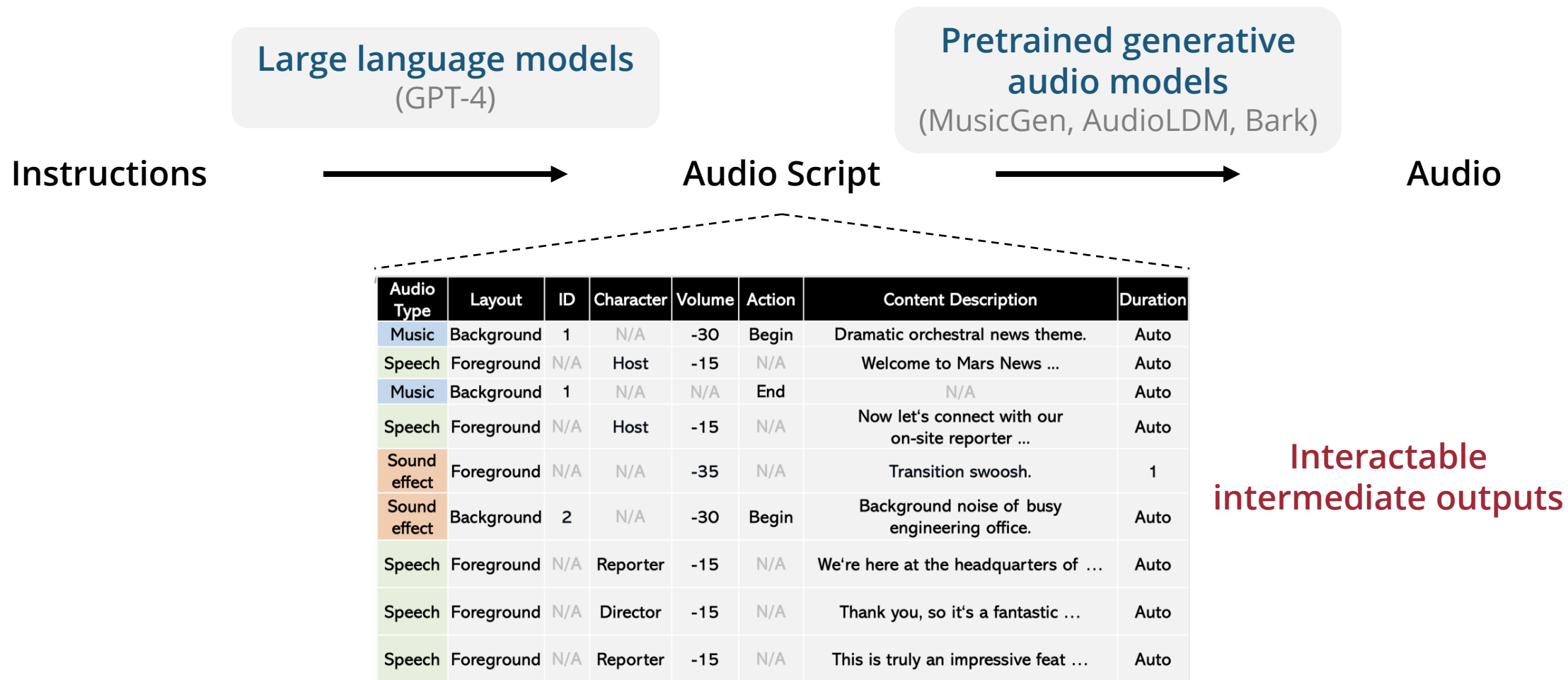
Challenge 2: Multimodality

Can AI learn to create music by “listening to” music rather than “reading” music?

Challenge 3: Usability

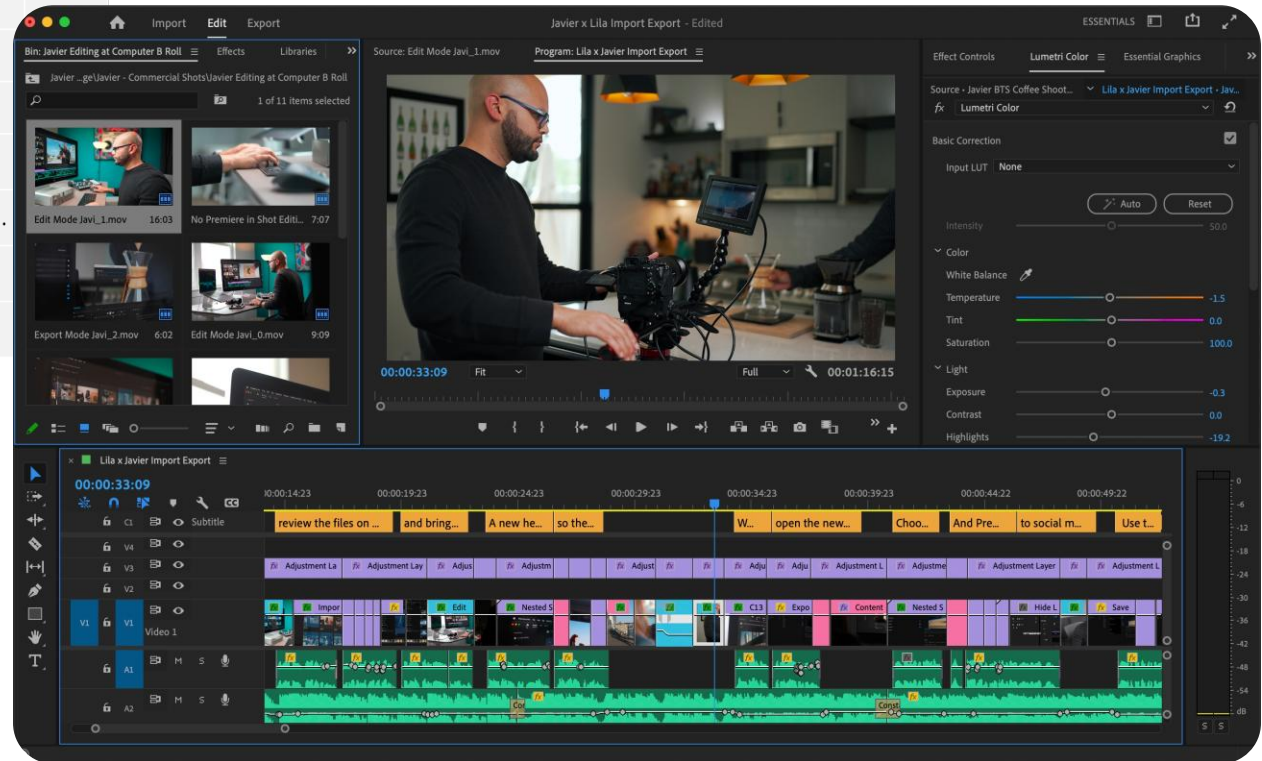
How can AI music tools be integrated into an artist's creative workflow?

WavJourney: Compositional Audio Creation (Liu et al., 2023)



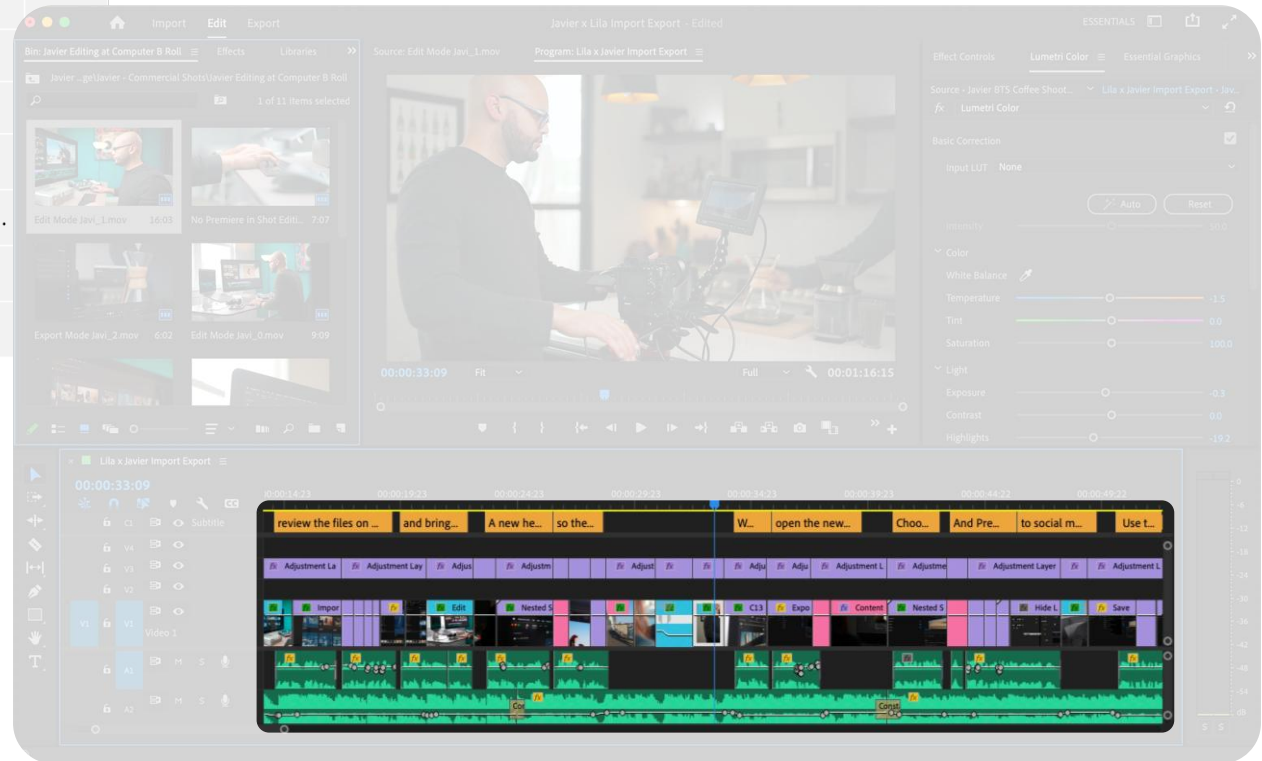
Integrating Generative AI into the Creative Workflow

Audio Type	Layout	ID	Character	Volume	Action	Content Description	Duration
Music	Background	1	N/A	-30	Begin	Dramatic orchestral news theme.	Auto
Speech	Foreground	N/A	Host	-15	N/A	Welcome to Mars News ...	Auto
Music	Background	1	N/A	N/A	End	N/A	
Speech	Foreground	N/A	Host	-15	N/A	Now let's connect with our on-site reporter ...	
Sound effect	Foreground	N/A	N/A	-35	N/A	Transition swoosh.	
Sound effect	Background	2	N/A	-30	Begin	Background noise of busy engineering office.	
Speech	Foreground	N/A	Reporter	-15	N/A	We're here at the headquarters of ...	
Speech	Foreground	N/A	Director	-15	N/A	Thank you, so it's a fantastic ...	
Speech	Foreground	N/A	Reporter	-15	N/A	This is truly an impressive feat ...	



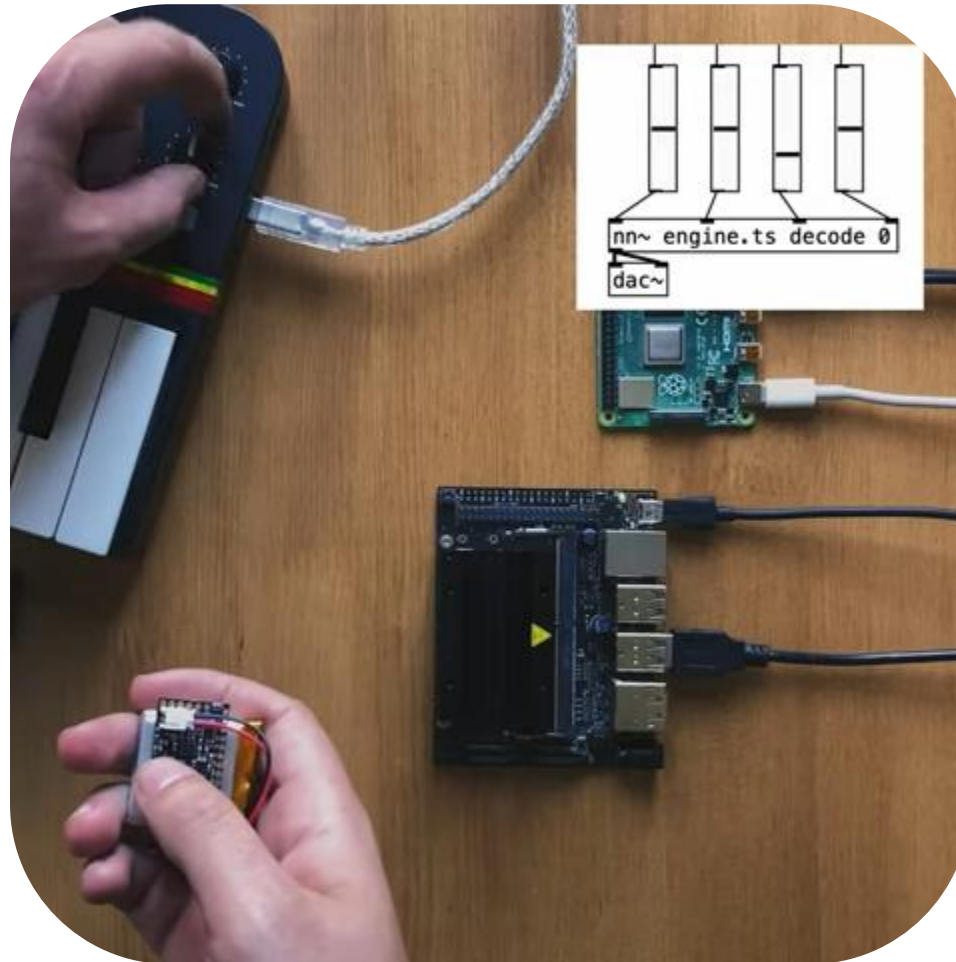
Integrating Generative AI into the Creative Workflow

Audio Type	Layout	ID	Character	Volume	Action	Content Description	Duration
Music	Background	1	N/A	-30	Begin	Dramatic orchestral news theme.	Auto
Speech	Foreground	N/A	Host	-15	N/A	Welcome to Mars News ...	Auto
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Speech	Foreground	N/A	Director	-15	N/A	Thank you, so it's a fantastic ...	
Speech	Foreground	N/A	Reporter	-15	N/A	This is truly an impressive feat ...	



Integration into professional creative workflow

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



youtu.be/jAIRf4nGgYI

Misusable Music Tools (Nao Tokui, 2023)

- “Throughout history, music and technology have often intertwined, with **new technologies being misused by artists** (turntables, etc)”
— Nao Tokui, 2024
- “AI is more challenging to misuse because **it lacks a physical entity and operates as a black box.**”
— Nao Tokui, 2024



Challenge 3: Usability

How can AI music tools be integrated into an artist's creative workflow?

Challenge 4: Personalization

How can we make “my personal AI music tools”?

YACHT & Google Magenta

“The band first took all 82 songs from their **back catalog** and isolated each part, from bass lines to vocal melodies to drum rhythms; they then took those isolated parts and broke them up into four-bar loops. Then, **they put those loops into the machine learning model**, which **put out new melodies based on their old work**. They did a similar process with **lyrics, using their old songs plus other material they considered inspiring**. The final task was to pick lyrics and melodies that made sense, and pair them together to make a song.”



youtu.be/_yz8QYzcfxI

YACHT, “YACHT — SCATTERHEAD (4K Lyric Video)”, *YouTube*, July 26, 2019.

Megan Friedman, “Behind Magenta, the tech that rocked I/O,” *The Keyword*, May 20, 2019.

Adam Roberts, “YACHT’s new album is powered by ML + Artists”, *Magenta Blog*, September 13, 2019.

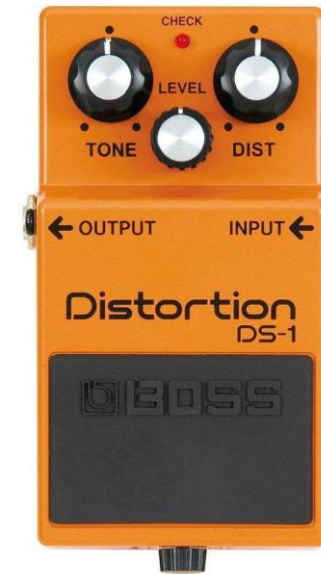
Ease of Personalization for Artists

- Through **finetuning our own models**
- Through **finetuning with live inputs**
- Python scripting vs friendly user interface

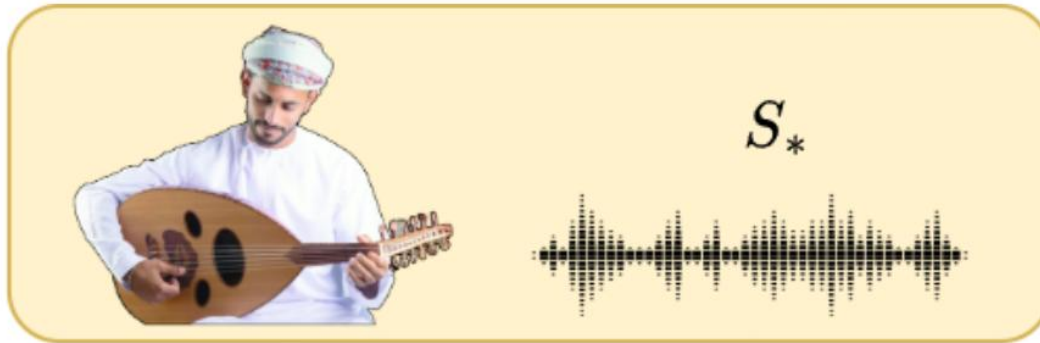
- **Can we do better?**

Overfitting vs Distortion

- Will **overfitting** be a new music expression, the “**distortion**” for AI music?



Personalized Text-to-Music Generation (Plitsis et al., 2024)



S^*

A disco song with a S^*



S_* in a cathedral



S_* in a jazz style

S^*

A recording of a S^* song with a hip hop drum beat accompaniment



(Source: Plitsis et al., 2024)

Challenge 4: Personalization

How can we make “my personal AI music tools”?

Challenge 5: Creativity

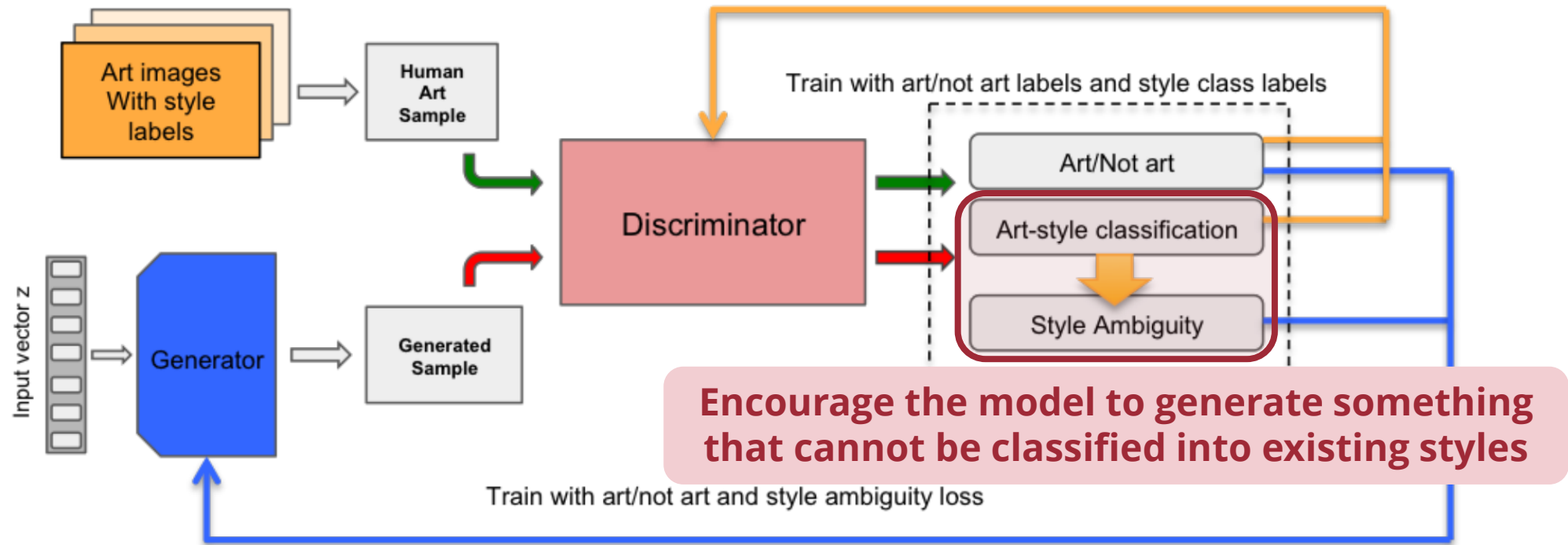
Can AI ever be creative? How can AI augment human creativity?

| The Curse of Machine Learning

- As the old saying goes, “**Artificial intelligence is only as good as the data it learns from.**”
- Machine learning models are trained to approximate some distribution in its formal formulation.
- This seems to contradict the idea of creativity that requires **the ability to extrapolate** and **think out of the box.**

- **Can AI ever be creative?**

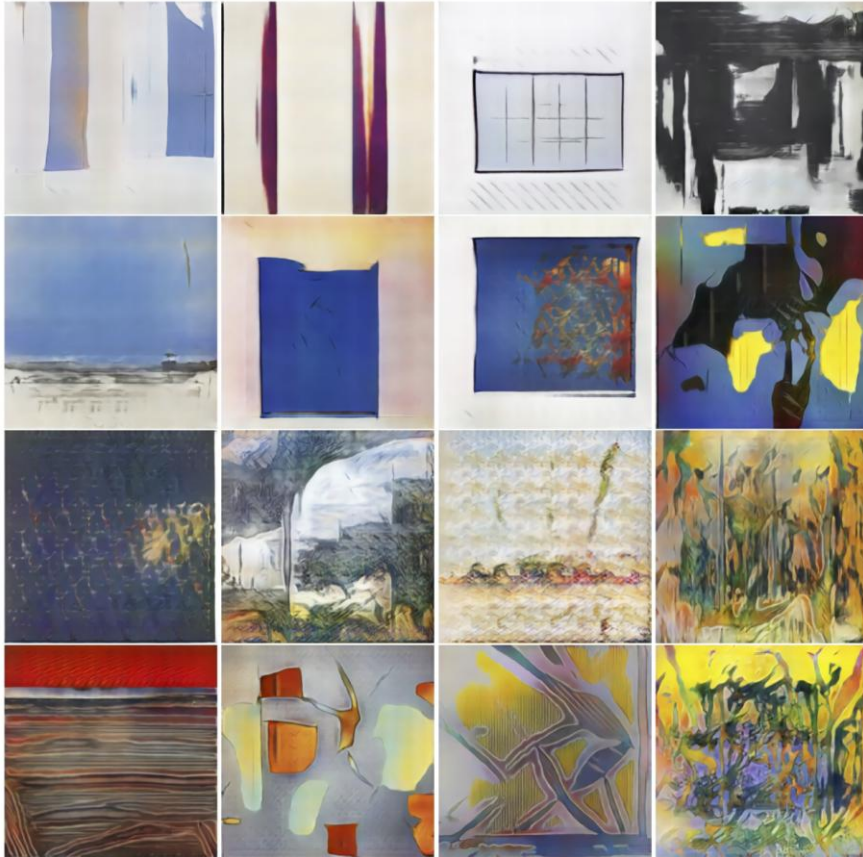
Creative Adversarial Network (Elgammal et al., 2017)



(Source: Elgammal et al., 2017)

Creative Adversarial Network (Elgammal et al., 2017)

Example generated images



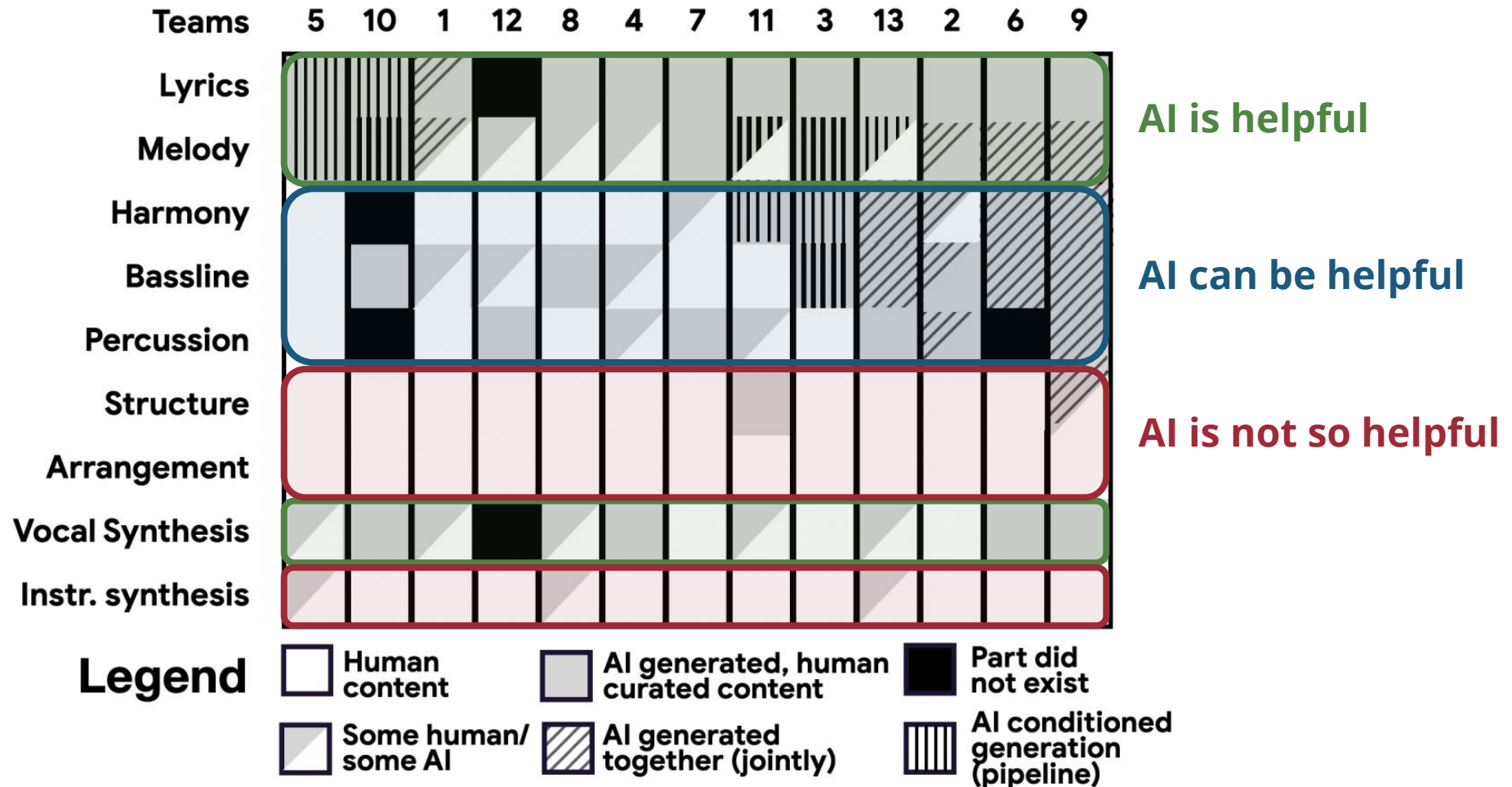
Best samples



(Source: Elgammal et al., 2017)

Ahmed Elgammal, Bingchen Liu, Mohamed Elhoseiny, and Marian Mazzone, "[CAN: Creative Adversarial Networks, Generating "Art" by Learning About Styles and Deviating from Style Norms](#)," ICCV, 2017.

How can AI Augment Human Creativity?



(Source: Huang et al., 2020)

| Creativity vs Art

Creativity is allowing yourself to make mistakes.
Art is knowing which ones to keep.

— Scott Adams

Challenge 5: Creativity

Can AI ever be creative? How can AI augment human creativity?

The Five Challenges

Representations

Multimodality

Usability

Personalization

Creativity

- **Representations:** How can we best represent music for machine learning?
- **Multimodality:** Can AI learn to create music by “listening to” music rather than “reading” music?
- **Usability:** How can AI music tools be integrated into an artist’s creative workflow?
- **Personalization:** How can we make “my personal AI music tools”?
- **Creativity:** Can AI ever be creative? How can AI augment human creativity?

Conclusion

Music & Technology Co-evolves



Hildegard Dodel, Public domain, via Wikimedia Commons.
Taken at Hamamatsu Museum of Musical Instruments, August 2019.
yan, [CC BY-SA 4.0](#), via Wikimedia Commons.

Art challenges Technology



Music

**Augmenting Human Creativity
with AI**



AI



Technology inspires the Art

| The Five Challenges

Representations

Usability

Creativity

Multimodality

Personalization

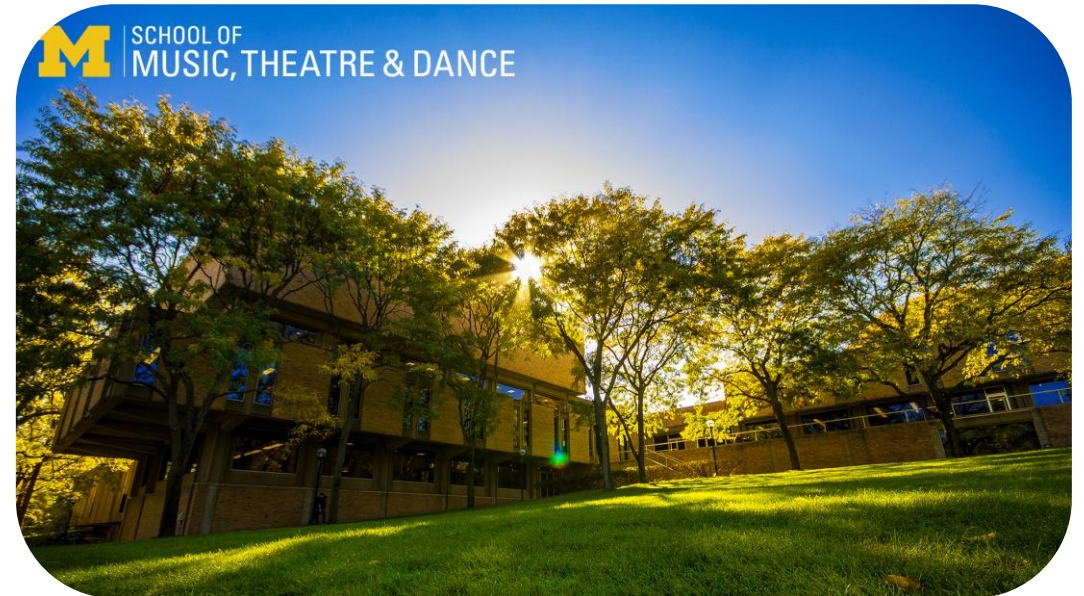
AI Music @ Michigan



Hao-Wen Dong



Julie Zhu



Generative AI for Music: Challenges & Opportunities

Nothing would have been possible without all my fantastic collaborators!



UC San Diego



SONY



hermandong.com / hwdong@umich.edu