Why is AI so Bad at Music?

(at least so far)?
There’s a lot of Artificial Intelligence swirling around us

**New Tool for Building and Fixing Roads and Bridges: Artificial Intelligence**
In Pennsylvania and elsewhere, A.I. is being applied to the nation’s aging infrastructure. Is that wise?

**What Do You Do When A.I. Takes Your Voice?**
Two voice actors say an A.I. company created clones of their voices without their permission. Now they’re suing. The company denies it did anything wrong.

**Can Artificial Intelligence Make the PC Cool Again?**

**An A.I. Robot Named Sophia Tells Graduates to Believe in Themselves**
D’Youville University in Buffalo had an A.I. robot speak at its commencement on Saturday. Not everyone was happy about it.

**A.I.’s ‘Her’ Era Has Arrived**
New chatbot technology can talk, laugh and sing like a human. What comes next is anyone’s guess.

**Can Google Give A.I. Answers Without Breaking the Web?**
Publishers have long worried that artificial intelligence would drive readers away from their sites. They’re about to find out if those fears are warranted.
There’s a lot of Artificial Intelligence swirling around us.

Udio and Suno lead the battle of the AI music generators.

Udio raised $10 million in funding from high-profile investors like a16z, will.i.am, Common, and Instagram co-founder Mike Krieger.

The AI Music Era Is Here. Not Everyone Is a Fan.

AI songwriting has gotten shockingly good — with big implications for the music world.

...but you have to look much harder to find buzz about AI that actually makes music.
Here’s what it sounds like

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The AI Music Era Is Here. Not Everyone Is a Fan

AI songwriting has gotten shockingly good — with big implications for the music world.
Music is hard for Large Language Models

- Musical AI is technologically behind
- Its output is less convincing
- It gets less attention from media and users

So... why is music so hard for LLMs?
Five Forces Effecting Musical AI

Motivation

Why are people making models of musical AI?
## Five Forces Effecting Musical AI

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- Examples: What datasets are people using to train and test their AI models?
- Representation: How are programmers representing musical events in their AI?
- Structure: What aspects of musical organization are being learned by the AI?
- Interpretation: What value are listeners drawing from music generated by AI?

...and they each have downstream effects on the next
First some definitions

• **Machine Learning**: A computer system that learns something about some medium or topic by observing a relevant dataset
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• A **transformer** is a type of neural network
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First some definitions

- To “train” (i.e., to machine-learn), it uses a dataset to set up lots of situations like this
  - If the Network guesses right, it strengthens that prediction
  - If it guesses wrong, it weakens that prediction
  - After it has trained, it can create new content using these honed predictions
First some definitions

- **Large Language Model**: A neural network (usually a transformer) that has many layers and trains on a lot of data.

- **Generative AI**: A machine-learned system that can create new content.
Force #1: Motivations

Why are people making models of musical AI?
Force #1: Motivations

Motivation

Why are people making models of musical AI?
Force #1: Motivations

There’s not a lot of time and resources allocated to musical AI, likely because folks don’t think it’ll make a lot of money.
Motivations

• Within Generative AI, music is **valued less** on the market

• And within the overall market, Generative AI is **valued less** than other types of AI

• In other words, music gets the **fewest resources**
Motivations

• And it costs so much to make and train one of these AIs, there needs to be some clear payoff

• And, given the lack of investment, it seems like market forces are skeptical that there’s as much money to be made in generative musical AI as other in domains of AI
Motivations

• Musical AI seems to be researched less as well

Papers published by OpenAI, a company that works on various different media:
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Force #2: Examples
Musical datasets are smaller because it’s hard to make music into data types that an AI can learn from.
Examples:

LLMs need **lots and lots** of data to train on, and musical data is sparse and hard to acquire.
Examples:

Problem #1: Musical datasets trend small
Examples:

Problem #1: Musical datasets trend small
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Examples:

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Problem #1: Musical datasets trend small
Problem #2: It’s hard to extract computer readable information from PDFs and audio.

Examples:
Examples:

Problem #2: It’s hard to extract computer readable information from pdfs and audio

The technology to extract reliable information from score images is way behind text recognition.
Examples: Problem #2 a
Examples: Problem #2 b

Scan 1: includes several added notes
Allegro con brio (Q = 108)

Scan 2: includes several deleted notes.
Scan 3:
links all staves
on a page
together

... etc (there are 5 more concurrent staves)
Yuck.

So let’s use audio!
How about…

Lizzo’s “Truth Hurts”
Hold on, let’s talk to 20 seconds about overtones

Complex and rich sounds contain complementary sound waves that create their unique timbre and quality.
Overtones are visualized using a graph where the horizontal axis represents time and the vertical axis represents frequency. This allows you to see all the complex overtones and complementary sounds that contribute to a rich timbre. So, higher pitches are higher on the page.
Here’s the problem: overtones look a lot like other notes.
Here’s the problem: overtones look a lot like other notes.
What's actually played:

The audio signal looks like:

The transcription looks like:

Different components of low C's overtone series in a bright piano sound
Clear note attacks in piano

Different components of A's overtone series misunderstood as pitches
Different components of low C's overtone series misunderstood as pitches
**Force #3: Representation**

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## Force #3: Representation

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Music has so many interrelated moving parts that it’s hard to cleanly chunk up musical events in ways that an AI can learn from and use.
Representation:

You can’t just turn on the radio and yell at your LLM to **start listening**.

You need to chunk the data up into **tokens** that the deep learning process can **analyze and learn from**.

However you **tokenize** your data is how the medium will be **represented** in the AI’s “mind”.
Representations

For instance, ChatGPT tokenizes using word chunks. This Emily Dickinson poem within its dataset would be tokenized like so:
For instance, ChatGPT *tokenizes* using word chunks. This Emily Dickinson poem within its dataset would be tokenized like so:

```
Surfeit? When the daffodil
   Doth of the dew:
Even as herself, O friend!
   I will of you!
```

Original poetry
For instance, ChatGPT tokenizes using word chunks. This Emily Dickinson poem within its dataset would be tokenized like so:

Original poetry

Surfeit? When the daffodil
Doth of the dew:
Even as herself, O friend!
I will of you!

Tokenized representation

Surfeit?-- When- the- d-aff-od-il-
Do-th- of- the- dew--:
Even- as- herself,-- O- friend!-:
I- will- of- you!-
ChatGPT’s mind (its neural network) knows then how these word chunks should be strung together, and how to arrange them into patterns similar to other poetry it’s seen.
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Representations

ChatGPT then produces new poems by stringing these word chunks into new patterns that get stitched together for the user:
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“Make me a new poem in the style of Emily Dickinson!”
ChatGPT then produces new poems by stringing these word chunks into new patterns that get stitched together for the user:

“Make me a new poem in the style of Emily Dickinson!”

(Please)
ChatGPT then produces new poems by stringing these word chunks into new patterns that get stitched together for the user:

B-ene-ath- the- distant- moon
with- its-soft- silver- hue,-
Whispering-‘s- stirs- abound
where- wild-flowers- grew!-

Tokens generated from data
ChatGPT then produces new poems by stringing these word chunks into new patterns that get stitched together for the user:

Beneath the distant moon with its soft silver hue,
Whispering’s stirs abound where wildflowers grew!

Tokens generated from data → New content
Musical tokenization is much less obvious.

But, if you wanted to play around with other ways to tokenize text, your options would be obvious—letters, full words, phrases, or different chunks.

Musical tokenization is.... much less obvious.
Just think of all the ways you can talk about what’s going on here
Just think of all the ways you can talk about what’s going on here

A-maz-ing Grace, how sweet the sound that saved a wretch like me!

\begin{align*}
\text{Note names:} & \quad \text{G} \quad \text{C} \quad \text{E} \quad \text{C} \quad \text{E} \quad \text{D} \quad \text{C} \quad \text{A} \quad \text{G} \quad \text{G} \quad \text{C} \quad \text{E} \quad \text{C} \quad \text{E} \quad \text{D} \quad \text{G} \\
\text{Scale degrees:} & \quad 5 \quad 1 \quad 3 \quad 1 \quad 3 \quad 2 \quad 1 \quad 6 \quad 5 \quad 5 \quad 1 \quad 3 \quad 1 \quad 3 \quad 2 \quad 5 \\
\text{Chord names:} & \quad \text{C} \quad \text{C} \quad \text{F/A} \quad \text{G}^7 \quad \text{a} \quad \text{C/G} \quad \text{G} \\
\text{Roman numerals:} & \quad \text{I} \quad \text{I} \quad \text{IV}^6 \quad \text{V}^7 \quad \text{vi} \quad \text{I}^\flat \quad \text{V}
\end{align*}
Just think of all the ways you can talk about what’s going on here.

Note names:
G C E C E D C A G G C E C E D G

Scale degrees:
5 4th 1 3rd 3rd 3rd 2nd 2nd 1 3rd 6 2nd 5th same 5 1 3rd 3rd 3rd 2nd 2 4th 5

Amaz-ing Grace, how sweet the sound that saved a wretch like me!

Beats:
3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3

Chord names:
C C F/A G7 A C/G G

Roman numerals:
I I IV6 V7 VI I6 V
So, how specifically do we represent these three moments?
So, how specifically do we represent these three moments?

Harmony/melody

Pitches:
{Low C, Low E, Low G, Mid C}
{Low C, Low E, Low G, Mid E}
{Low C, Low E, Low G, Mid C}
So, how specifically do we represent these three moments?

**Harmony/melody**

**Pitches:**
- {Low C, Low E, Low G, Mid C}
- {Low C, Low E, Low G, Mid E}
- {Low C, Low E, Low G, Mid C}

**Scale degree & intervals:**
- {SD 1, & 3rd, 5th, 8th}
- {SD 1, & 3rd, 5th, 10th}
- {SD 1, & 3rd, 5th, 8th}
So, how specifically do we represent these three moments?

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- {SD 1, & 3rd, 5th, 10th}
- {SD 1, & 3rd, 5th, 8th}

**Chord types:**
- {SD 1, 3, 5 w- SD 1 lowest}
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**Chord types:**
{SD 1, 3, 5 w- SD 1 lowest}
{SD 1, 3, 5 w- SD 1 lowest}
{SD 1, 3, 5 w- SD 1 lowest}

**Outer voices:**
{SD 1 octave above last note, & octave above}
{SD 1 octave above last note, & tenth above}
{SD 1 octave above last note, & octave above}
So, how specifically do we represent these three moments?

**Harmony/melody**

**Pitches:**
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**Chord types:**
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**Outer voices:**
- {SD 1 octave above last note, & octave above}
- {SD 1 octave above last note, & tenth above}
- {SD 1 octave above last note, & octave above}

**Intervals**

**Linear intervals**
(from previous upbeat Low G)
- {↓ 5th, ↓ 3rd, Hold, ↑ 3rd}
- {Hold, Hold, Hold, ↑ 3rd}
- {Hold, Hold, Hold, ↓ 3rd}
So, how specifically do we represent these three moments?

**Harmony/melody**

**Pitches:**
- {Low C, Low E, Low G, Mid C}
- {Low C, Low E, Low G, Mid E}
- {Low C, Low E, Low G, Mid C}

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- {SD 1, & 3rd, 5th, 8th}
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- {SD 1, & 3rd, 5th, 8th}

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- {SD 1 octave above last note, & octave above}
- {SD 1 octave above last note, & tenth above}
- {SD 1 octave above last note, & octave above}

**Intervals**

**Linear intervals**
(from previous upbeat Low G)
- ↓ 5th, ↓ 3rd, Hold, ↑ 3rd
- {Hold, Hold, Hold, ↑ 3rd}
- {Hold, Hold, Hold, ↓ 3rd}

**Just vertical intervals:**
- {3rd, 5th, 8th}
- {3rd, 5th, 10th}
- {3rd, 5th, 8th}
So, how specifically do we represent these three moments?

**Harmony/melody**

- **Pitches:**
  - {Low C, Low E, Low G, Mid C}
  - {Low C, Low E, Low G, Mid E}
  - {Low C, Low E, Low G, Mid C}

- **Scale degree & intervals:**
  - {SD 1, & 3rd, 5th, 8th}
  - {SD 1, & 3rd, 5th, 10th}
  - {SD 1, & 3rd, 5th, 8th}

- **Chord types:**
  - {SD 1, 3, 5 w- SD 1 lowest}
  - {SD 1, 3, 5 w- SD 1 lowest}
  - {SD 1, 3, 5 w- SD 1 lowest}

- **Outer voices:**
  - {SD 1 octave above last note, & octave above}
  - {SD 1 octave above last note, & tenth above}
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**Intervals**

- **Linear intervals**
  - (from previous upbeat Low G)
    - {↓ 5th, ↓ 3rd, Hold, ↑ 3rd}
    - {Hold, Hold, Hold, ↑ 3rd}
    - {Hold, Hold, Hold, ↓ 3rd}

- **Just vertical intervals:**
  - {3rd, 5th, 8th}
  - {3rd, 5th, 10th}
  - {3rd, 5th, 8th}

**Meter/rhythm**

- **Duration & Metric Position:**
  - {2 beats on downbeat}
  - {.5 beat on beat 3}
  - {.5 beat on beat 3.5}
So, how specifically do we represent these three moments?

**Harmony/melody**

- **Pitches:**
  - {Low C, Low E, Low G, Mid C}
  - {Low C, Low E, Low G, Mid E}
  - {Low C, Low E, Low G, Mid C}

- **Scale degree & intervals:**
  - {SD 1, & 3rd, 5th, 8th}
  - {SD 1, & 3rd, 5th, 10th}
  - {SD 1, & 3rd, 5th, 8th}

- **Chord types:**
  - {SD 1, 3, 5 w- SD 1 lowest}
  - {SD 1, 3, 5 w- SD 1 lowest}
  - {SD 1, 3, 5 w- SD 1 lowest}

- **Outer voices:**
  - {SD 1 octave above last note, & octave above}
  - {SD 1 octave above last note, & tenth above}
  - {SD 1 octave above last note, & octave above}

**Intervals**

- **Linear intervals**
  - (from previous upbeat Low G)
  - ↓ 5th, ↓ 3rd, Hold, ↑ 3rd}
  - {Hold, Hold, Hold, ↑ 3rd }
  - {Hold, Hold, Hold, ↓ 3rd }

- **Just vertical intervals:**
  - {3rd, 5th, 8th}
  - {3rd, 5th, 10th}
  - {3rd, 5th, 8th}

**Meter/rhythm**

- **Duration & Metric Position:**
  - {2 beats on downbeat}
  - {.5 beat on beat 3}
  - {.5 beat on beat 3.5}

- **Duration:**
  - {2 beats}
  - {.5 beat}
  - {.5 beat}
So, how specifically do we represent these three moments?

**Harmony/melody**
- **Pitches:**
  - {Low C, Low E, Low G, Mid C}
  - {Low C, Low E, Low G, Mid E}
  - {Low C, Low E, Low G, Mid C}
- **Scale degree & intervals:**
  - {SD 1, & 3rd, 5th, 8th}
  - {SD 1, & 3rd, 5th, 10th}
  - {SD 1, & 3rd, 5th, 8th}
- **Chord types:**
  - {SD 1, 3, 5 w- SD 1 lowest}
  - {SD 1, 3, 5 w- SD 1 lowest}
  - {SD 1, 3, 5 w- SD 1 lowest}
- **Outer voices:**
  - {SD 1 octave above last note, & octave above}
  - {SD 1 octave above last note, & tenth above}
  - {SD 1 octave above last note, & octave above}

**Intervals**
- **Linear intervals** (from previous upbeat Low G)
  - ↓ 5th, ↓ 3rd, Hold, ↑ 3rd
  - Hold, Hold, Hold, ↑ 3rd
  - Hold, Hold, Hold, ↓ 3rd
- **Just vertical intervals:**
  - {3rd, 5th, 8th}
  - {3rd, 5th, 10th}
  - {3rd, 5th, 8th}

**Meter/rhythm**
- **Duration & Metric Position:**
  - {2 beats on downbeat}
  - {.5 beat on beat 3}
  - {.5 beat on beat 3.5}
- **Duration:**
  - {2 beats}
  - {.5 beat}
  - {.5 beat}
- **Position in measure:**
  - {Downbeat}
  - {Beat 3}
  - {Beat 3.5}
So, how specifically do we represent these three moments?

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<th>Meter/rhythm</th>
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<td><strong>Duration &amp; Metric Position:</strong></td>
</tr>
<tr>
<td>{Low C, Low E, Low G, Mid C}</td>
<td>{↓ 5th, ↓ 3rd, Hold, ↑ 3rd}</td>
<td>{2 beats on downbeat}</td>
</tr>
<tr>
<td>{Low C, Low E, Low G, Mid C}</td>
<td>{Hold, Hold, Hold, ↑ 3rd}</td>
<td>{.5 beat on beat 3}</td>
</tr>
<tr>
<td>{Low C, Low E, Low G, Mid C}</td>
<td>{Hold, Hold, Hold, ↓ 3rd}</td>
<td>{.5 beat on beat 3.5}</td>
</tr>
<tr>
<td><strong>Scale degree &amp; intervals:</strong></td>
<td><strong>Just vertical intervals:</strong></td>
<td><strong>Duration:</strong></td>
</tr>
<tr>
<td>{SD 1, &amp; 3rd, 5th, 8th}</td>
<td>{3rd, 5th, 8th}</td>
<td>{2 beats}</td>
</tr>
<tr>
<td>{SD 1, &amp; 3rd, 5th, 10th}</td>
<td>{3rd, 5th, 10th}</td>
<td>{.5 beat}</td>
</tr>
<tr>
<td>{SD 1, &amp; 3rd, 5th, 8th}</td>
<td>{3rd, 5th, 8th}</td>
<td>{.5 beat}</td>
</tr>
<tr>
<td><strong>Chord types:</strong></td>
<td><strong>Position in measure:</strong></td>
<td><strong>Beat strength:</strong></td>
</tr>
<tr>
<td>{SD 1, 3, 5 w- SD 1 lowest}</td>
<td>{Downbeat}</td>
<td>{strong}</td>
</tr>
<tr>
<td>{SD 1, 3, 5 w- SD 1 lowest}</td>
<td>{Beat 3}</td>
<td>{weak}</td>
</tr>
<tr>
<td>{SD 1, 3, 5 w- SD 1 lowest}</td>
<td>{Beat 3.5}</td>
<td>{weaker}</td>
</tr>
<tr>
<td><strong>Outer voices:</strong></td>
<td></td>
<td></td>
</tr>
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<td>{SD 1 octave above last note, &amp; octave above}</td>
<td></td>
<td></td>
</tr>
<tr>
<td>{SD 1 octave above last note, &amp; tenth above}</td>
<td></td>
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Representation

• It’s just **not obvious** what data engineers should be feeding to a deep learning model

• This means that **many people** are trying **many different approaches**

• And this **spreads musical AI’s already-limited resources thin**, as different teams try out many different solutions
## Force #4: Structure

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Music is constructed in complex ways that are hard for an AI to learn.
• Deep Learning groups its data based on patterns and regularities

• This means it’s very good at learning nested determined proximities:
  • Things which are near to each other (proximities)
  • Things that occur a lot (they’re determined)
  • Things that it can chunk (they’re nested)
Structure

- Neural networks have a hard time with things that:
  - can take many forms (aren’t determined)
  - are spread out (aren’t proximate), and
  - Have independent components (aren’t nested)
  - Like hands…
Musical structure is like hands

Musical connections are spread apart, occur in many different ways, and don’t always combine into some predictable whole
Amazing Grace, how sweet the sound that saved a wretch like me!

I once was lost but now I am found. 'Twas blind but now I see.
**A1**

```
G C E C E D C A → G
```

```
A - maz - ing - Grace, how sweet the sound that saved a - wretch like me!
```

**A2**

```
G C E E D
```

```
T'mas blind but - now I see.
```

**B**

```
E G E E E C A C A → G
```

```
I once - was - lost but now I am - found.
```

```
G
```

```
C E C E D C
```

```
T'mas blind but - now I see.
```
Musical structure is like hands

• All of this makes musical sense and contribute to a flowing and coherent tune

• But none of it was absolutely determined to occur, much of it is spread over larger non-proximate swaths of time, and while some of the music can chunk together, not all of its components nest neatly.
This example is a “Protestant Christian Hymn Tune” from Udio.
Structure: State of the Art AI

- This example is a “Protestant Christian Hymn Tune” from Udio.
Structure: State of the Art AI

- It’s got some nice elements...
Structure: State of the Art AI

- It’s got some nice elements...
Structure: State of the Art AI

- It’s got some nice elements...
Its structure is very stilted to try to cram in nested determined proximities.
**Structure: State of the Art AI**

- Its structure is very stilted to try to cram in nested determined proximities
Structure: State of the Art AI

- Its structure is very stilted to try to cram in nested determined proximities
Structure: State of the Art AI

• My recomposition:

Ending on s.d. 2 adds more tension, and connects to later s.d. 1

Phase 1

C D E
D D G
E F D E A
G E D

Phrase 2

C D E
D D G
C D E F D
G B C G

Variation provides motion between the first two phrases
Recomposed ending makes phrases same length
**Force #5: Interpretation**

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Force #5: Interpretation

We might really only like music we know was created by other humans
When describing the designs for the very first computer in 1842, Ada King, Countess of Lovelace, wrote that she believed that Artificial Intelligence would never be able to create original content because it’s always simply recombining content that’s fed into it.
In 1949, when describing the new-fangled **calculating machines** that helped win the war,

the **neurosurgeon** and professor George Jefferson wrote in a medical journal that the “**mind of the mechanical man**” would never...

“write a sonnet or compose a concerto because of thoughts and emotions felt... no mechanism could feel (and not merely artificially signal...) grief... be warmed by flattery, be made miserable... be angry or depressed when it cannot get what it wants.”
Interpretation

• All of this is arguable, but it comes down to two big issues, the symbol grounding problem and the embodiment problem

• And both are particularly pronounced in music
Symbol grounding

• Meaning arises from a combination of:
  
  • experiencing something and connecting an image, word, or gesture to that experience (Experiential Knowledge)
  
  • and connecting those symbols to one another, like reading about some event, attributing some description to music, or interpreting a poem (Associational Knowledge)
Symbol grounding

• Because Artificial Intelligence learns from identifying patterns in a dataset,
  • It becomes an expert in all the contexts in which the words “happy” or “cold” are associated — it knows where these words are appropriate
  • But it will never experience what it means to be “cold” or “happy”
  • It’s reasonable to be very skeptical about whether the computer understands temperature or happiness because it learns only through identifying patterns, connections, and orderings—association
Embodiment

• And in order to experience the world, you need a **body**
  • Human emotions, perceptions, understanding, cognition, are all mediated through the human body
  • In order to **experience** the world, that experience needs to be fleshy
  • It’s reasonable to be very skeptical about whether a silicon-based intelligence can ever actually experience that world
Music

• We particularly value **embodied experiential content** in music

• Music doesn’t communicate information. Instead, music is a way for humans to **socially connect**, and to **embed and share experiences**

  • I’ll spare you the philosophy and cognition behind this claim, because this fact is so visceral and easily demonstrated...
Music

• Imagine a bullied, closeted teenager running to their room, and throwing on their headphones.

• Would they ever listen to an AI generated track? No!
  • To them, music is a way to process their own lived experience
  • And it’s a way to connect that experience to a shared human experience
• Imagine if these tracks created in the Kendrick/Drake conflict were random tunes generated by AI, not derived from actual human drama

• We wouldn’t take a second listen!

• We care about the human stories behind music, and music’s ability to embed lived experiences that we can empathize with
• Imagine you’re a jazz musician of the future, and you’re improvising with an AI on stage

  • What a weird and unfulfilling experience!

  • Part of performing is the thrill of engaging with another musician, looking at them, and conversing and collaborating with them in the moment

  • Removing the human removes the fun!
• Imagine using an AI-generated hymn for your parent’s funeral.

• This would feel very inappropriate because…
  • This music encapsulates the lived experience of grief
  • This music connects us as a community to that shared experience
Interpretation

• AI music will simply be interpreted differently than human music

• As AI grows in sophistication, I believe we’re going to increasingly realize how important the **fact that a human made it** is important to our enjoyment of music

• We’re going to want to know that a human (with the same experiential and embodied life as ours) is on the other end of our music, and we’ll want to search for the particular assurance
• There’s little **motivation** behind musical AI, partly because we just don’t want AI-made music

• This makes **examples** hard to come by, which makes it difficult to research how to **represent** music and to build models capable of understanding its **structure**

• Because of these dynamics, musical AI finds itself lagging behind AI in other media, with outputs that aren’t particularly convincing to an audience
All of this is from my book draft,

and if you know any agents who might be interested, please let me know!

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Thank you!

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