2025 edition

Deep Learning for Music Analysis and Generation

MIDI Generation

(x → MIDI)

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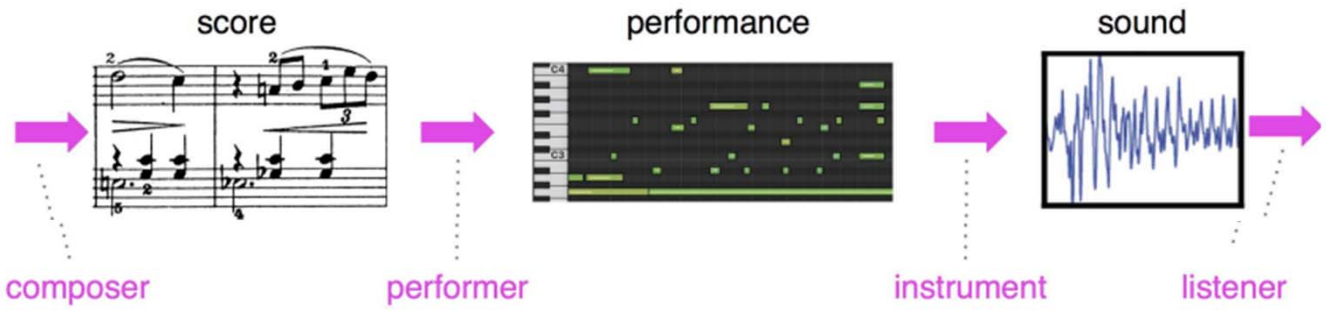
Why Symbolic Music



- There are meaningful problems in symbolic music **analysis** and **generation**
- Reasons to work on symbolic music generation
  - Focus on the musical content instead of sounds
  - Care about long-range structure instead of acoustic quality or diversity
  - Still relevant (given the progress in audio) as it's interpretable and editable
  - Less compute-demanding (compared to text-to-music generation)
  - Good first step toward generative systems for music

Outline

- **Sheet music & symbolic representations for music**
- Token representation of MIDI music
- MIDI generation
- Evaluation metrics

Sheet Music

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C1/C1S1_SheetMusic.html

- A *visual* representation (*.PDF, *.PNG, etc)
  - A **guide** for performing a piece of music leaving room for different interpretations
  - Musicians may vary the **tempo**, **dynamics**, and **articulation**, thus resulting in a personal interpretation of the given musical score

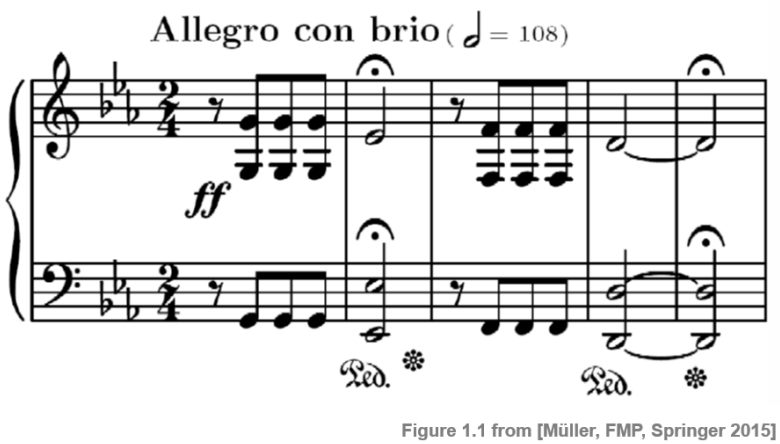
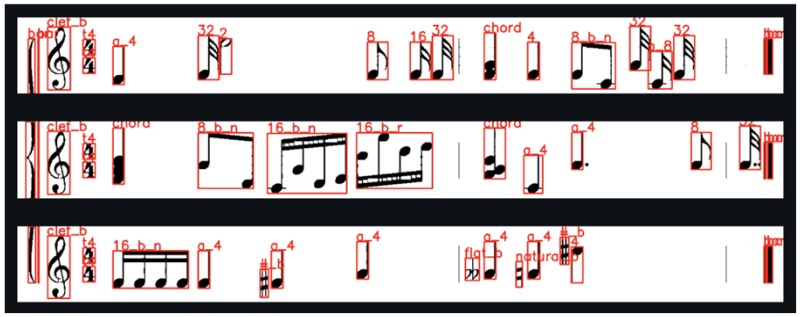


Figure 1.1 from [Müller, FMP, Springer 2015]

- ***Rarely*** directly used as input to neural network models
  - Exception: *optical music recognition* (OMR)

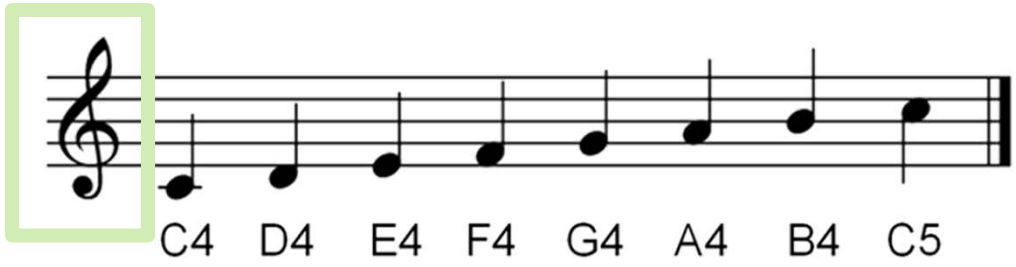


Sheet Music: Key Signature & Note Duration

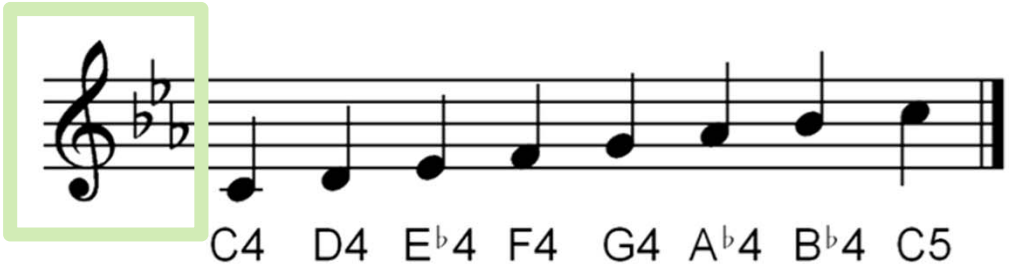
https://nicechord.com/post/major-and-minor-modes/

https://nicechord.com/post/notation-essentials/

C major: 全全半全全全半



C minor:全半全全全半全



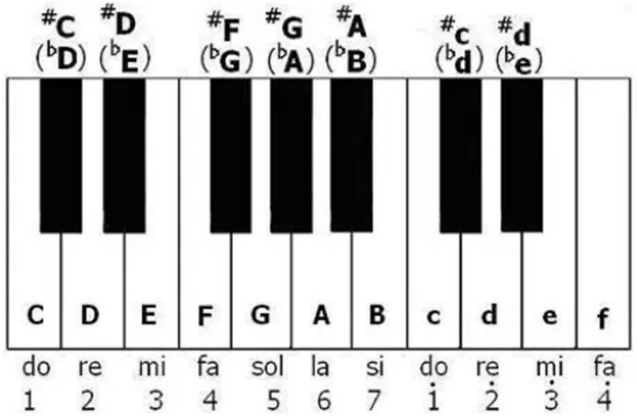
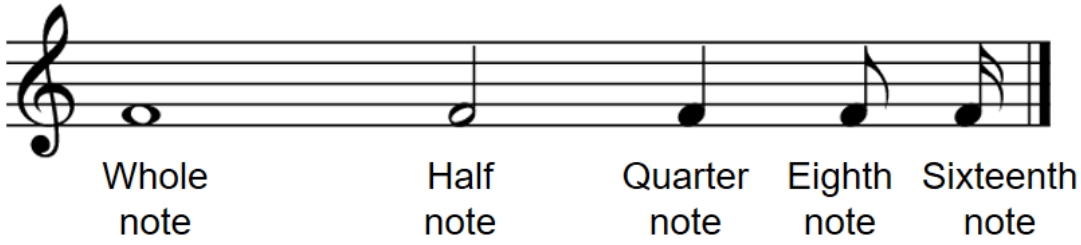


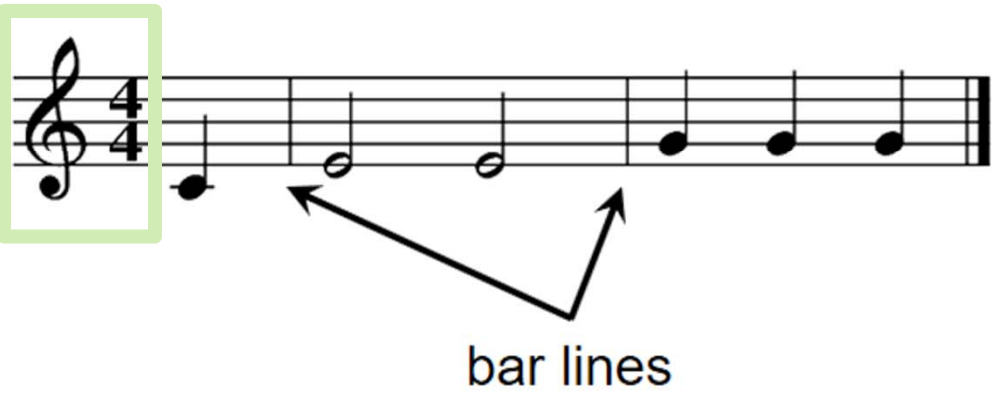
Figure 1.7 from [Müller, FMP, Springer 2015]

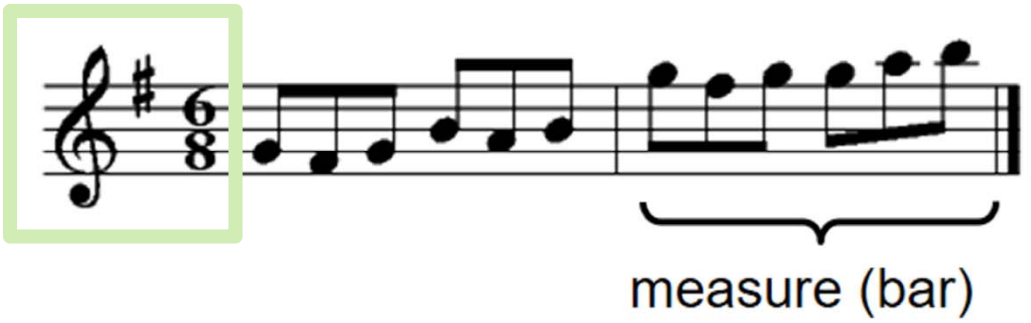


Sheet Music: Meter, Bar, Beat, Rhythm

- Dividing music into measures (bars) not only reflects its rhythmic nature, but also provides regular reference points within it

Figure 1.6 from [Müller, FMP, Springer 2015]





Sheet Music: Articulation Marks

- How certain notes are to be played

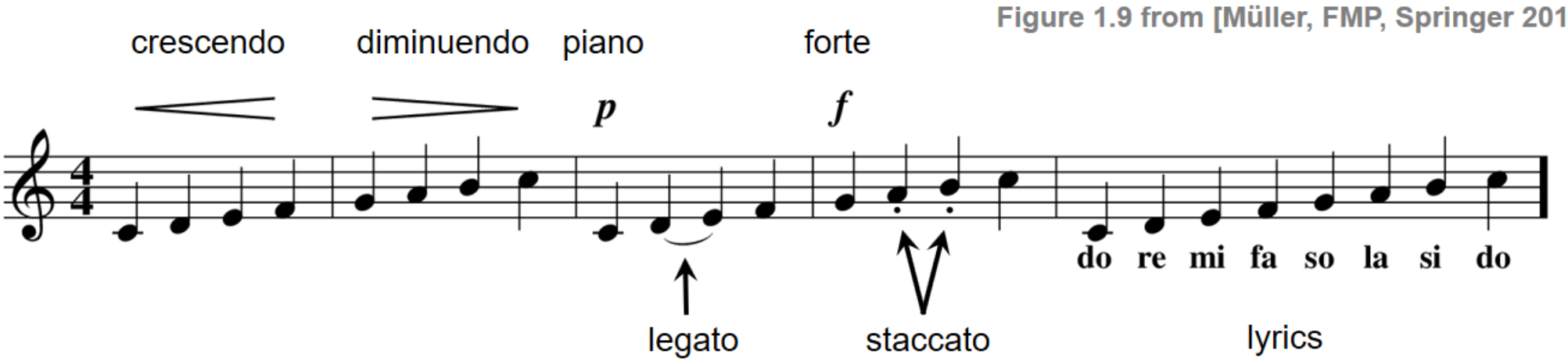
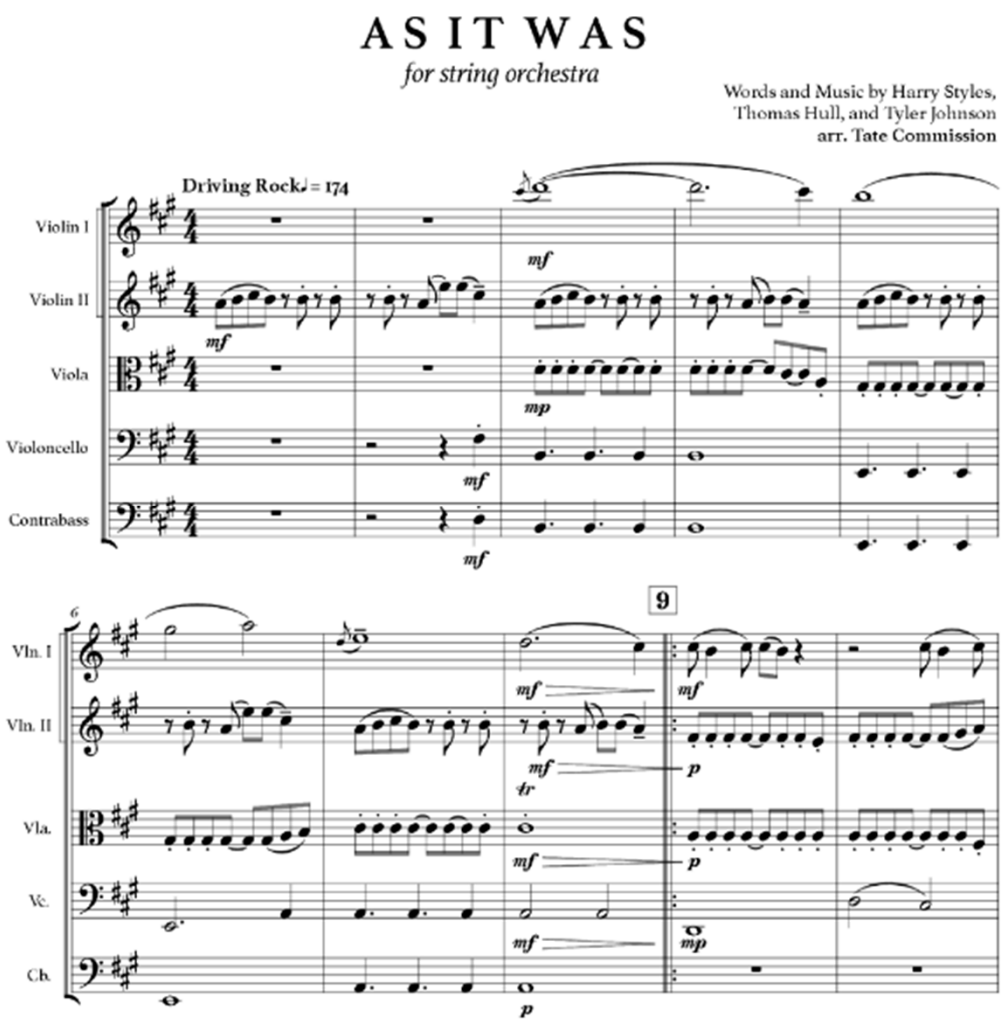
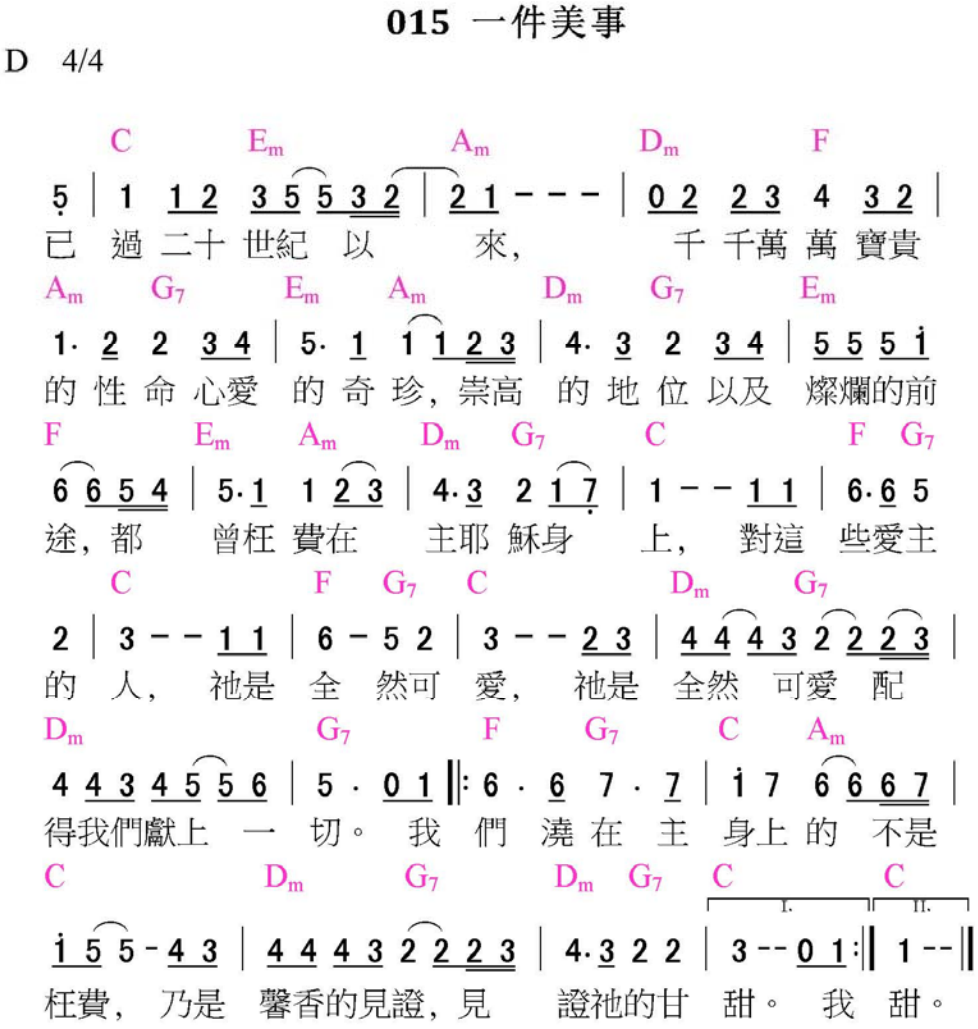


Figure 1.9 from [Müller, FMP, Springer 2015]

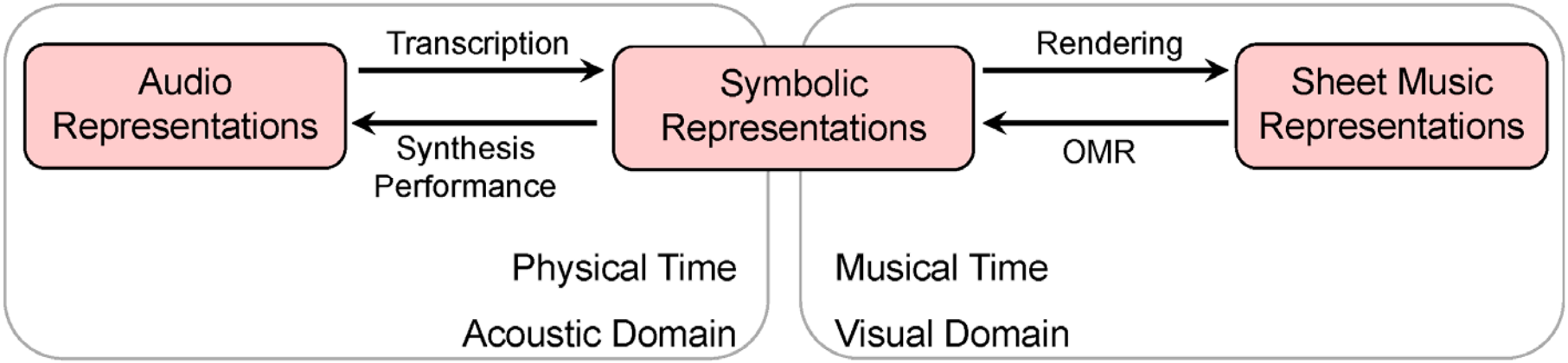
Sheet Music vs. Lead Sheet





Data Representation of Music

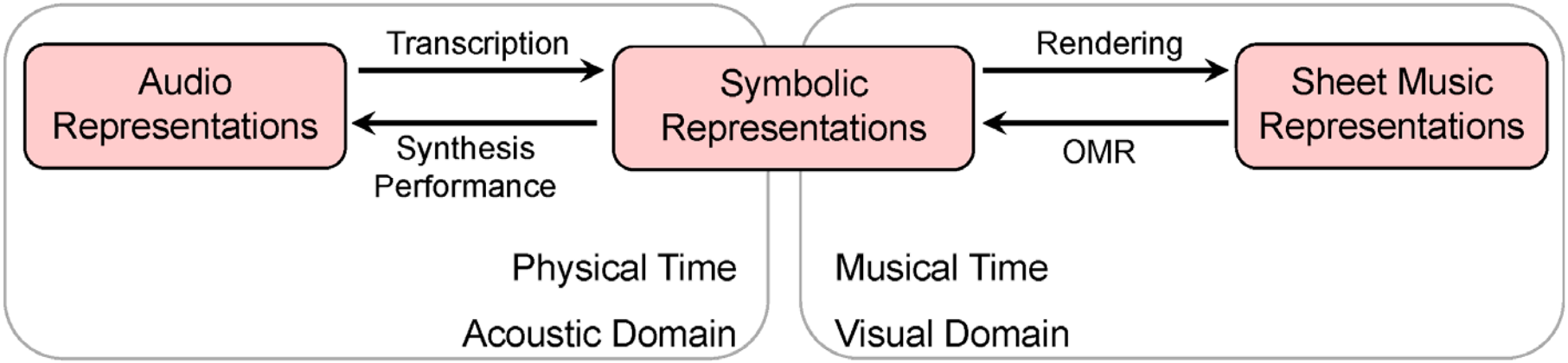
(Figure source: https://www.mdpi.com/2624-6120/2/2/18)



- **Musical audio** (waveforms, spectrograms)
  - what we "hear"
  - involve sounds
- **Symbolic representations** (e.g., MIDI, MusicXML)
  - the way music can be represented in a Digital Audio Workstation (DAW)
  - still relevant today as it's *interpretable* and *editable*
- **Sheet music** (visual representations of a musical score)
  - what musicians "compose"

Sheet Music and Symbolic-domain Representations

(Figure source: https://www.mdpi.com/2624-6120/2/2/18)



- **Physical time:** in milliseconds or alike, good for representation **performances** (*timing variations*)
- **Musical time:** 1/4, 1/8, 1/16 etc, good for representation **scores**

- Symbolic music can take either physical time or musical time

Piano Roll Representation

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C1/C1S2_PianoRoll.html

- A *visual, **image-like*** representation of *.MIDI (also how DAWs visualize MIDI files)
  - Horizontal axis: **Time**
  - Vertical axis: **Pitch**
  - Rectangle: **Note**
    - Leftmost point**: Onset**
    - Lowermost point**: Pitch**
    - Width**: Duration**
    - (Can also indicate **Velocity**)

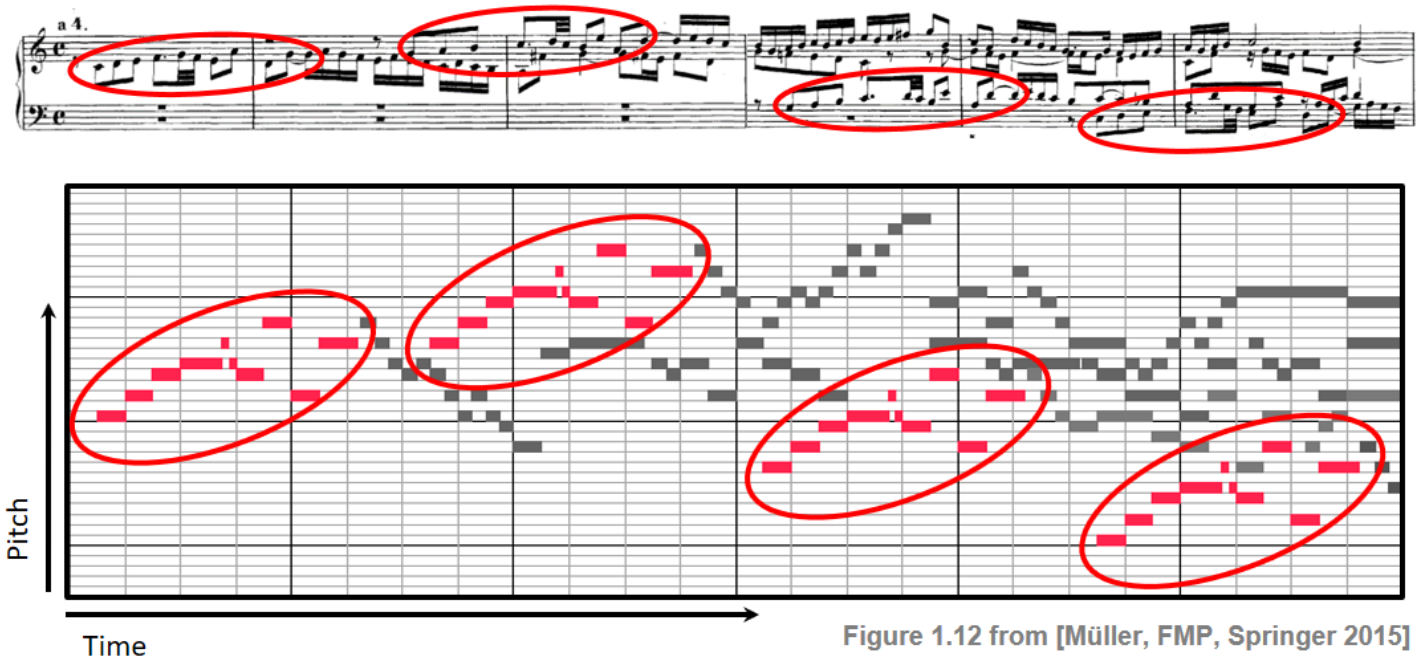
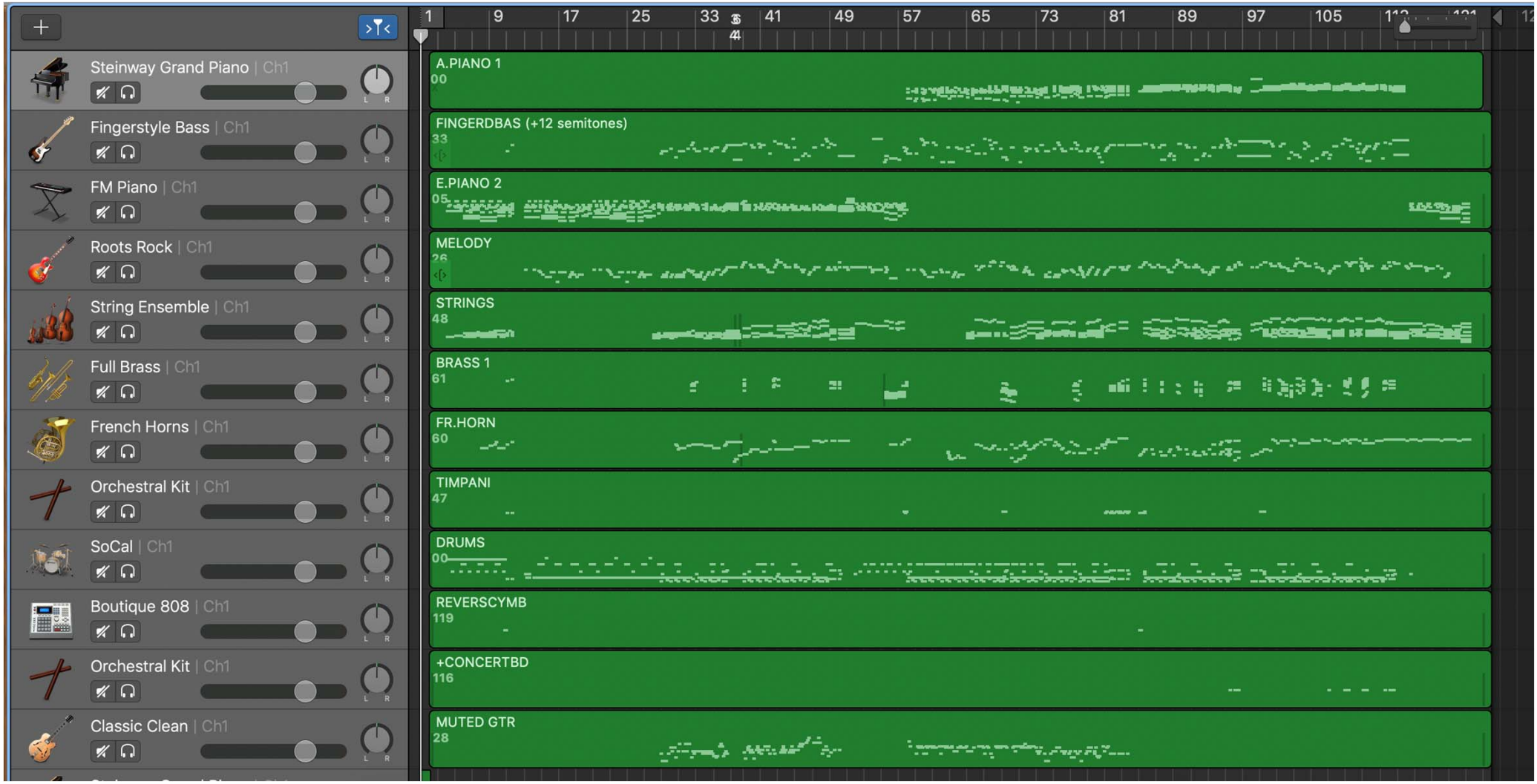


Figure 1.12 from [Müller, FMP, Springer 2015]

ps. The four occurrences of the theme of the music are highlighted

Piano Roll Representation

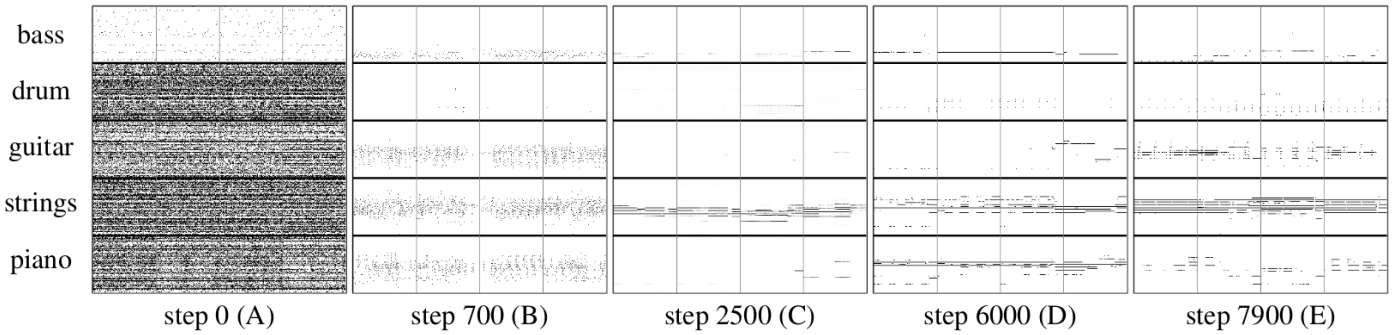
(image from the internet)



Piano Roll Representation

- A *visual,* ***image-like*** representation of *.MIDI
- Multi-track MIDI → multiple piano rolls (i.e., a tensor)
- ***Widely*** used by deep generative neural networks
  - *MidiNet* (2017) [GAN-based]
  - *MuseGAN* (2018) [GAN-based]: https://salu133445.github.io/musegan/results
  - *DiffRoll* (2023) [diffusion-based]: https://polyffusion.github.io/

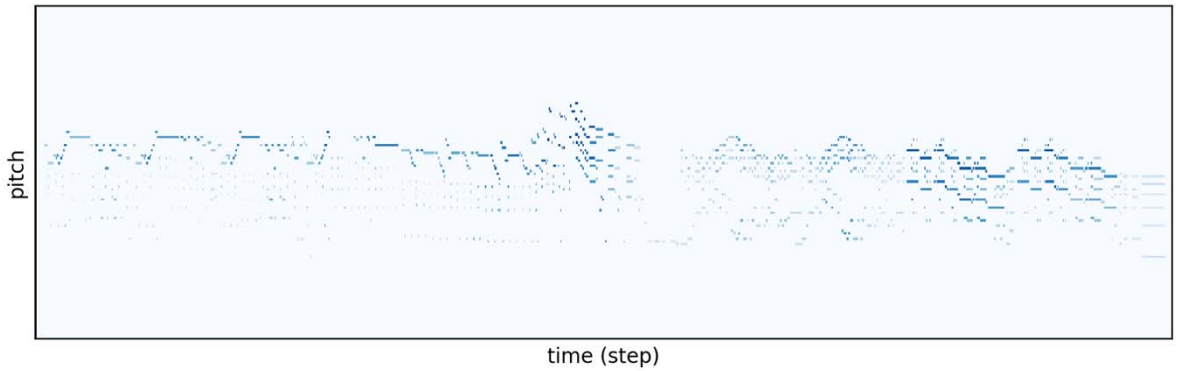
MuseGAN



DiffRoll

Library: PyPianoroll

https://salu133445.github.io/pypianoroll/



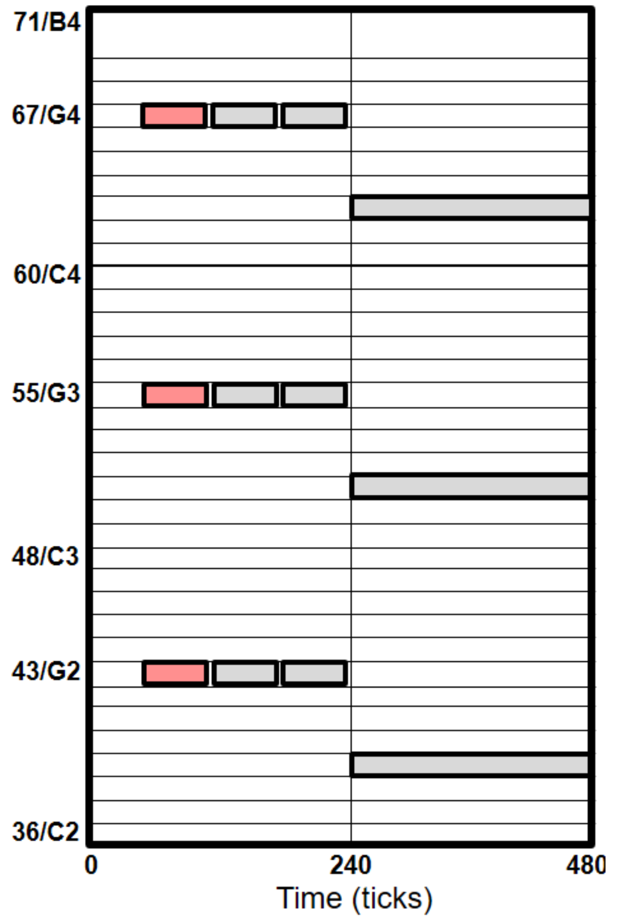
- Features
  - Manipulate multitrack piano rolls intuitively
  - Visualize multitrack piano rolls beautifully
  - Save and load multitrack piano rolls in a space-efficient format
  - Parse **MIDI** files into multitrack piano rolls
  - Write multitrack piano rolls into **MIDI** files

MIDI Representation

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C1/C1S2_MIDI.html

- A ***text-like*** representation of *.MIDI, using **MIDI messages** and **timestamps**
  - *MIDI note number* (0-127)
  - *Key velocity* (0-127): intensity of the sound
  - *MIDI channel* (different instruments)
  - *Time stamp*: how many *clock pulses or ticks* **to wait** before the command is executed

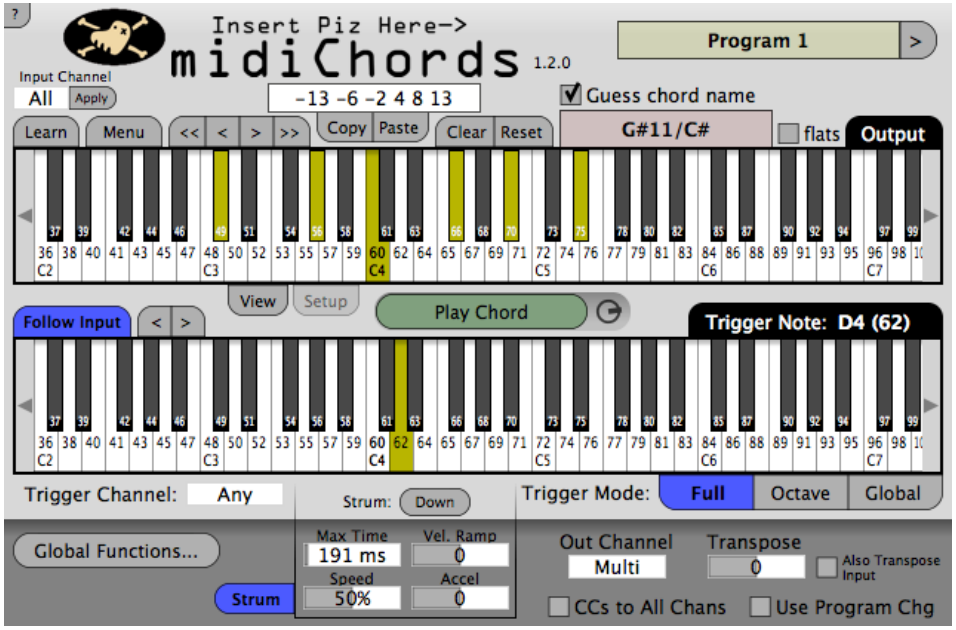
Time (Ticks)	Message	Channel	Note Number	Velocity
60	NOTE ON	1	67	100
0	NOTE ON	1	55	100
0	NOTE ON	2	43	100
55	NOTE OFF	1	67	0
0	NOTE OFF	1	55	0
0	NOTE OFF	2	43	0
5	NOTE ON	1	67	100
0	NOTE ON	1	55	100
0	NOTE ON	2	43	100
55	NOTE OFF	1	67	0
0	NOTE OFF	1	55	0
0	NOTE OFF	2	43	0
5	NOTE ON	1	67	100
0	NOTE ON	1	55	100
0	NOTE ON	2	43	100
55	NOTE OFF	1	67	0
0	NOTE OFF	1	55	0
0	NOTE OFF	2	43	0
5	NOTE ON	1	63	100
0	NOTE ON	2	51	100
0	NOTE ON	2	39	100
240	NOTE OFF	1	63	0
0	NOTE OFF	2	51	0
0	NOTE OFF	2	39	0



Piano Roll vs MIDI Representation

- Both represent a *.MIDI file
  - Piano roll: image-like
  - MIDI Representation: text-like

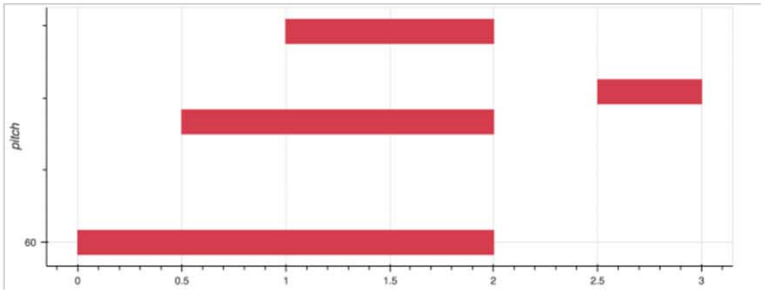
- Piano roll are like fixed-shape images
- MIDI representation is more flexible as it allows for *additional information* to be added
  - For example, **chord tokens, key tokens**, etc



Ref: Figure from https://www.kvraudio.com/product/midichords-by-insert-piz-here

MIDI Representation

- A ***text-like*** representation of *.MIDI
- ***Widely*** used by deep generative neural networks, especially Transformers
  - By viewing the MIDI messages as **"tokens"**
  - *Music Transformer* (2019) : https://magenta.tensorflow.org/music-transformer
  - *MuseNet* (2019): https://openai.com/research/musenet
  - *Pop Music Transformer* (2020): https://github.com/YatingMusic/remi
  - *MuseCoco* (2023): https://ai-muzic.github.io/musecoco/




```
SET_VELOCITY<80>, NOTE_ON<60>
TIME_SHIFT<500>, NOTE_ON<64>
TIME_SHIFT<500>, NOTE_ON<67>
TIME_SHIFT<1000>, NOTE_OFF<60>, NOTE_OFF<64>,
NOTE_OFF<67>
TIME_SHIFT<500>, SET_VELOCITY<100>, NOTE_ON<65>
TIME_SHIFT<500>, NOTE_OFF<65>
```

Timing in Piano Roll & MIDI

- The time axis can either be in *physical time* or in *musical time*
  - For **physical** timing, the actual timing of note occurrence is used, for example by indicating the tempo for each bar or each beat
  - For **musical** timing, the **tempo** information is removed and thereby each beat has the same length

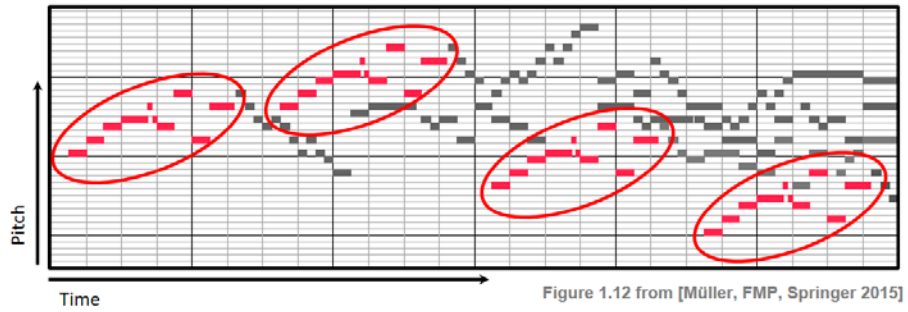


Figure 1.12 from [Müller, FMP, Springer 2015]

- MIDI subdivides a **quarter note** into basic time units referred to as *clock pulses* or *ticks*
  - Pulses per quarter note (PPQN): commonly 120
  - PPQN determines the resolution of the time stamps associated to note events

Ref1: https://salu133445.github.io/lakh-pianoroll-dataset/representation.html
Ref2: https://www.audiolabs-erlangen.de/resources/MIR/FMP/C1/C1S2_MIDI.html

MIDI Score vs MIDI Performance

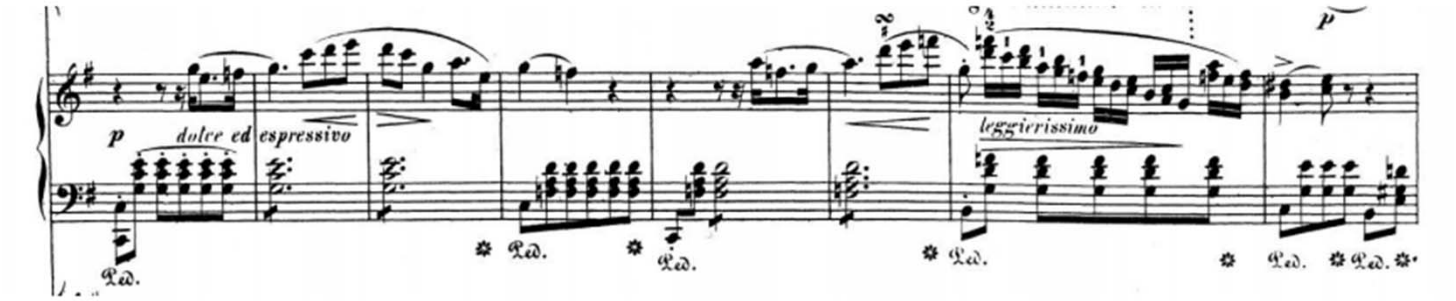
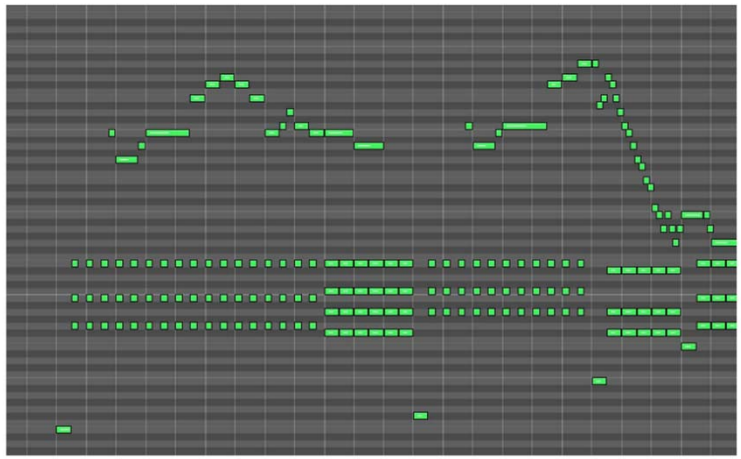


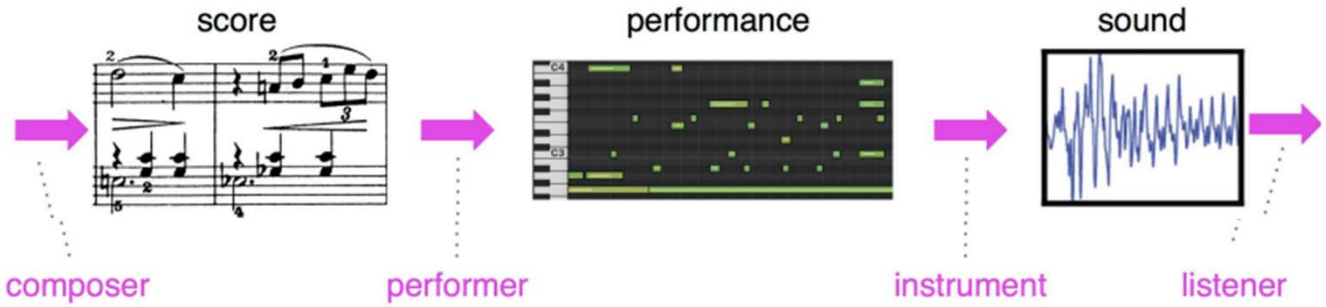
Figure 1: Excerpt from the score of Chopin's Piano Concerto No. 1.



- MIDI score
  - https://clyp.it/jhdkghso
- MIDI performance
  - https://clyp.it/x24hp1pq

Ref: Oore et al, "This time with feeling: Learning expressive musical performance," arXiv 2018

MIDI Score vs MIDI Performance



- **MIDI score**
  - A score that has been rendered **directly** into a MIDI file
  - Rendered with **NO** dynamics and **NO** expressive timing (i.e., exactly according to the written metrical grid)
- **MIDI performance**
  - A score has been performed, and that performance has been encoded into a MIDI stream, through either **MIDI keyboards** or by **automatic music transcription**
  - With expressive timing, tempo changes, dynamics, and articulation

Ref: Oore et al, "This time with feeling: Learning expressive musical performance," arXiv 2018

Library: Miditoolkit

https://github.com/YatingMusic/miditoolkit

- **Miditoolkit** is designed for handling MIDI in **symbolic timing** (ticks), which is the native format of MIDI timing
- **PrettyMIDI** (https://github.com/craffel/pretty-midi) can parse MIDI files and generate pianorolls in absolute timing
- **PyPianoroll** can parse MIDI files into pianorolls in symbolic timing
- **mido** (https://github.com/mido/mido) processes MIDI files in the lower level such as messages and ports
- **music21** (https://web.mit.edu/music21/) provides analysis modules

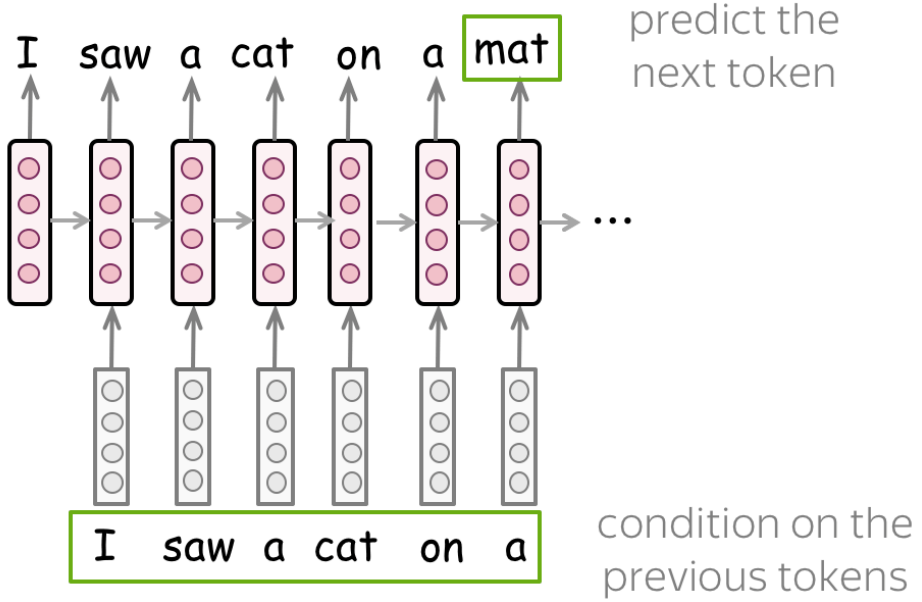
Outline

- Sheet music & symbolic representations for music
- **Token representation of MIDI music**
- MIDI generation
- Evaluation metrics

Text Tokens

https://wikidocs.net/178448

- Token
  - Words, character sets, or combinations of words
  - The **smallest unit of text data**
- First step in training LMs
- Two factors
  - Number of unique tokens (vocabulary size)
  - Length of a token sequence



Text Tokens

- Different types of text tokenizers
  - **Word**-based tokenizers `["Let", "us", "learn", "tokenization."]`
    - Large vocabulary size
    - May have out-of-vocabulary (OOV; unknown) tokens
  - **Character**-based tokenizers `["L", "e", "t", "u", "s", "l", "e", "a", "r", "n", "t", "o", "k", "e", "n", "i", "z", "a", "t", "i", "o", "n", "."]`
    - Small vocabulary size
    - No OOV
    - Long token sequence
  - **Sub-word** tokenizers (e.g., byte-pair encoding) `["Let", "us", "learn", "token", "ization."]`
    - Middle ground

Ref 1: https://medium.com/@nimritakoul01/tokenizers-for-natural-language-transformer-models-simply-explained-ee7167a844da
Ref 2: https://blog.csdn.net/zhaohongfei_358/article/details/123379481

Text Tokens

https://help.openai.com/en/articles/4936856-what-are-tokens-and-how-to-count-them

https://platform.openai.com/tokenizer

My favorite color is red.

[3666, 4004, 3124, 318, 2266, 13]

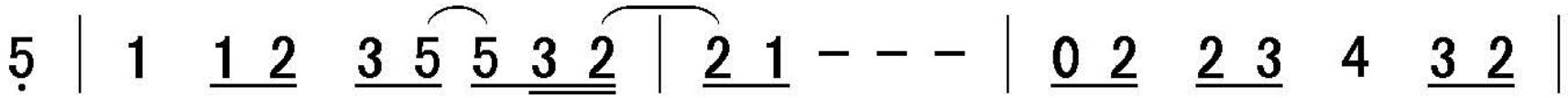
Observations:

The more probable/frequent a token is, the lower the token number assigned to it:

- The token generated for 'red' varies depending on its placement within the sentence:
  - Lowercase in the middle of a sentence: ' red' - (token: "2266")
  - Uppercase in the middle of a sentence: ' Red' - (token: "2297")
  - Uppercase at the beginning of a sentence: 'Red' - (token: "7738")

Representing Symbolic Music as Tokens

- How to represent a **melody** sequence?



Representing Symbolic Music as Tokens

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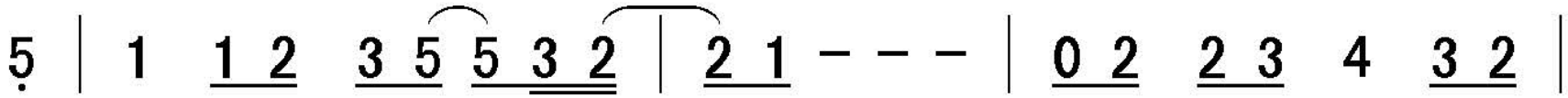
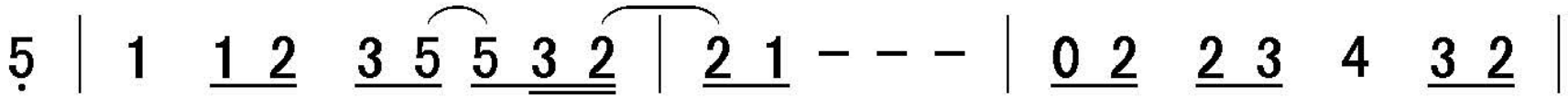


- [pitch] [duration] [pitch] [duration] [pitch] [duration] [pitch] [duration] …
- [pitch=G3] [duration=¼] [pitch=C4] [duration=¼] [pitch=C4] [duration=⅛] …
- [G3] [¼] [C4] [¼] [C4] [⅛] [D4] [⅛] …

- **Each note** is uniformly represented by **two tokens**
- **The ending of a note marks the beginning of the next note**

Representing Symbolic Music as Tokens

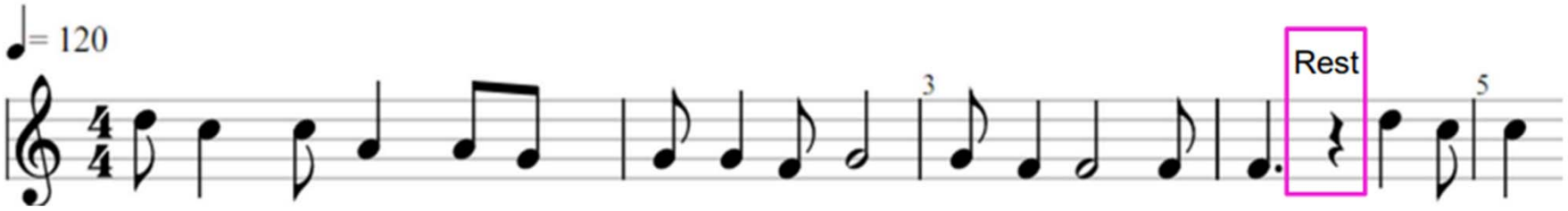
- How to represent a **melody** sequence?



- [G3:¼] [C4:¼] [C4:⅛] [D4:⅛] …
- **Each note** is uniformly represented by **one token**
- **Shorter sequence length but larger vocabulary size**

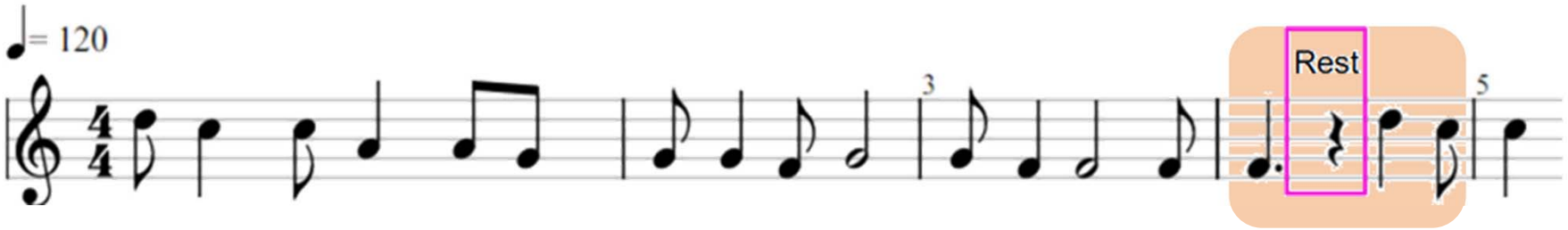
Representing Symbolic Music: Melody

- How to represent a **melody** sequence **with rest**?



Representing Symbolic Music: Melody

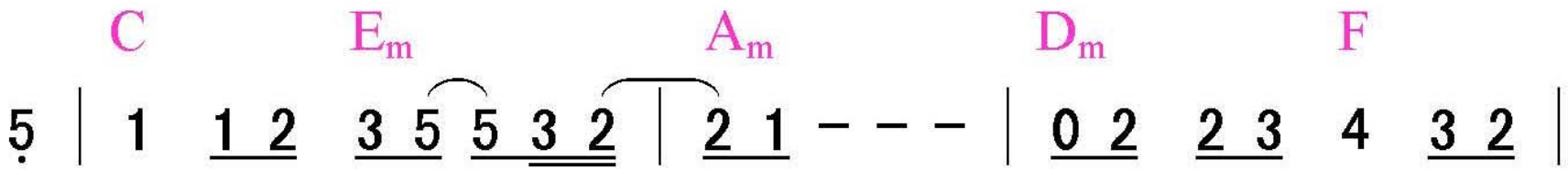
- How to represent a **melody** sequence **with rest**?



- Different methods
  1. [pitch] [duration] [rest-duration] [pitch] [duration] [pitch] [duration]
  2. [pitch] [duration] [pitch=0] [duration] [pitch] [duration] [pitch] [duration]
  3. [pitch] [duration] [rest=¼] [pitch] [duration] [rest=0] [pitch] [duration] [rest=0]

Representing Symbolic Music: Lead Sheet

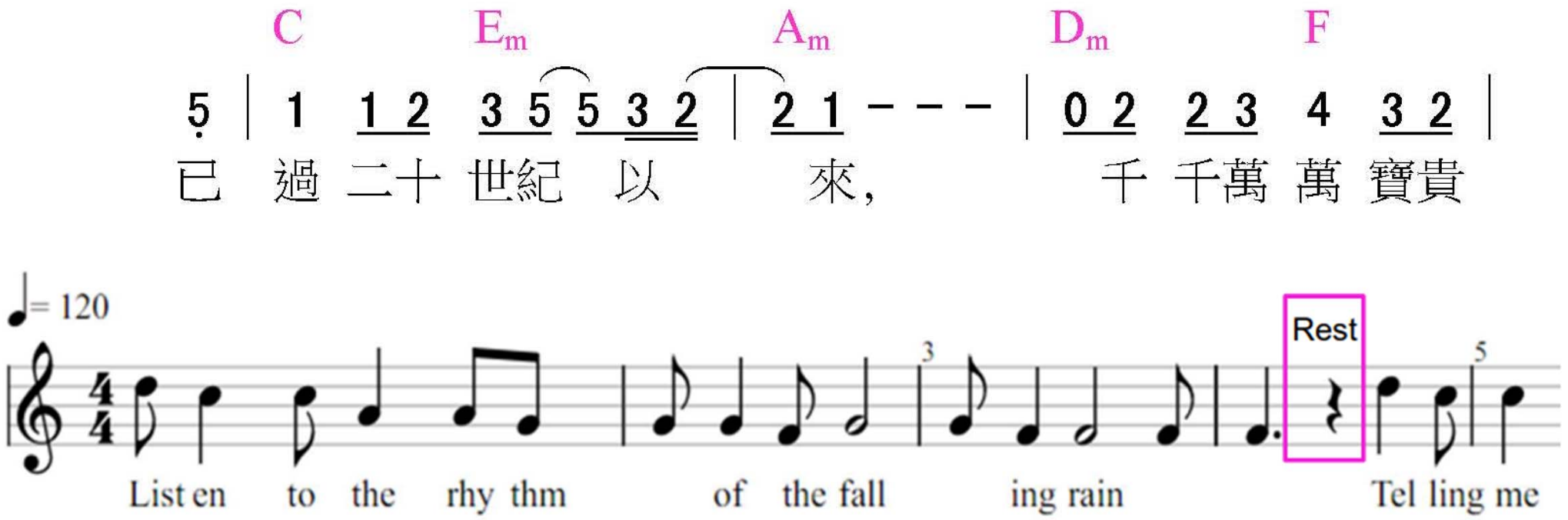
- How to represent a **lead sheet** sequence (i.e., melody+chord)?



- [pitch] [duration] [chord] [pitch] [duration] [pitch] [duration] …
  - Each musical note is still represented by two tokens, but there are *another type of tokens* (not for notes) in the token sequence
  - Getting more complicated

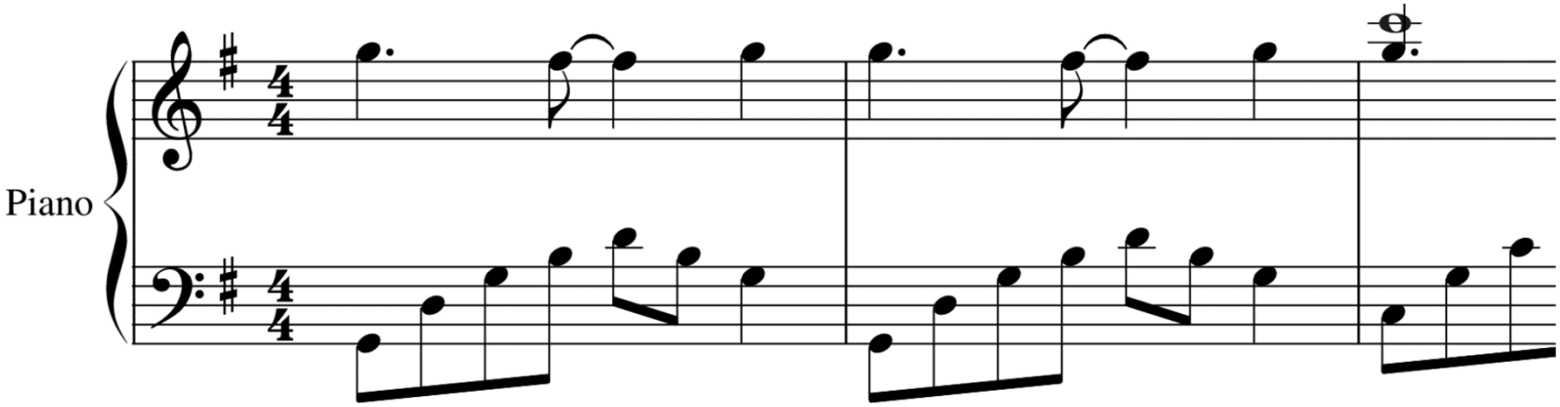
Representing Symbolic Music: Lead Sheet

- How to represent a **lead sheet** sequence (i.e., melody+chord+lyrics)?



Representing Symbolic Music: Piano Music Score

- How to represent a sequence of **piano music score**?

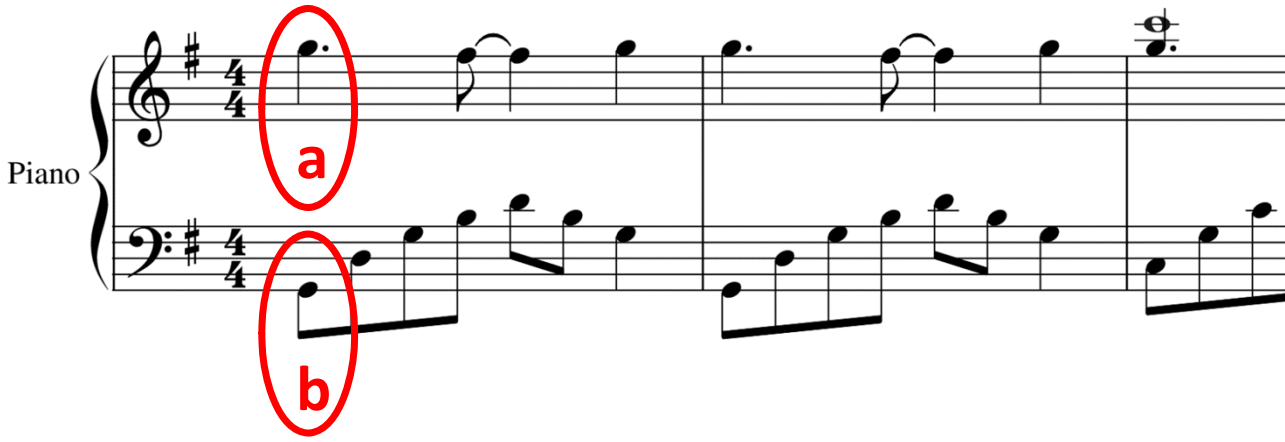


- The ending of a note is **no longer** the beginning of the next note
  - concurrent notes, temporally overlapping notes, …
- Need a way to mark the "flow of **time**"

Representing Symbolic Music: Piano Music Score

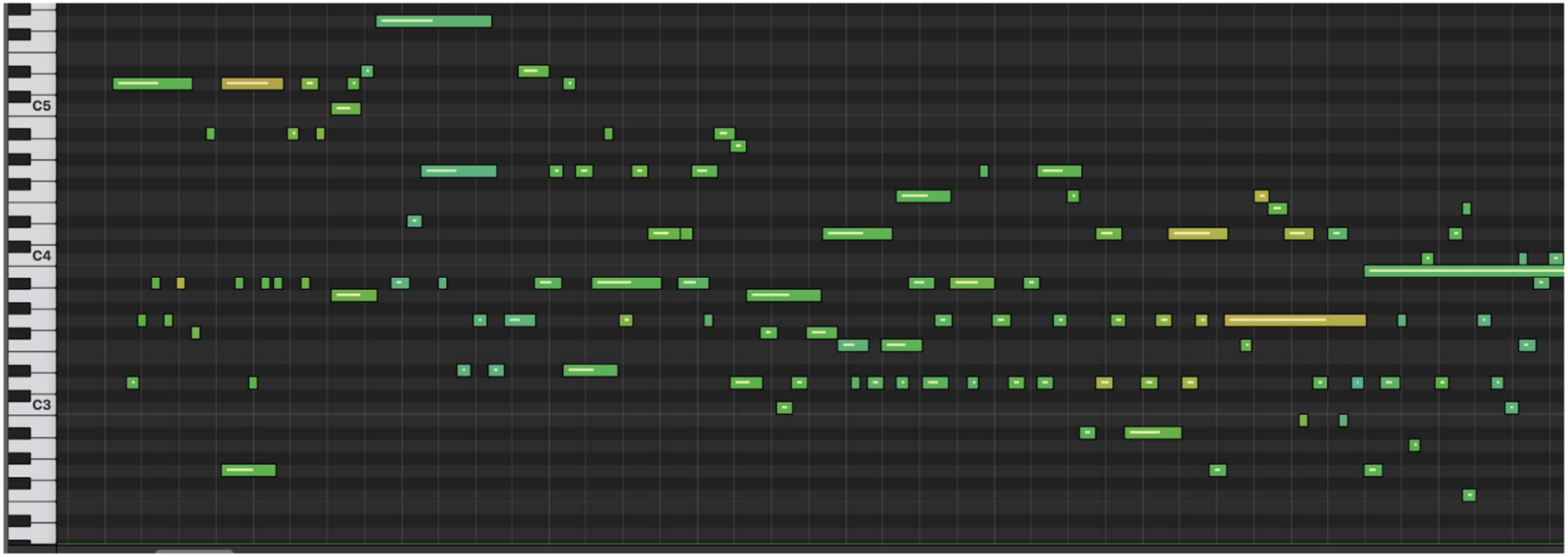
- How to represent a sequence of **piano music score**?
- Add one additional token to mark "**time-shift**" (i.e., ΔT; interval time)

- [pitch] [duration] [time-shift] [pitch] [duration] [time-shift] …



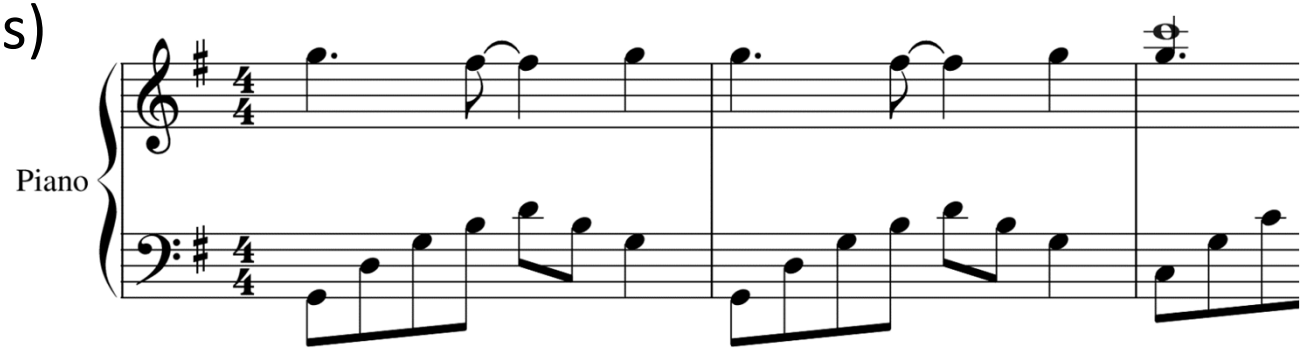
Representing Symbolic Music: Piano Music Performance

- How to represent a sequence of **piano music performance**?
  - Note **timings** are based on human performance rather than a score
  - Note **velocities** are based on human performance, i.e. with how much force did the performer strike each note



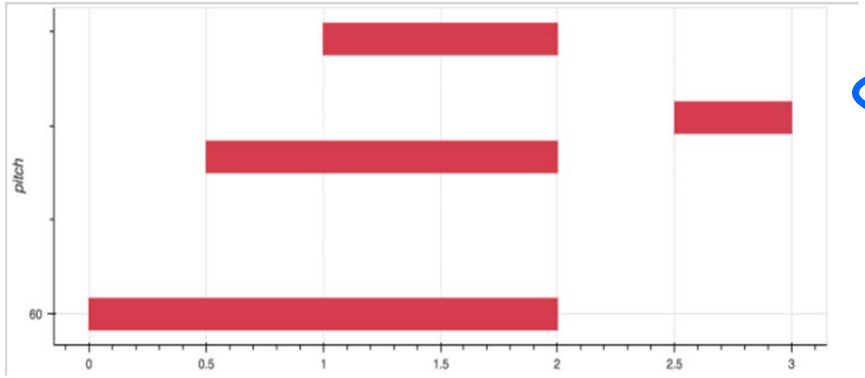
Text vs. Symbolic-domain Music

1. **Temporally overlapping** events (notes) in music
   - Need a way to represent time
2. A musical note is associated with **multiple attributes**
   - Pitch, duration, instrument, velocity, etc
3. **Rich mid-level features**
   - Chord progression, grooving pattern, etc
4. **Music is long** (>4k tokens)
5. **Music form/structure**
   - Verse, chorus, etc
   - Like a story



The MIDI-like Representation

- The **MIDI-like representation** for **piano music performance**
  - 128 note-on events + 128 note-off events: start or release a MIDI note
  - 100 time-shift events in increments of 10 ms up to 1 second; move forward in time to the next note event
  - 32 velocity events, corresponding to MIDI velocities quantized into 32 bins




```
SET_VELOCITY<80>, NOTE_ON<60>
TIME_SHIFT<500>, NOTE_ON<64>
TIME_SHIFT<500>, NOTE_ON<67>
TIME_SHIFT<1000>, NOTE_OFF<60>, NOTE_OFF<64>,
NOTE_OFF<67>
TIME_SHIFT<500>, SET_VELOCITY<100>, NOTE_ON<65>
TIME_SHIFT<500>, NOTE_OFF<65>
```

Ref: Simon & Oore, “Performance RNN: Generating music with expressive timing and dynamics,” 2017

Representing Multi-track Music

OpenAI's **MuseNet**

https://openai.com/index/musenet/

v — **velocity** (volume), in [0, 127]
v0 — **offset** of a note
v72 — **onset** of a note
G1 — **pitch**
piano — **instrument**
wait — move the **time** marker

```
bach piano_strings start tempo90 piano:v72:G1
piano:v72:G2 piano:v72:B4 piano:v72:D4 violin:v80:G4
piano:v72:G4 piano:v72:B5 piano:v72:D5 wait:12
piano:v0:B5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:4 piano:v0:G1 piano:v0:G2 piano:v0:B4 piano:v0:D4
violin:v0:G4 piano:v0:G4 wait:1 piano:v72:G5 wait:12
piano:v0:G5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:5 piano:v72:B5 wait:12
```

(v72: onset of the piano note G1)

Representing Multi-track Music

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v0 — **offset** of a note
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piano:v0:B5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:4 piano:v0:G1 piano:v0:G2 piano:v0:B4 piano:v0:D4
violin:v0:G4 piano:v0:G4 wait:1 piano:v72:G5 wait:12
piano:v0:G5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:5 piano:v72:B5 wait:12
```

(special "wait" token to indicates the delta time between events)

Representing Multi-track Music

OpenAI's **MuseNet**

https://openai.com/index/musenet/

v — **velocity** (volume), in [0, 127]
v0 — **offset** of a note
v72 — **onset** of a note
G1 — **pitch**
piano — **instrument**
wait — move the **time** marker

```
bach piano_strings start tempo90 (1)piano:v72:G1
(2)piano:v72:G2 (3)piano:v72:B4 (4)piano:v72:D4 (5)violin:v80:G4
(6)piano:v72:G4 (7)piano:v72:B5 (8)piano:v72:D5 wait:12
piano:v0:B5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:4 piano:v0:G1 piano:v0:G2 piano:v0:B4 piano:v0:D4
violin:v0:G4 piano:v0:G4 wait:1 piano:v72:G5 wait:12
piano:v0:G5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:5 piano:v72:B5 wait:12
```

(all these eight notes are played at the same time)

Representing Multi-track Music

OpenAI's **MuseNet**

https://openai.com/index/musenet/

v — **velocity** (volume), in [0, 127]
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v72 — **onset** of a note
G1 — **pitch**
piano — **instrument**
wait — move the **time** marker

```
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piano:v72:G2 piano:v72:B4 piano:v72:D4 violin:v80:G4
piano:v72:G4 piano:v72:B5 piano:v72:D5 wait:12
piano:v0:B5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:4 piano:v0:G1 piano:v0:G2 piano:v0:B4 piano:v0:D4
violin:v0:G4 piano:v0:G4 wait:1 piano:v72:G5 wait:12
piano:v0:G5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:5 piano:v72:B5 wait:12
```

(duration of the note G1: 12+5+12+4=33 ms)

Representing Multi-track Music

OpenAI's **MuseNet**

https://openai.com/index/musenet/

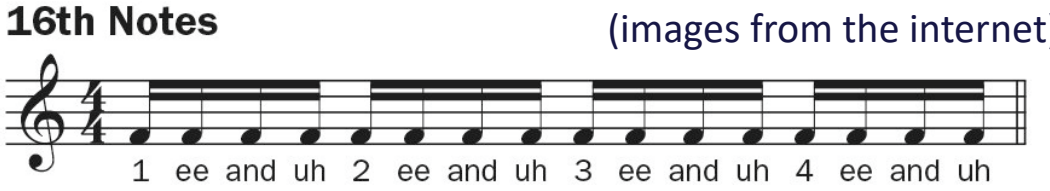
v — **velocity** (volume), in [0, 127]
v0 — **offset** of a note
v72 — **onset** of a note
G1 — **pitch**
piano — **instrument**
wait — move the **time** marker

```
bach piano_strings start tempo90 piano:v72:G1
piano:v72:G2 piano:v72:B4 piano:v72:D4 violin:v80:G4
piano:v72:G4 piano:v72:B5 piano:v72:D5 wait:12
piano:v0:B5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:4 piano:v0:G1 piano:v0:G2 piano:v0:B4 piano:v0:D4
violin:v0:G4 piano:v0:G4 wait:1 piano:v72:G5 wait:12
piano:v0:G5 wait:5 piano:v72:D5 wait:12 piano:v0:D5
wait:5 piano:v72:B5 wait:12
```

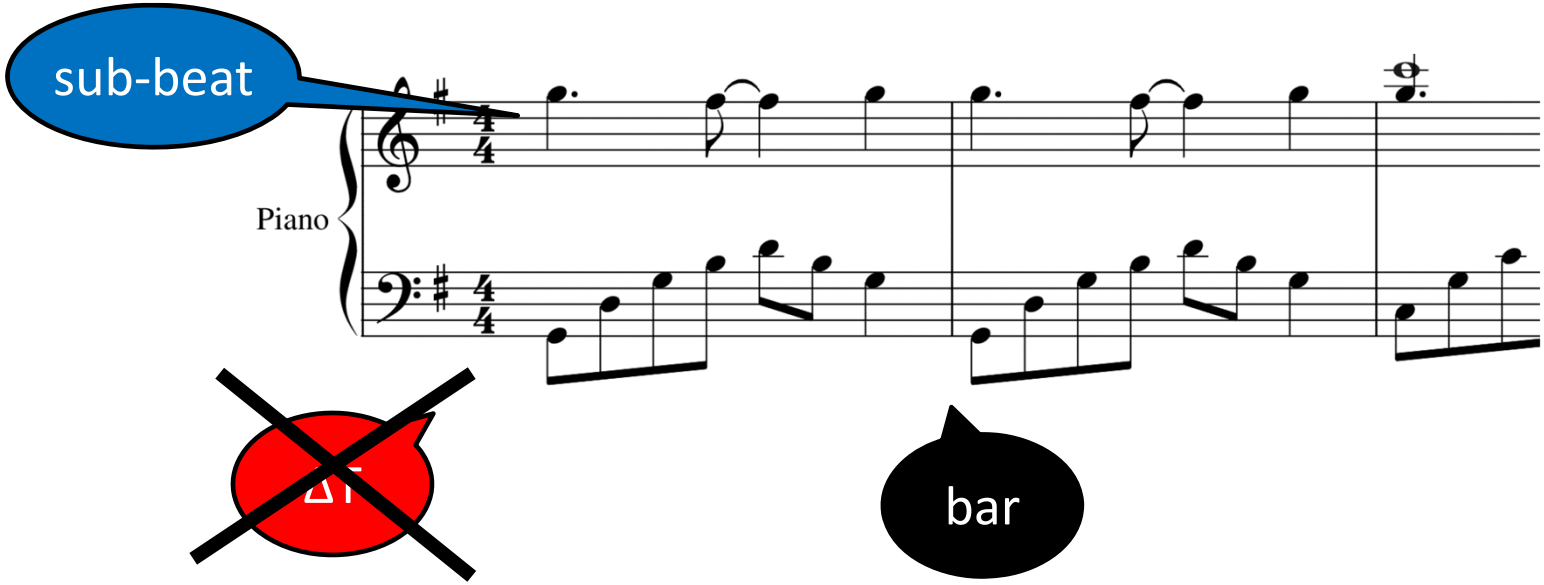
No bar lines!

REMI: Revamped MIDI Representation

- **REMI**: An alternative token representation of music
  - **Mark the bar lines** by "**bar**" tokens
  - **Indicate the position of a note within a bar** by "**sub-beat**" tokens (after timing quantization)



(images from the internet)



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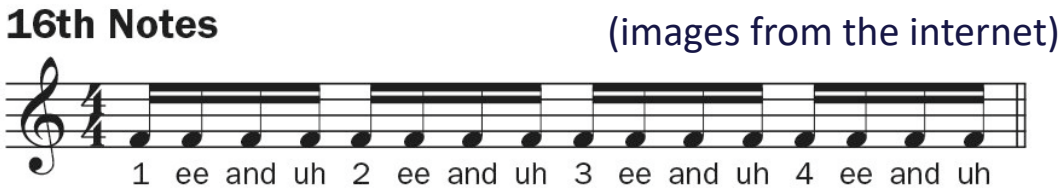
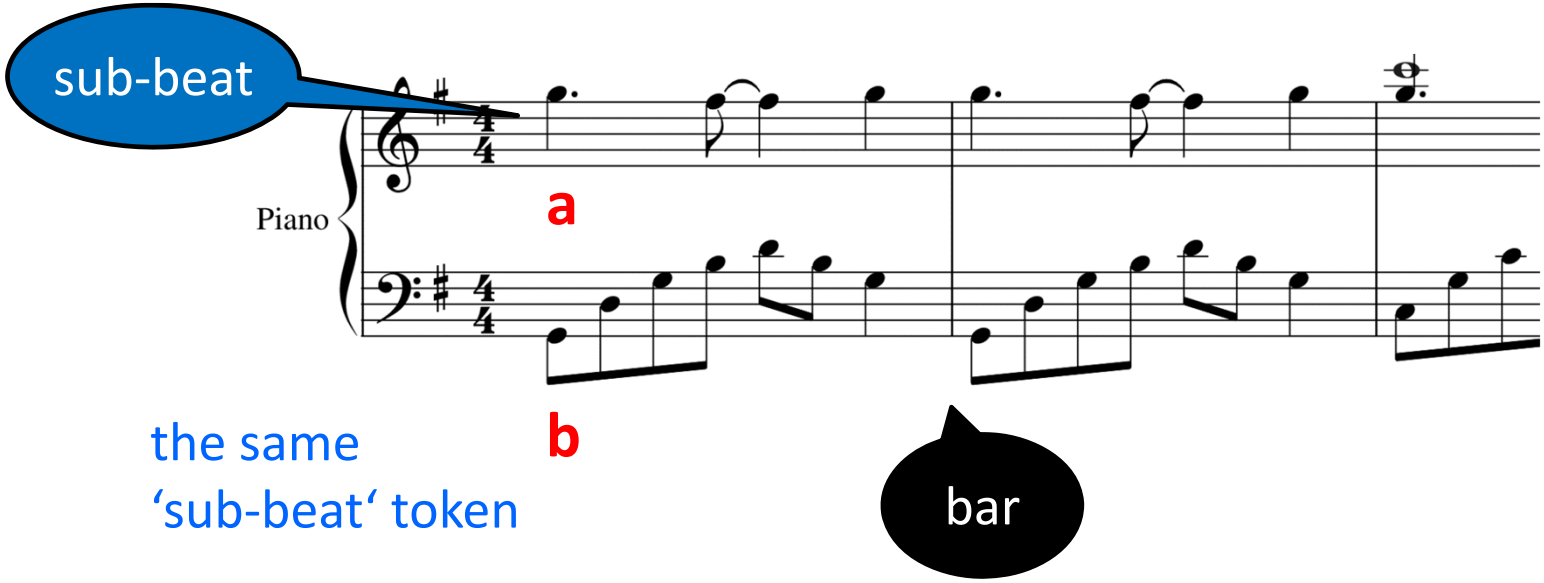
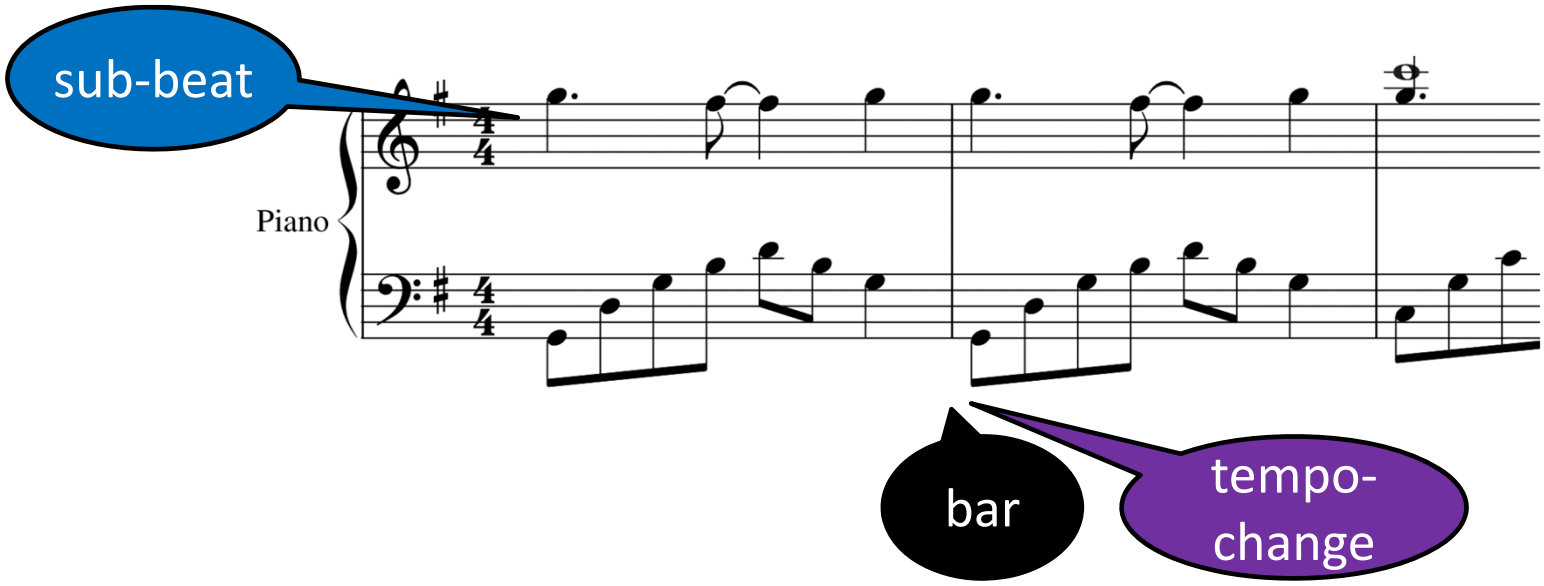


(images from the internet)



REMI: Revamped MIDI Representation

- **REMI**: An alternative token representation of music
  - Add **bar-wise tempo-change** tokens when needed to account for **tempo variations within a song** (the "tempo-change" tokens are after "bar" tokens)



REMI: Revamped MIDI Representation

- **REMI**
  - Use `**Sub-beat, Bar, and Tempo**` instead of **Time-Shift**
  - Use `**Note-Duration**` instead of **Note-Off**
    - note-on and note-off are native MIDI events
    - but using note-duration seems to have better musical meaning
  - Add `**Chord**` tokens

	MIDI-like	REMI
Note onset	NOTE-ON (0-127)	NOTE-ON (0-127)
Note offset	NOTE-OFF (0-127)	NOTE DURATION (32th note multiples)
Note velocity	NOTE VELOCITY (32 bins)	NOTE VELOCITY (32 bins)
Time grid	TIME-SHIFT (10-1000ms)	POSITION (16 bins) & BAR (1)
Tempo changes	✗	TEMPO (30-209 BPM)
Chord	✗	CHORD (60 types)

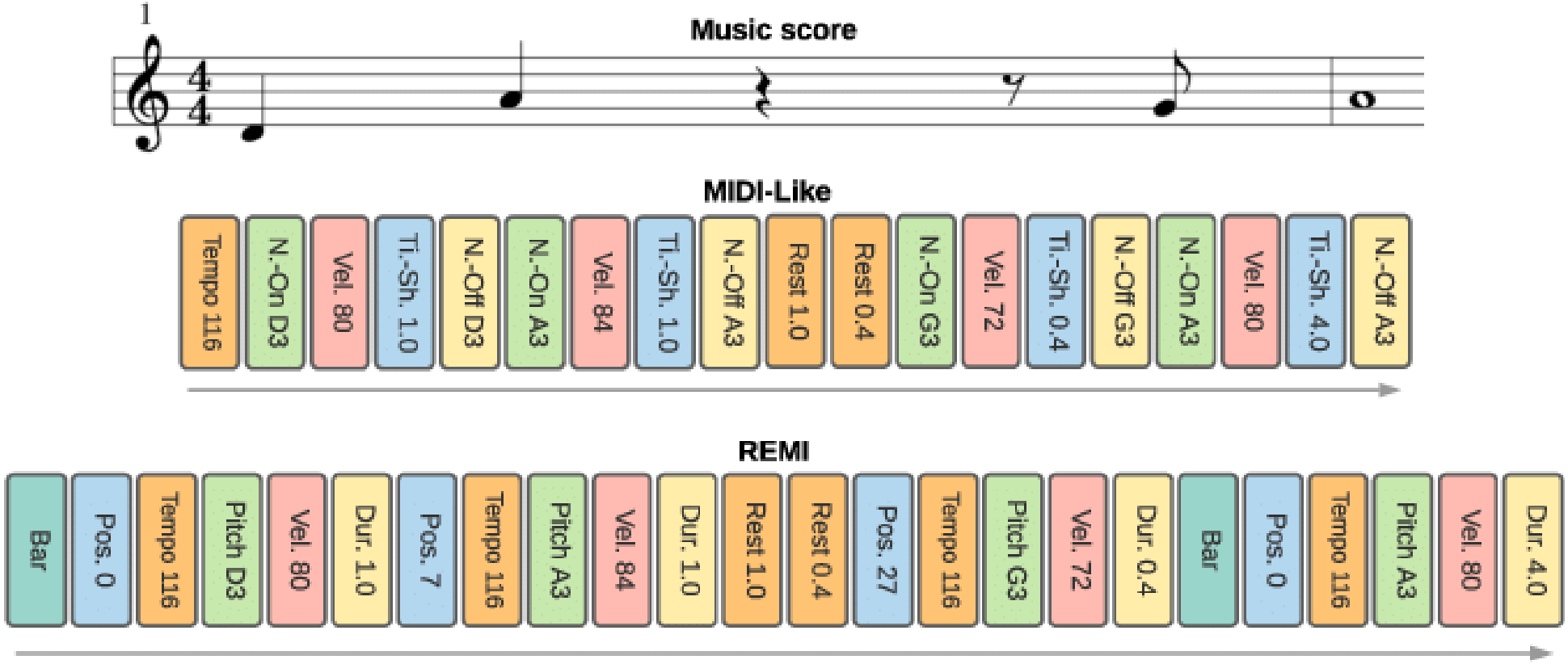
Table 1: A comparison of the commonly-used MIDI-like event representation with the proposed one, REMI. In the brackets, we show the corresponding ranges.

Ref: Huang et al, "Pop Music Transformer: Beat-based modeling and generation of expressive Pop piano compositions", ACM Multimedia 2020

MIDI-like vs. REMI

- **REMI**
  - Mark the bar lines **bar** tokens and divide a bar into 16 discrete **sub-beats**
  - **Symbolic timing + explicit time grid**
  - More timing quantization
  - Good for **MIDI scores**
  - Good for MIDI performances with **steady beats** like the **Pop music**
  - Good for **multi-track music**
    - The bar tokens make it easy to synchronize
- **MIDI-like**
  - Use **time-shift** tokens
  - **Physical timing & relative time intervals**
  - **Less timing quantitation**
  - Good for expressive MIDI performances such as the **Classical music**

MIDI-like vs REMI



Ref: Fradet et al, “MidiTok: A Python package for MIDI file tokenization”, ISMIR LBD 2021

Text vs Symbolic Music Tokens

- **Text tokenizers**
  - **Word**-based tokenizers
    - Large vocabulary size
    - OOV issue
  - **Character**-based tokenizers
    - Small vocabulary size (**tens**)
    - No OOV
    - Long token sequence
  - **Sub-word** tokenizers (e.g., byte-pair encoding)
    - Middle ground
- **Symbolic music tokenizers**
  - Need multiple tokens to describe the *various aspects* of a musical note
  - Need other auxiliary tokens to denote *time* or *musical structure*
  - It's like *character-level* tokenizers
    - Small vocabulary size (**hundreds**)
    - No OOV
    - Long token sequence
  - Can also do sub-word tokenization
    - Ref: Fradet et al, "Byte pair encoding for symbolic music," EMNLP 2023.

Library: MIDITok

https://miditok.readthedocs.io/

- “MidiTok can take care of converting (tokenizing) your symbolic music files (**MIDI**, **abc**) into **tokens**, ready to be fed to models such as **Transformer**, for any generation, transcription or MIR task”
  - “MidiTok features most known MIDI tokenizations (e.g. REMI, Compound Word...), and is built around the idea that they all share common parameters and methods”
  - “It supports Byte Pair Encoding (BPE) and data augmentation.”

Library: MIDITok

https://miditok.readthedocs.io/en/latest/examples.html

Create a tokenizer

A basic example showing how to create a tokenizer, with a selection of custom parameters.

```python
from miditok import REMI, TokenizerConfig  # here we choose to use REMI

# Our parameters
TOKENIZER_PARAMS = {
    "pitch_range": (21, 109),
    "beat_res": {(0, 4): 8, (4, 12): 4},
    "num_velocities": 32,
    "special_tokens": ["PAD", "BOS", "EOS", "MASK"],
    "use_chords": True,
    "use_rests": False,
    "use_tempos": True,
    "use_time_signatures": False,
    "use_programs": False,
    "num_tempos": 32,  # number of tempo bins
    "tempo_range": (40, 250),  # (min, max)
}
config = TokenizerConfig(**TOKENIZER_PARAMS)

# Creates the tokenizer
tokenizer = REMI(config)
```

MIDI - Tokens conversion ¶

Here we convert a MIDI to tokens, decode them back to a MIDI.

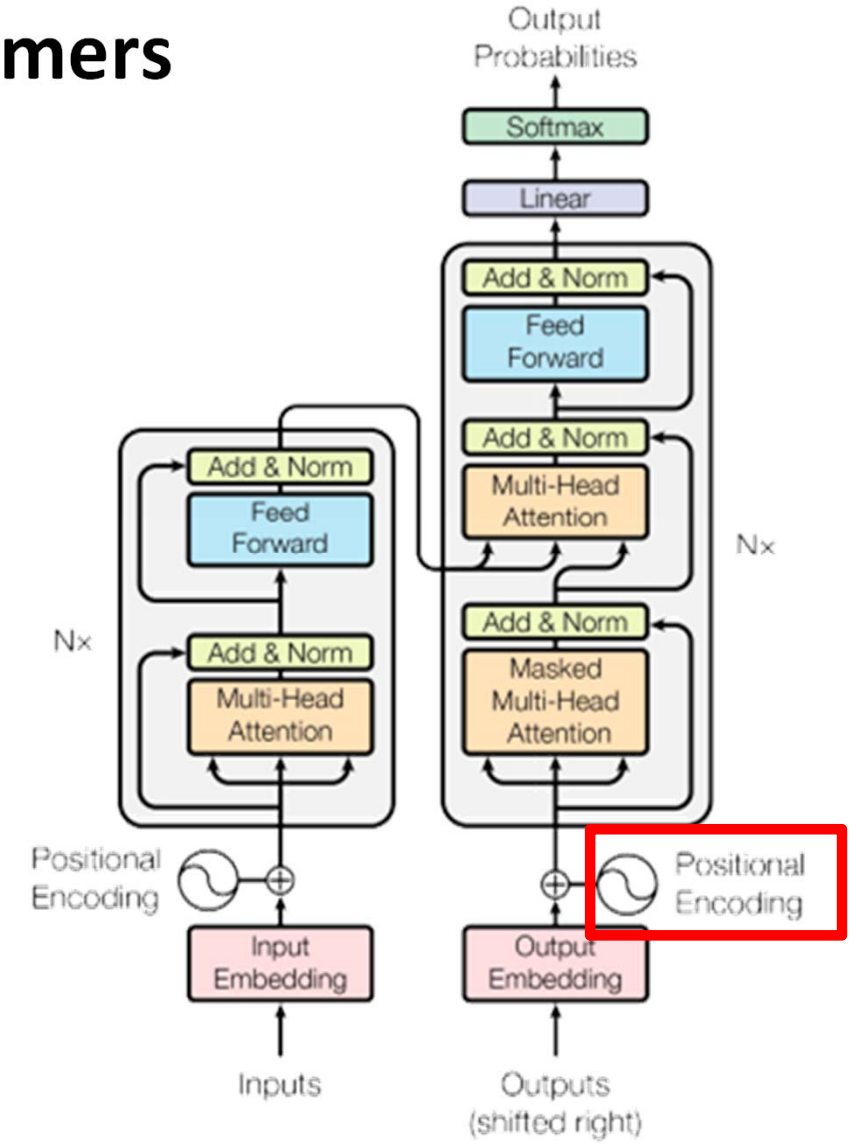
```python
from pathlib import Path

# Tokenize a MIDI file
tokens = tokenizer(Path("to", "your_midi.mid"))  # automatically detects Score objects, paths, tokens

# Convert to MIDI and save it
generated_midi = tokenizer(tokens)  # MidiTok can handle PyTorch/Numpy/Tensorflow tensors
generated_midi.dump_midi(Path("to", "decoded_midi.mid"))
```

Outline

- Sheet music & symbolic representations for music
- Token representation of MIDI music
- **MIDI generation**
- Evaluation metrics

Transformers

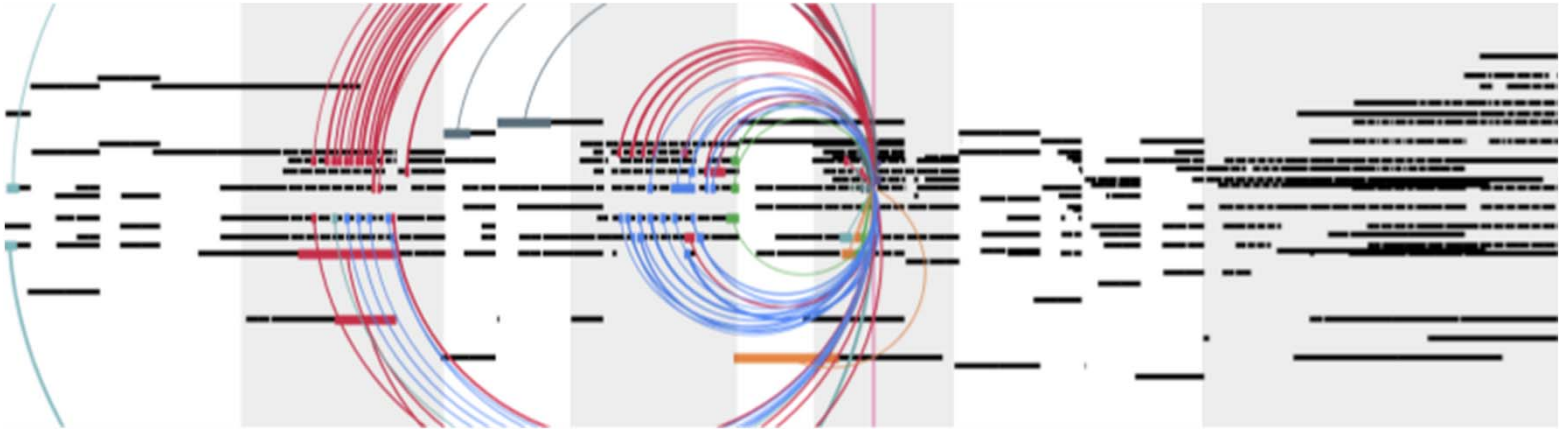
- There are encoders & decoders
  - Encoder: cross-attention
  - Decoder: self-attention
- **Decoder-only** architecture
  - Usually used for unconditional, or prompt-based generation
  - Mainly talk about this one today
- **Encoder/decoder** architecture
  - Usually used for sequence-to-sequence generation



Transformer Example 1: Music Transformer [huang19iclr]

https://magenta.github.io/listen-to-transformer/

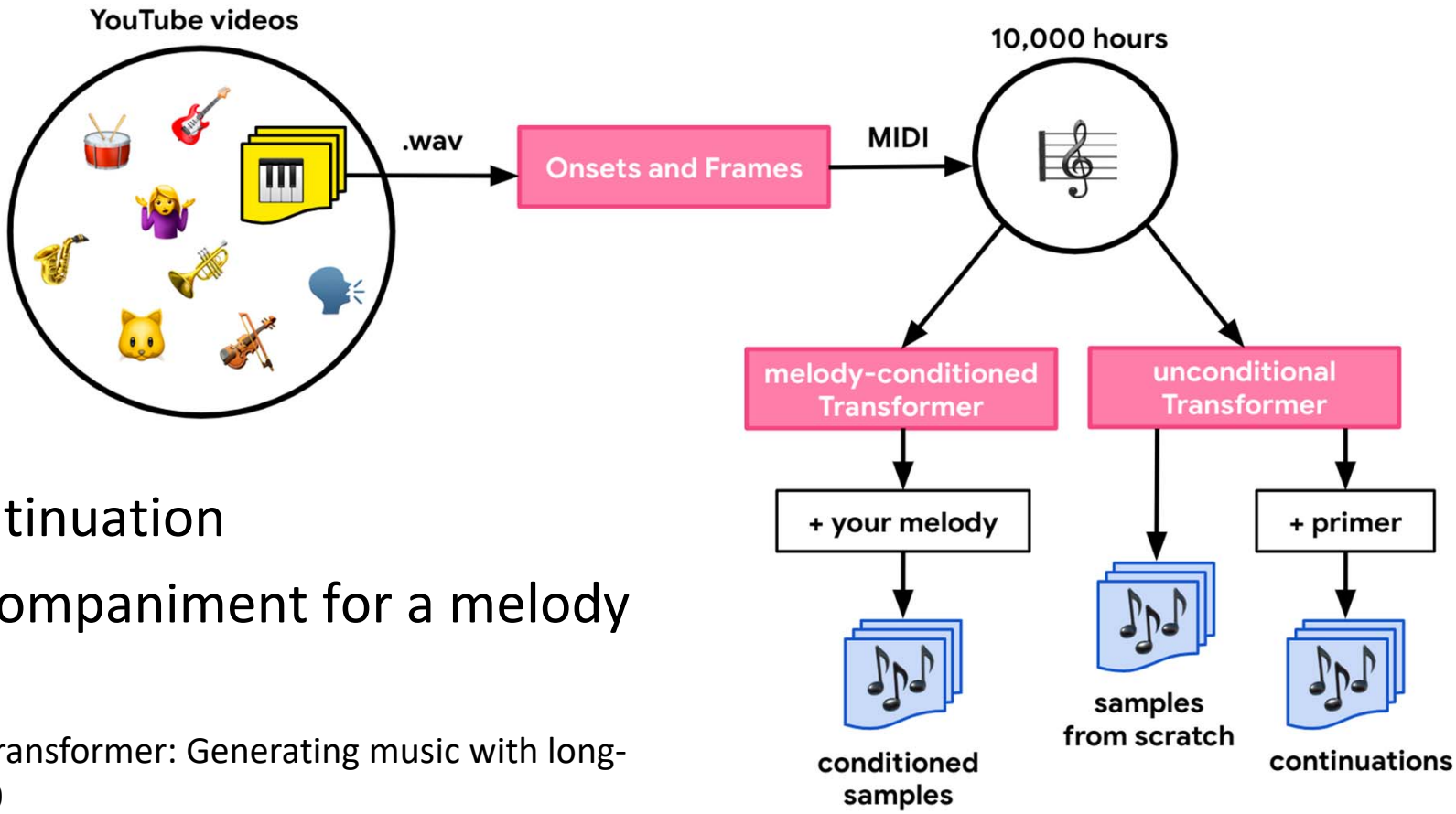
- Generate full piano performances (one note at a time)
  - "… can generate **minute-long** compositions (thousands of steps) with compelling structure, generate continuations that coherently elaborate on a given motif, and in a seq2seq setup generate accompaniments conditioned on melodies."



Ref: Huang et al, "Music Transformer: Generating music with long-term structure", ICLR 2019

Music Transformer [huang19iclr]

https://magenta.tensorflow.org/piano-transformer



- Generate continuation
- Generate accompaniment for a melody

Ref: Huang et al, "Music Transformer: Generating music with long-term structure", ICLR 2019

Transformer Example 2: MuseNet [payne19]

https://openai.com/blog/musenet/

- Generate multi-track MIDIs by a **72-layer** sparse Transformer decoder
  - *Instrument-related* tokens

```
bach piano_strings start tempo90 piano:v72:G1 piano:v72:G2
piano:v72:B4 piano:v72:D4 violin:v80:G4 piano:v72:G4
piano:v72:B5 piano:v72:D5 wait:12 piano:v0:B5 wait:5
piano:v72:D5 wait:12 piano:v0:D5 wait:4 piano:v0:G1 piano:v0:G2
piano:v0:B4 piano:v0:D4 violin:v0:G4 piano:v0:G4 wait:1
piano:v72:G5 wait:12 piano:v0:G5 wait:5 piano:v72:D5 wait:12
piano:v0:D5 wait:5 piano:v72:B5 wait:12
```

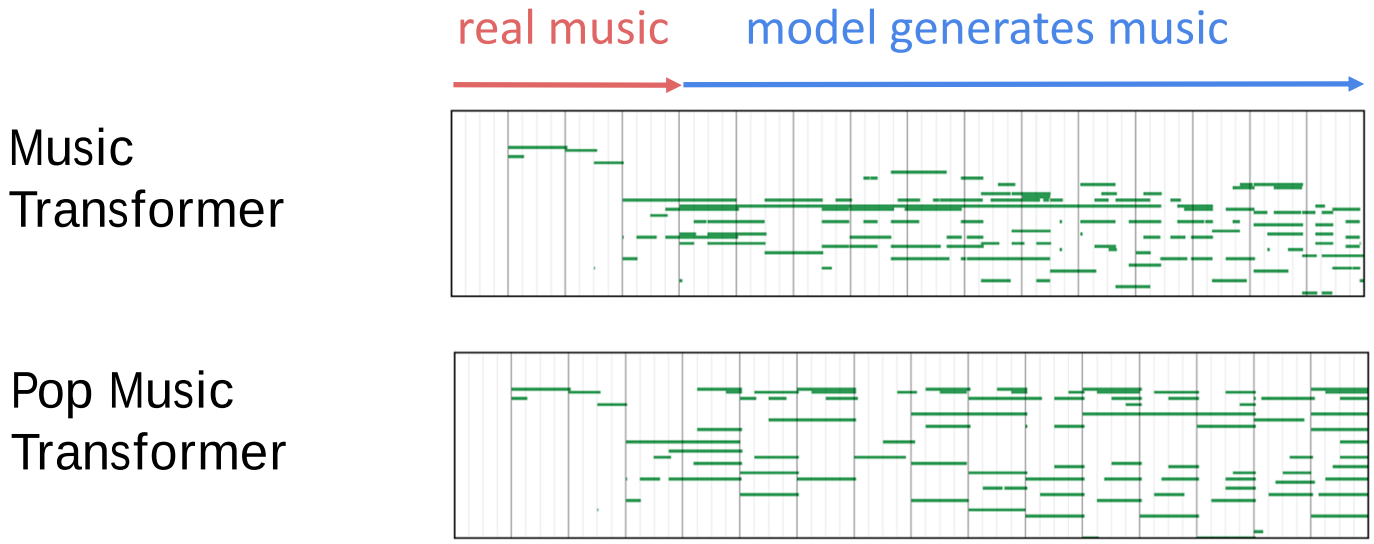
  - Another early multitrack Transformer: LakhNES [donahue19ismir]

Ref 1: Payne et al, “MuseNet,” OpenAI blog, 2019
Ref 2: Donahue et al, “LakhNES: Improving multi-instrumental music generation with cross-domain pre-training”, ISMIR 2019

Transformer Example 3: Pop Music Transformer [huang20mm]

https://github.com/YatingMusic/remi

- Adopt the **REMI** representation
- Outperforms the Music Transformer ("MIDI-like") for generating pop piano performances



Ref: Huang et al, "Pop Music Transformer: Beat-based modeling and generation of expressive Pop piano compositions", ACM Multimedia 2020

Pop Music Transformer [huang20mm]

Pop Music Transformer ("REMI") outscores Music Transformer ("Baselines 1 & 3") in a user study that involves 76 raters

Pairs		Wins	Losses	p-value
REMI	Baseline 1	103	49	5.623e-5
REMI	Baseline 3	92	60	0.0187
Baseline 3	Baseline 1	90	62	0.0440

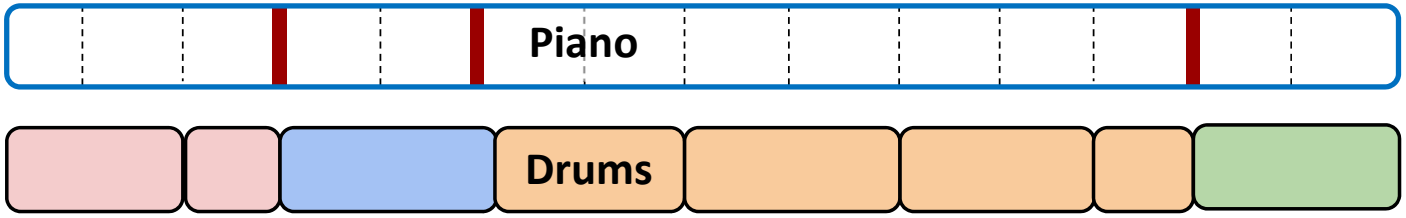
Table 5: The result of pairwise comparison from the user study, with the p-value of the Wilcoxon signed-rank test.

Method	Note offset	Time grid	TEMPO	CHORD	Beat STD	Downbeat STD	Downbeat salience
Baseline 1	NOTE-OFF	TIME-SHIFT (10-1000ms)			0.0968	0.3561	0.1033
Baseline 2	DURATION	TIME-SHIFT (10-1000ms)			0.0394	0.1372	0.1651
Baseline 3	DURATION	TIME-SHIFT (16th-note multiples)			0.0396	0.1383	0.1702
REMI	DURATION	POSITION & BAR	✓	✓	0.0386	0.1376	0.2279
	DURATION	POSITION & BAR	✓		0.0363	0.1265	0.1936
	DURATION	POSITION & BAR		✓	0.0292	0.0932	0.1742
	DURATION	POSITION & BAR			0.0199	0.0595	0.1880
Real data					0.0607	0.2163	0.2055

Pop Music Transformer

piano + drum guitar


- **Easier to add drums** (via structure analysis and grooving analysis)
  - https://soundcloud.com/yating_ai/sets/ai-piano-generation-demo-202004
  - https://soundcloud.com/yating_ai/sets/ai-pianodrum-generation-demo-202004



(Figure made by Wen-Yi Hsiao)

- Extensions can also generate **guitar tabs** [chen20ismir]
  - https://soundcloud.com/yating_ai/ai-guitar-tab-generation-202003/s-KHozfW0PTv5

Ref 1: Huang et al, “Pop Music Transformer: Beat-based modeling and generation of expressive Pop piano compositions”, ACM Multimedia 2020
Ref 2: Chen et al, “Automatic composition of guitar tabs by Transformers and groove modeling”, ISMIR 2020

Building Your First MIDI Transformer Decoder

- Step (1): Task & Data
- Step (2): Token representation
- Step (3): Choose a model
- Step (4): Train the model till the loss is sufficiently low
- Step (5): Do inference
- Step (6): Listen to the generated music!
- Step (7): Do evaluation

DIY Step (1): Task & Data

- Choose a task, and a dataset
  - https://github.com/affige/genmusic_demo_list
- List of symbolic musical datasets
  - https://github.com/wayne391/symbolic-music-datasets
- Three relatively more frequently studied cases
  - Lead sheets (MIDI score) — Jazz Transformer (ISMIR'20), Compose & Embellish (ICASSP'23)
  - Multi-track MIDI (MIDI score) — Multitrack Music Transformer (ICASSP'23)
  - Piano performance — Pop Music Transformer (MM'20), Compose & Embellish (ICASSP'23)

Dataset: MelodyHub

https://huggingface.co/datasets/sander-wood/melodyhub

Table 1. The MelodyHub collection statistics include the number of instances for each task along with the corresponding data sources. The JSB Chorales dataset is augmented to 15 keys due to its small size and original data in the C key.

Data Sources	Cataloging	Generation	Harmonization	Melodization	Segmentation	Transcription	Variation
ABC Notation [31]	184,660	184,738	31,732	31,690	——	174,779	——
FolkWiki [32]	6,610	6,767	1,207	1,205	——	6,218	——
JSB Chorales [33]	4,980	4,980	4,950	4,950	19,125	4,980	——
KernScores [34]	1,731	1,776	——	——	1,275	1,754	——
Meertens Tune Collections [35]	16,662	16,662	——	——	16,660	16,297	——
Nottingham [36]	1,031	1,031	1,014	1,014	——	1,021	——
OpenScore Lieder [37]	1,326	1,326	——	——	——	1,255	——
The Session [38]	44,620	44,620	3,081	3,078	——	42,838	174,104
Total	261,620	261,900	41,984	41,937	37,060	249,142	174,104

Dataset: Piano MIDI

Dataset	Size			Artist		Modality		
	Performances	Hours	Compositions	Composers	Performers	Perf. MIDI	Score	CER
SUPRA [18]	478	52	408	111	153	✓	×	×
SMD [19]	50	4.7	50	11	unknown	✓	×	×
MazurkaBL [20]	2000	110	44	1	135	×	100%	✓
Maestro v3.0 [21]	1276	172	864	60	205*	✓	×	×
CrestMusePEDB [22]	443	unknown	35	14	12	✓	✓	×
GP† Curated [23]	7236	875	7236	1787	unknown	✓	×	×
ASAP [24]	1068	92	222	15	unknown	✓	100%	×
ATEPP	11742	1007	1580	25	49	✓	43%	✓

Table 1. Overview of major symbolic piano datasets. CER: composition entity resolution. *Number obtained from crawling the Piano-e-Competition website for performer names and aligning with Maestro data. †GP stands for GiantMIDI-Piano.

Ref: Zhang et al, "ATEPP: A dataset of automatically transcribed expressive piano performance", ISMIR 2022

Dataset: Jazz Piano MIDI

https://almostimplemented.github.io/PiJAMA/

https://zenodo.org/records/8354955

PiJAMA: Piano Jazz With Automatic MIDI Annotations

This notebook provides supplementary material and demonstrations of results associated with our dataset publication

The MIDI is available for download here: https://zenodo.org/record/8354955

Table of Contents:

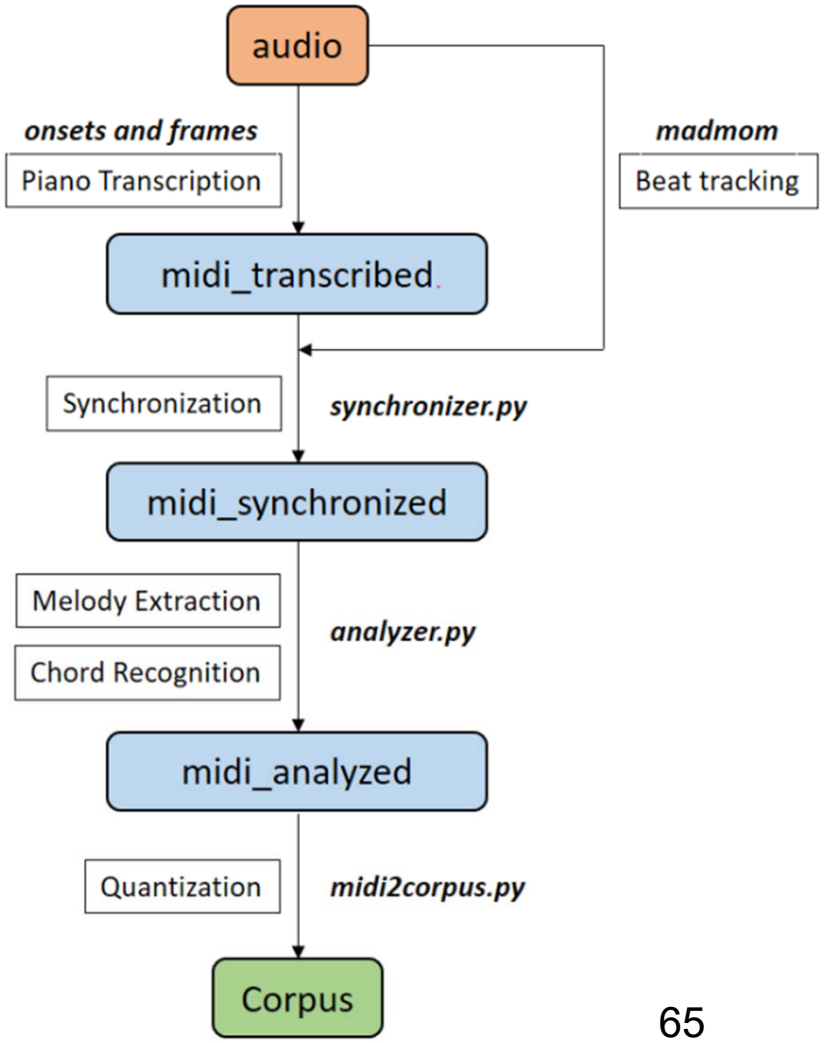
Ref: Zhang et al, “ATEPP: A dataset of automatically transcribed expressive piano performance”, ISMIR 2022

DIY: To Prepare a Dataset of Piano "Performances"

https://github.com/YatingMusic/compound-word-transformer/blob/main/dataset/Dataset.md

- Piano transcription
- Beat and downbeat tracking
- Melody extraction
- Chord recognition
- Quantization

- Additional steps
  - Auto-tagging
  - Source separation



DIY Step (2): Choose A Token Representation

- Ref: https://miditok.readthedocs.io/
- Single-track
  - MIDI-like, REMI, CP, etc
- Multi-track
  - REMI+, Octuple, MMM, MuMIDI, etc
- Depend on your GPU VRAM, you may need to decide a sequence length and cut your musical pieces into segments

DIY Step (3): Choose A Model

- PyTorch 2 Transformers
  https://pytorch.org/blog/accelerated-pytorch-2/

- Huggingface Transformer
  https://huggingface.co/docs/transformers/index

- x-Transformers
  https://github.com/lucidrains/x-transformers

DIY Step (4): Train the Model

- Train the model till the loss is ***sufficiently*** low
- Our experience on pop piano
  - Training loss around **0.30** gives better result
  - The model **overfits** and generates overly repeating content when loss is nearly 0
  - Keep several **checkpoints** and **listen to** them to choose one

- No need to consider validation data
  - Unless you are building a conditional generation model with, for example, an encoder/decoder architecture

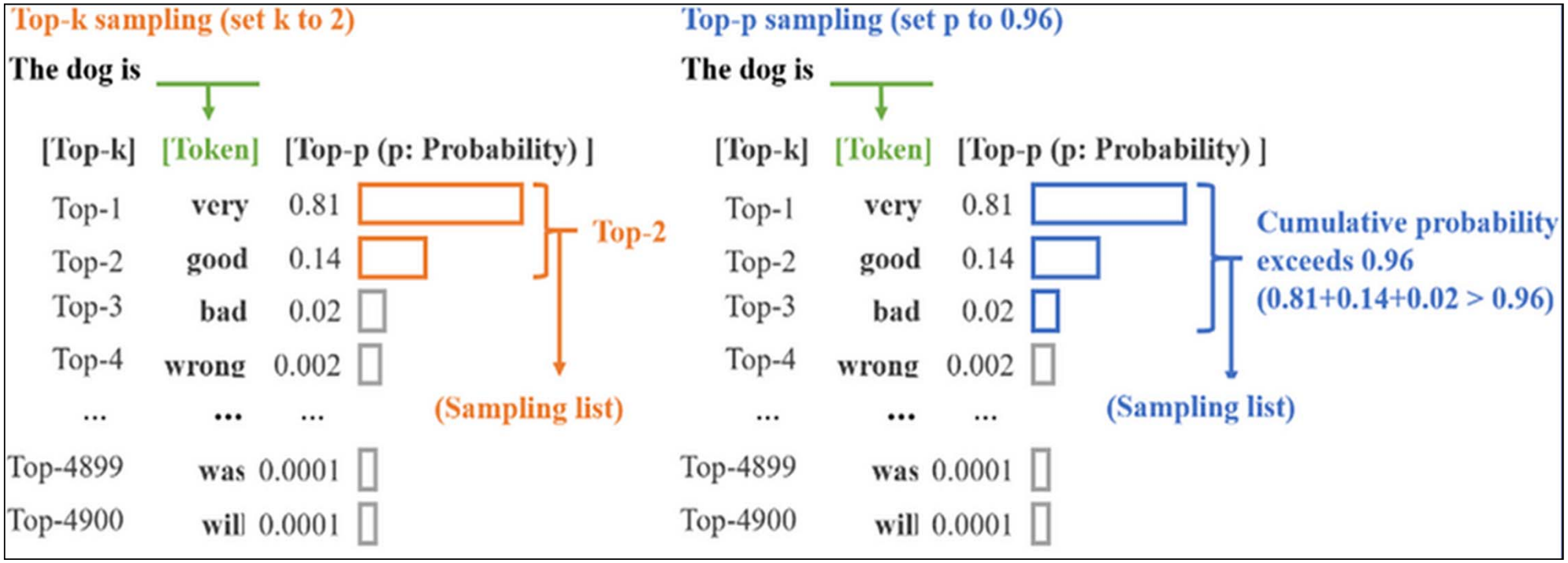
DIY Step (5): Do Inference

https://blog.csdn.net/qq_43243579/article/details/136331123

https://www.youtube.com/watch?v=_3DWwb96exY

- **Sampling strategy**
  - Greedy
  - Beam search
  - Random sampling
  - **Top-K Sampling**
    - Only top K probable tokens should be considered for a generation
  - **Nucleus Sampling**
    - Focuses on the smallest possible sets of top-V words with the sum of their probability is ≥ p
- **Temperature**

Top-K Sampling & Nucleus Sampling



(image from the Internet)

- Top-K Sampling: fixed number of candidates
- Nucleus Sampling: variable number of candidates

Temperature

- Tweak the prob. distribution *before* sampling
  - set the value **>1** for **diversity**

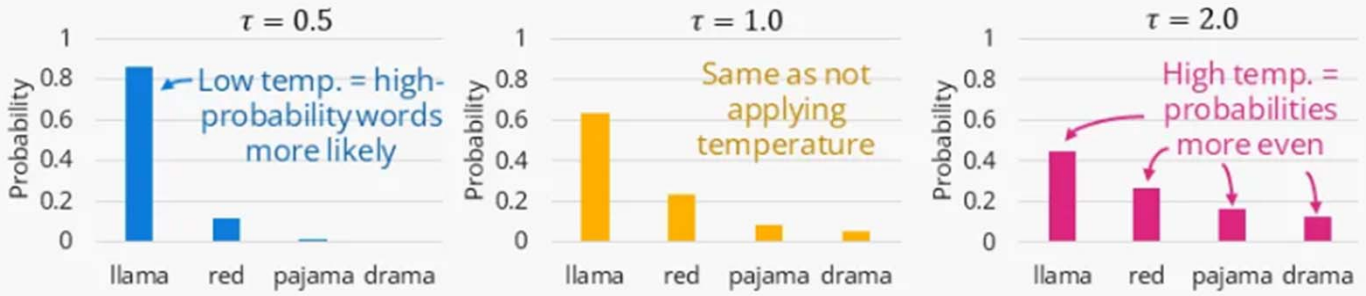
$$\frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

TEMPERATURE SAMPLING

Sampling is a common method used by LLMs for generating output tokens: the next token is randomly chosen based on the token probabilities learned by the LLM. Temperature sampling affects the shape of the probability distribution of tokens by introducing a scaling factor τ (temperature):

Final normalized token probabilities → $y = \text{softmax}\left(\frac{\text{logits}}{\tau}\right)$ ← Raw model scores; ← Temperature

If $\tau = 1.0$, the probabilities are unchanged. When τ is closer to 0, the probability of high-probability words is increased and probability of low-probability words is decreased (i.e., randomness is reduced and the model is more likely to pick a high-probability word). Setting τ to a value greater than 1 has the opposite effect. Top-k and top-p sampling are alternatives to and can be used in conjunction with temperature sampling.



DIY Step (5): Do Inference

- **Tweak the sampling parameters** to strike a better balance between **diversity** and **quality**
  - The sampling parameters can influence the generation result **A LOT**
    - But, oftentimes people did not describe how they choose the sampling parameters for their proposed models and the evaluated baseline models, leading to unfair performance comparison
  - **A good practice in our Compose & Embellish (ICASSP'23) paper**

> Nucleus sampling [21] with temperatured softmax is employed during inference. We discover that the temperature τ and probability mass truncation point p greatly affect the intra-sequence repetitiveness and diversity of generated lead sheets. Thus, we follow [22] and search within $\tau = \{1.2, 1.3, 1.4\}$ and $p = \{.95, .97, .98, .99\}$ to find a combination with which our lead sheet model generates outputs with the closest mean perplexity (measured by the model itself) to that of validation real data. Finally, $\tau = 1.2$ and $p = .97$ are cho-

Ref: Wu et al, "Compose & Embellish: Well-structured piano performance generation via a two-stage approach", ICASSP 2023

DIY Step (5): Do Inference

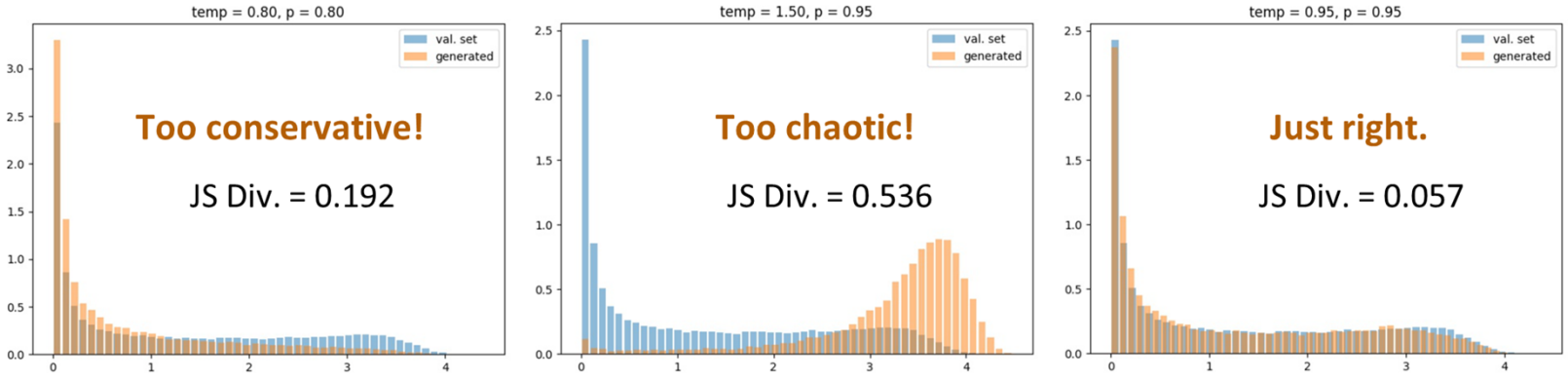
- **Nucleus Sampling w/ Temperature** [Holtzman et al., 2019]
  - Temperature -- **Reshape distribution**
  - Top-*p* -- **Truncate long tail**

→ collectively control how **aggressive** the sampling is

$$\mathrm{PPL}(X) = \exp\left\{-\frac{1}{t}\sum_{i}^{t}\log p_\theta(x_i|x_{<i})\right\}$$

https://huggingface.co/docs/transformers/perplexity

- Goal: match the **entropy histogram** during **sampling** to that computed on **val. set** by tuning temp. and top-*p*



(Slide made by Shih-Lun Wu)

Ref: Wu et al, “Compose & Embellish: Well-structured piano performance generation via a two-stage approach”, ICASSP 2023

DIY Step (6): Listen to the Generated Music!

https://www.fluidsynth.org/

https://github.com/bzamecnik/midi2audio

- Use a synthesizer if you prefer to listen to audio

FluidSynth

A SoundFont Synthesizer

FluidSynth is a real-time software synthesizer based on the SoundFont 2 specifications and has reached widespread distribution. FluidSynth itself does not have a graphical user interface, but due to its powerful API several applications utilize it and it has even found its way onto embedded systems and is used in some mobile apps.

```
from midi2audio import FluidSynth
```

Play MIDI:

```
FluidSynth().play_midi('input.mid')
```

Synthesize MIDI to audio:

```
# using the default sound font in 44100 Hz sample rate
fs = FluidSynth()
fs.midi_to_audio('input.mid', 'output.wav')
```

DIY Step (7): Do Evaluation

- Objective evaluation
- Subjective evaluation

Outline

- Sheet music & symbolic representations for music
- Token representation of MIDI music
- MIDI generation
- **Evaluation metrics**

Evaluation Metrics for MIDI Generation

- Subjective evaluation metrics (e.g., MOS)
  - Tend to be more convincing
  - Many details about the design of a user study, though

Table 4. User study MOS results. (**Coh**erence, **Cor**rectness, **S**tructureness, **R**ichness, **O**verall. SDs across individual data points follow ±.)

	Ch	Cr	S	R	O
CPT [4]	2.38±0.9	2.49±0.9	2.33±0.9	2.64±0.9	2.33±0.9
C&E (ours)	3.53±0.9	3.11±1.0	3.36±1.2	3.29±1.0	3.18±0.9
Real data	4.42±0.7	4.13±0.8	4.44±0.8	4.24±0.8	4.40±0.7

Ref: Wu & Yang, "Compose & Embellish: Well-structured piano performance generation via a two-stage approach", ICASSP 2023

- Objective evaluation metrics
  - May not reflect human perception
  - Good for preliminary experiments

Objective Evaluation Metrics for MIDI Generation

- Important aspects of MIDI generation
  - **Correctness**: "Is the music free of inharmonious notes, unnatural rhythms, and awkward phrasing?"
  - **Coherence**: over time & across different tracks
  - **Structureness**: "Are recurring motifs / phrases / sections, and reasonable musical development present?"
  - **Richness**: "Is the music intriguing and full of variations within?"
  - **Controllability**: Can the generation process be easily steered? Does the model allow for easy human-AI co-generation?

Ref: Wu & Yang, "Compose & Embellish: Well-structured piano performance generation via a two-stage approach", ICASSP 2023

Objective Measures for Correctness and Coherence

https://github.com/slSeanWU/MusDr

- For single-track MIDI (e.g., Piano) → use **MusDr**
  - Pitch-Class Histogram Entropy (**H**)
    -- measures erraticity of **pitch usage** in shorter timescales (e.g., 1 or 4 bars)
  - Grooving Pattern Similarity (**GS**)
    -- measures consistency of **rhythm** across the entire piece
  - Chord Progression Irregularity (**CPI**)
    -- measures consistency of **harmony** across the entire piece

Ref: Wu & Yang, "The Jazz Transformer on the front line: Exploring the shortcomings of AI-composed music through quantitative measures", ISMIR 2020

Pitch Class Histogram Entropy

- "If a piece's **tonality** is clear, some **pitch classes** should dominate the pitch histogram (e.g., the tonic and dominant), resulting in low-entropy"

To gain insight into the usage of different pitches, we first collect the notes appeared in a certain period (e.g., a bar) and construct the 12-dimensional pitch class histogram $\overrightarrow{\mathbf{h}}$, according to the notes' pitch classes (i.e. `C`, `C#`, ..., `A#`, `B`), normalized by the total note count in the period such that $\sum_i h_i = 1$. Then, we calculate the entropy of $\overrightarrow{\mathbf{h}}$:

$$\mathcal{H}(\overrightarrow{\mathbf{h}}) = -\sum_{i=0}^{11} h_i \log_2(h_i)\,. \tag{2}$$

The entropy, in information theory, is a measure of "uncertainty" of a probability distribution [40], hence we adopt it here as a metric to help assessing the music's quality in tonality. If a piece's tonality is clear, several pitch classes should dominate the pitch histogram (e.g., the tonic and the dominant), resulting in a low-entropy $\overrightarrow{\mathbf{h}}$; on the contrary, if the tonality is unstable, the usage of pitch classes is likely scattered, giving rise to an $\overrightarrow{\mathbf{h}}$ with high entropy.

Ref: Wu & Yang, "The Jazz Transformer on the front line: Exploring the shortcomings of AI-composed music through quantitative measures", ISMIR 2020

Grooving Pattern Similarity

- If a piece possesses a clear sense of **rhythm**, the **grooving patterns** between pairs of bars should be similar, thereby producing high GS scores

The grooving pattern represents the positions in a bar at which there is at least a note onset, denoted by $\overrightarrow{\mathbf{g}}$, a 64-dimensional binary vector in our setting.[6] We define the similarity between a pair of grooving patterns $\overrightarrow{\mathbf{g}}^a$, $\overrightarrow{\mathbf{g}}^b$ as:

$$\mathcal{GS}(\overrightarrow{\mathbf{g}}^a, \overrightarrow{\mathbf{g}}^b) = 1 - \frac{1}{Q}\sum_{i=0}^{Q-1} \mathrm{XOR}(g_i^a, g_i^b)\,, \qquad (3)$$

where Q is the dimensionality of $\overrightarrow{\mathbf{g}}^a$, $\overrightarrow{\mathbf{g}}^b$, and $\mathrm{XOR}(\cdot,\cdot)$ is the exclusive OR operation. Note that the value of $\mathcal{GS}(\cdot,\cdot)$ would always lie in between 0 and 1.

The grooving pattern similarity helps in measuring the music's rhythmicity. If a piece possesses a clear sense of rhythm, the grooving patterns between pairs of bars should be similar, thereby producing high $\mathcal{GS}$ scores; on the other hand, if the rhythm feels unsteady, the grooving patterns across bars should be erratic, resulting in low $\mathcal{GS}$ scores.

Ref: Wu & Yang, "The Jazz Transformer on the front line: Exploring the shortcomings of AI-composed music through quantitative measures", ISMIR 2020

Chord Progression Irregularity

- A well-composed Jazz piece should have a chord progression irregularity that is not too high

To measure the irregularity of a chord progression, we begin by introducing the term *chord trigram*, which is a triple composed of 3 consecutive chords in a chord progression; for example, (`Dm7`, `G7`, `CM7`). Then, *the chord progression irregularity* (*CPI*) is defined as the percentage of *unique chord trigrams* in the chord progression of an entire piece. Please note that 2 chord trigrams are considered different if any of their elements does not match.

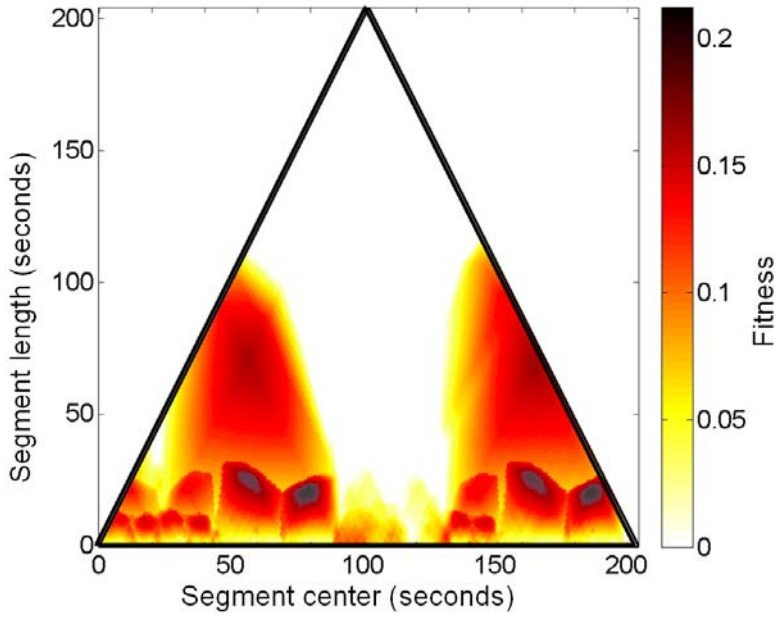
It is common for Jazz compositions to make use of 8- or 12-bar-long templates of chord progressions (known as the *8-*, or *12-bar blues*), which themselves can be broken down into similar substructures [25, 35], as the foundation of a section, and more or less "copy-paste" them to form the complete song with, say, `AABA` parts. Therefore, a well-composed Jazz piece should have a chord progression irregularity that is not too high.

Ref: Wu & Yang, "The Jazz Transformer on the front line: Exploring the shortcomings of AI-composed music through quantitative measures", ISMIR 2020

Objective Measures for Structureness

https://github.com/slSeanWU/MusDr

- **MusDr**



Ref: Wu & Yang, "The Jazz Transformer on the front line: Exploring the shortcomings of AI-composed music through quantitative measures", ISMIR 2020

Our *structureness indicator* is based on the fitness scape plot and designed to capture the most salient repeat within a certain duration interval. For brevity of the mathematical representation, we assume the sampling frame rate of S is 1 Hz (hence N will be the piece's duration in seconds), and define the structureness indicator as follows:

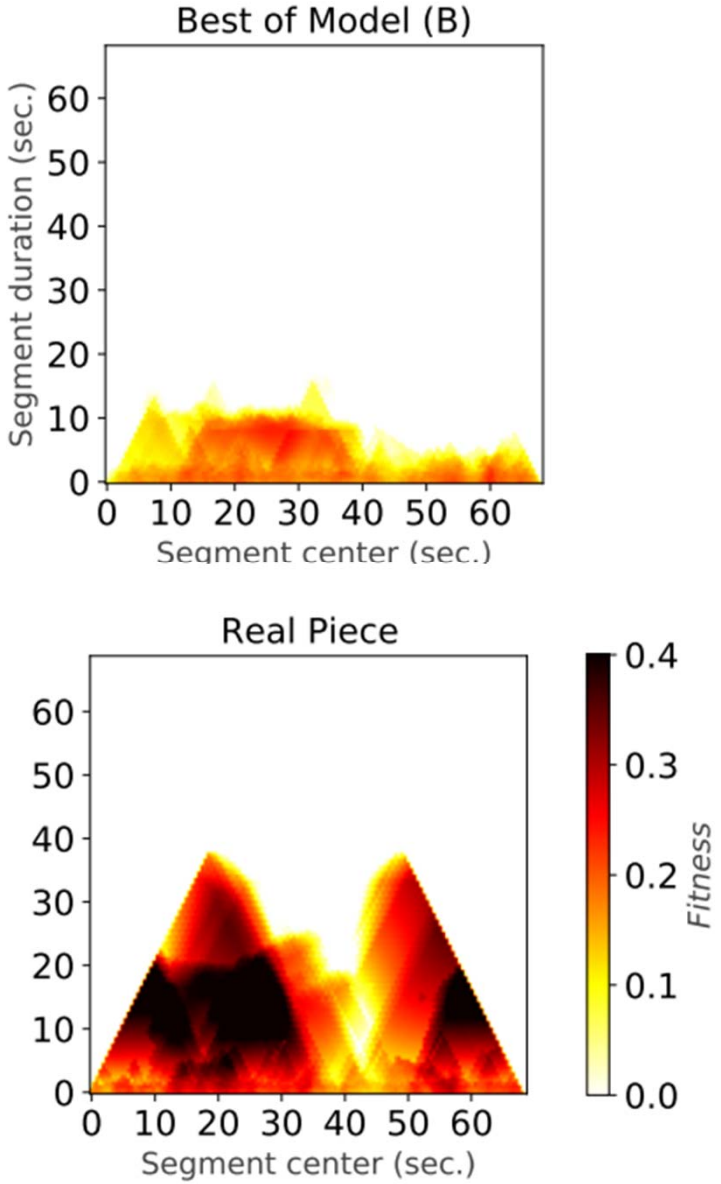
$$\mathcal{SI}_l^u(S) = \max_{\substack{l \le i \le u \\ 1 \le j \le N}} S\,, \tag{4}$$

where l, u [8] are the lower and upper bounds of the duration interval (in seconds) one is interested in. In our experiments, we choose the structureness indicators of $\mathcal{SI}_3^8$, $\mathcal{SI}_8^{15}$, and $\mathcal{SI}_{15}$ to examine the short-, medium-, and long-term structureness respectively.

Evaluation Result of a 2020 Paper

	Model (A)		Model (B)			Real
loss	*0.80*	*0.25*	*0.80*	*0.25*	*0.10*	- -
$\mathcal{H}_1$	2.29	2.45	2.26	2.20	**2.17**	1.94
$\mathcal{H}_4$	3.12	3.05	3.04	**2.91**	2.94	2.87
$\mathcal{GS}$	**0.76**	0.69	0.75	**0.76**	**0.76**	0.86
$\mathcal{CPI}$	81.2	77.6	79.2	**72.6**	75.9	40.4
$\mathcal{SI}_3^8$	0.18	0.22	0.25	**0.27**	0.26	0.36
$\mathcal{SI}_8^{15}$	0.15	0.17	**0.18**	**0.18**	0.17	0.36
$\mathcal{SI}_{15}$	0.11	**0.14**	0.10	0.12	0.11	0.35

Ref: Wu & Yang, “The Jazz Transformer on the front line: Exploring the shortcomings of AI-composed music through quantitative measures”, ISMIR 2020



Objective Measures for Correctness and Coherence

https://salu133445.github.io/muspy/doc/metrics.html

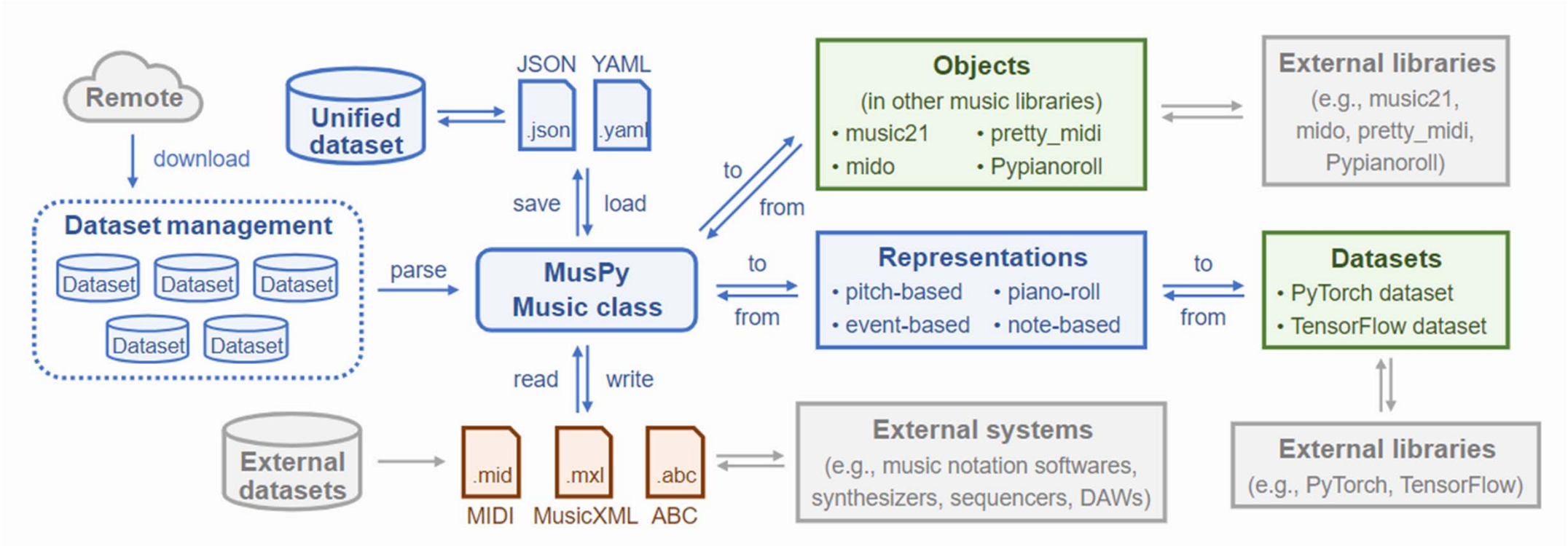
- For general MIDI → use **MusPy**

- drum_in_pattern_rate
- drum_pattern_consistency
- empty_beat_rate
- empty_measure_rate
- groove_consistency
- n_pitch_classes_used
- n_pitches_used
- pitch_class_entropy
- pitch_entropy
- pitch_in_scale_rate
- pitch_range
- polyphony
- polyphony_rate
- scale_consistency

Ref 1: Dong et al,"MusPy: A toolkit for symbolic music generation", ISMIR 2020
Ref 2: Dong et al, "MuseGAN: Multi-track sequential generative adversarial networks for symbolic music generation and accompaniment", AAAI 2018

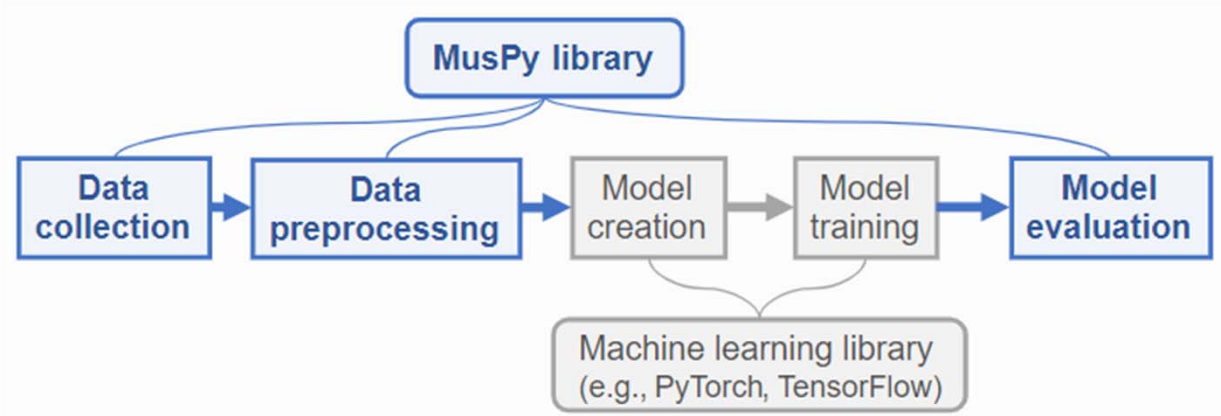
Library: MusPy

https://salu133445.github.io/muspy/index.html



Library: MusPy

https://salu133445.github.io/muspy/index.html



- **Features**
  - Dataset management system for commonly used **datasets** with interfaces to PyTorch and TensorFlow
  - Data **I/O** for common symbolic music formats and interfaces to other symbolic music libraries
  - Implementations of common **representations** for music generation, including the pitch-based, the event-based, the piano-roll and the note-based representations
  - Model **evaluation tools** for music generation systems, including audio rendering, score and piano-roll visualizations and objective metrics