MusPy: Symbolic Music Processing in Python

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UC San Diego

About me

Hi, I'm Herman.
I do Music x AI research.
I love music and movies!

National Taiwan University
B.S. in Electrical Engineering
2013 – 2017

2017 – 2019
Academia Sinica
Research Assistant

Summer 2019
Yamaha
Research Intern

University of California San Diego
M.S. in Computer Science
2019 – 2021

Summer 2021
Dolby
Deep Learning Audio Intern

University of California San Diego
PhD Candidate in Computer Science
UC San Diego
2019 – present

(Summer 2022)
Sony
Student Intern

(Fall 2022)
Amazon
Applied Scientist Intern

Outline

- Intro to MusPy
- Experiments
- Case Study I – Automatic Instrumentation
- Case Study II – Music Performance Synthesis

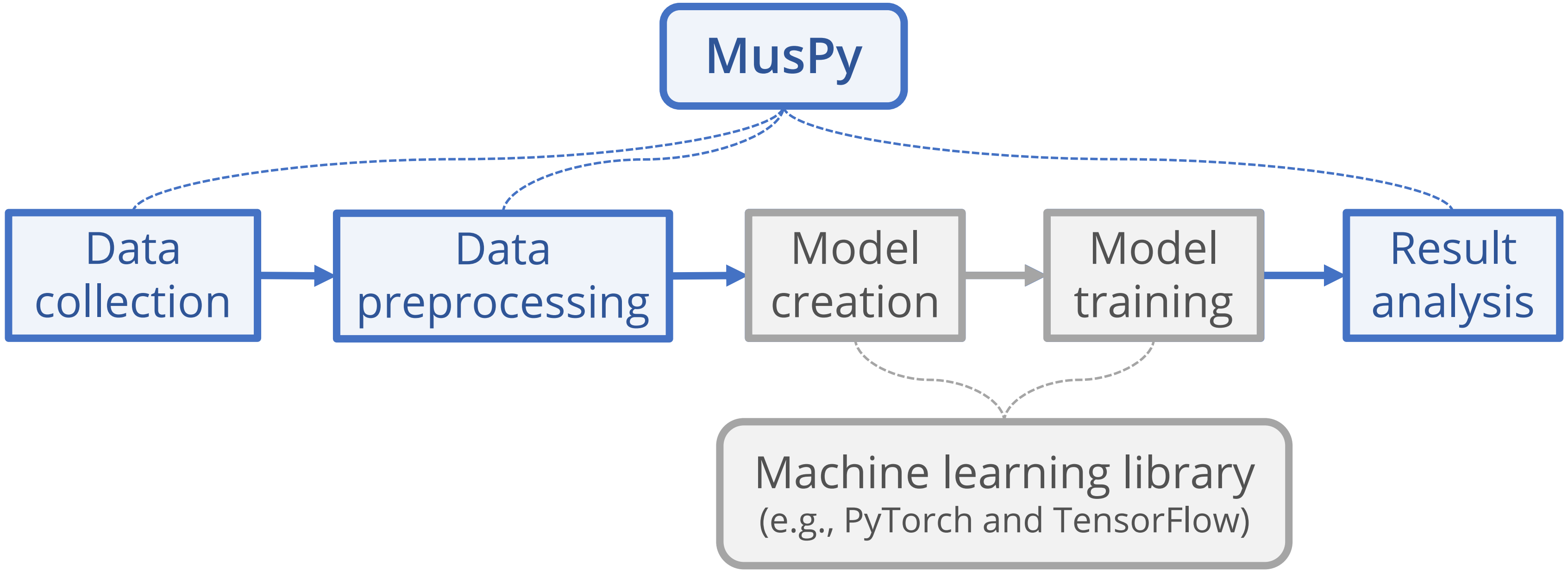
Intro to MusPy

"MusPy: A Toolkit for Symbolic Music Generation" (ISMIR 2020)

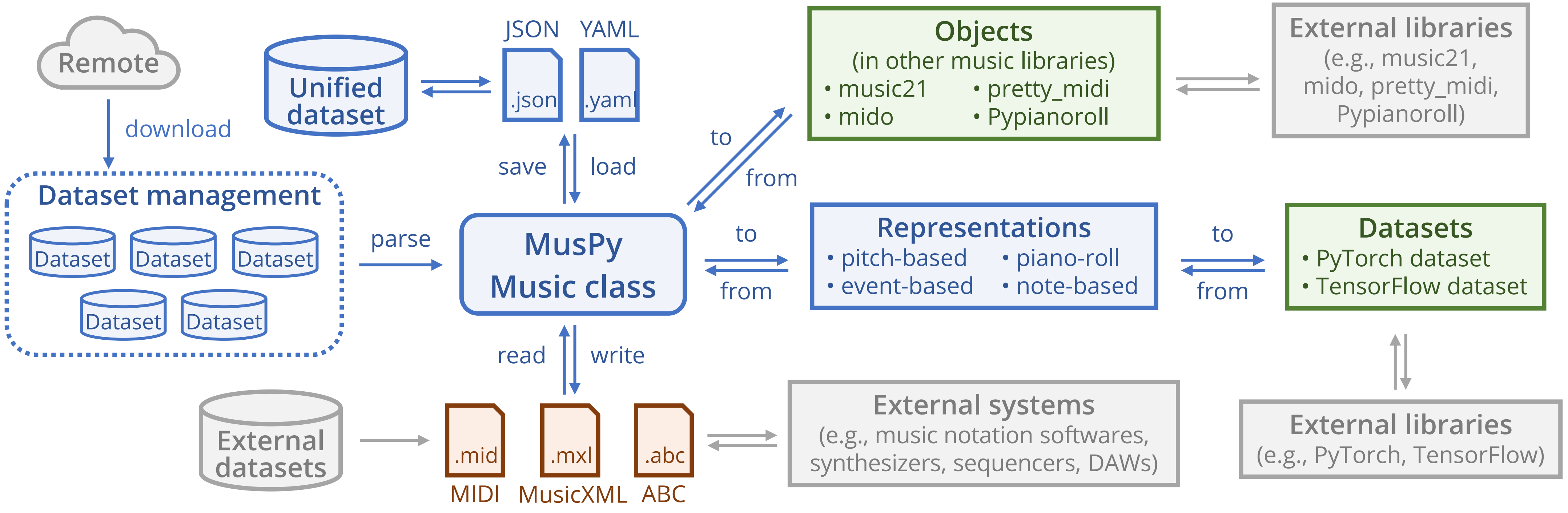
Hao-Wen Dong   Ke Chen   Julian McAuley   Taylor Berg-Kirkpatrick

Why MusPy?


MusPy
Data collection
Data preprocessing
Model creation
Model training
Result analysis
Machine learning library
(e.g., PyTorch and TensorFlow)

Overview



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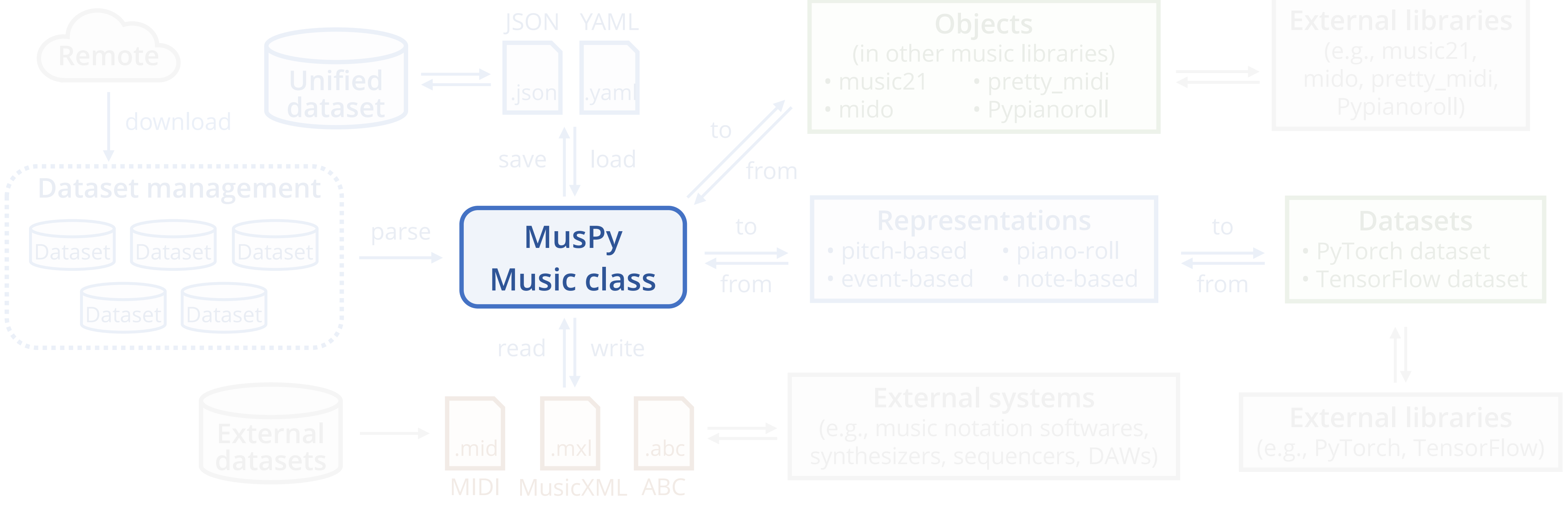

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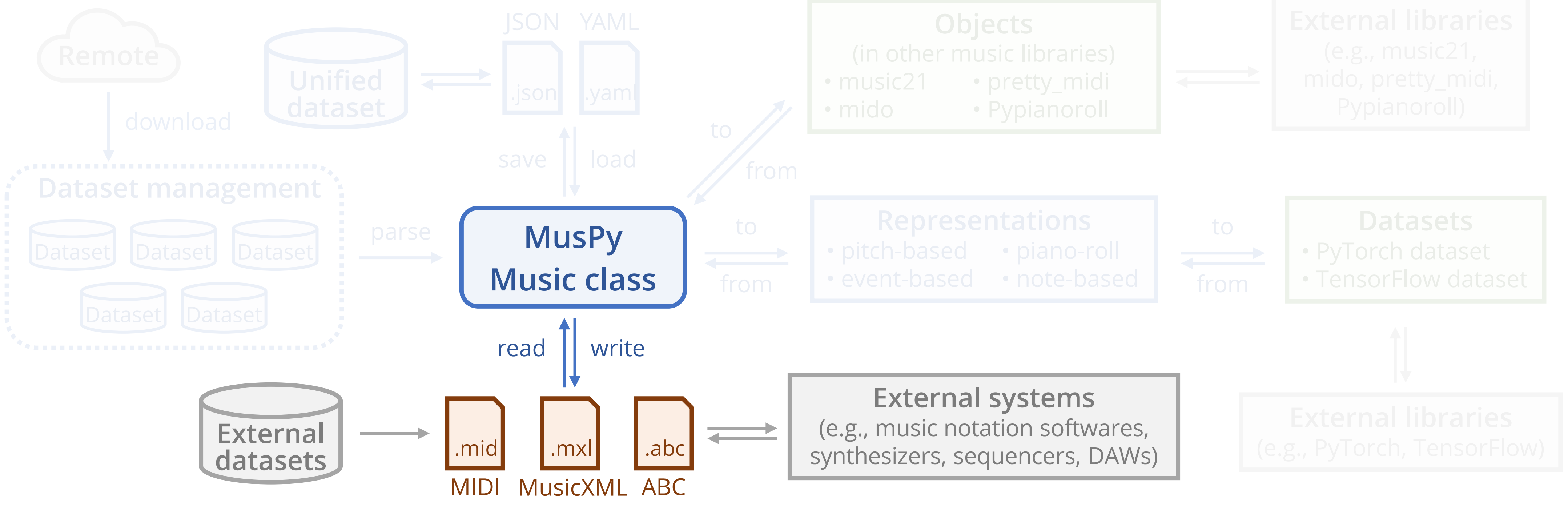

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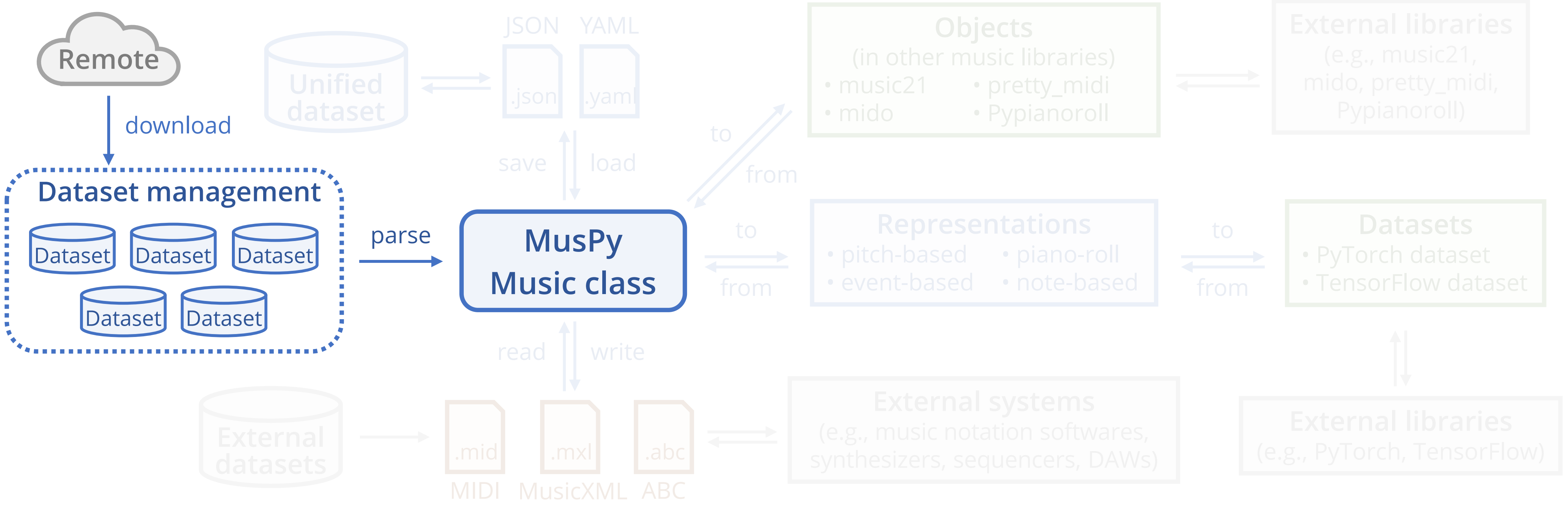

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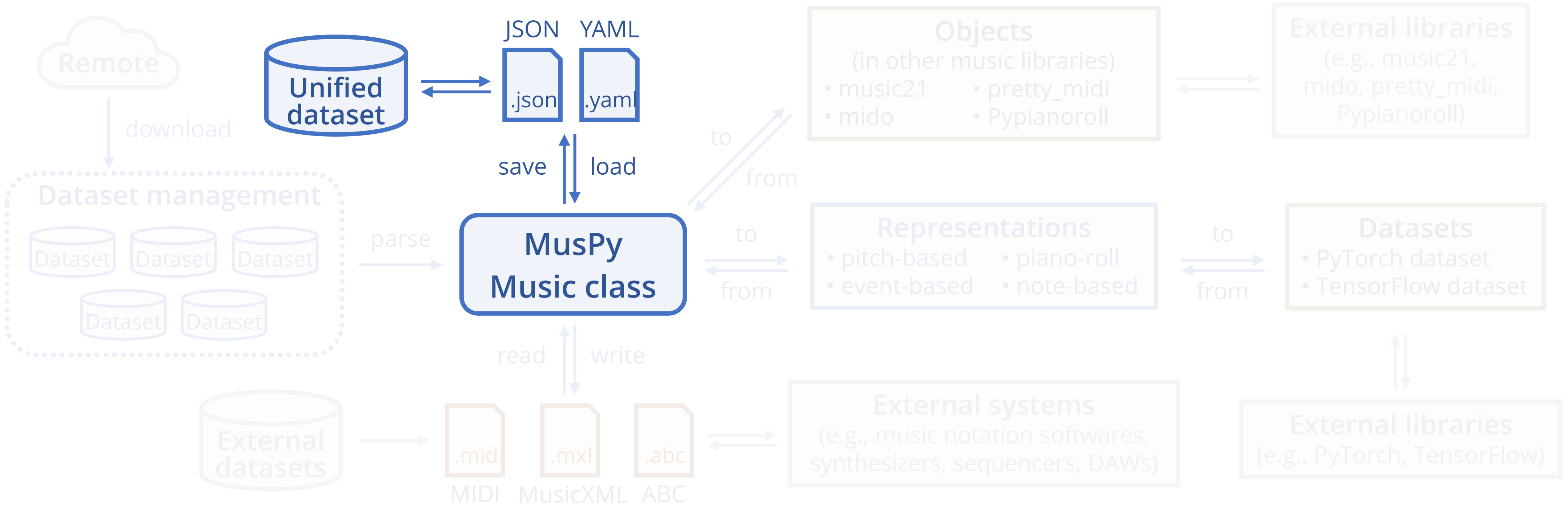

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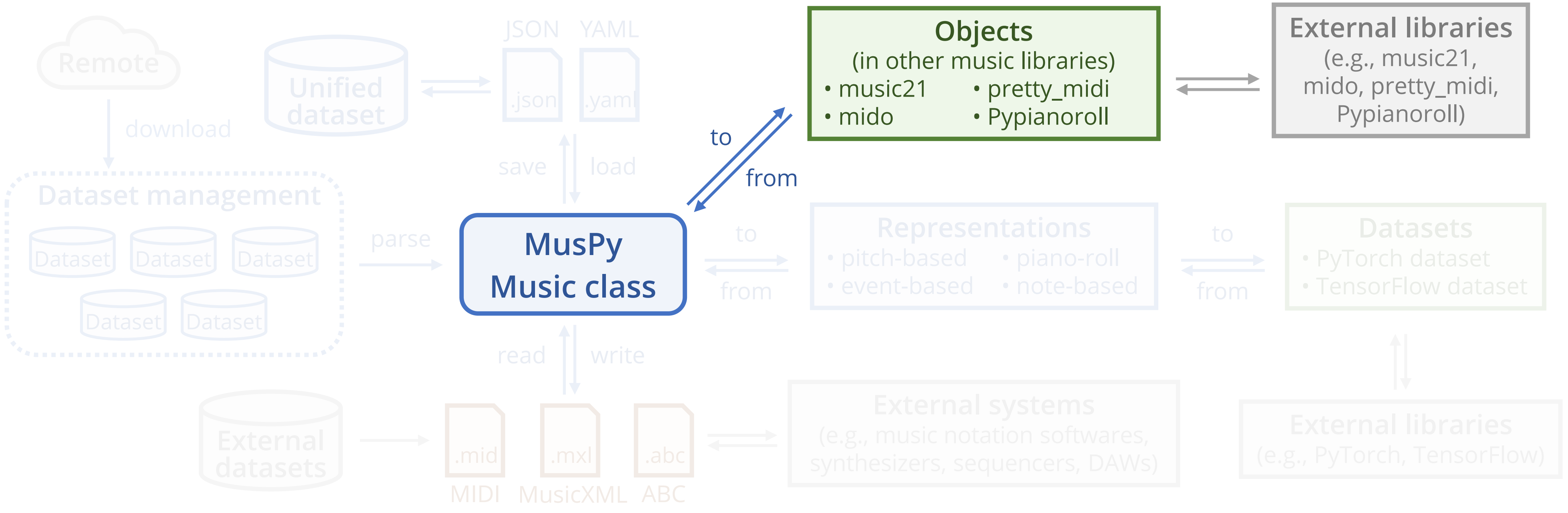
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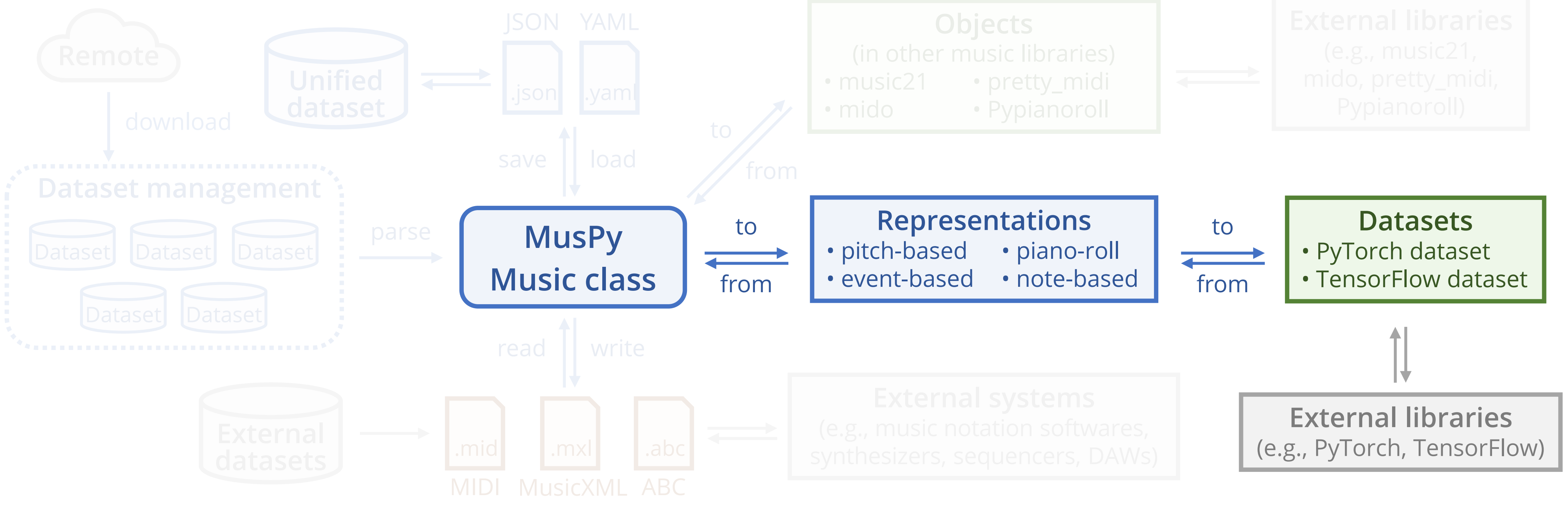

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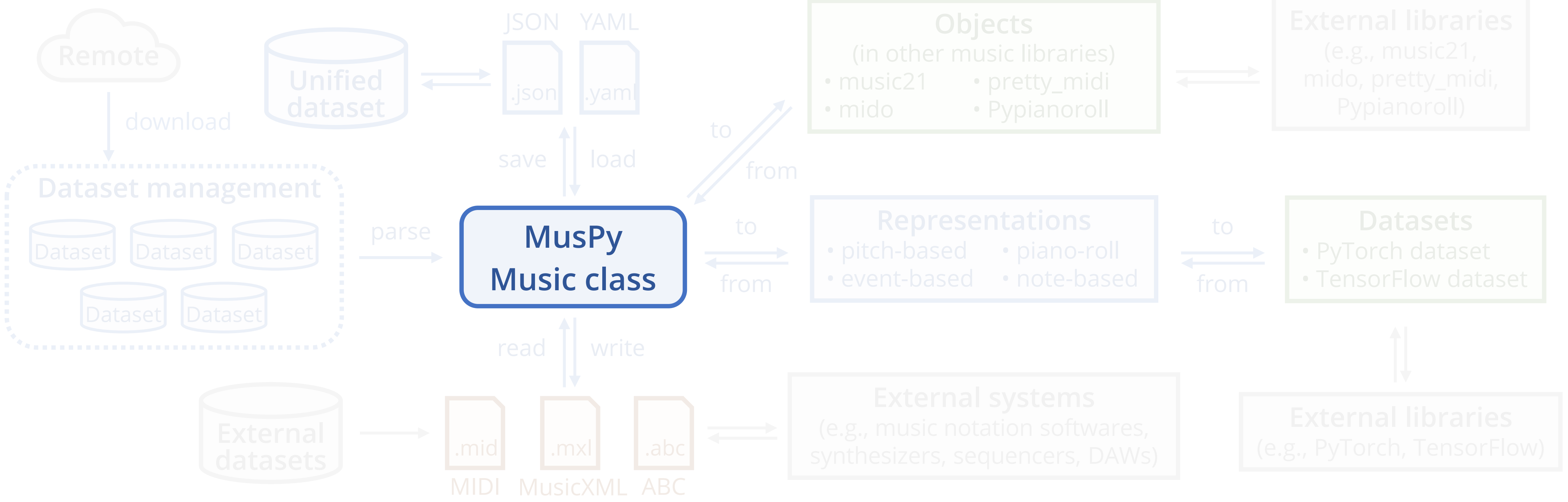
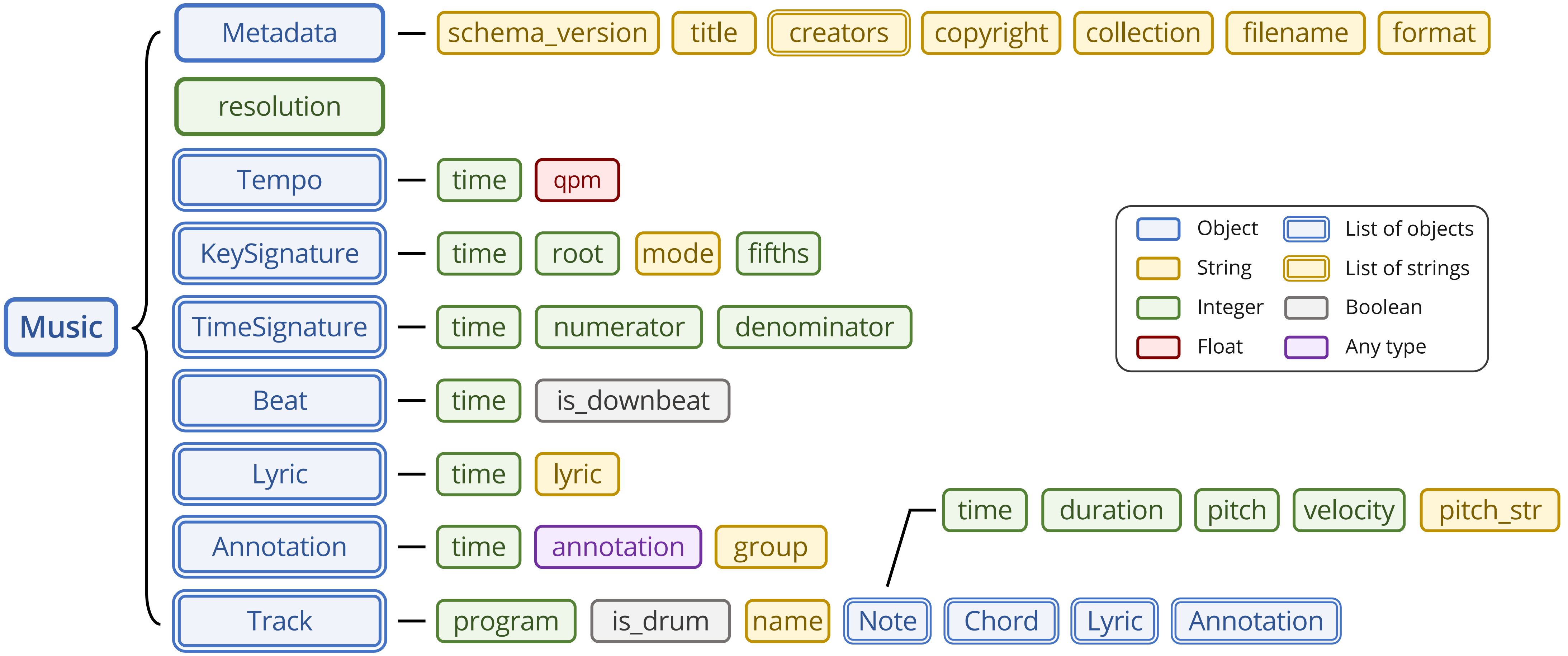


MusPy Music class



MusPy native format

- A universal container for symbolic music
- Serializable to JSON/YAML
- Human-readable and machine-friendly


```yaml
metadata:
  schema_version: "0.0"
  title: Für Elise
  creators: [Ludwig van Beethoven]
  copyright: null
  collection: Example dataset
  source_filename: example.yaml
  source_format: yaml
resolution: 24
tempos:
  - {time: 0, qpm: 72}
key_signatures:
  - {time: 0, root: 9, mode: minor, fifths: 0}
time_signatures:
  - {time: 0, numerator: 3, denominator: 8}
beats:
  - {time: 0, is_downbeat: false}
  - {time: 12, is_downbeat: true}
  - {time: 24, is_downbeat: false}
  - {time: 36, is_downbeat: false}
  - {time: 48, is_downbeat: true}
lyrics:
  - {time: 0, lyric: Nothing but a lyric}
annotations:
  - {time: 0, annotation: Nothing but an annotation, group: null}
tracks:
  - program: 0
    is_drum: false
    name: Melody
    notes:
      - {time: 0, duration: 6, pitch: 76, velocity: 64}
      - {time: 6, duration: 6, pitch: 75, velocity: 64}
      - {time: 12, duration: 6, pitch: 76, velocity: 64}
      - {time: 18, duration: 6, pitch: 75, velocity: 64}
      - {time: 24, duration: 6, pitch: 76, velocity: 64
      - {time: 30, duration: 6, pitch: 71, velocity: 64}
      - {time: 36, duration: 6, pitch: 74, velocity: 64}
      - {time: 42, duration: 6, pitch: 72, velocity: 64}
      - {time: 48, duration: 6, pitch: 69, velocity: 64}
    chords: null
    lyrics:
      - {time: 0, lyric: Nothing but a lyric}
    annotations:
      - {time: 0, annotation: Nothing but an annotation, group: null}
```

Comparisons to MIDI & MusicXML

	MIDI	MusicXML	MusPy
Sequential timing	✓		✓
Playback velocities	✓	△	✓
Program information	✓	△	✓
Layout information		✓	
Note beams and slurs		✓	
Song/source meta data	△	✓	✓
Track/part information	△	✓	✓
Dynamic/tempo markings		✓	✓
Concept of notes		✓	✓
Measure boundaries		✓	✓
Human readability		△	✓

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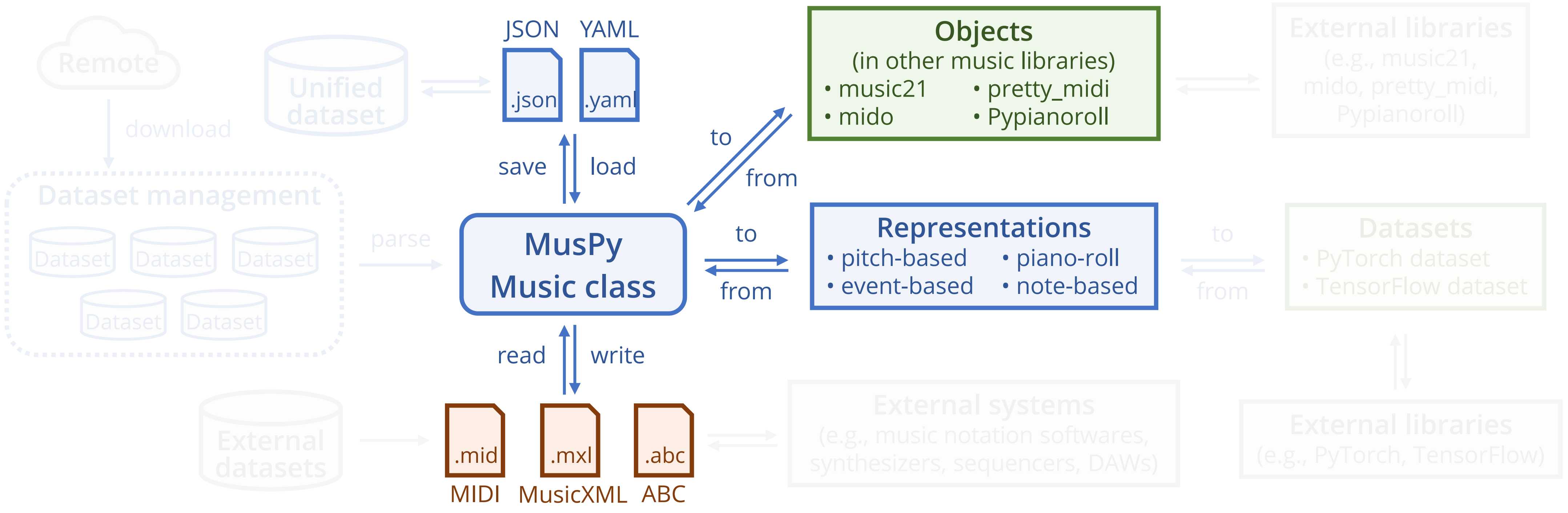
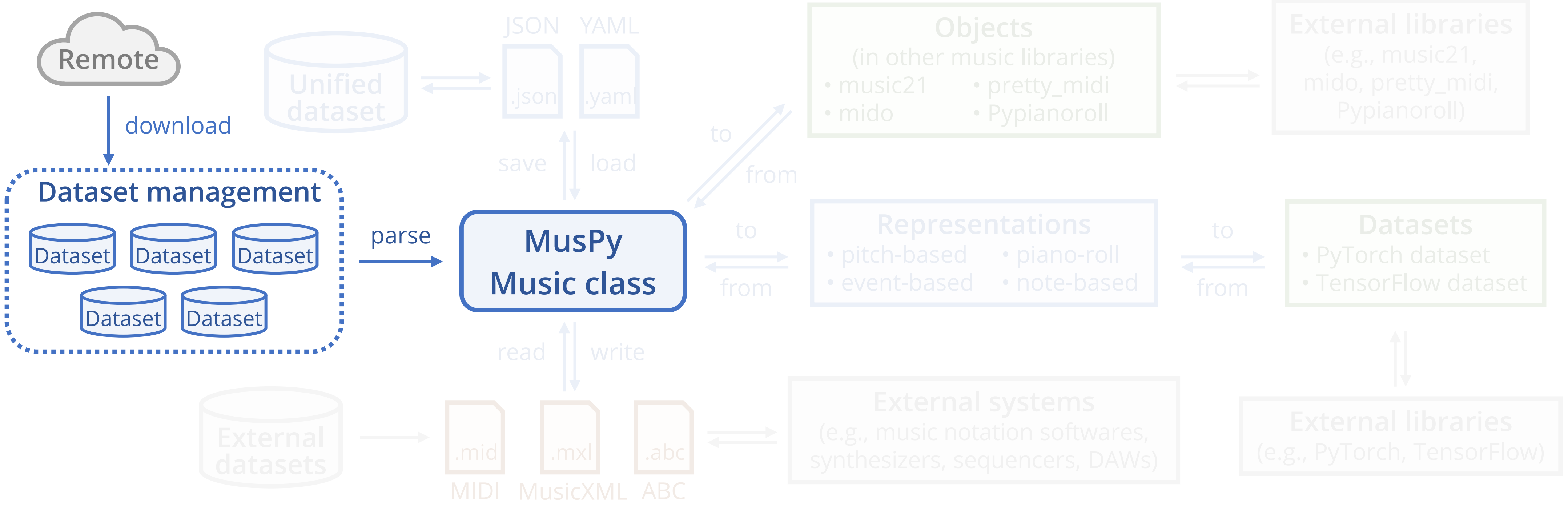
Human readability		△	✓

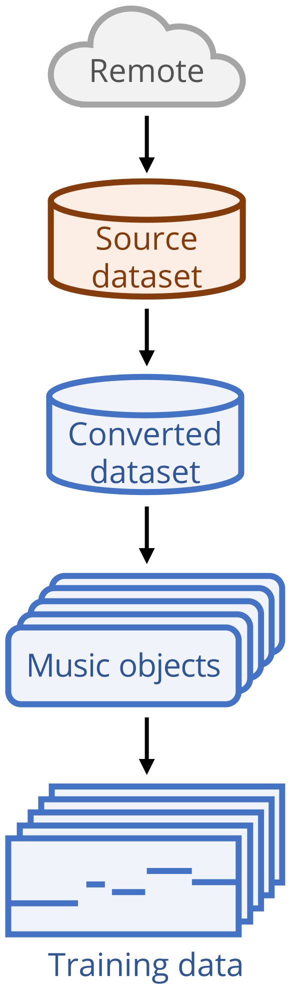
I/O interfaces



Dataset management



Dataset management – An example




```python
# Download and extract the dataset
nes = muspy.NESMusicDatabase(root="data/nes/",
                             download_and_extract=True)

# Convert the dataset to MusPy Music objects
nes.convert()

# Iterate over the dataset
for music in nes:
  do_something(music)

# Convert to a PyTorch dataset
dataset = nes.to_pytorch_dataset(representation="pianoroll")
```

Datasets supported

Dataset	**Format**	**Hours**	**Songs**	**Genre**	**Melody**	**Chords**	**Multitrack**
Lakh MIDI Dataset	MIDI	>5000	174,533	misc	△	△	△
MAESTRO Dataset	MIDI	201.21	1,282	classical			
Wikifonia Lead Sheet Dataset	MusicXML	198.40	6,405	misc	✓	✓	
Essen Folk Song Dataset	ABC	56.62	9,034	folk	✓	✓	
NES Music Database	MIDI	46.11	5,278	game	✓		✓
MusicNet Dataset	MIDI	30.36	323	classical			△
Hymnal Tune Dataset	MIDI	18.74	1,756	hymn	✓		
Hymnal Dataset	MIDI	17.50	1,723	hymn			
music21's Corpus	misc	16.86	613	misc	△		△
EMOPIA Dataset	MIDI	10.98	387	pop			
Nottingham Database	ABC	10.54	1,036	folk	✓	✓	
music21's JSBach Corpus	MusicXML	3.46	410	classical			✓
JSBach Chorale Dataset	MIDI	3.21	382	classical			✓
Haydn Op.20 Dataset	Humdrum	1.26	24	classical		✓	

Result analysis tools

Pitch-related metrics

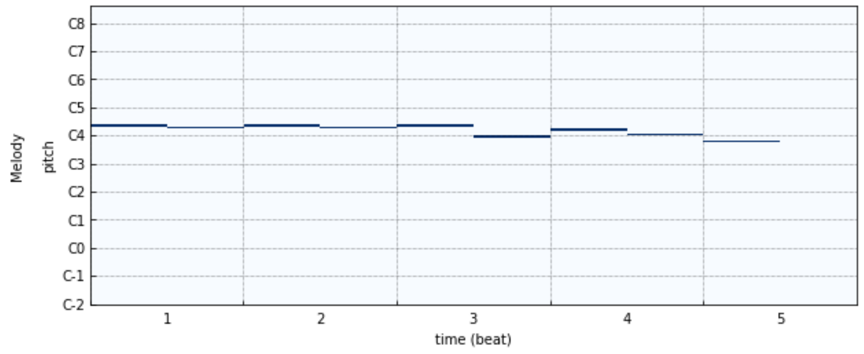
- pitch_range
- n_pitches_used
- n_pitch_classes_used
- polyphony
- polyphony_rate
- pitch_in_scale_rate
- scale_consistency
- pitch_entropy
- pitch_class_entropy

Rhythm-related metrics

- empty_beat_rate
- empty_measure_rate
- drum_in_pattern_rate
- drum_pattern_consistency
- groove_consistency

Audio rendering

Piano-roll visualization



Related work

- Magenta
  - Provides several model instances in TensorFlow
- music21 (Cuthbert and Ariza 2010)
  - Provides powerful tools for computational musicology
  - Comes with its own corpus
- jSymbolic (McKay and Fujinaga 2006)
  - Extracts statistical information from symbolic music data

Magenta, https://magenta.tensorflow.org/.
Cuthbert and Ariza, "A Toolkit for Computer-Aided Musicology and Symbolic Music Data," *Proc. ISMIR*, 2010.
McKay and Fujinaga, "jSymbolic: A Feature Extractor for MIDI Files," *Proc. ICMC*, 2006.

Summary

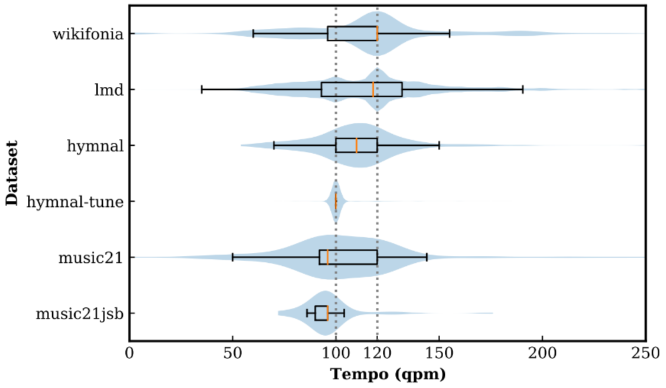
MusPy provides

- Dataset management
- Data I/O for common formats
- Interfaces to common music libraries
- Implementations of common music representations
- Result analysis tools

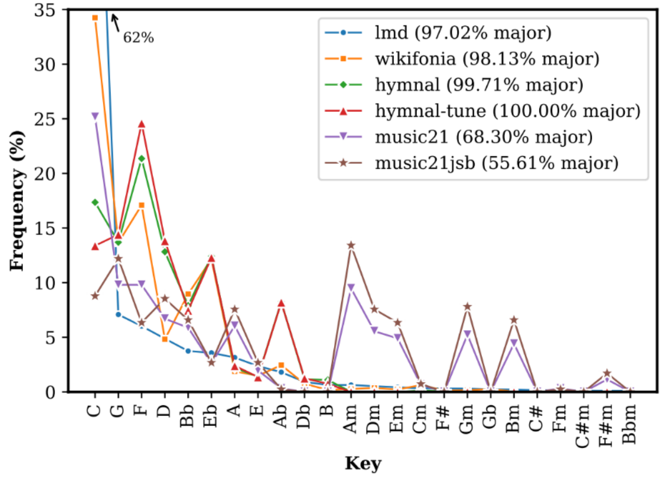
Experiments

Dataset analysis

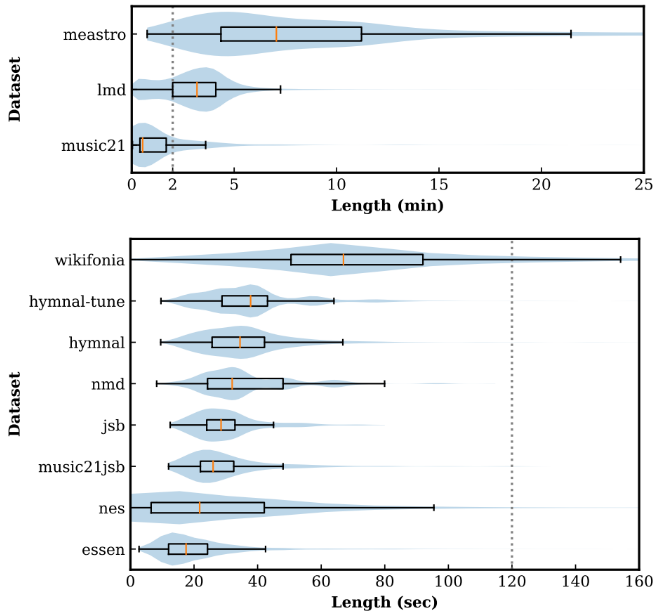
Tempo



Key



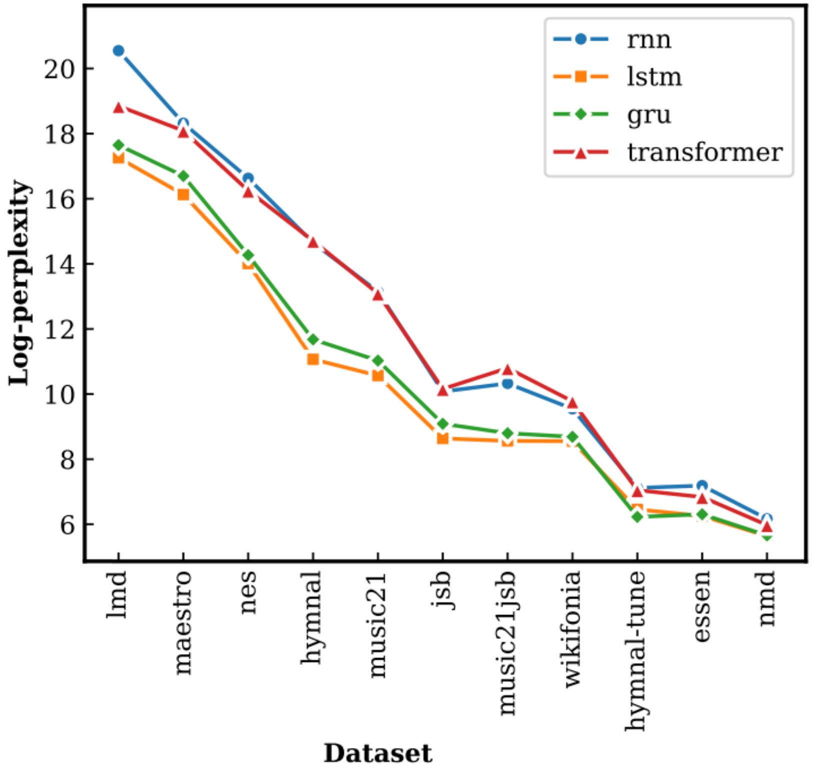
Length



Music language models

Settings

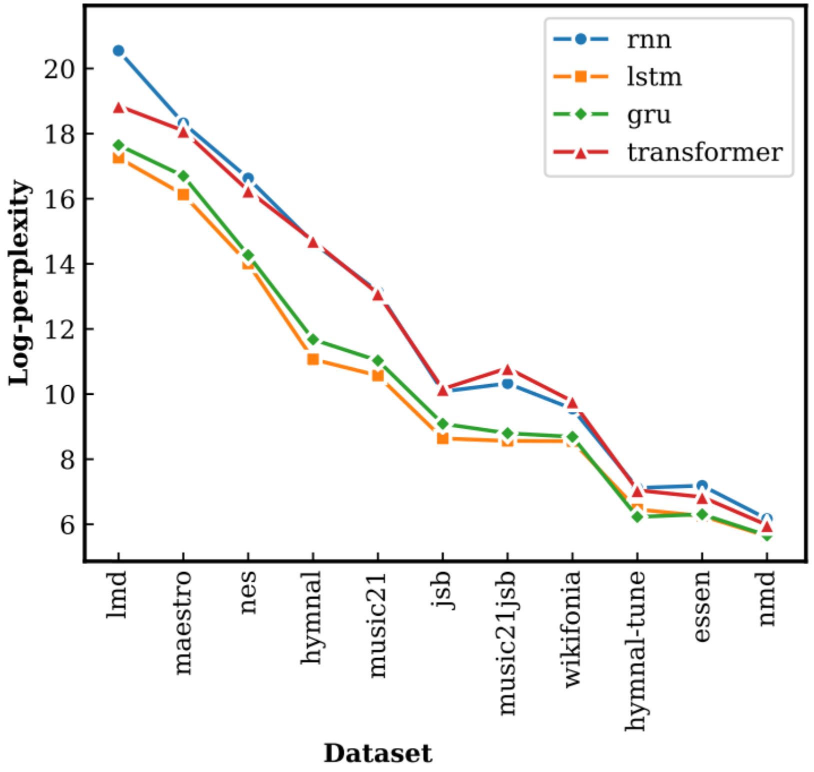
- Implement four autoregressive models
  - RNN, LSTM, GRU and Transformer
- Use a MIDI-like event representation
- Measure the perplexity of 1000 test samples



Music language models

Results

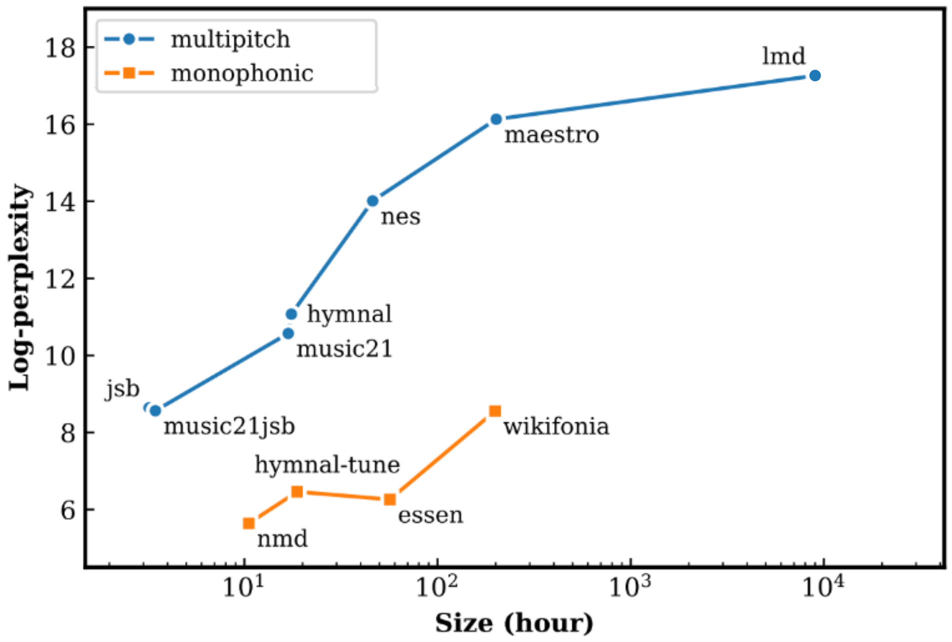
- All models have similar tendencies



Music language models

Results

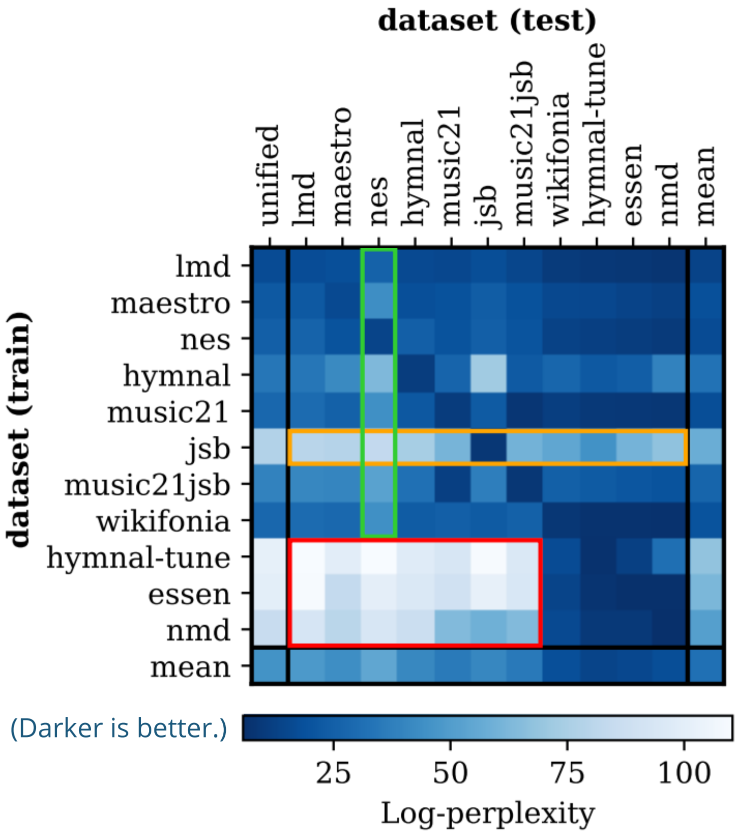
- All models have similar tendencies.
- Perplexity is positively correlated to dataset size.
  - Within each group (multipitch vs monophonic)



Measuring cross-dataset generalizability

Settings

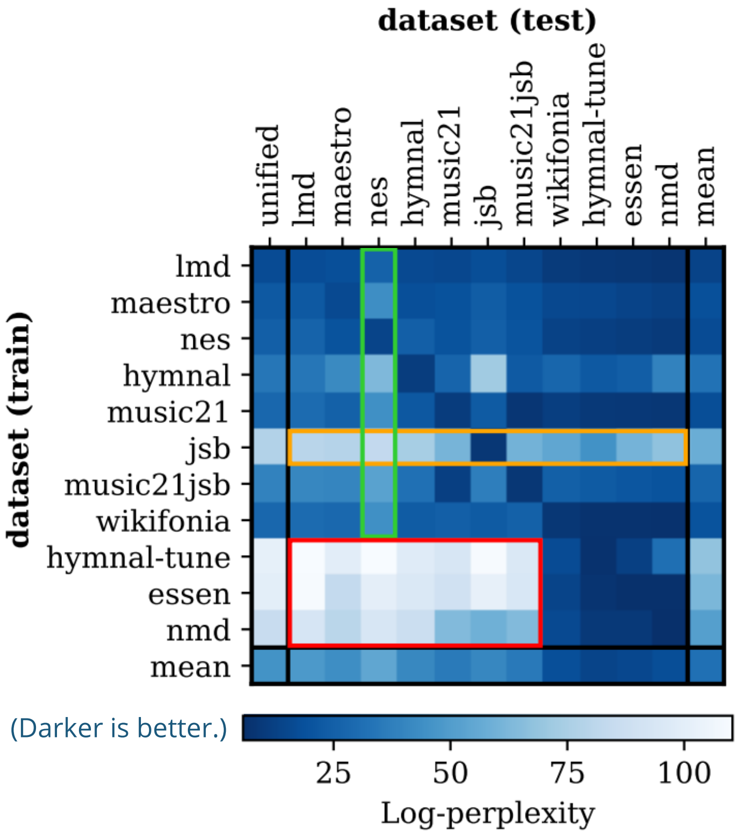
1. Train the model on a dataset $\mathcal{D}$
2. Test the trained model on dataset $\mathcal{D}'$
3. Repeat for all 11x11 pairs of $(\mathcal{D}, \mathcal{D}')$



Measuring cross-dataset generalizability

Results

- Cross-dataset generalizability is asymmetric.
- A model trained on a multi-pitch dataset generalizes well to a monophonic dataset.
  - Yet not the other way around (red block)



(Darker is better.)

Combining heterogeneous datasets

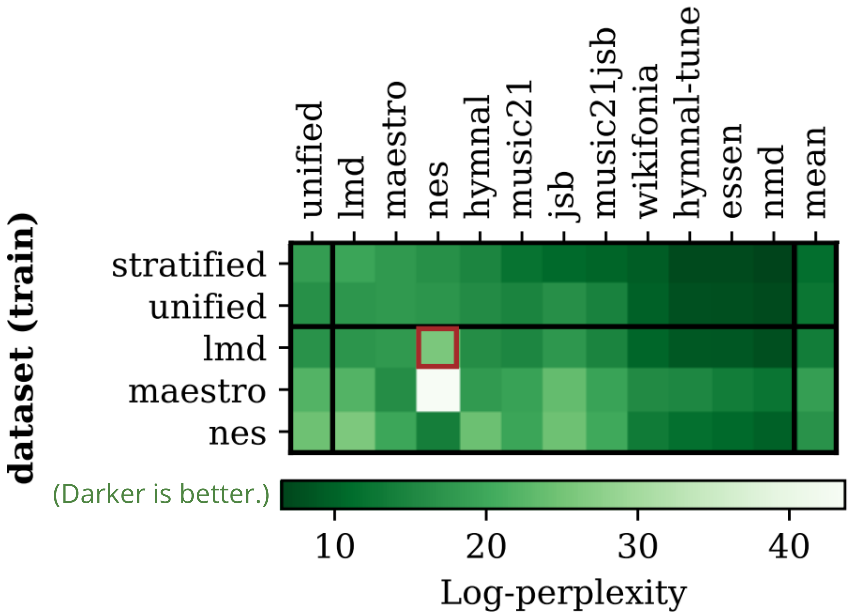
Settings

- **Unified**

  Sample uniformly from the pool of all data of different datasets

- **Stratified**

  Pick a dataset randomly and sample uniformly from that dataset (to alleviate data imbalance issue)



Combining heterogeneous datasets

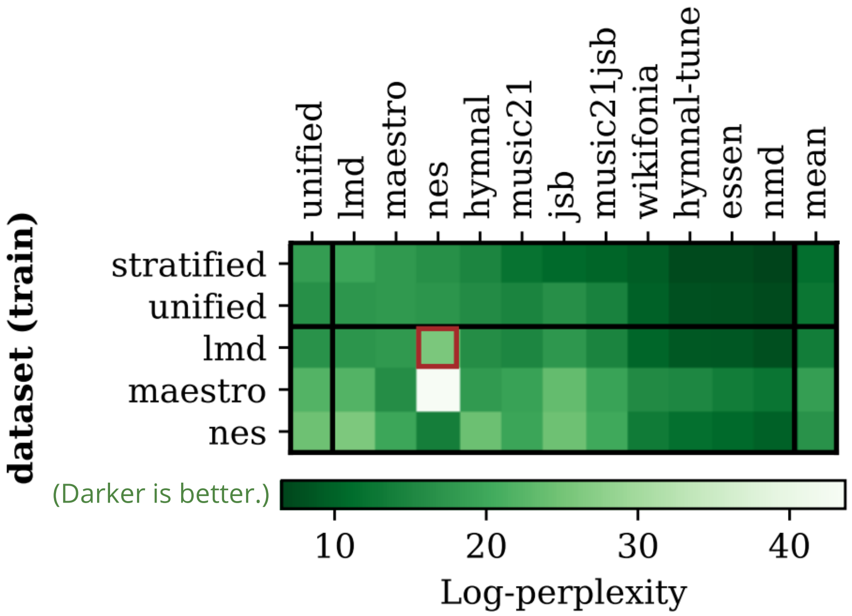
Results

- **Unified**

  The model trained on the unified dataset yields a lower perplexity on each dataset.

- **Stratified**

  Stratified sampling reduce perplexities on most datasets with a sacrifice of an increased perplexity on LMD. (LMD is the largest dataset.)



Summary

- Measured the relative diversities of 11 datasets
- Analyzed the cross-dataset generalizabilities of a music generation system
- Showed how combining heterogenous datasets can help improve generalizability

Case Study I – Automatic Instrumentation

"Towards Automatic Instrumentation by Learning to Separate Parts in Symbolic Multitrack Music" (ISMIR 2021)

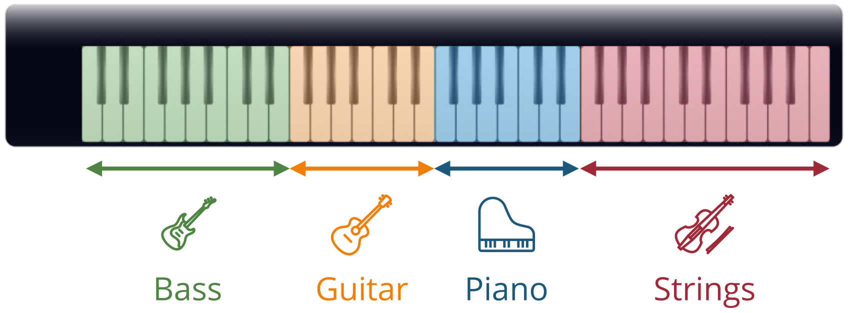
Hao-Wen Dong Chris Donahue Taylor Berg-Kirkpatrick Julian McAuley

Motivation

- Automatic instrumentation – Dynamically assign instruments to notes in solo music

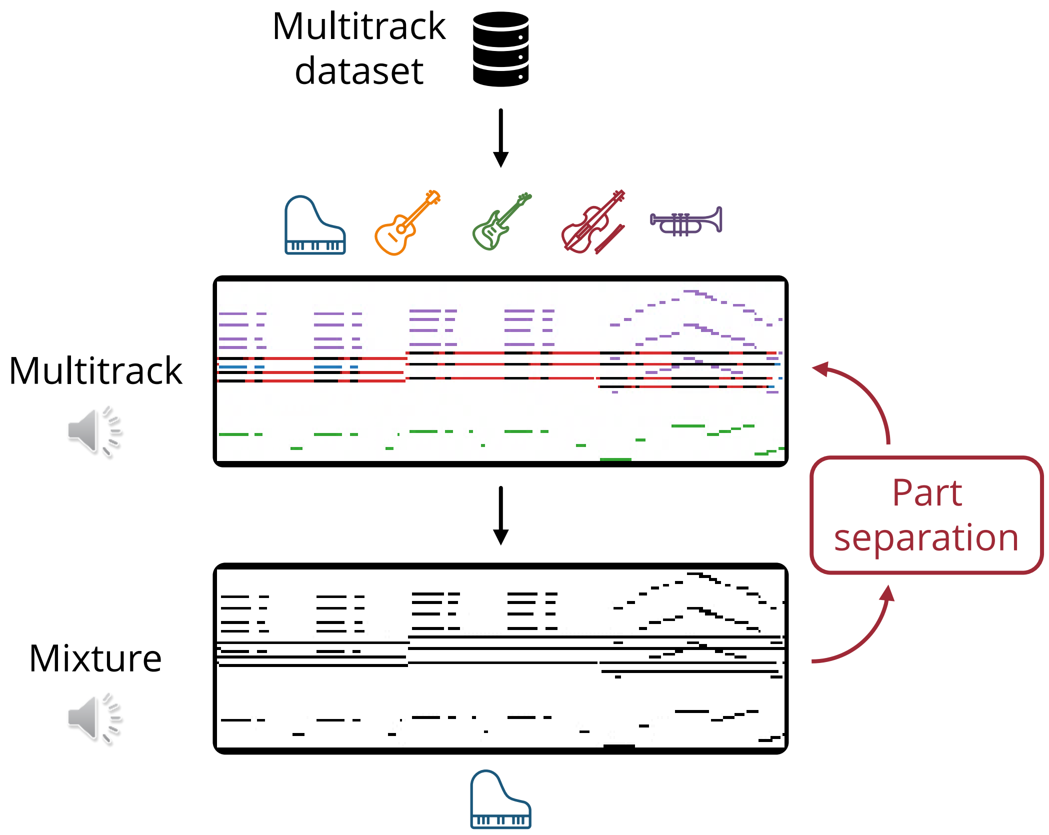
Intelligent musical instruments



Assistive composing tools

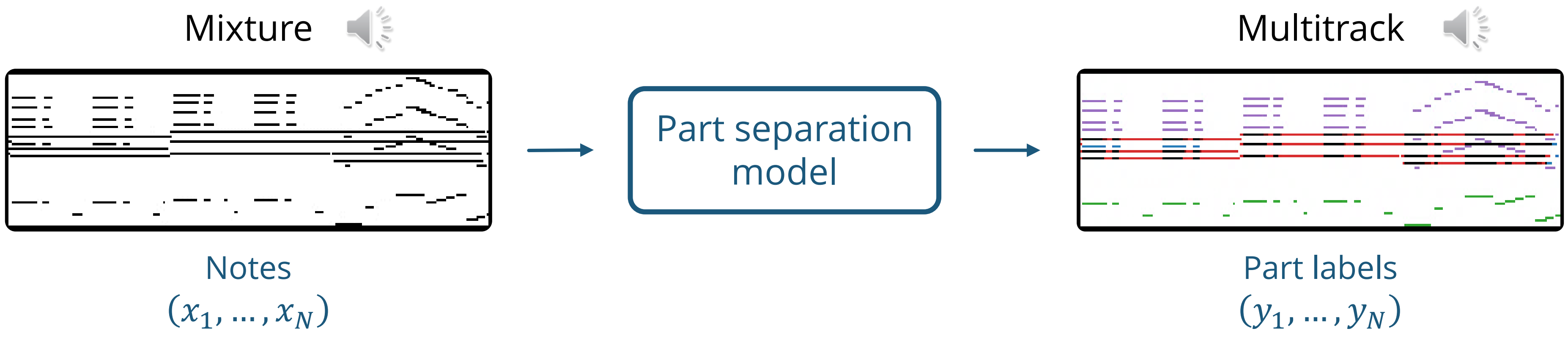
Overview

- Acquire paired data
- Train a part separation model
- Perform automatic instrumentation



Problem formulation

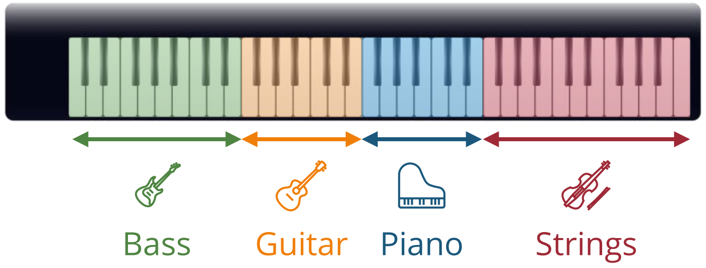
- Part separation – Separate parts from their mixture in multitrack music
- Frame as a sequential multiclass classification problem



Models

Online models

- LSTMs
- Transformer decoders



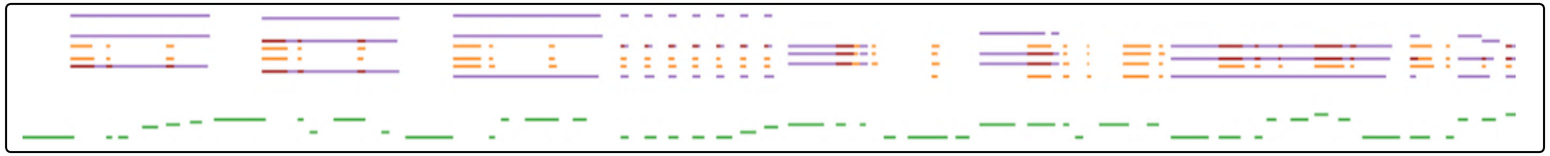
Offline models

- BiLSTMs
- Transformer encoders

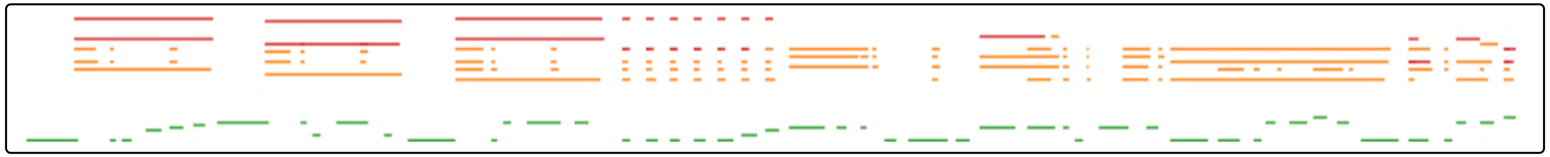
Demo

- Produce convincing alternative instrumentations for an existing arrangement

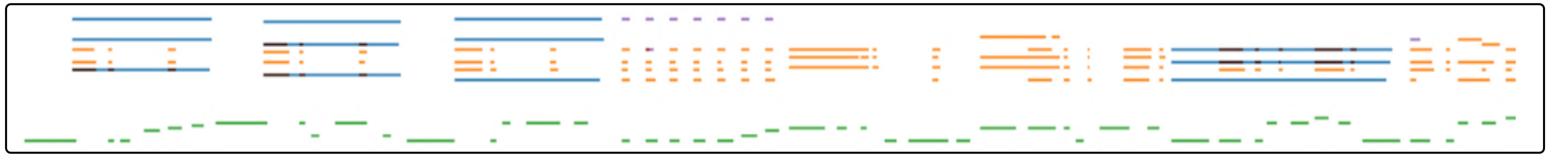
Original



LSTM
(without entry hints)

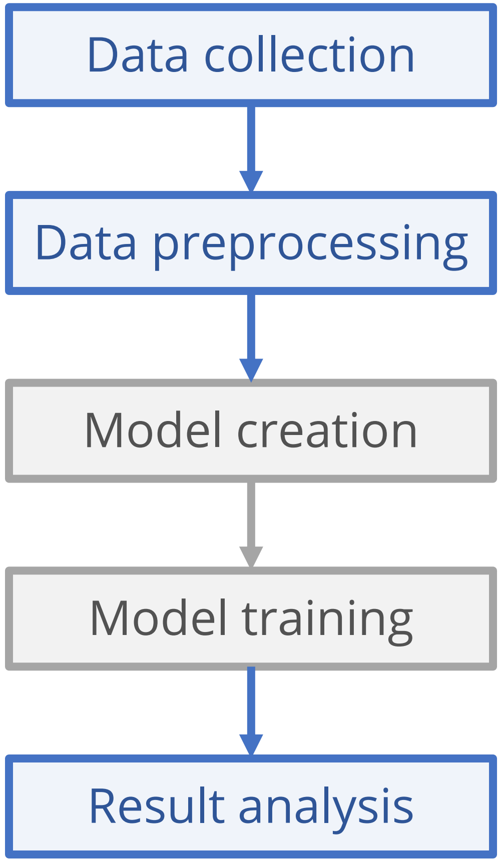


BiLSTM
(with entry hints)



More samples can be found at salu133445.github.io/arranger/.

MusPy in the pipeline



- Download datasets
- Convert data into MusPy JSON format

- Adjust temporal resolution
- Map instrument names
- Convert data into note representation

- Save the results as MIDI files
- Synthesize the results into audio
- Visualize the results in the piano roll form

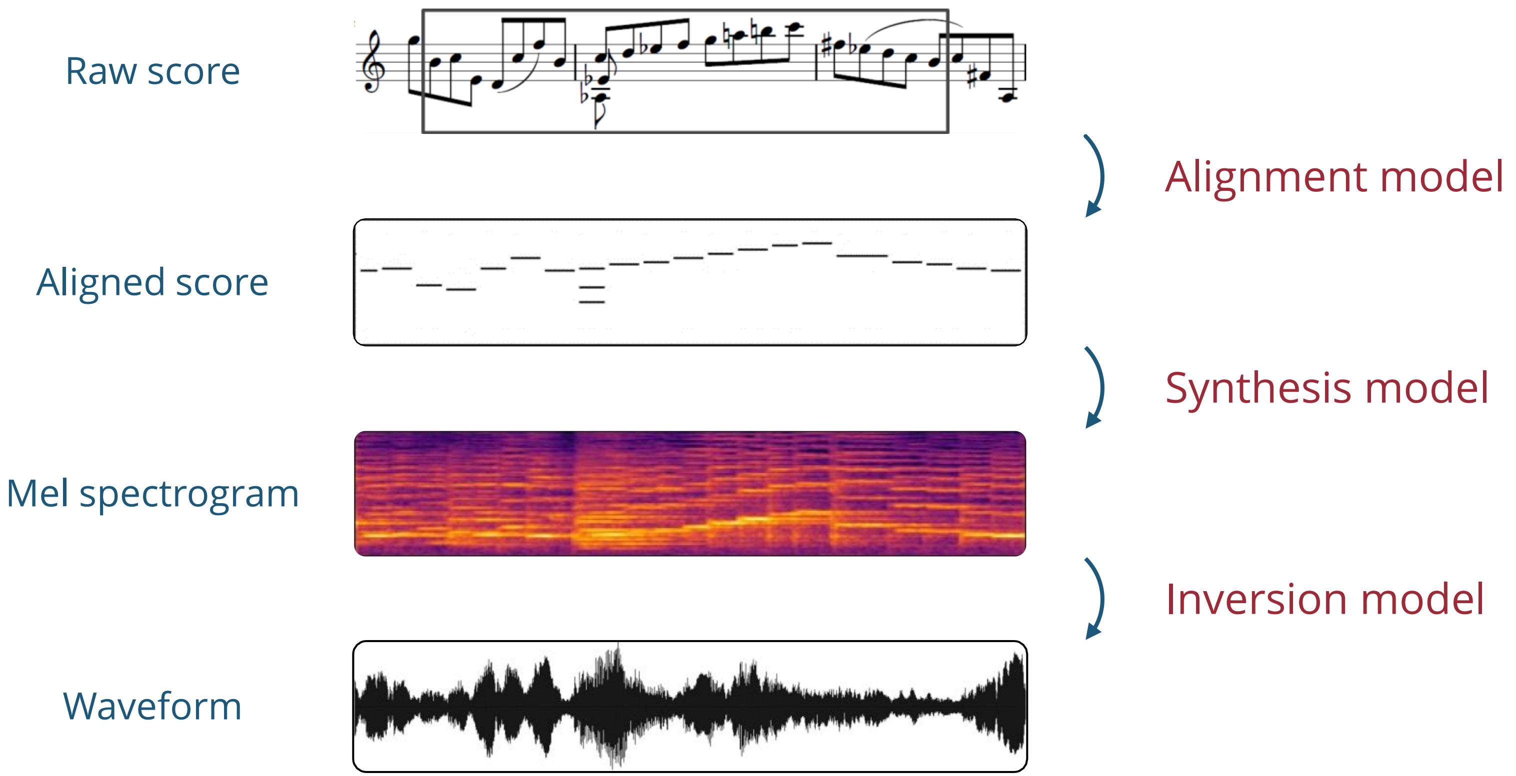
Case Study II – Music Performance Synthesis

"Deep Performer: Score-to-Audio Music Performance Synthesis" (ICASSP 2022)

Hao-Wen Dong Cong Zhou Taylor Berg-Kirkpatrick Julian McAuley




Overview


Raw score
Alignment model
Aligned score
Synthesis model
Mel spectrogram
Inversion model
Waveform

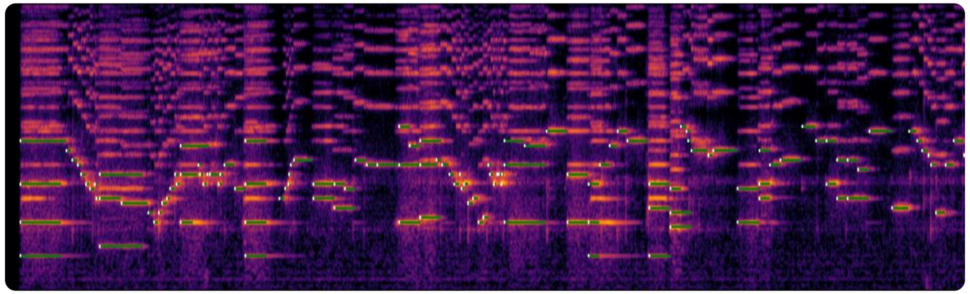
Bach Violin Dataset

- Bach's sonatas and partitas for solo violin (BWV 1001–1006)
- 6.7 hours, 17 violinists

Alignment derivation

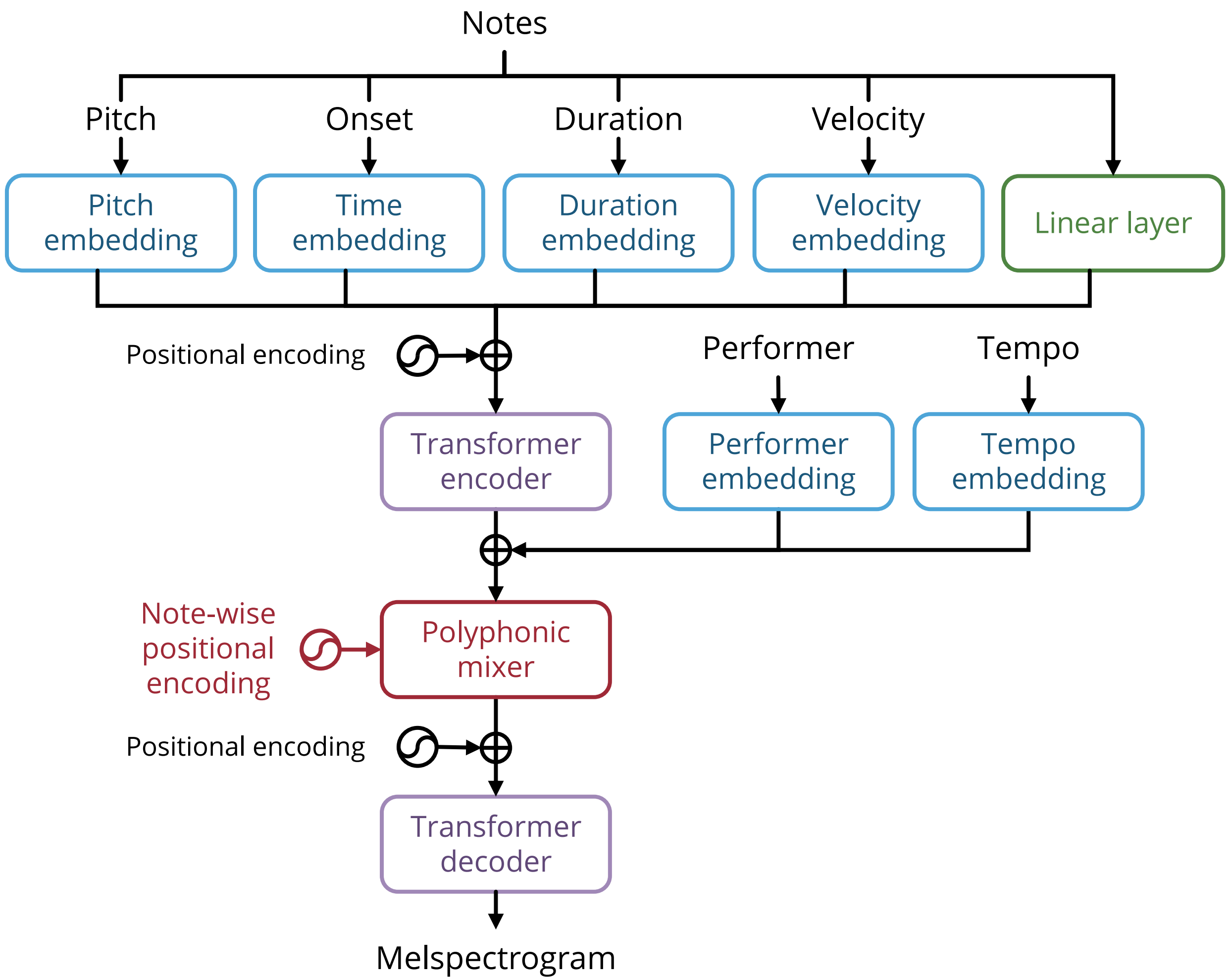
1. Synthesize the scores using FluidSynth (a free software synthesizer)
2. Run dynamic time warping on the spectrograms (of the recording & synthesized audio)

Alignment result



Synthesis model

- A transformer network
  based on FastSpeech (Ren et al. 2019)



Ren et al., "FastSpeech: Fast, robust and controllable text to speech," *Proc. NeurIPS*, 2019.

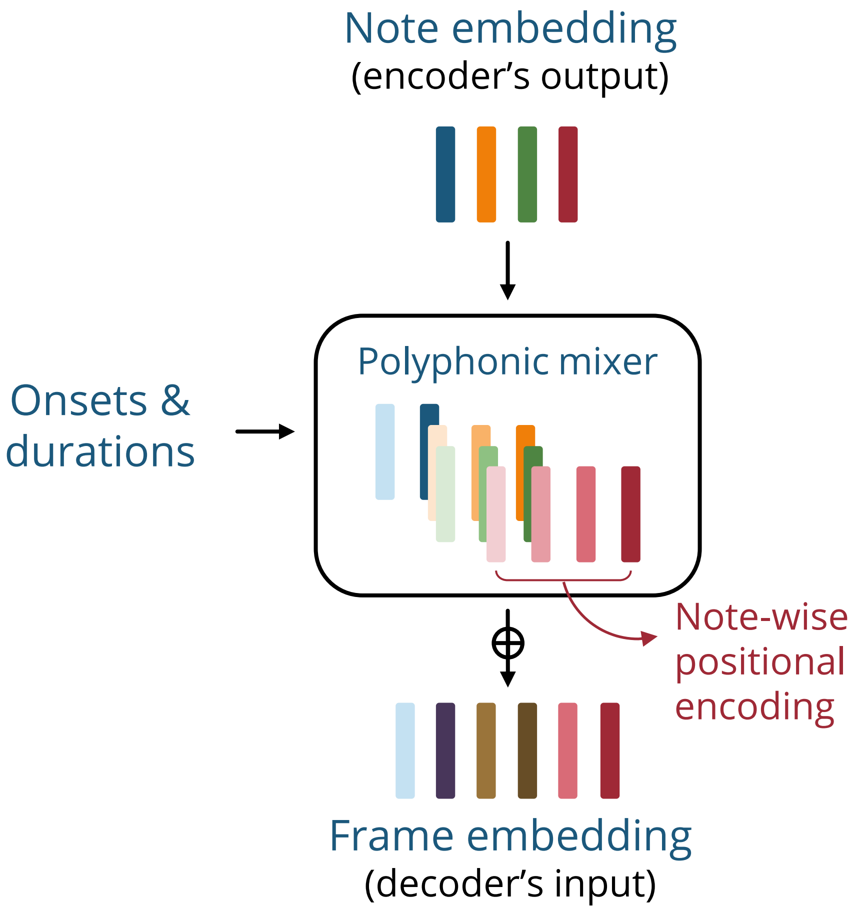
Methods

- Polyphonic mixer

  Extend the state expansion mechanism to handle polyphonic inputs

- Note-wise positional encoding

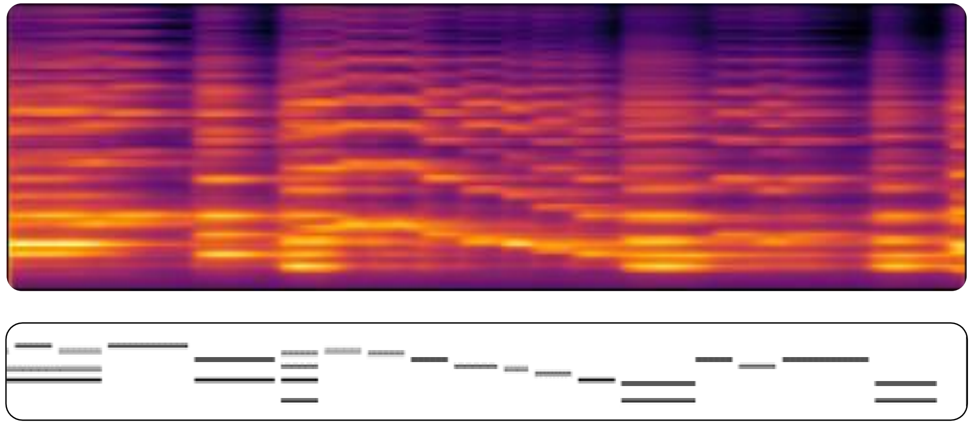
  Provide positional information within each note for a fine-grained conditioning



Demo

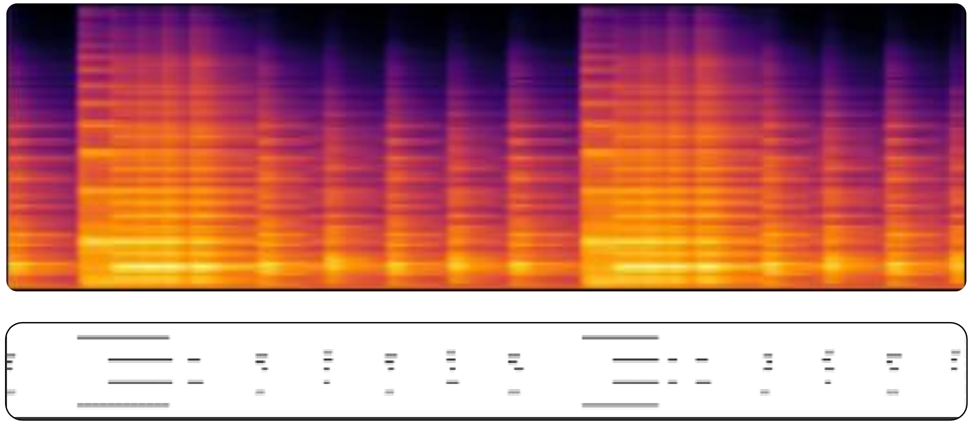
Violin

(trained on Bach Violin Dataset)



Piano

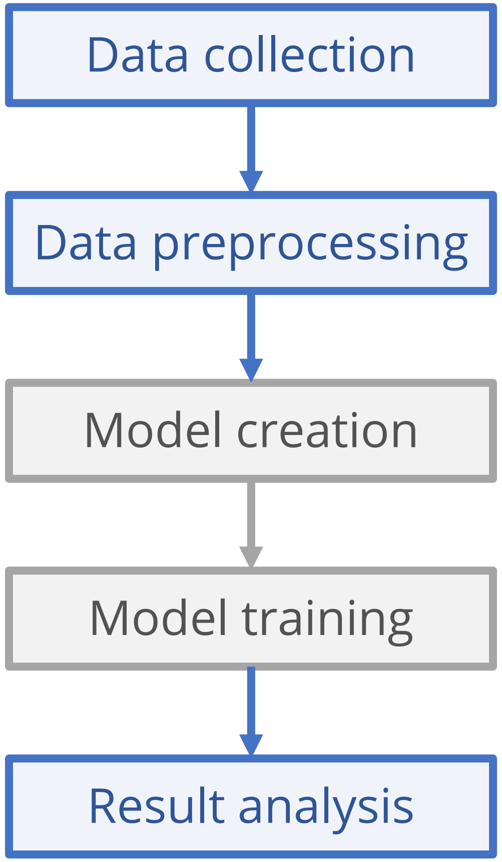
(trained on MAESTRO Dataset)



More samples can be found at salu133445.github.io/deepperformer/.

Hawthorne et al., "Enabling Factorized Piano Music Modeling and Generation with the MAESTRO Dataset," *Proc. ICLR*, 2019.

MusPy in the pipeline



- Convert data into MusPy JSON format
- Synthesize the data for alignment purpose
- Convert data into note representation
- Visualize the results in the piano roll form

Conclusion

Conclusion

- Presented a Python library for processing symbolic music
- Showcased how MusPy enabled large-scale cross-dataset analysis
  - Relative diversities of the 11 supported datasets
  - Cross-dataset generalizabilities of a music generation system
- Studied how we used MusPy in two recent projects
  - Automatic instrumentation
  - Music performance synthesis

Thank you!

```
pip install muspy
```

Learn more at salu133445.github.io/muspy/