



### Towards Automatic Instrumentation by Learning to Separate Parts in Symbolic Multitrack Music

**Hao-Wen Dong** 

### 董皓文 Department of Computer Science and Engineering

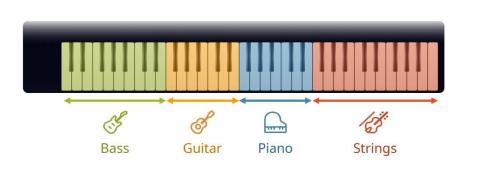
Advisors: Prof. Julian McAuley and Prof. Taylor Berg-Kirkpatrick

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### Automatic instrumentation

• **Goal**—Dynamically assign instruments to notes in solo music

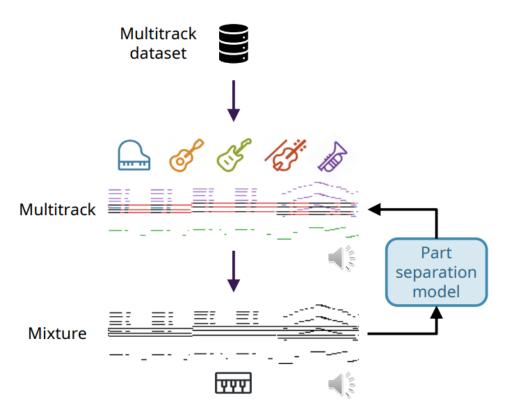




Hao-Wen Dong, Chris Donahue, Taylor Berg-Kirkpatrick and Julian McAuley, "Towards Automatic Instrumentation by Learning to Separate Parts in Symbolic Multitrack Music," Proceedings of the 22nd International Society for Music Information Retrieval Conference (ISMIR), in press, 2021.

### Overview

- Acquire paired data of solo music and its instrumentation
  - Downmix multitracks into single-track mixtures
- Train a part separation model
  - Learn to infer the part label for each note in a mixture
- Approach automatic instrumentation
  - Treat input from a keyboard player as a downmixed mixture
  - Separate out the relevant parts



### Data

• Four datasets of diverse genres and ensembles

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



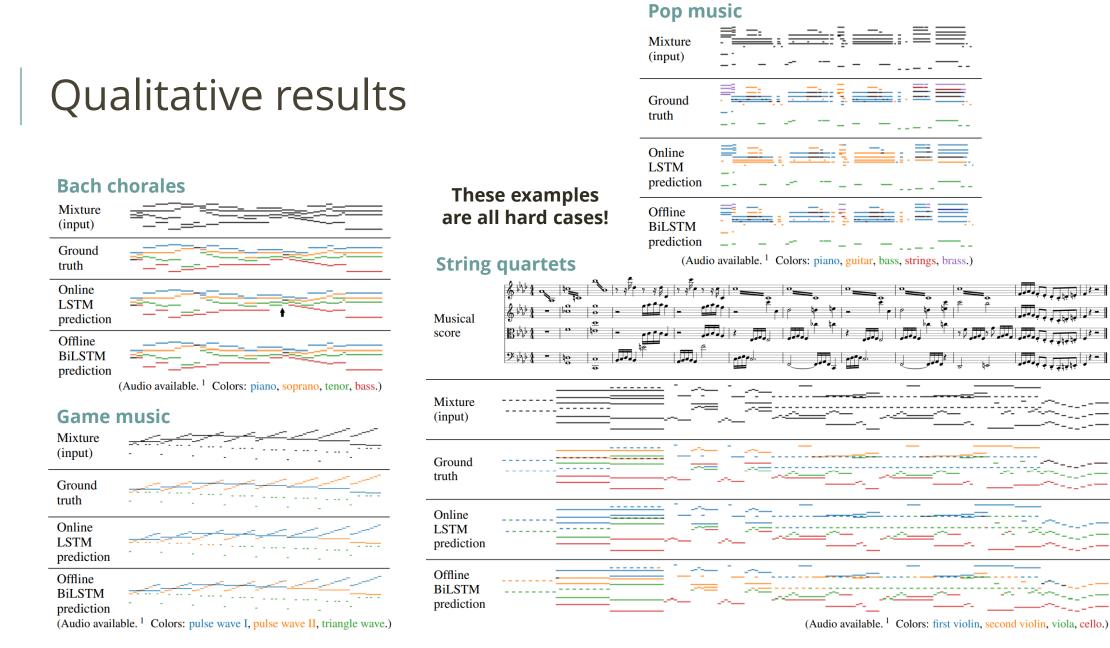
### Models & input features

#### Models

- Deep sequential models
  - Online: LSTM & Transformer Encoder
  - Offline: BiLSTM & Transformer Decoder
- Baseline models
  - Zone-based algorithm
  - Closest-pitch algorithm
  - Multilayer perceptron (MLP)

#### **Input features**

- time—onset time (in time step)
- pitch—pitch as a MIDI note number
- duration—note length (in time step)
- frequency—frequency of the pitch (in Hz)
- beat—onset time (in beat)
- position—position within a beat (in time step)



### Quantitative results

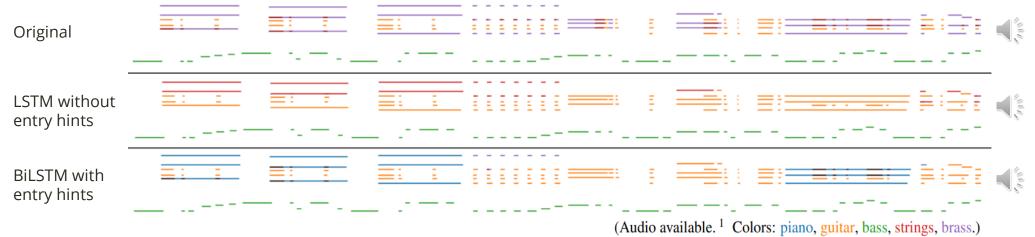
- Proposed models outperform baseline models
- BiLSTM outperforms LSTM
- LSTM models outperform their Transformer counterparts

Model	Bach	String	Game	Рор					
Online models									
Zone-based	73.14	58.85	43.67	57.07					
MLP [9]	81.63	29.85	43.08*	33.50*					
LSTM	93.02	67.43	50.22	74.14					
Transformer-Dec	91.51	57.03	45.82	62.14					
Zone-based (oracle)	78.33	66.89	79.54*	†					
MLP [9] (oracle)	97.59	58.16	65.30	44.62					
Offline models									
BiLSTM	97.13	<b>74.3</b> 8	52.93	77.23					
Transformer-Enc	96.81	58.86	49.14	66.57					
Online models (+entry hints)									
Closest-pitch	68.87	50.69	57.14	47.45					
Closest-pitch (mono)	89.76	42.82	49.91	32.28					
LSTM	92.70	62.64	<b>62.11</b>	74.19					
Transformer-Dec	91.17	62.12	56.73	67.19					
Offline models (+entry hints)									
BiLSTM	97.39	71.51	64.79	75.59					
Transformer-Enc	93.81	56.72	54.67	67.23					

### Demo

• The proposed models can produce alternative convincing instrumentations for an existing arrangement





# Summary

- Proposed a new task of part separation
- Showed that our proposed models outperform various baselines
- Presented promising results for applying a part separation model to automatic instrumentation

## Future directions

- Generative modeling of automatic instrumentation
- Unpaired automatic instrumentation
- Large-scale pretraining for symbolic music models

Acknowledgement

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