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

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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
Music and AI Lab, Research Center for IT Innovation

Summer 2019
Yamaha Corporation
Research Intern
AI Group, Research and Development Division

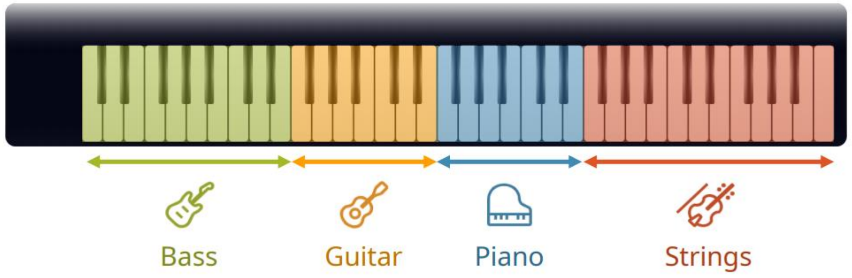
University of California San Diego
M.S. in Computer Science
2019 – 2021

Summer 2021 - present
Dolby Laboratories
Deep Learning Audio Intern
Applied AI Team, Advanced Technology Group

University of California San Diego
Ph.D. in Computer Science (in progress)
2019 – present

Automatic instrumentation

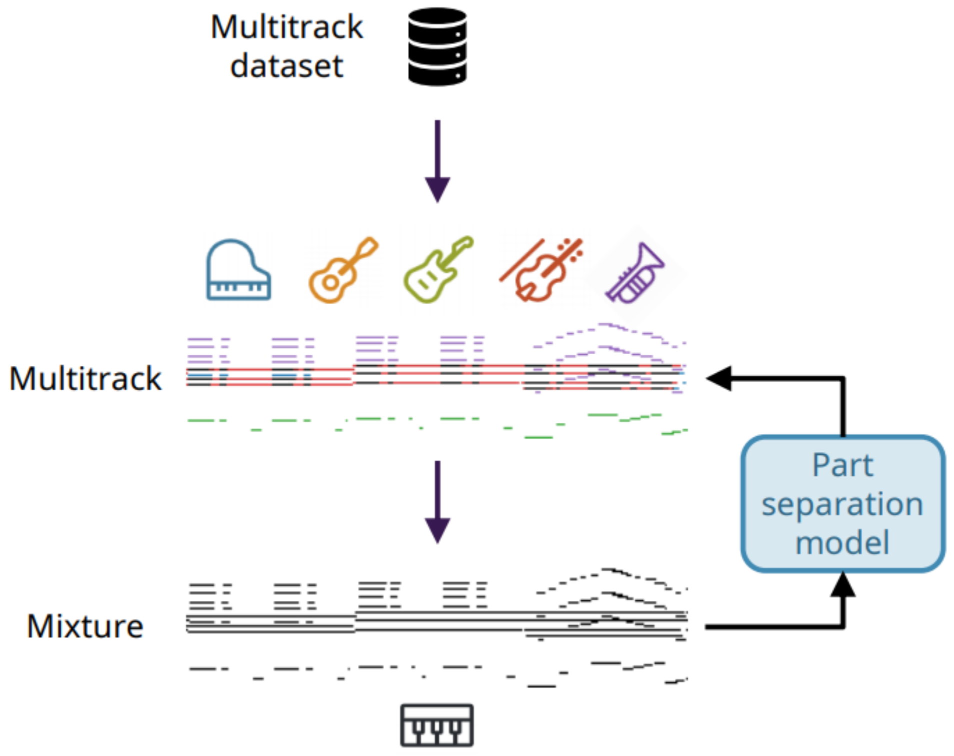
- **Goal**—Dynamically assign instruments to notes in solo music



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
  - Offline BiLSTM
- Baseline models
  - Zone-based algorithm
  - Closest-pitch algorithm
  - Multilayer perceptron (MLP)

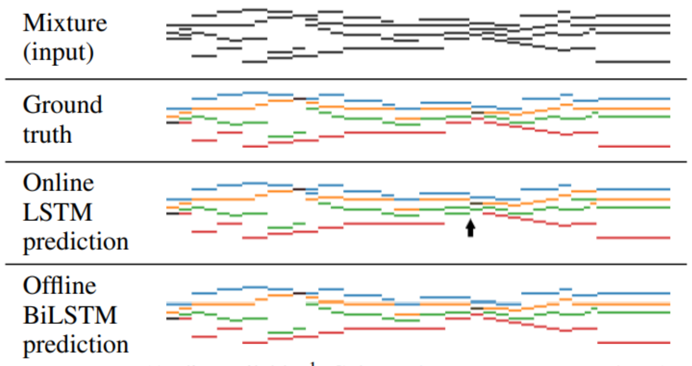
Input features

- 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)

Qualitative results

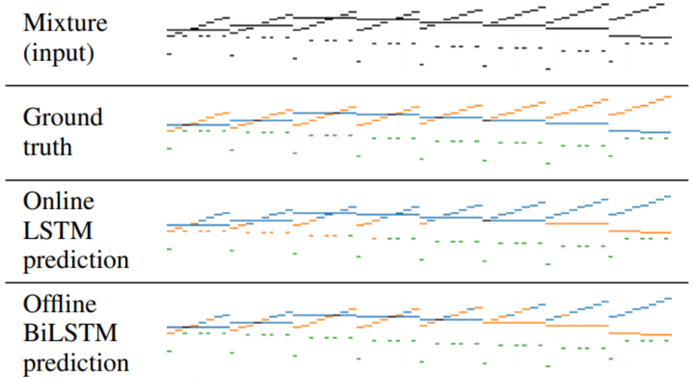
These examples are all hard cases!

Bach chorales



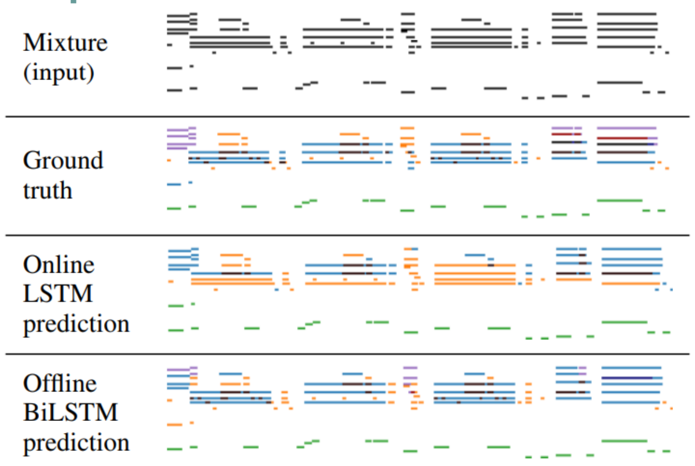
(Audio available. [1] Colors: piano, soprano, tenor, bass.)

Game music



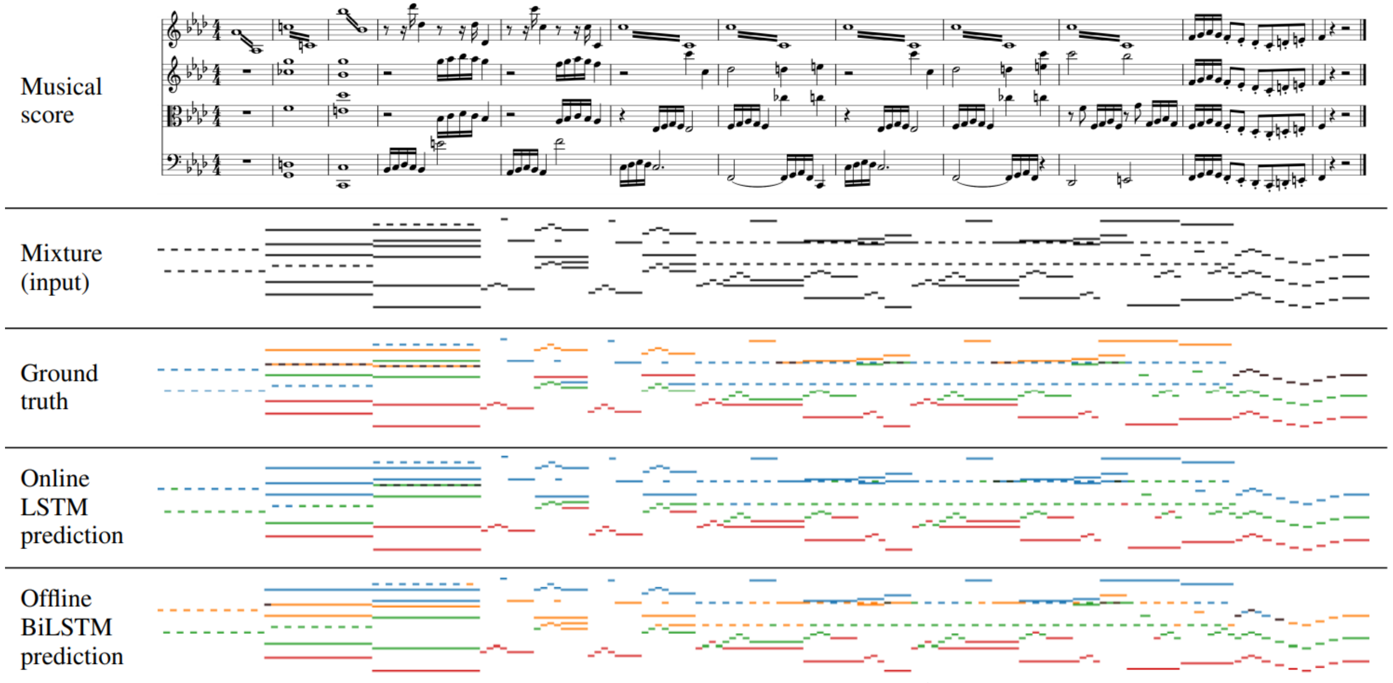
(Audio available. [1] Colors: pulse wave I, pulse wave II, triangle wave.)

Pop music



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

String quartets



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

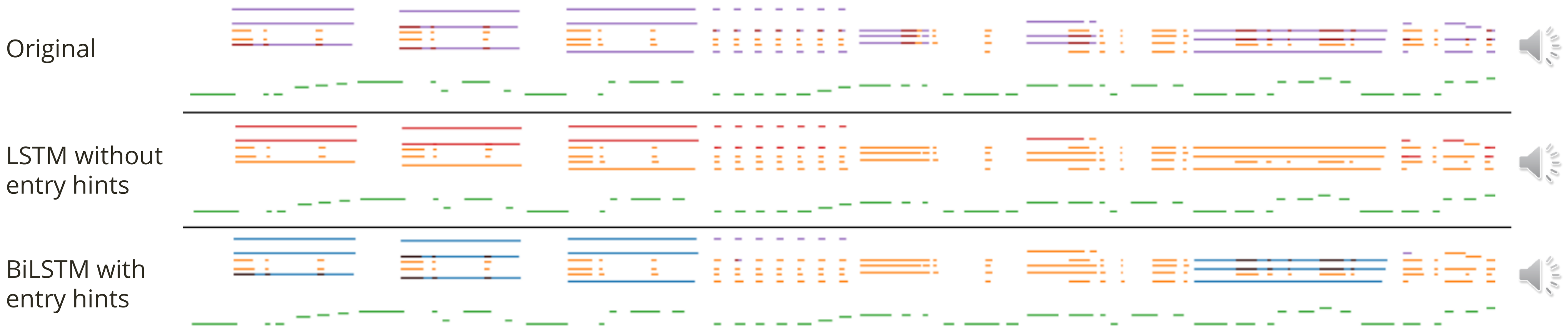
Quantitative results

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

Model	Bach	String	Game	Pop
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**	**74.38**	**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**	**62.11**	**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



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

More examples are available at salu133445.github.io/arranger/ .

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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Thank you!