# a software framework for Musical Data Augmentation

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# Modeling music is hard!

Musical concepts are necessarily complex

Complex concepts require big models

Big models need big data!

... but good data is hard to find



http://photos.jdhancock.com/photo/2012-09-28-001422-big-data.html

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A



https://commons.wikimedia.org/wiki/File:Horizontal\_milling\_machine--Cincinnati--early\_1900s--001.png





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# Deforming inputs and outputs



https://commons.wikimedia.org/wiki/File:Horizontal\_milling\_machine--Cincinnati--early\_1900s--001.png

# The big idea

Musical data augmentation applies to **both** 

**input** (audio) and **output** (annotations)

## ... but how will we keep everything contained?

ccorre

https://www.flickr.com/photos/shreveportbossier/6015498526

# JAMS

JSON Annotated Music Specification [Humphrey et al., ISMIR 2014] A simple container for all annotations

A structure to store (meta) data

But v0.1 lacked a unified, cross-task interface

# Pump up the JAMS: v0.2.0

**Unified** annotation interface

DataFrame backing for easy manipulation

- Query engine to filter annotations by type
  - □ chord, tag, beat, *etc*.

Per-task schema and validation

	time	duration	value	confidence
0	00:00:00	00:00:01.511000	N	1
1	00:00:01.511000	00:00:03.425000	С	1
2	00:00:04.936000	00:00:01.742000	G:9	chord

	time	duration	value	confidence
0	00:00:00	00:00:01.437000	silence	1
1	00:00:01.437000	00:00:35.111000	intro	1
2	00:00:36.548000	00:00:12.864000	verse	segment

	time	duration	value	confidence
0	00:00:01.561542	0 days	1	1
1	00:00:02.008526	0 days	2	1
2	00:00:02.446077	0 days	3	1
3	00:00:02.886395	0 days	4	heat

# Musical data augmentation

In [1]: import muda

transform(input JAMS **J\_orig**)

- 1. For each state **S**:
  - a. **J** := copy **J\_orig**
  - b. modify *J.audio* by **S**
  - c. modify *J.metadata* by *S*
  - d. Deform each annotation by **S**
  - e. Append **S** to **J.history**
  - f. yield **J**



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- **G** State encapsulates a deformation's parameters
- Lerating over states implements 1-to-Many mapping
- **Examples:** 
  - □ pitch\_shift  $\in$  [-2, -1, 0, 1, 2]
  - □ time\_stretch ∈ [0.8, 1.0, 1.25]
  - □ background noise ∈ sample library

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Audio is temporarily stored within the JAMS object

 $\Box$  All deformations depend on the state **S** 

□ All steps are optional

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- Each deformer knows how to handle different annotation types, *e.g.*:
  - PitchShift.deform\_chord()
  - PitchShift.deform\_pitch\_hz()
  - TimeStretch.deform\_tempo()
  - □ TimeStretch.deform\_all()
- JAMS makes it trivial to filter annotations by type
- □ Multiple deformations may apply to a single annotation

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#### This provides **data provenance**

All deformations are **fully reproducible** 

The constructed JAMS contains all state and object parameters

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# Deformation pipelines



# Example application

instrument recognition in mixtures



## Data: MedleyDB

122 tracks/stems, mixed instruments [Bittner et al., ISMIR 2014]

75 unique artist identifiers

U We model (the top) 15 instrument classes

Time-varying instrument activation labels



http://medleydb.weebly.com/

# Convolutional model

#### Input

- a. ~1sec log-CQT patches
- b. 36 bins per octave
- c. 6 octaves (C2-C8)

#### Convolutional layers

- a. 24x ReLU, 3x2 max-pool
- b. 48x ReLU, 1x2 max-pool

#### Dense layers

- a. 96d ReLU, dropout=0.5
- b. 15d sigmoid,  $\ell_2$  penalty



# Experiment

How does training with data augmentation impact model stability?

Note: test data remains unchanged

**G** Five augmentation conditions:

- N Baseline
- **P** pitch shift [+- 1 semitone]
- **PT** + time-stretch  $[\sqrt{2}, 1/\sqrt{2}]$
- **PTB** ++ background noise [3x noise]

**PTBC** +++ dynamic range compression [2x]

- $\Box \quad 1 \text{ input} \Rightarrow \text{up to 108 outputs}$
- □ 15x (artist-conditional) 4:1 shuffle-splits
- Predict instrument activity on 1sec clips

# Results across all categories

Pitch-shift improves model stability

Additional transformations don't seem to help (on average)



But is this the whole story?

# Results by category

All augmentations help for most classes

synthesizer may be ill-defined

Time-stretch can hurt high-vibrato instruments



Change in F1-score

# Conclusions

U We developed a general framework for musical data augmentation

Training with augmented data can improve model stability

Care must be taken in selecting deformations

Implementation is available at <u>https://github.com/bmcfee/muda</u> soon: pip install muda

# Thanks!

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https://bmcfee.github.io

https://github.com/bmcfee/muda