

# LEARNING INVARIANTS FOR POLYPHONIC INSTRUMENT RECOGNITION

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## ABSTRACT

The abstract should be placed at the top left column and should contain about 150-200 words.

## 1. INTRODUCTION

Music information is mostly available under two forms: the auditory domain of acoustic waves, and the symbolic domain of polyphonic scores and semantic attributes. Whereas scores may be represented as time-frequency matrices, other semantic attributes, such as instruments, are

## 2. DEEP CONVOLUTIONAL NETWORKS

### 2.1 Time-frequency representation

We used the implementation from the librosa package [4] with  $Q = 12$  filters per octave, center frequencies ranging from 55 Hz to 14 kHz (8 octaves from A1 to A9), and a hop size of 23 ms. Furthermore, we applied perceptual weighting of loudness in order to reduce the dynamic range between the fundamental partial and its upper harmonics. A 3-second sound excerpt  $x(t)$  is represented by a time-frequency matrix  $\mathbf{x}_1(t, k_1)$  of width  $T = 128$  samples and height  $K_1 = 96$  MIDI indices.

### 2.2 Architecture

First of all, we apply a family  $\mathbf{W}_2(\tau, \kappa_1, k_2)$  of  $K_2 = 50$  learned time-frequency convolutional operators, whose supports are constrained to have width  $\Delta t$  and height  $\Delta k_1$ .

$$\mathbf{W}_2^{t, k_1} * \mathbf{x}_1 = \sum_{\substack{0 \leq \tau < \Delta t \\ 0 \leq \kappa_1 < \Delta k_1}} \mathbf{W}_2(\tau, \kappa_1, k_2) \mathbf{x}_1(t - \tau, k_1 - \kappa_1) \quad (1)$$

Furthermore, element-wise biases  $\mathbf{b}_2(k_2)$  are added to the convolutions, resulting in the tensor

$$\mathbf{y}_2(t, k_1, k_2) = \mathbf{b}_2(k_2) + (\mathbf{W}_2^{t, k_1} * \mathbf{x}_1)(t, k_1, k_2). \quad (2)$$

The second step is the application of a pointwise nonlinearity. We have chosen the *rectified linear unit* (ReLU) because

of its popularity in computer vision and its computational efficiency.

$$\mathbf{y}_2^+(t, k_1, k_2) = \max(\mathbf{y}_2(t, k_1, k_2), 0) \quad (3)$$

To achieve invariance to translation as well as frequency transposition, we pool neighboring units in the time-frequency domain  $(t, k_1)$  over non-overlapping rectangles of width  $\Delta t$  and height  $\Delta k_1$ .

$$\mathbf{x}_2(t, k_1, k_2) = \max_{\substack{0 \leq \tau < \Delta t \\ 0 \leq \kappa_1 < \Delta k_1}} \left\{ \mathbf{y}_2^+(t + \tau, k_1 + \kappa_1, k_2) \right\} \quad (4)$$

We apply a family  $\mathbf{W}_3(\tau, \kappa_1, k_2, k_3)$  of  $K_3$  convolutional operators that perform a linear combination of time-frequency feature maps in  $\mathbf{x}_2$  along the channel variable  $k_2$ .

$$\mathbf{y}_3(t, k_1, k_3) = \sum_{k_2} \mathbf{W}_3(t, k_1, k_3) \overset{t, k_1}{*} \mathbf{x}_2(t, k_1, k_2) \quad (5)$$

After nonlinear rectification and max-pooling, the layer  $\mathbf{y}_3$  turns into a non-negative tensor  $\mathbf{x}_3(t, k_1, k_3)$ .

$$\mathbf{y}_4(k_4) = \sum_{t, k_1, k_3} \mathbf{W}_4(t, k_1, k_3, k_4) \mathbf{x}_3(t, k_1, k_3) \quad (6)$$

We apply nonlinear rectification, yielding  $\mathbf{x}_4(k_4) = \mathbf{y}_4^+(k_4)$ .  $\mathbf{y}_5(k_5) = \sum_{k_5} \mathbf{W}_5(k_4, k_5) \mathbf{x}_4(k_4)$ .  $\mathbf{x}_5(k_5) = \mathbf{y}_5^+$ .  $\mathbf{y}_6(k_6) = \sum_{k_6} \mathbf{W}_6(k_5, k_6) \mathbf{x}_5(k_5)$ .

$$\mathbf{x}_6(k_6) = \frac{\exp \mathbf{y}_6(k_6)}{\|\exp \mathbf{y}_6(k_6)\|_1} \quad (7)$$

The above ensures that the coefficients of  $\mathbf{x}_6$  are non-negative and sum to one, hence can fit a We define the categorical cross-entropy as

$$\mathcal{L}(\mathbf{x}_6, \mathcal{I}) = - \sum_{k_6 \in \mathcal{I}} \log \mathbf{x}_6(k_6). \quad (8)$$

The goal is to minimize the average loss  $\mathcal{L}(\mathbf{x}_6, \mathcal{I})$  for across all pairs  $(\mathbf{x}_6, \mathcal{I})$  in the training set.

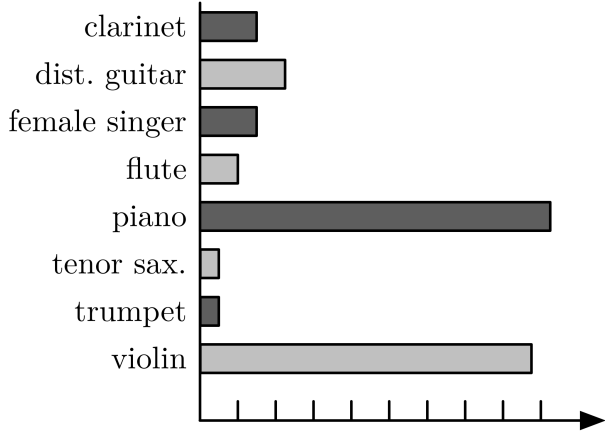
## 2.3 Training

The network is trained on categorical cross-entropy over shuffled mini-batches of size 512 with uniform class distribution. The learning rate policy for each scalar weight in the network is *Adam* [3], a state-of-the-art online optimizer for gradient-based learning.



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**Figure 1:** Amount of training data per instrument in MedleyDB, in minutes.

### 3. DEEP SUPERVISION OF MELODIC CONTOUR

#### 3.1 Disentangling pitch from timbre

#### 3.2 Extraneous supervision

$$\mathcal{L}(\mathbf{x}_2, \mathcal{P}) = - \sum_{(t, k_1) \in \mathcal{P}} \log \sigma \left( \sum_{k_2} \mathbf{x}_2(t, k_1, k_2) \right) \quad (9)$$

#### 3.3 Joint supervision

### 4. SINGLE-INSTRUMENT CLASSIFICATION

#### 4.1 Experimental design

In order to train the proposed algorithms, we used MedleyDB v1.1. [1], a dataset of 122 multitracks annotated with instrument activations as well as melodic  $f_0$  curves when present. We extracted the monophonic stems corresponding to a selection of eight pitched instruments (see Figure 1. Stems with leaking instruments in the background were discarded. The resulting set was double-checked manually, and annotation mistakes were reported to MedleyDB curators for the next release. The evaluation set consists of 120 recordings of solo music collected by Joder et al. [2]. We discarded recordings with extended instrumental techniques, since they are under-represented in MedleyDB. Moreover, since the

#### 4.2 Results

### 5. POLYPHONIC CLASSIFICATION

#### 5.1 Experimental design

#### 5.2 Results

### 6. CONCLUSIONS

### 7. REFERENCES

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