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

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 $\boldsymbol{x_1}(t, k_1)$ of width $T = 128$ samples and height $K_1 = 96$ MIDI indices.

2.2 Architecture

First of all, we apply a family $\boldsymbol{W_2}(\tau, \kappa_1, k_2)$ of $K_2 = 50$ learned time-frequency convolutional operators, whose supports are constrained to have width Δt and height Δk_1.

$$\boldsymbol{W_2} \overset{t,k_1}{*} \boldsymbol{x_1} = \sum_{\substack{0 \leq \tau < \Delta t \\ 0 \leq \kappa_1 < \Delta k_1}} \boldsymbol{W_2}(\tau, \kappa_1, k_2) \boldsymbol{x_1}(t - \tau, k_1 - \kappa_1) \quad (1)$$

Furthermore, element-wise biases $\boldsymbol{b_2}(k_2)$ are added to the convolutions, resulting in the tensor

$$\boldsymbol{y_2}(t, k_1, k_2) = \boldsymbol{b_2} + (\boldsymbol{x_1} \overset{t,k_1}{*} \boldsymbol{W_2}). \quad (2)$$

The second step is the application of a pointwise non-linearity. We have chosen the *rectified linear unit* (ReLU) because of its popularity in computer vision and its computational efficiency.

$$\boldsymbol{y_2^+}(t, k_1, k_2) = \max(\boldsymbol{y_2}(t, k_1, k_2), 0) \quad (3)$$

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 Δt and height Δk_1.

$$\boldsymbol{x_2}(t, k_1, k_2) = \max_{\substack{0 \leq \tau < \Delta t \\ 0 \leq \kappa_1 < \Delta k_1}} \left\{ \boldsymbol{y_2^+}(t + \tau, k_1 + \kappa_1, k_2) \right\} \quad (4)$$

$$\boldsymbol{y_3}(t, k_1, k_3) = \sum_{k_2} (\boldsymbol{x_2} \overset{t,k_1}{*} \boldsymbol{W_3}) \quad (5)$$

$$\boldsymbol{x_4}(k_4) = \left(\sum_{v_3} \boldsymbol{W_4}(k_4, v_3) \boldsymbol{x_3}(v_3) \right)^+ \quad (6)$$

$$\boldsymbol{x_5}(k_5) = \left(\sum_{k_4} \boldsymbol{W_5}(k_5, k_4) \boldsymbol{x_4}(k_4) \right)^+ \quad (7)$$

$$\boldsymbol{y_6}(k_6) = \sum_{k_6} \boldsymbol{W_6}(k_6, k_5) \boldsymbol{x_5}(k_5) \quad (8)$$

We define the categorical cross-entropy as

$$\mathscr{L}(\boldsymbol{x_6}, \mathcal{I}) = - \sum_{k_5 \in \mathcal{I}} \log \sigma(\boldsymbol{y_6}(k_6)). \quad (9)$$

The goal is to minimize the average loss $\mathscr{L}(\boldsymbol{x_6}, \mathcal{I})$ for across all pairs $(\boldsymbol{x_6}, \mathcal{I})$ in the training set.

2.3 Training

The network is trained on categorical cross-entropy with *Adam* [3], a state-of-the-art stochastic optimizer for gradient-based learning.

3. DEEP SUPERVISION OF MELODIC CONTOUR

3.1 Disentangling pitch from timbre

3.2 Extraneous supervision

$$\mathscr{L}(\boldsymbol{x_2}, \mathcal{P}) = - \sum_{(t, k_1) \in \mathcal{P}} \log \sigma \left(\sum_{k_2} \boldsymbol{x_2}(t, k_1, k_2) \right) \quad (10)$$

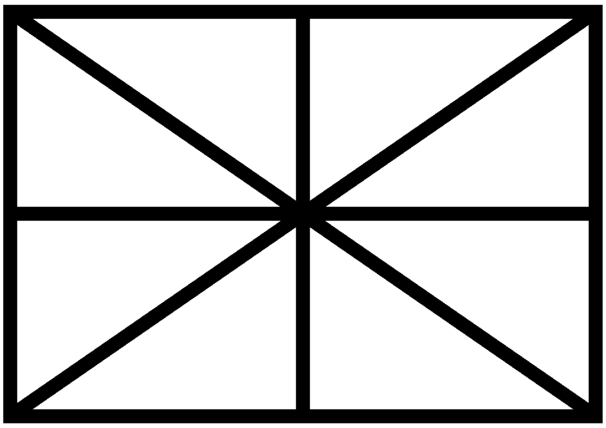

Figure 1: oi oi oi

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.

4.2 Results

5. POLYPHONIC CLASSIFICATION

5.1 Experimental design

5.2 Results

6. CONCLUSIONS

7. REFERENCES

[1] Rachel Bittner, Justin Salamon, Mike Tierney, Matthias Mauch, Chris Cannam, and Juan Bello. Medleydb: a multitrack dataset for annotation-intensive mir research. *International Society for Music Information Retrieval Conference*, 2014.

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