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 [3] 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* [2], 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

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

3.3 Joint supervision

4. SINGLE-INSTRUMENT CLASSIFICATION

4.1 Experimental design

In order to train the proposed algorithms, we used MedleyDB [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. Stems with undesirable sources in the background – a phenomenon known as *bleed* – were discarded. We manually checked the resulting training set, and ruled out controversial annotations, such as multiple players, prepared guitar, and trumpet with sordina.

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.

[2] Diederik P. Kingma and Jimmy Lei Ba. Adam: a Method for Stochastic Optimization. *International Conference on Learning Representations*, pages 1–13, 2015.

[3] Brian McFee, Matt McVicar, Colin Raffel, Dawen Liang, Oriol Nieto, Eric Battenberg, Josh Moore, Dan Ellis, Ryuichi Yamamoto, Rachel Bittner, Douglas Repetto, Petr Viktorin, Joo Felipe Santos, and Adrian Holovaty. librosa: 0.4.1. zenodo. 10.5281/zenodo.18369, October 2015.