

USING SPECTROGRAMS & CNNs FOR MUSIC GENRE CLASSIFICATION

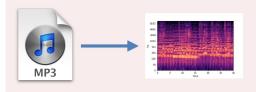
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Introduction

Modern academics argue that grouping music into genres is inaccurate and outdated – categorizations are mostly based on arbitrary conventions. We investigated how accurately convolutional networks can identify these "patterns" in music of shared genres.

Dataset & Preprocessing

- Free Music Archive
- 8000 .mp3 files, accompanied by .csv file containing genres
- 85 different genres
- LibROSA Python package
- Use library to extract time-series and frequencies from audio files
- Converts .mp3 files into spectrograms
- 432 × 288 RGB images (.png files)
- Crop spectrogram to 64x64



Model

- 6 convolutional layers with increasing filter density to extract features of images
- Pooling and dropout layers to reduce overfitting
- ReLU activation
- 2 fully connected layers at end, softmax output



FIGURE A - Early iteration - Overfitting - Train Accuracy: 98% - Dev Accuracy: 10% - Figure B - Reduced overfitting with batch-norm, L2 regularization, dropout, more data - Train Accuracy: 72% - Dev Accuracy: 38%

Discussion

- Smaller filters led to greater accuracy
- Our accuracy was not as high as we would have liked it to be for a number of reasons:
- Small dataset (8000 training examples)
- Too many genres (85)
- Some songs had no genres or multiple genres
- Genres are not truly based on audio patterns

References

III Close, et al. "Florider Leurning be Monic Clausifications and Regissersia Telestic Monic on 13 Med." An average labor 12 Monic 11 (Holdwedge et al., 2005). A Monic on 13 Med. 2007. A monic of labor 12 Med. 13 M





