Music Classification Using Convolutional Neural Networks

Abel Putovici **Zsombor Molnár**

Abstract

In this paper we describe a convolutional neural network designed to classify music by genre. The base idea came from an article we read about the combination of CNN and mathematical algorithms for music classification [3]. At the moment the network can categorise at a 61% accuracy. We use the GTZAN dataset with slight modifications as it covers all our needs. During the building of this neural network we encountered numerous challenges, especially with the activation functions. A constant problem was overlearning, which we could only delay.

1 Introduction

Music is and has always been one of the most popular forms of art and entertainment. The number of people who use streaming services to consume music has grown to a magnitude of millions in this decade. These services make use of complicated and complex recommender systems to help grow the number of daily active users and to improve their experience of the service. These recommender systems rely on extremely large labeled datasets in order to work properly, and labeling these datasets manually is a very resource-heavy endeavour.

1.1 Our Goal

Music Genres in General One possible way of labeling songs is doing it by genre though this introduces other difficulties, since these are ment to indicate the artistic nature of music, an aspect which tends to be highly subjective and controversial. Music genres do not have a proper, formal definition and often overlap as well, making music classification by genre a more difficult task to do right.

Our Primary Goal Our primary goal was do deliver a solution which can effectively recognize some of the most popular and generic music genres and assign these as labels to songs of music.

2 Our Approach

There are many existing solutions and research papers regarding the subject and these show absolutely usable methods and results, though each of them tend to have a major drawback: every solution aims to work in *centralized environments* due to their computational requirements. We decided that our approach had to be able to work on edge devices such as smart phones or other, more constrained environments, even on cost of precision. This decision implied a rather small model size and great model simplicity, this is why we chose to try a simple convolutional neural network.

3 The dataset

We wanted to have a great vatiety of song samples in large quantity. The first dataset we took into account is the *Million Song Dataset* [1]. The sheer number of samples was quite promissing, but it turned out to be overwhelming. Not to mention the fact that it contained numerous pieces of information that we did not need, like the authors, the release year and other different identifiers for database use. It needed a lot of time just to extract the necessary information we need, which would make the extension of the used dataset unnecessarily time consuming.

Our second option was the GTZAN [2] dataset used in the *Musical genre classification of audio signals* [5]. It suited our needs and it covered samples from 10 clearly distinct music genres, 100 tracks each. As for the length of the songs, the dataset contained 30 second long samples from different parts of the songs. An analysis done by Bob L. Strum [4] describes more precisely the capacity of this dataset.

4 The Model

4.1 Trial and Error

We went through numerous iterations and tried various convolutional neural network architectures during development. At first we tried to use convolutional windows that would overlap the whole frequency domain and move only in the time domain, since although spectrograms can be regarded as arbitrary two dimensional data, the two axises have different meanings. This path led nowhere, as the model was not able to overfit on a small subset of the dataset. We decided to use simple, rectangular convolutional windows, which could be called standard by now. This approach was indeed able to overfit, meaning it was worth to try learning on the whole dataset. Validation error would cease to decrease after the first few epochs. This would be followed by decreasing the input size of the model by splitting the samples of 30 seconds length into 4 smaller fragments.

4.2 The Final Model Architecture

The final model consists of the following layers:

- a convolutional layer with a depth of 32 and a window shape of (2, 6)
- another convolutional layer with a depth of 32 and a window shape of (2, 6)
- a convolutional layer with a depth of 64 and a window shape identical to the previous ones
- a fully connected layer of 512 neurons

Each convolutional layer was followed by a batch normalization layer and a max-pooling layer. L1 and L2 regularizers were adopted to the fully connected layer. The model has an output layer of 10 neurons with *softmax* as activation function.

4.3 Hyperparameters

Activation functions At first we tried using *ReLU* activations between each layer. This lead to many issues, since in the context of Mel spectrograms negative numbers have significance. Perceiving this, we decided to use *Hyperbolic Tangent* as activation function.

Loss Function The loss function used is *Sparse Categorical Crossentropy* since the labels are not one-hot encoded.

Optimizer The optimizer algorithm used during training was Stochastic Gradient Descent with a learning rate of 0.01. At first we've tried with *Adam* but it did not perform quite as expected. The next choice was *Adadelta* which showed promising results, but it did not appear to stabilize due to the fluctuation we have observed on both the graphs of training and validation accuracy.

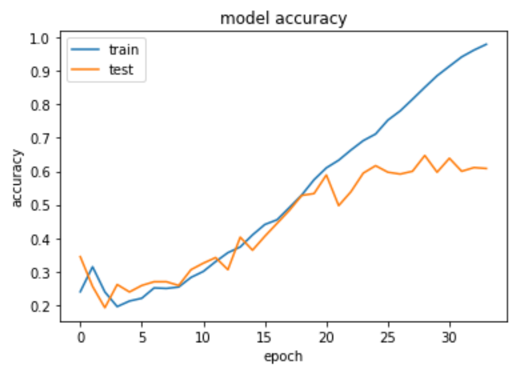
Number of Epoch and Data Split The model was trained for 100 epochs with a batch size of 5. 80 percent of the data was used for training, 10 percent was used for validation and the last 10 percent was used for testing.

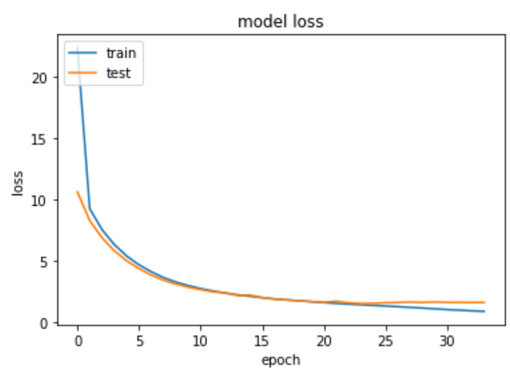
Vanishing Gradient During the training process we've noticed that after a certain number of epochs the validation accuracy would cease to converge. This was due to the Vanishing Gradient problem, which led to the choice of using *Linear* activation between the convolutional layers, leaving *Hyperbolic Tangent* only between the output and the fully connected layer.

5 Results

5.1 Training and Validation

The model is still overfitting with the validation accuracy being stuck at $\tilde{6}0\%$ and the training accuracy soaring.





5.2 Testing Accuracy

The final testing accuracy of the model is **61%**. Below are the Classication Matrix and the final Classification Report.

Table 1: Confusion Matrix

Genre	Metal	Classical	Reggae	Jazz	Country	Rock	Hiphop	Disco	Pop	Blues
Metal	44	0	0	0	0	0	0	0	0	0
Classical	0	28	0	0	1	1	0	0	0	0
Reggae	1	1	18	0	1	2	5	3	8	5
Jazz	1	11	0	28	1	1	0	0	1	2
Country	0	2	0	3	20	1	0	0	0	4
Rock	12	0	0	2	5	16	4	2	1	4
Hiphop	7	0	1	0	0	0	28	0	1	2
Disco	4	1	4	0	1	9	7	8	7	2
Pop	0	3	1	0	3	2	2	0	35	2
Blues	1	1	0	5	2	0	0	1	0	20

Table 2: Classification Report

Genre	Precision	Recall	F1-Score	Support (number of samples)
metal	1.00	0.63	0.77	70
classical	0.93	0.60	0.73	47
reggae	0.41	0.75	0.53	24
jazz	0.63	0.74	0.68	39
country	0.67	0.59	0.62	34
rock	0.35	0.50	0.41	32
hiphop	0.72	0.61	0.66	46
disco	0.19	0.57	0.28	14
pop	0.73	0.66	0.69	53
blues	0.67	0.49	0.56	41

Table 3: Classification Report Averages

Type	Precision	Recall	F1-Score	Support (number of samples)
Macro Average	0.63	0.61	0.59	400
Weighted Average	0.71	0.61	0.64	400

6 Future Improvements

There are many ways the solution could be improved. Our plans include

- augmenting the dataset by time-stretching (and squeezing) and splitting the 30 second samples using slightly overlapping windows
- experimenting with different network architectures
- applying *Hyperparameter Optimization*
- maybe searching for network architectures using experimental solutions like *AutoML*

References

[1] Thierry Bertin-Mahieux, Daniel PW Ellis, Brian Whitman, and Paul Lamere. The million song dataset. 2011.

[2] Jakob Leben. Gtzan genre collection. 2015.

[3] Haojun Li, Siqi Xue, and Jialun Zhang. Combining cnn and classical algorithms for music genre classification.

[4] Bob L Sturm. An analysis of the gtzan music genre dataset. In *Proceedings of the second international ACM workshop on Music information retrieval with user-centered and multimodal strategies*, pages 7–12. ACM, 2012.

[5] George Tzanetakis and Perry Cook. Musical genre classification of audio signals. *IEEE Transactions on speech and audio processing*, 10(5):293–302, 2002.