Music Genre Classification

Springboard DSC Program
Capstone Project 2
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Introduction

The Problem:

Classifying songs by genre is useful for library management and recommendation engines. It can be labor intensive.

The Client:

Music streaming services like Spotify, Apple Music, etc. use recommendation engines to better serve new music to users. Classifying accurately by features in the music might improve these services.

The Goal:

Sufficiently accurate genre classification based on audio features.

Data Science Problem and the data

This is a supervised learning problem, a multiclass classification problem with one of 8 labels assigned to each sample.

The data used is the Free Music Archive, a collection of music samples made available for machine learning.

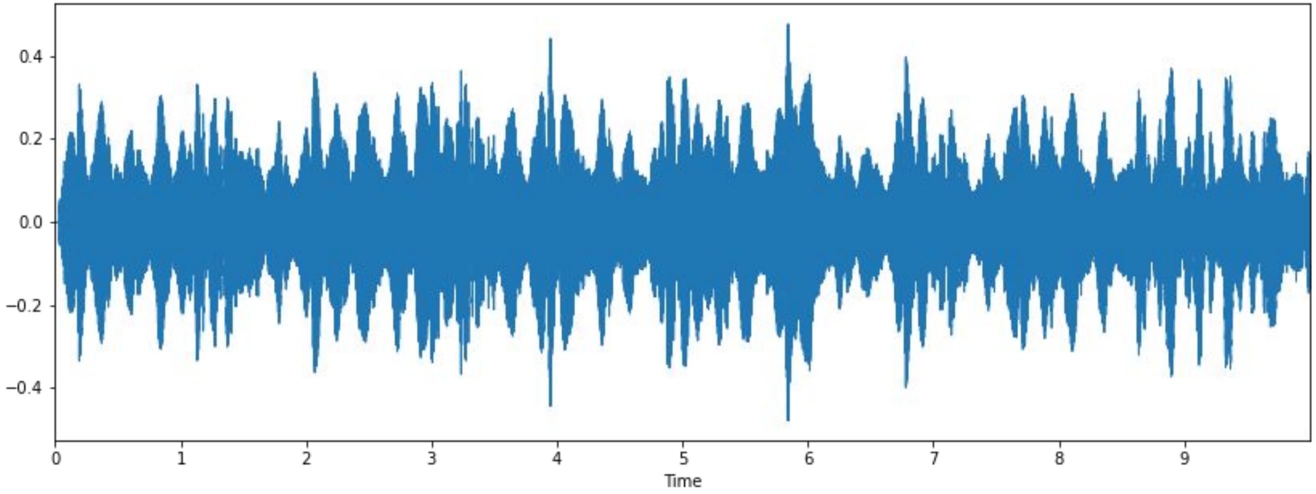
Data Wrangling and Acquisition

Data from FMA is already well organized.

- 100,000 30-second clips
- Already split into train, validation, test groups
- Decoded with Tensorflow TFIO tools
- A few (164) corrupted files
- Using an 8000 sample subset with 8 classes

Exploratory Data Analysis (EDA)

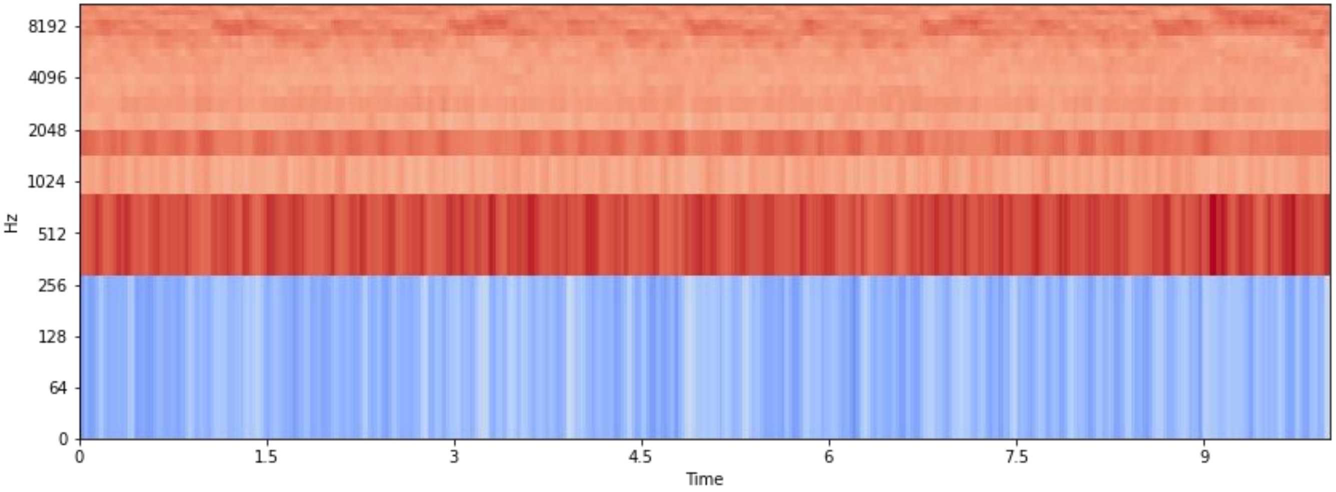
Using mp3 files -- when decompressed, the plot of the a .wav file:



EDA (cont.)

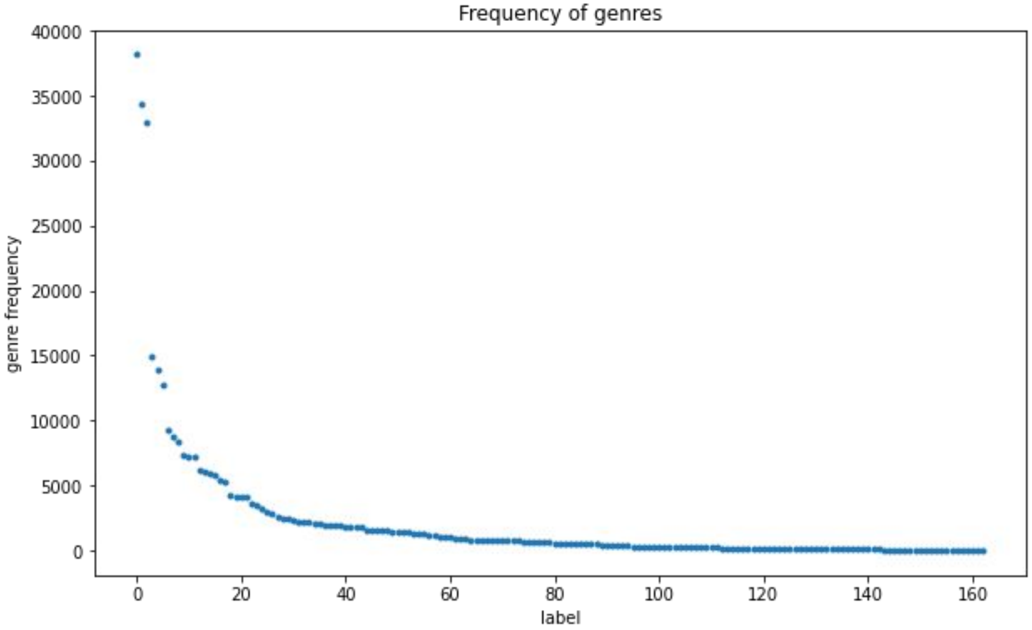
Relevant features for extraction:

MFCC (indication of timbre of audio)



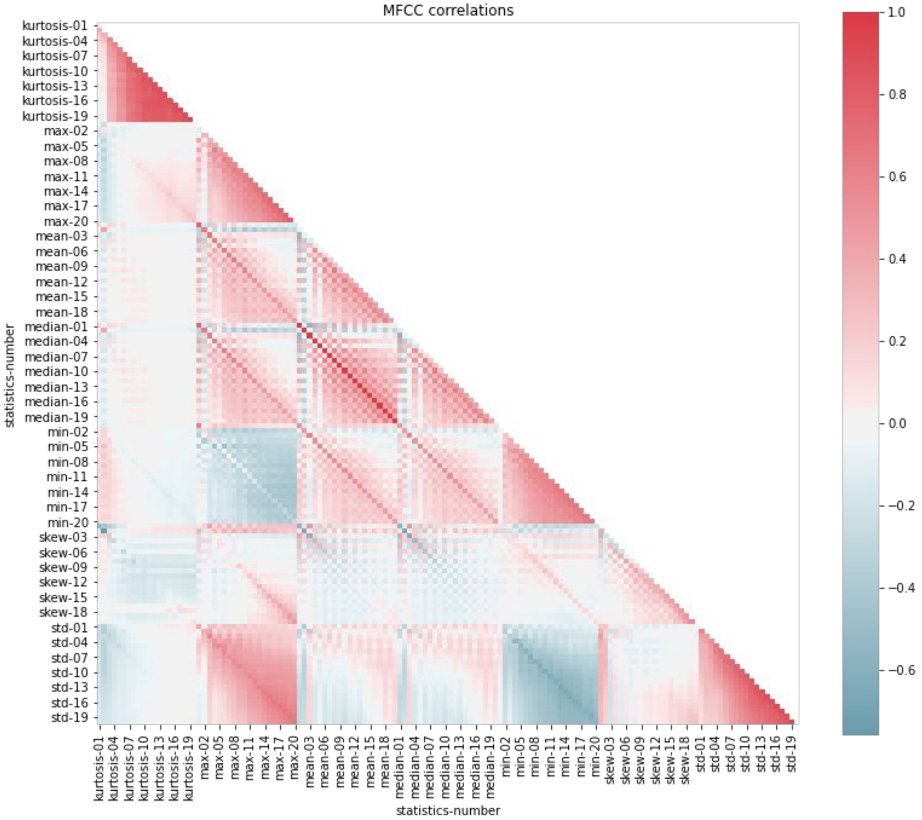
EDA (cont.)

Distribution of all genres (classes) over entire dataset:



EDA (cont.)

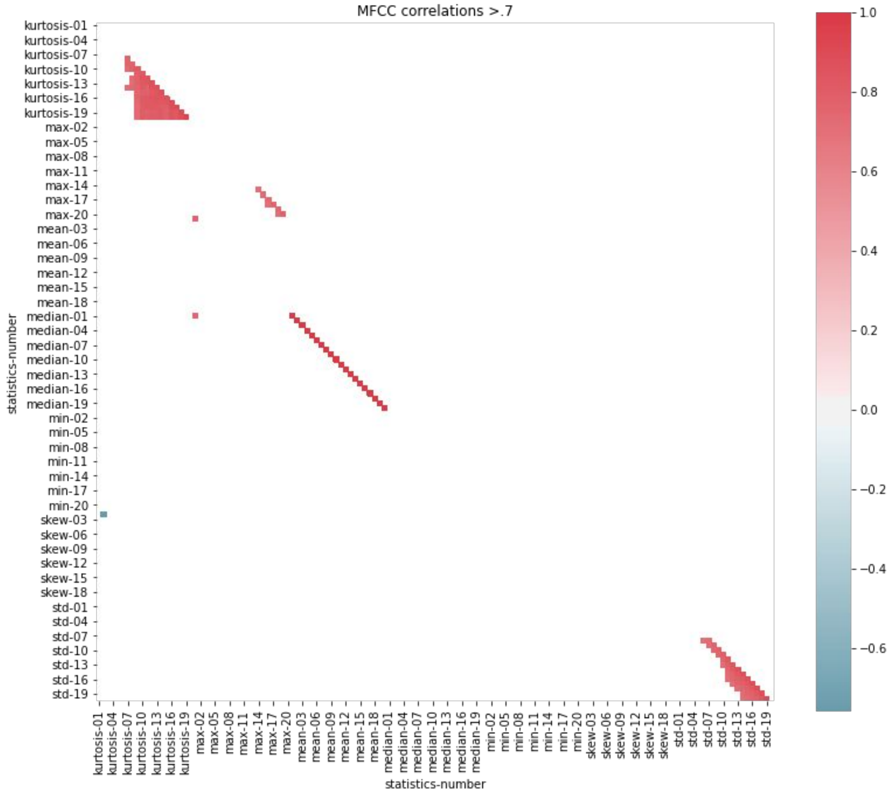
Correlation of features (MFCC)



EDA (cont.)

Isolating very high correlations:

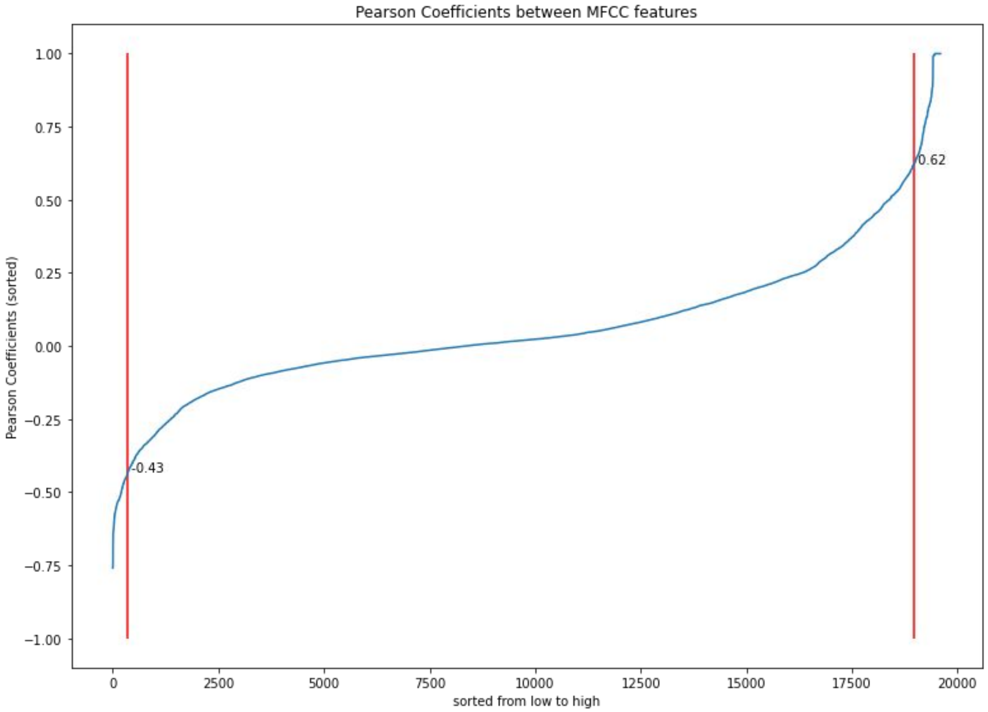
- Not many highly correlated pairs
- Highly correlated pairs limited to near neighbors in time



EDA (cont.)

Pearson Coefficients between MFCC features:

- Few highly correlated pairs
- 95% of correlations between -0.43 and 0.62



Baseline Model

Logistic regression:

```
Classification Report (test set)
              precision    recall  f1-score   support

           0       0.26      0.35      0.30        96
           1       0.15      0.21      0.18        98
           2       0.15      0.13      0.14       100
           3       0.32      0.19      0.24       100
           4       0.24      0.25      0.25       100
           5       0.23      0.16      0.19       100
           6       0.08      0.08      0.08       100
           7       0.30      0.34      0.32       100

    accuracy                           0.21       794
   macro avg       0.22      0.21      0.21       794
weighted avg       0.22      0.21      0.21       794
```

Baseline Model (cont.)

Fully Connected Neural Net results:

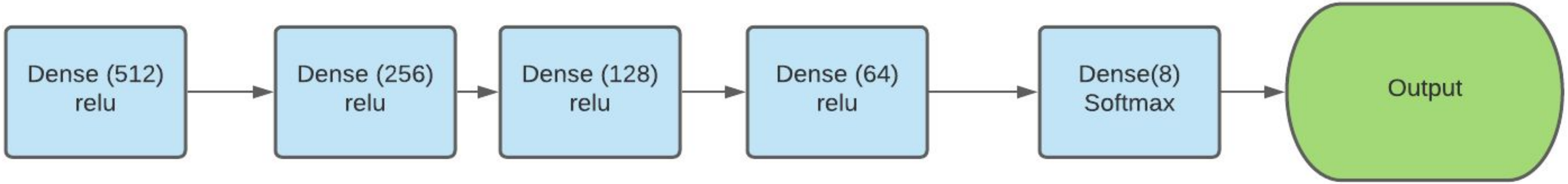
```
Classification Report (test set)
              precision    recall  f1-score   support

           0       0.34      0.50      0.40        96
           1       0.19      0.14      0.16        98
           2       0.19      0.13      0.15       100
           3       0.47      0.38      0.42       100
           4       0.30      0.39      0.34       100
           5       0.34      0.33      0.34       100
           6       0.18      0.19      0.19       100
           7       0.42      0.41      0.41       100

    accuracy                           0.31       794
   macro avg       0.30      0.31      0.30       794
weighted avg       0.30      0.31      0.30       794
```

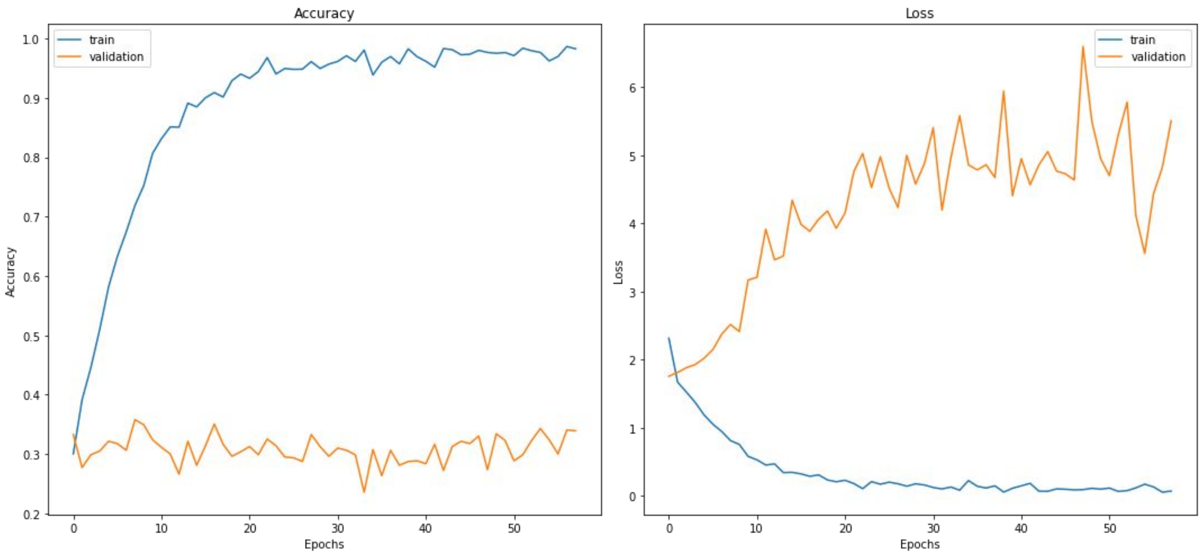
Baseline Model (cont.)

Fully connected Neural Net architecture



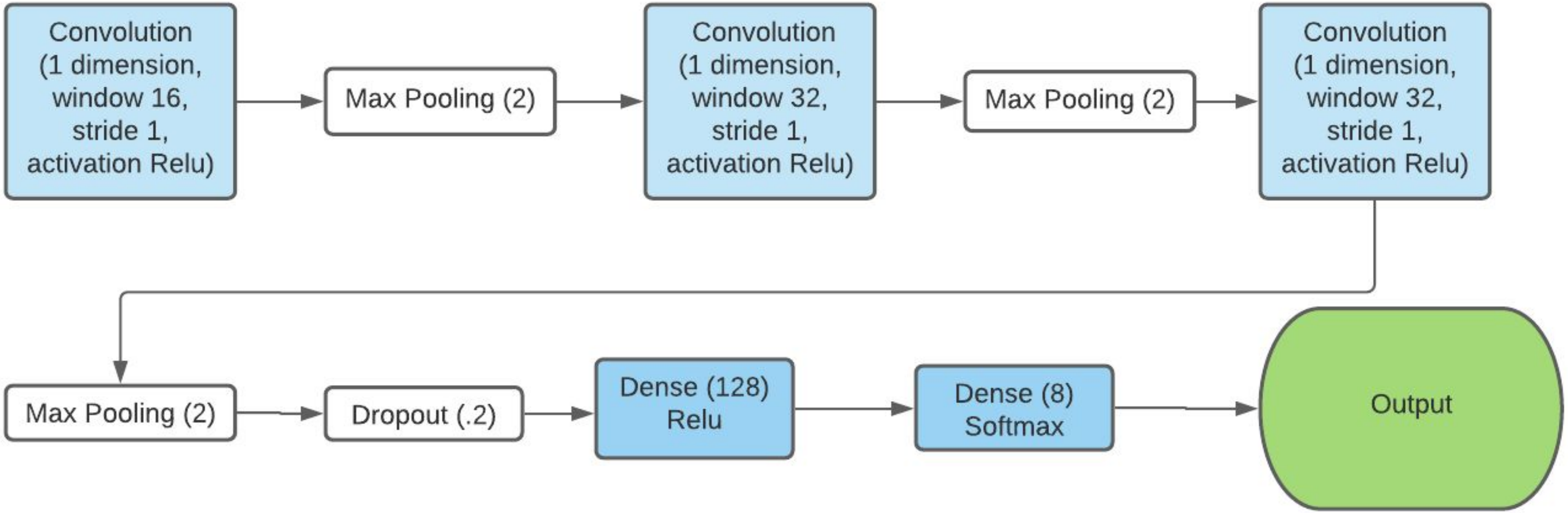
Baseline Model (cont.)

Neural Net training:



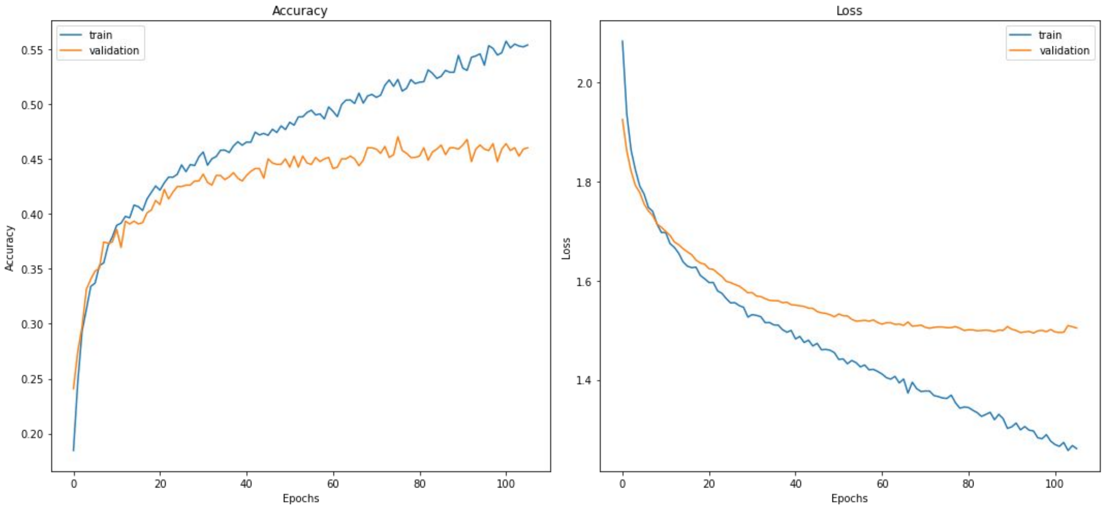
Convolutional Neural Net (CNN)

CNN Architecture:



CNN (cont.)

CNN Training:



CNN (cont.)

CNN Results:

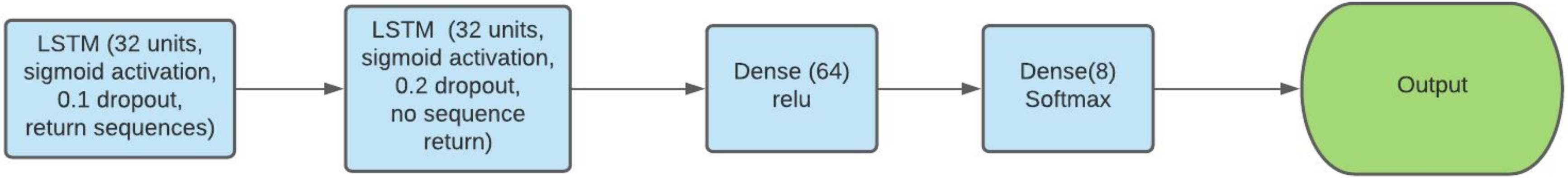
```
Classification Report (test set)
              precision    recall  f1-score   support

           0       0.47      0.42      0.44        96
           1       0.13      0.10      0.11        98
           2       0.18      0.24      0.21       100
           3       0.49      0.71      0.58       100
           4       0.33      0.40      0.36       100
           5       0.41      0.36      0.38       100
           6       0.17      0.07      0.10       100
           7       0.52      0.56      0.54       100

    accuracy                           0.36       794
   macro avg       0.34      0.36      0.34       794
weighted avg       0.34      0.36      0.34       794
```

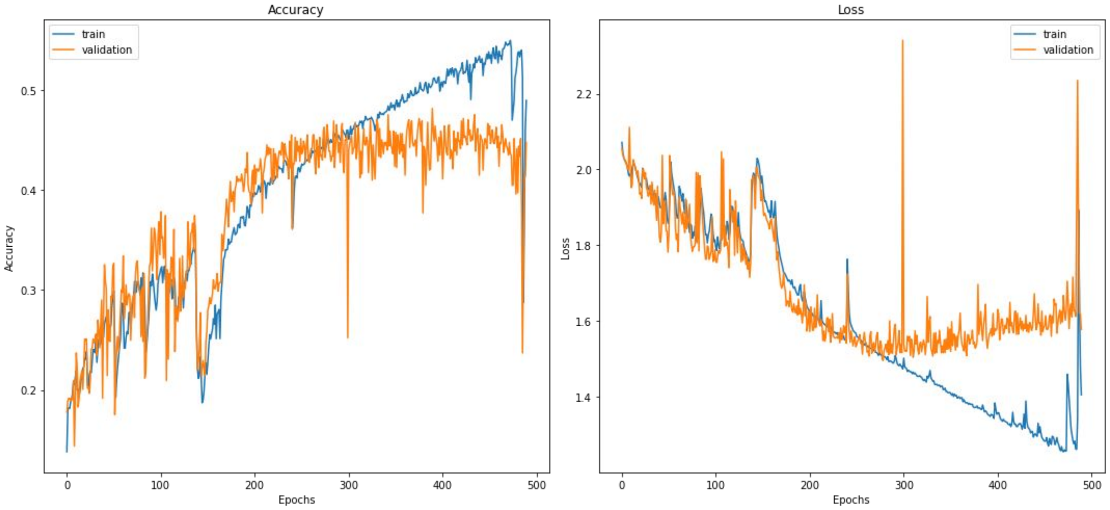
Long Short Term Memory (LSTM)

LSTM Architecture:



LSTM (cont.)

LSTM Training:



LSTM (cont.)

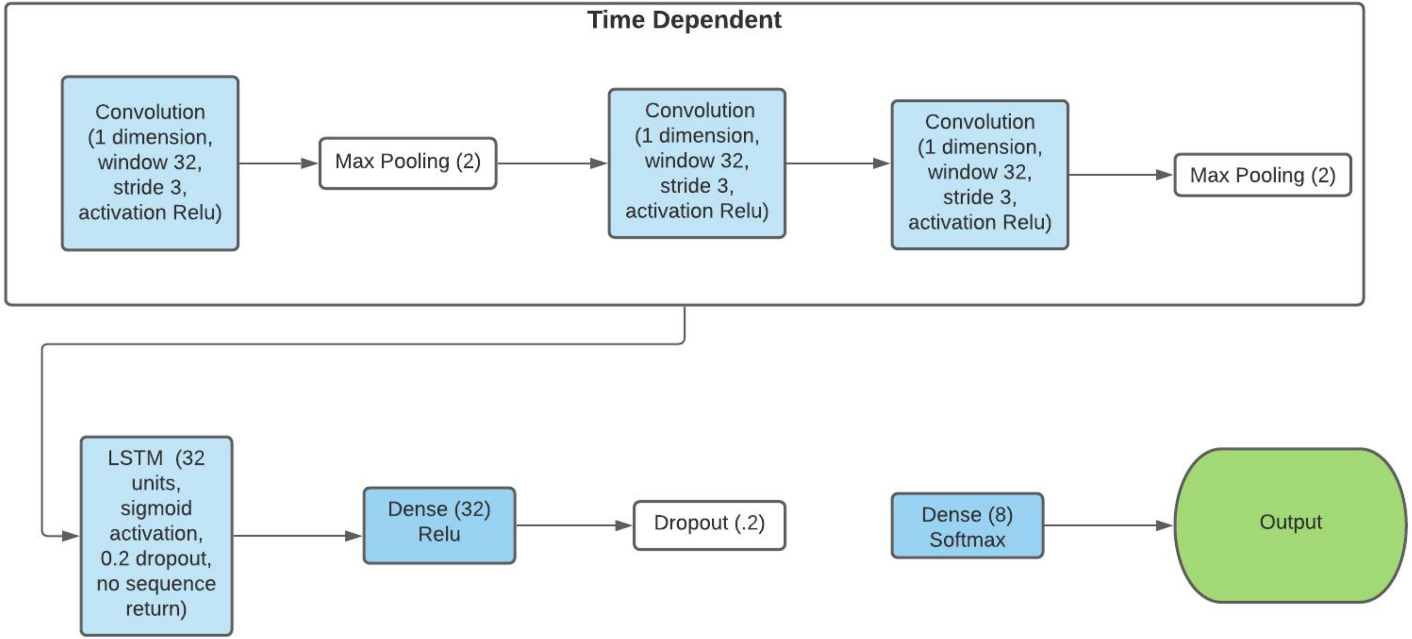
LSTM Results:

Classification Report (test set)

	precision	recall	f1-score	support
0	0.50	0.27	0.35	96
1	0.26	0.17	0.21	98
2	0.22	0.23	0.23	100
3	0.53	0.61	0.56	100
4	0.33	0.33	0.33	100
5	0.36	0.28	0.32	100
6	0.27	0.31	0.29	100
7	0.34	0.57	0.43	100
accuracy			0.35	794
macro avg	0.35	0.35	0.34	794
weighted avg	0.35	0.35	0.34	794

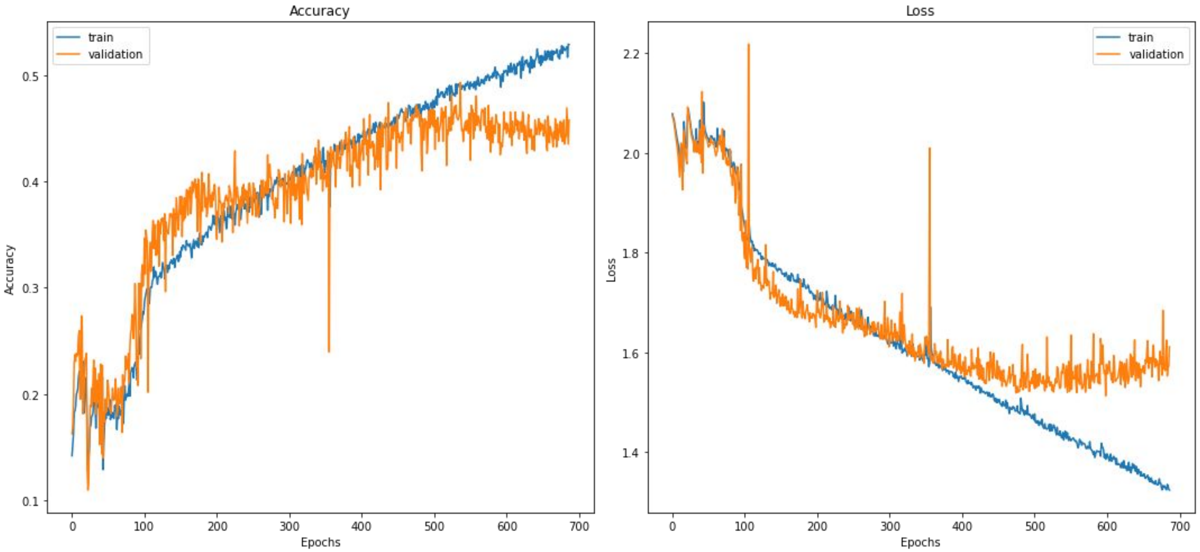
Time-Dependent CNN (TD-CNN)

TD-CNN Architecture:



TD-C-N (cont.)

TD-CNN Training:



TD-CNN (cont.)

TD-CNN Results:

Classification Report (test set)

	precision	recall	f1-score	support
0	0.42	0.51	0.46	96
1	0.32	0.11	0.17	98
2	0.34	0.48	0.40	100
3	0.63	0.66	0.64	100
4	0.38	0.47	0.42	100
5	0.42	0.33	0.37	100
6	0.34	0.31	0.32	100
7	0.49	0.49	0.49	100
accuracy			0.42	794
macro avg	0.42	0.42	0.41	794
weighted avg	0.42	0.42	0.41	794

Overall Results

Model	**Accuracy(all classes)**	**Train Time**
Baseline	.30	5m
CNN	.36	3m
LSTM	.35	90m
TD-CNN	.42	3h 20m

Results (cont.)

Class	**Genre**	**F1 (CNN)**	**F1(LSTM)**	**F1(TD-CNN)**
0	Electronic	.45	.35	.46
1	Experimental	.18	.21	.17
2	Folk	.19	.23	.40
3	Hip-Hop	.66	.56	.64
4	Instrumental	.33	.33	.42
5	International	.44	.32	.37
6	Pop	.22	.29	.32
7	Rock	.52	.43	.49

Conclusions