Music Genre Classification

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1. Intro

A music sharing platform wants to increase user experience during the upload process

- ➔ **Speed**
  Make the upload process quicker
- ➔ **Automation**
  Automatically tag a genre
- ➔ **Simple**
  Quick, easy and use-friendly

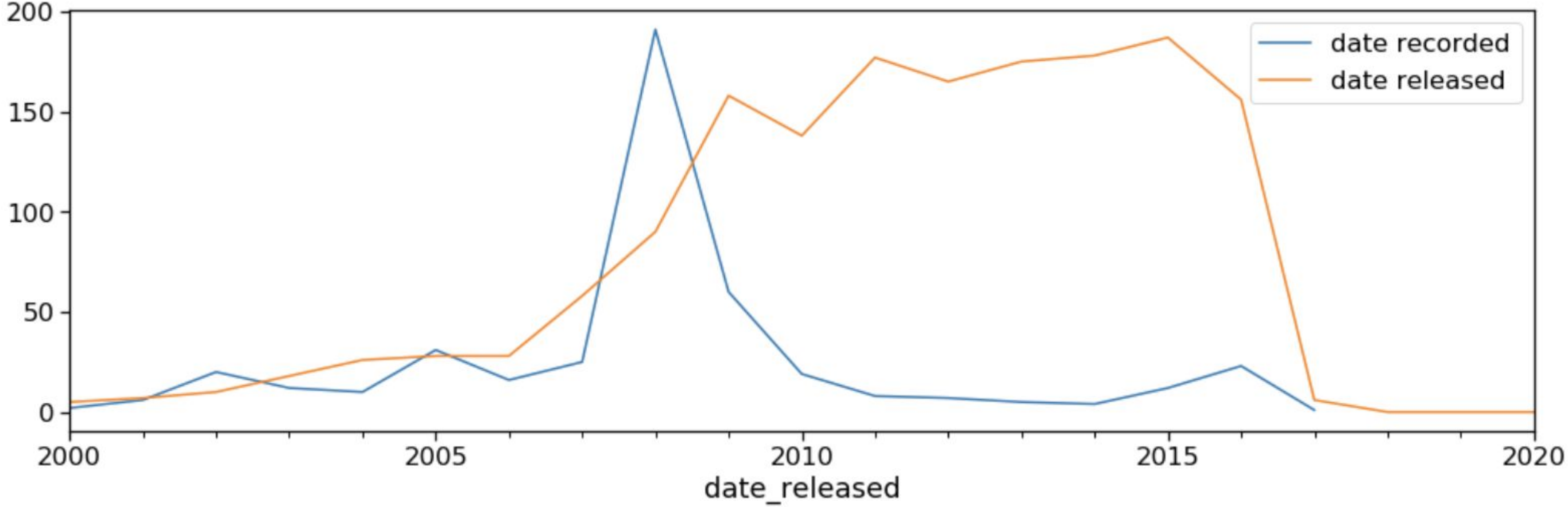
The Data

8 Genres

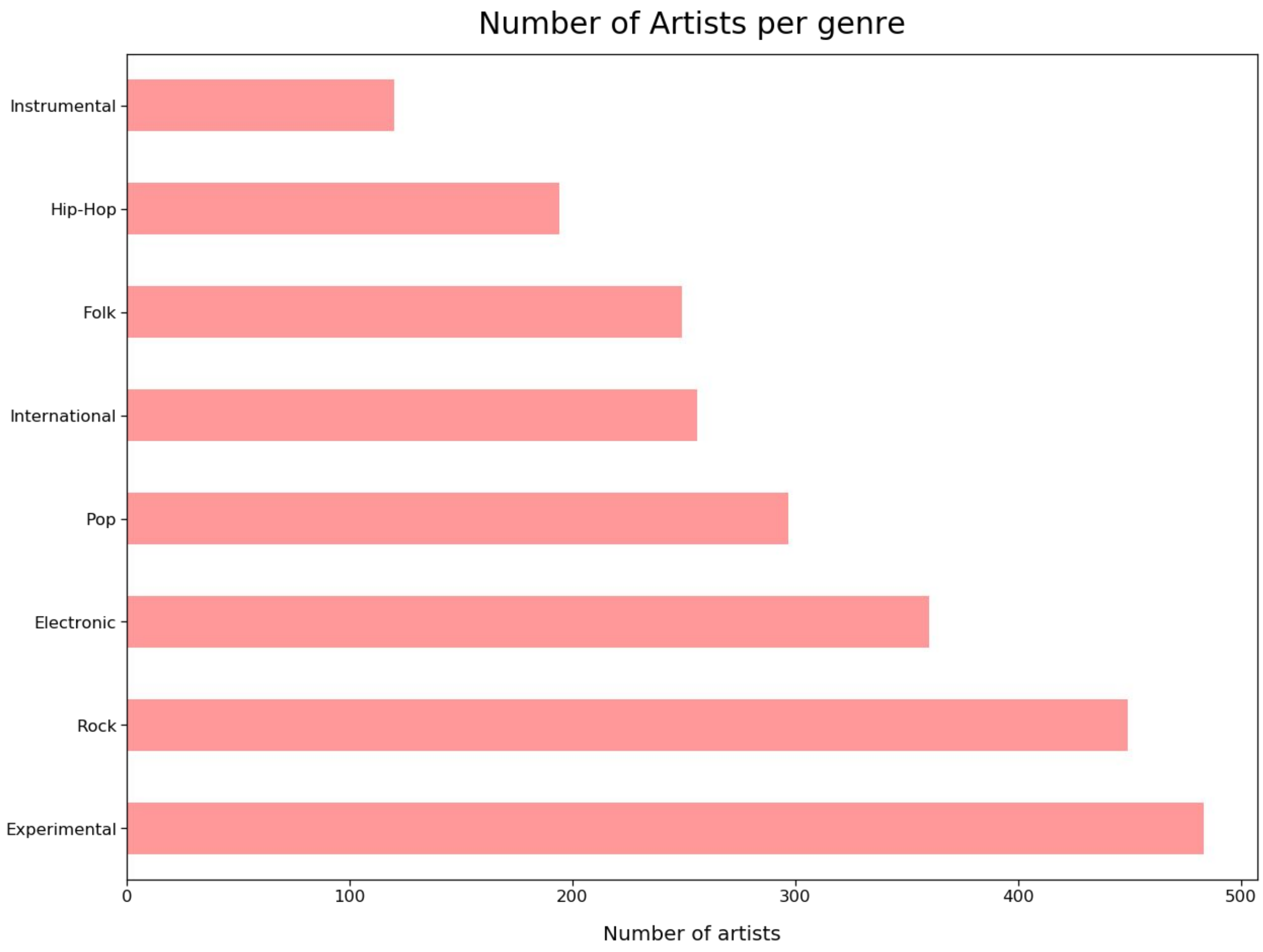
8000	2308	2464
Tracks	Artists	Albums

When were these songs released?

Track Recorded vs Released

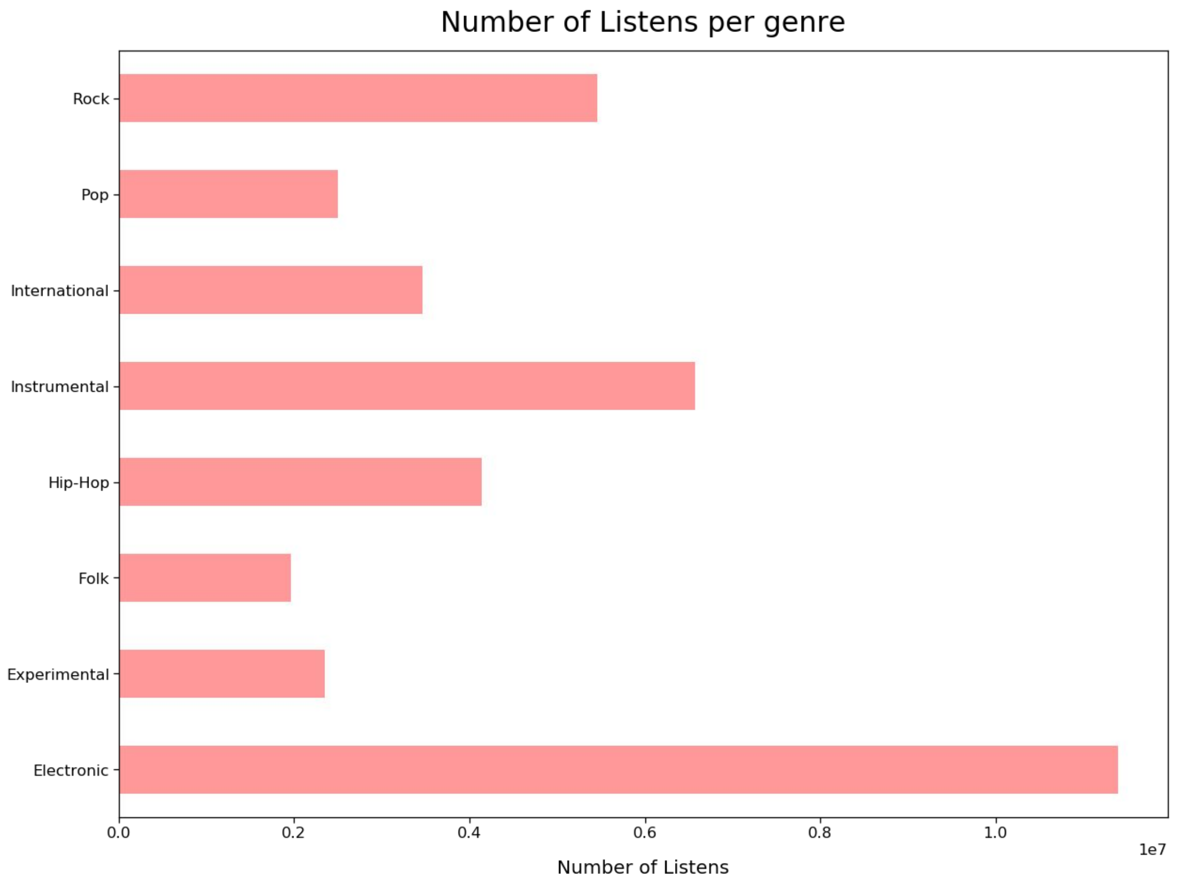


Which genre is most popular



400%

More experimental tracks than instrumental



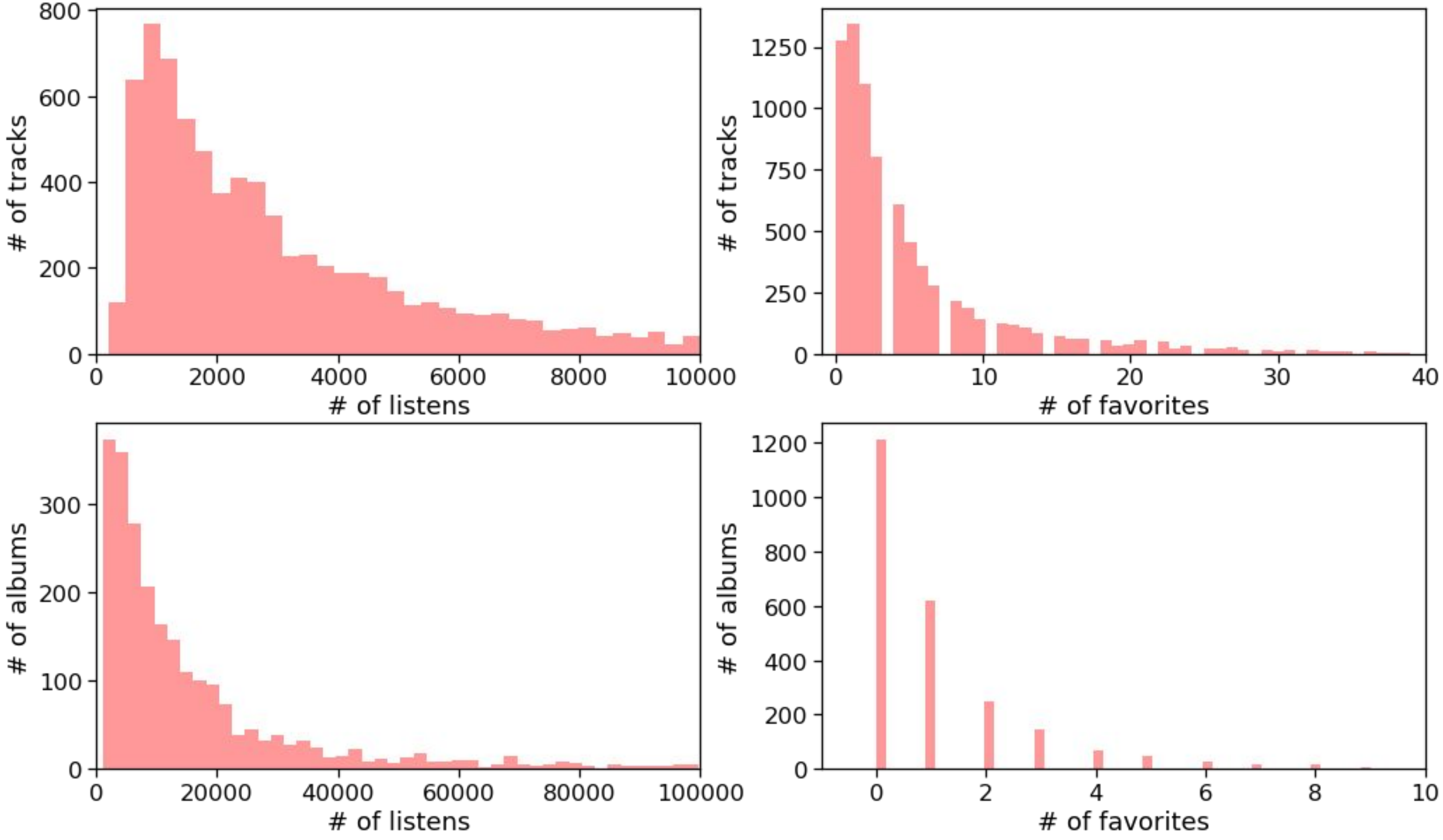
11 million

Electronic Listens

1.96 million

Folk Listens

Listen & Favourite Distribution

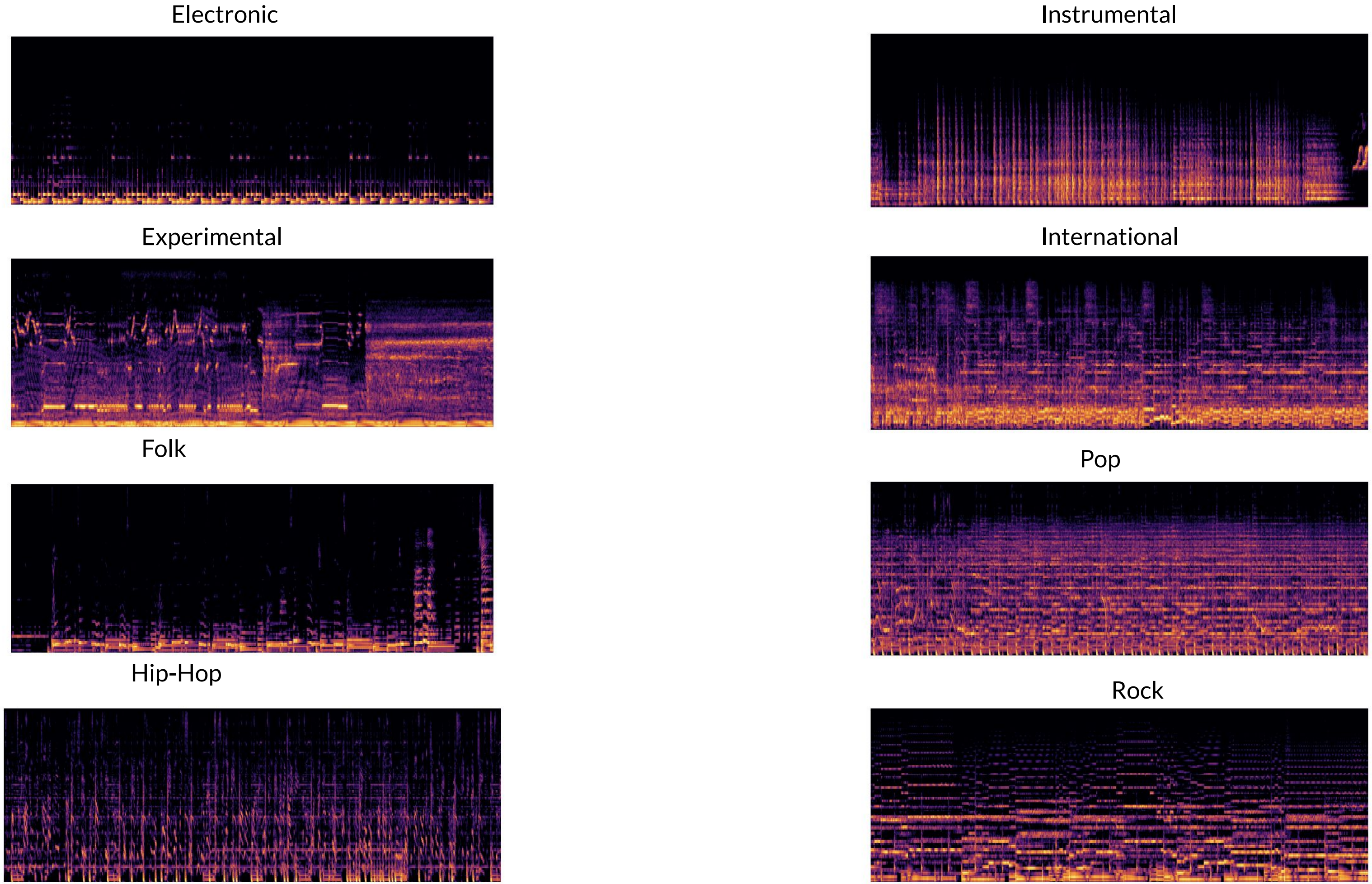


# of tracks
# of listens
# of tracks
# of favorites
# of albums
# of listens
# of albums
# of favorites

Extracting Features

Music Information Retrieval

1. Spectral Features
2. Temporal Features
3. MFCCs
4. Mel-Spectrograms

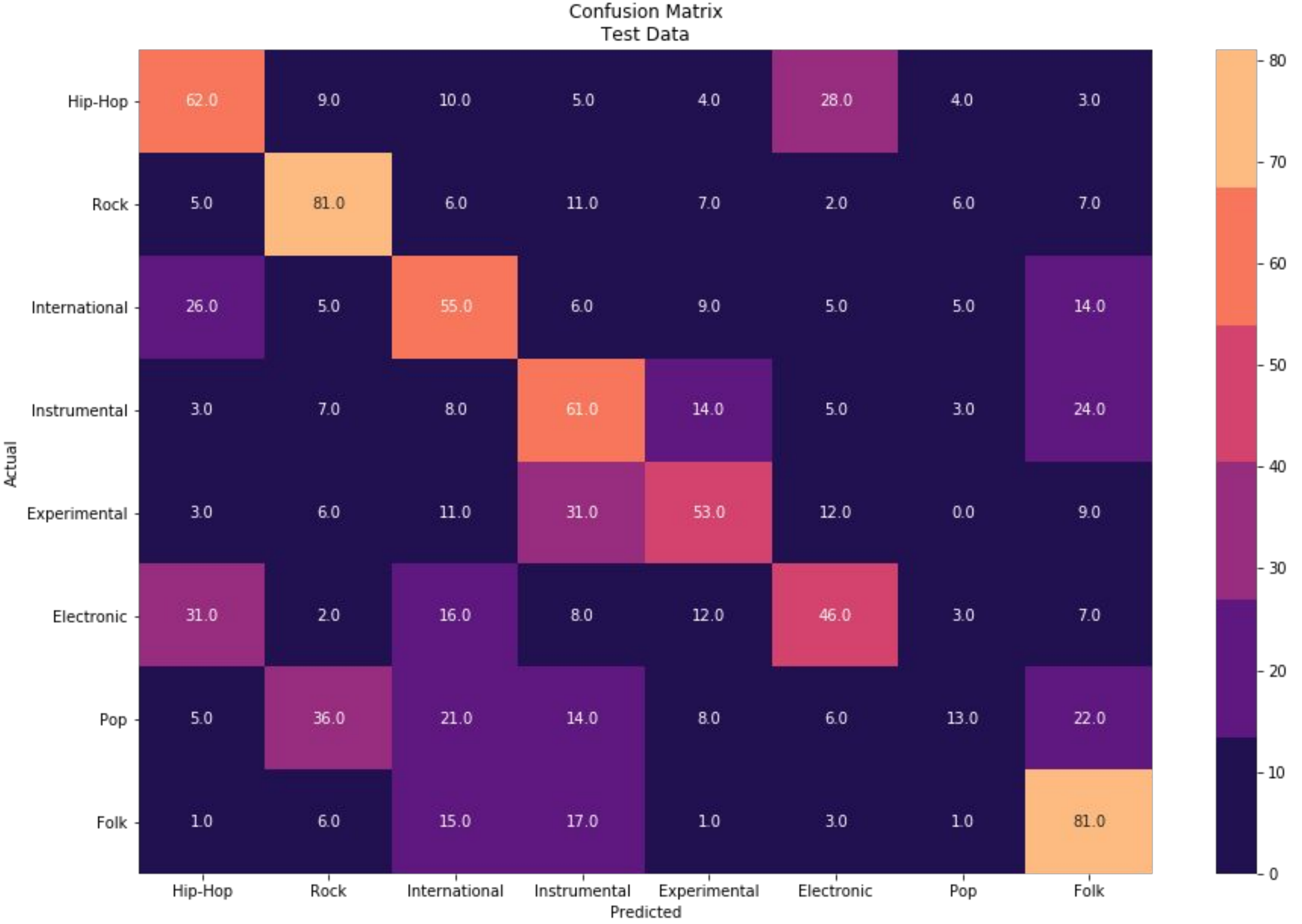

Electronic
Instrumental
Experimental
International
Folk
Pop
Hip-Hop
Rock

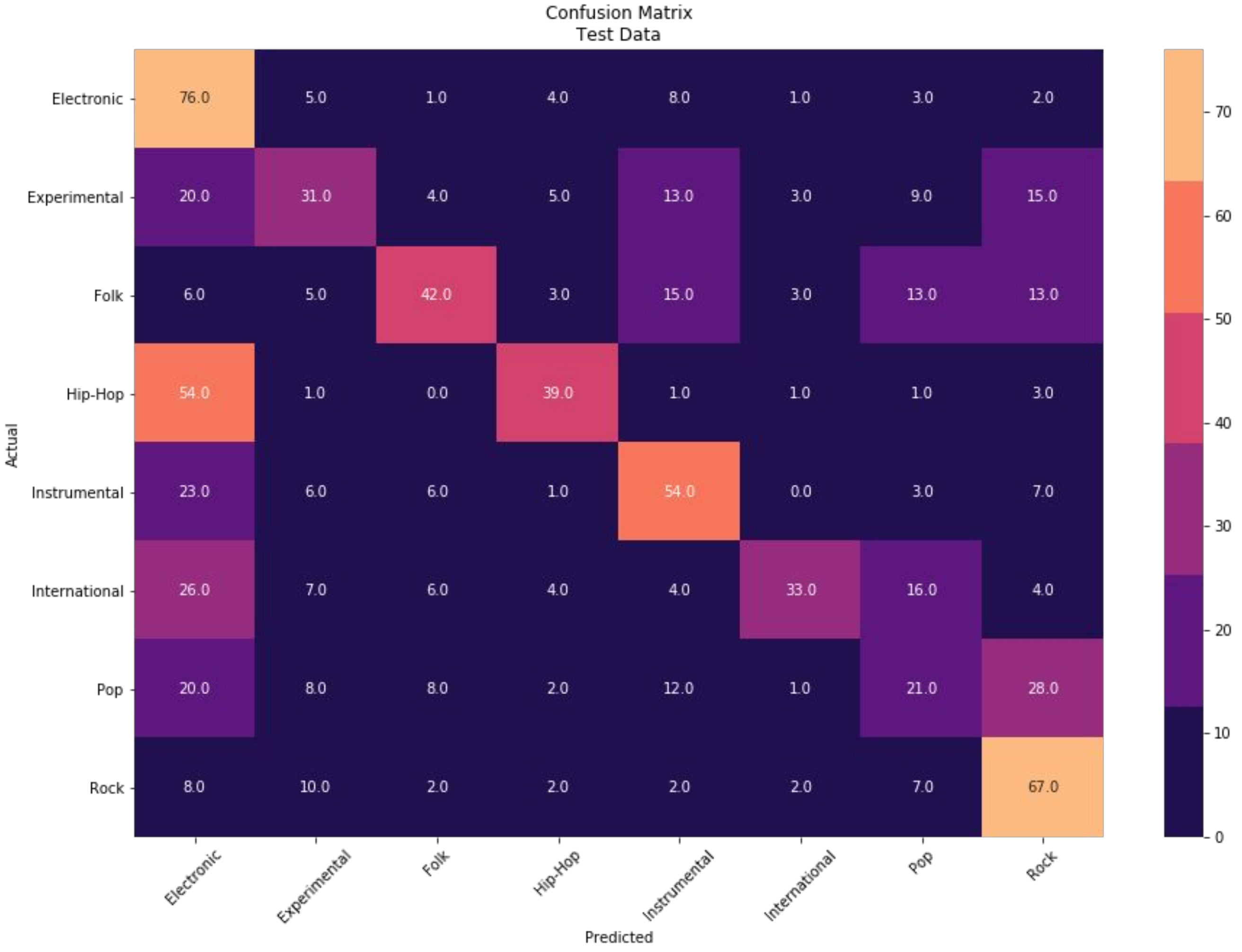
Classification Model

2 Final Models using different inputs:

1. Music features
2. Mel-Spectrograms

See Appendix for more detailed explanation


Confusion Matrix
Test Data
Hip-Hop
Rock
International
Instrumental
Experimental
Electronic
Pop
Folk
Actual
Predicted
62.0 9.0 10.0 5.0 4.0 28.0 4.0 3.0
5.0 81.0 6.0 11.0 7.0 2.0 6.0 7.0
26.0 5.0 55.0 6.0 9.0 5.0 5.0 14.0
3.0 7.0 8.0 61.0 14.0 5.0 3.0 24.0
3.0 6.0 11.0 31.0 53.0 12.0 0.0 9.0
31.0 2.0 16.0 8.0 12.0 46.0 3.0 7.0
5.0 36.0 21.0 14.0 8.0 6.0 13.0 22.0
1.0 6.0 15.0 17.0 1.0 3.0 1.0 81.0
0
10
20
30
40
50
60
70
80



Confusion Matrix
Test Data
Actual
Electronic
Experimental
Folk
Hip-Hop
Instrumental
International
Pop
Rock
76.0
5.0
1.0
4.0
8.0
1.0
3.0
2.0
20.0
31.0
4.0
5.0
13.0
3.0
9.0
15.0
6.0
5.0
42.0
3.0
15.0
3.0
13.0
13.0
54.0
1.0
0.0
39.0
1.0
1.0
1.0
3.0
23.0
6.0
6.0
1.0
54.0
0.0
3.0
7.0
26.0
7.0
6.0
4.0
4.0
33.0
16.0
4.0
20.0
8.0
8.0
2.0
12.0
1.0
21.0
28.0
8.0
10.0
2.0
2.0
2.0
2.0
7.0
67.0
Predicted
70
60
50
40
30
20
10
0

Music Genre Classification - Conclusions

Music Features

Model is very poor at identifying Pop tracks

Further investigations:

- Further explore what features of these songs contribute to misclassification
- Misclassified most as Hip-Hop,Rock and Folk

Mel-Spectrogram images

Model very good at Electronic and Rock but it is over estimating the number of tracks

Further Investigations

- Accurately predicts 588 songs
- Predicts 1435

Future Work

1

More Data

Gather far more audio files, and run models on larger quantities of data.

2

Image Quality

Run CNN models on full images

3

One vs All

Use a one vs all approach to train. i.e. Pop or not Pop

4

Features

Explore different combinations of features for optimum results

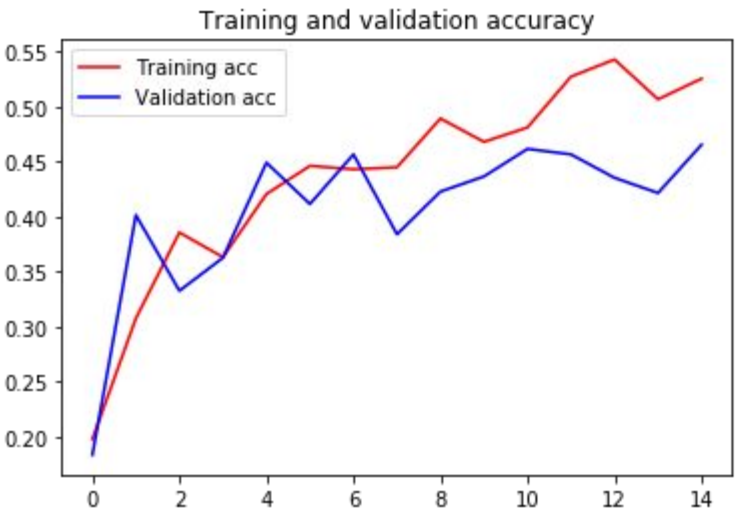
Thank You

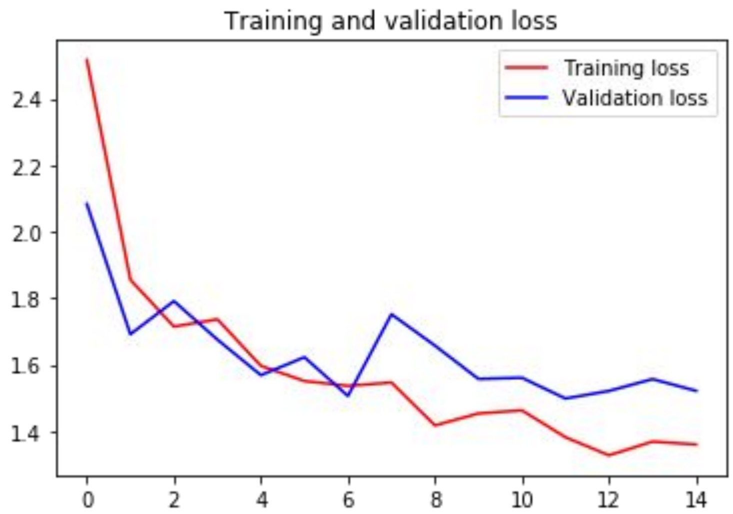
Questions :)

Appendix

Confusion Matrices for different models

Transfer Learning



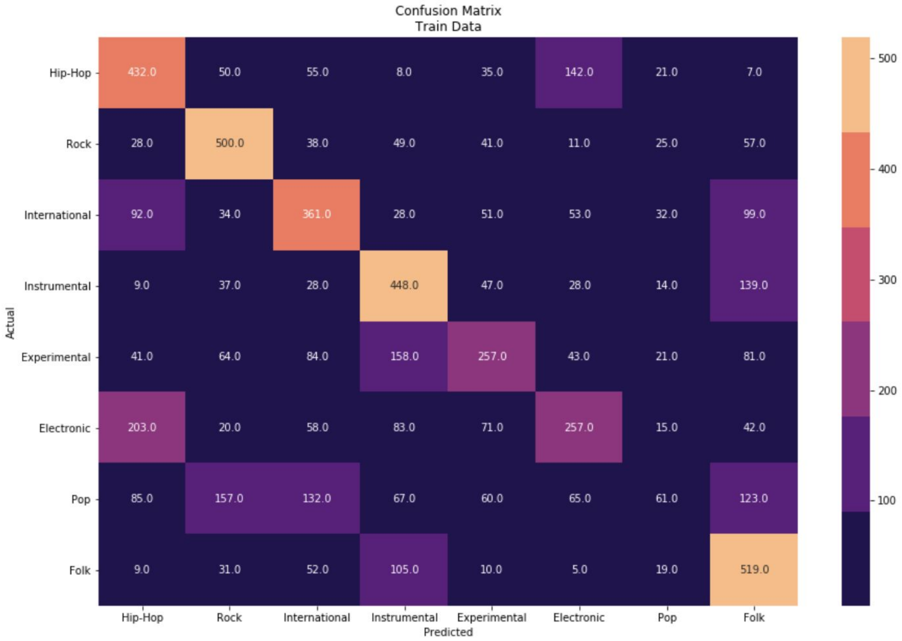


43% Testing Accuracy

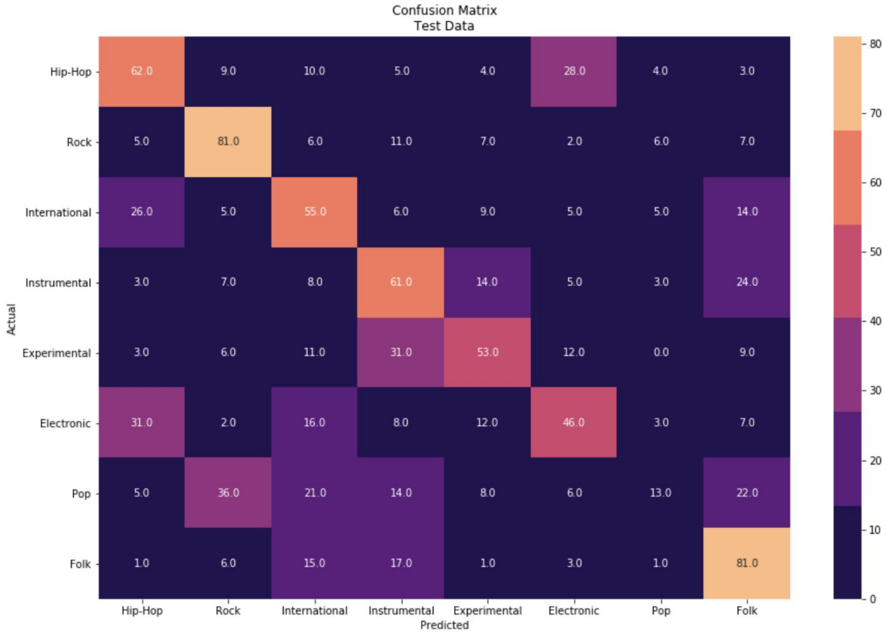
56% Training Accuracy

Neural Network

```
Accuracy: 0.472736
Precision: 0.451910
Recall: 0.472726
F1 score: 0.449037
```



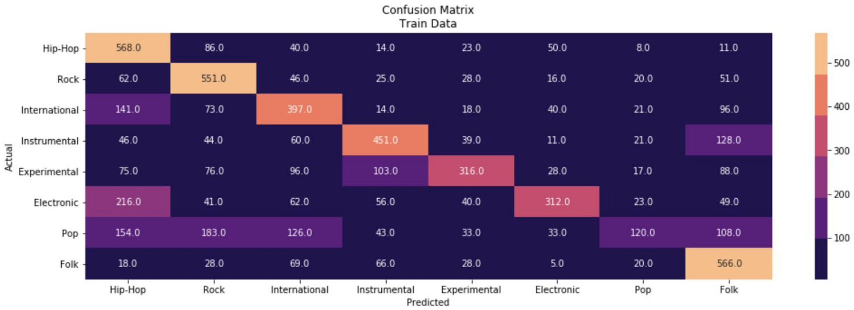

```
Accuracy: 0.452000
Precision: 0.443987
Recall: 0.452000
F1 score: 0.434944
```



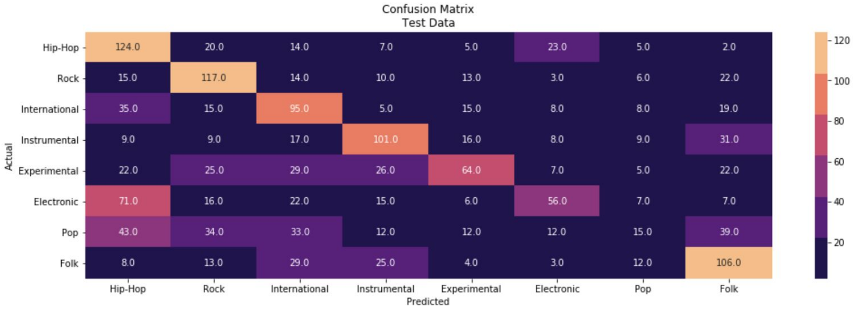
Random Forest

In [200]:
```
rf_best.score(X_train,y_train),rf_best.score(X_test,y_test)
```
Out[200]:
```
(0.5128966703142098, 0.42375)
```

In [435]:
```
plot_confusion_matrix(y_train,rf_best.predict(X_train),'Train')
```



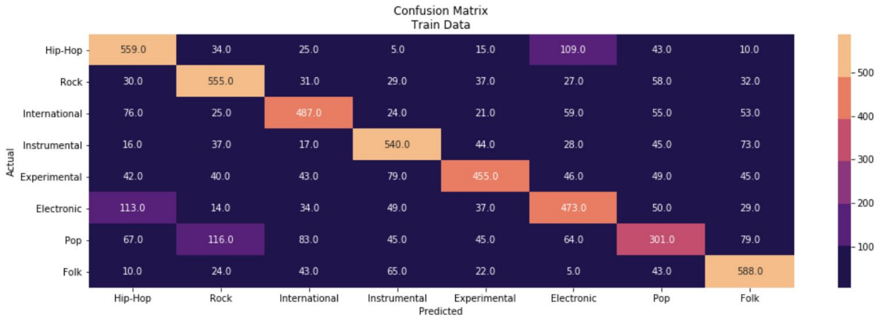
In [436]:
```
plot_confusion_matrix(y_test,rf_best.predict(X_test),'Test')
```



Support Vector Machine

In [234]:
```
svc_pipeline.score(X_train,y_train),svc_pipeline.score(X_test,y_test)
```
Out[234]:
```
(0.6187275285289979, 0.5)
```

In [439]:
```
plot_confusion_matrix(y_train,svc_pipeline.predict(X_train),'Train')
```



In [440]:
```
plot_confusion_matrix(y_test,svc_pipeline.predict(X_test),'Test')
```