Spotify Classification

February 21, 2021

0.1 Description of the final model

The final model for the classifiction problem uses an ensemble learning method. This combines different predictors that were explored in this report. This allows for better predictions than with a single predictor that does pretty well. To measure the performance of a predictor, precision, recall, and f1 scores are used. The voting classifier has a precision of 14%, recall of 25% and f1 score of 17%. The voting classifier was used as the 3 different methods used do not classify the genre well as they make different errors. The classifier uses hard voting which predicts the class that gets the most votes.

0.1.1 Importing packages and datasets

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
Test = pd.read_csv('CS98XClassificationTest.csv')
Train = pd.read_csv('CS98XClassificationTrain.csv')
```

0.1.2 Viewing data

[3]:
```
Test.head(2)
```

[3]:
```
    Id                                              title  \
0  454                                            Pump It
1  455  Circle of Life - From "The Lion King"/Soundtra...

                artist  year  bpm  nrgy  dnce  dB  live  val  dur  acous  \
0  The Black Eyed Peas  2005  154    93    65  -3    75   74  213      1
1           Elton John  1994  161    39    30 -15    11   14  292     26

   spch  pop
0    18   72
1     3   59
```

[4]:
```
Train.head(2)
```

[4]:
```
   Id             title           artist  year  bpm  nrgy  dnce  dB  live  \
0   1      My Happiness   Connie Francis  1996  107    31    45  -8    13   
1   2  Unchained Melody  The Teddy Bears  2011  114    44    53  -8    13   

   val  dur  acous  spch  pop         top genre  
0   28  150     75     3   44  adult standards  
1   47  139     49     3   37              NaN  
```

[5]:
```
Test.shape
```

[5]: (113, 14)

[6]:
```
Train.shape
```

[6]: (453, 15)

[7]:
```
Train.describe()
```

[7]:
```
               Id         year         bpm        nrgy        dnce  \
count  453.000000   453.000000  453.000000  453.000000  453.000000   
mean   227.000000  1991.443709  118.399558   60.070640   59.565121   
std    130.914094    16.776103   25.238713   22.205284   15.484458   
min      1.000000  1948.000000   62.000000    7.000000   18.000000   
25%    114.000000  1976.000000  100.000000   43.000000   49.000000   
50%    227.000000  1994.000000  119.000000   63.000000   61.000000   
75%    340.000000  2007.000000  133.000000   78.000000   70.000000   
max    453.000000  2019.000000  199.000000  100.000000   96.000000   

               dB        live         val         dur       acous        spch  \
count  453.000000  453.000000  453.000000  453.000000  453.000000  453.000000   
mean    -8.836645   17.757174   59.465784  226.278146   32.982340    5.660044   
std      3.577187   13.830300   24.539868   63.770380   29.530015    5.550581   
min    -24.000000    2.000000    6.000000   98.000000    0.000000    2.000000   
25%    -11.000000    9.000000   42.000000  181.000000    7.000000    3.000000   
50%     -8.000000   13.000000   61.000000  223.000000   24.000000    4.000000   
75%     -6.000000   23.000000   80.000000  262.000000   58.000000    6.000000   
max     -1.000000   93.000000   99.000000  511.000000  100.000000   47.000000   

              pop  
count  453.000000  
mean    60.743929  
std     13.470083  
min     26.000000  
25%     53.000000  
50%     63.000000  
75%     71.000000  
max     84.000000  
```

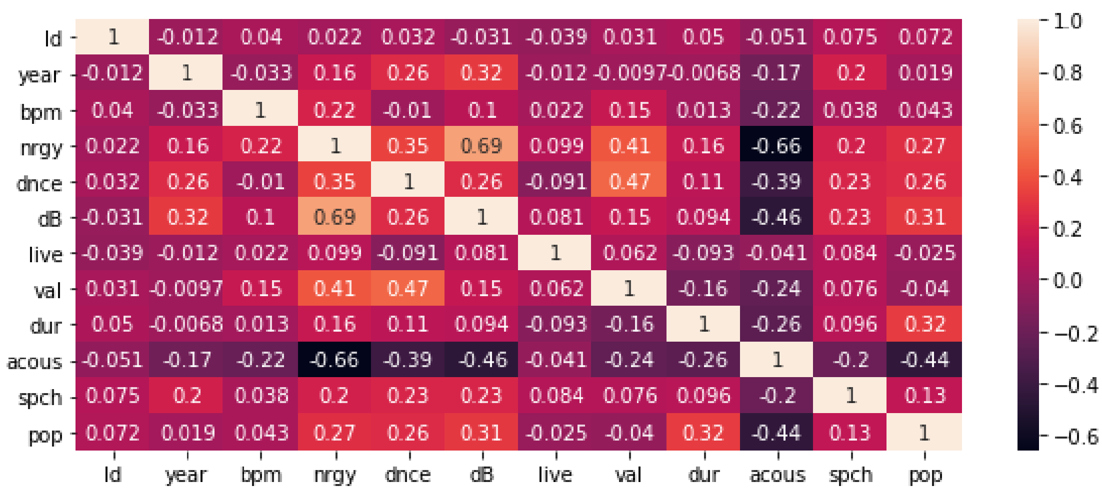
[ ]:
```
Train.dtypes
```

[ ]:
```
Train.isnull().sum()
```

[ ]:
```
Test.isnull().sum()
```

[56]:
```
plt.figure(figsize =(10,4))
correlation = Train.corr()
sns.heatmap(correlation, annot=True)
```

[56]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe5ee862ee0>
```



1 Preparing the data

To get the data tables ready for the analysis, there are some columns that will not work with the methods as they prefer integers. The Id, title, artist, and year are variables that will not add to the classification analysis as they would not impact the classfication of a song.

There are also 15 missing values from the top genre column in the training dataset. Since the missing values are less than 20%, this will not affect the analysis too much so will be dropped to make for improved classification.

[12]:
```
Train = Train.dropna(subset=["top genre"])
```

[13]:
```
Train.head(2)
```

[13]:
```
   Id               title          artist  year  bpm  nrgy  dnce  dB  live  \
0   1        My Happiness  Connie Francis  1996  107    31    45  -8    13
2   3  How Deep Is Your Love        Bee Gees  1979  105    36    63  -9    13
```

	val	dur	acous	spch	pop	top genre
0	28	150	75	3	44	adult standards
2	67	245	11	3	77	adult standards

[14]:
```
spotify_cat = Train[["top genre"]]
spotify_cat.head(2)
```

[14]:

	top genre
0	adult standards
2	adult standards

[15]:
```
from sklearn.preprocessing import OrdinalEncoder
ordinal_encoder = OrdinalEncoder()
spotify_cat_encoded = ordinal_encoder.fit_transform(spotify_cat)
spotify_cat_encoded[:5]
```

[15]:
```
array([[ 1.],
       [ 1.],
       [ 1.],
       [68.],
       [80.]])
```

[16]:
```
from sklearn.preprocessing import OneHotEncoder
spotify_encoder = OneHotEncoder()
spotify_cat_1hot = spotify_encoder.fit_transform(spotify_cat)
spotify_cat_1hot
```

[16]:
```
<438x86 sparse matrix of type '<class 'numpy.float64'>'
        with 438 stored elements in Compressed Sparse Row format>
```

[ ]:
```
spotify_cat_1hot.toarray()
```

[18]:
```
y= spotify_cat_encoded
```

[19]:
```
X = Train.drop(['title','artist', 'Id', 'year', 'top genre', 'pop'], axis=1)
```

[57]:
```
X.head(2)
```

[57]:

	bpm	nrgy	dnce	dB	live	val	dur	acous	spch
0	107	31	45	-8	13	28	150	75	3
2	105	36	63	-9	13	67	245	11	3

1.1 Scaling and splitting data

Machine learning techniques prefer to work on numerical attributes with similar scales. Standardisation is less affected by outliers in the data.

[21]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
```

[22]:
```python
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_state=42)
```

[23]:
```python
scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

[ ]:
```python
X_train
```

[ ]:
```python
X_test
```

2 Select and training models

2.1 Using logistic regression

[ ]:
```python
from sklearn.linear_model import LogisticRegression

log_reg = LogisticRegression()
log_reg.fit(X_train,y_train)
```

[27]:
```python
pred = log_reg.predict(X_test)
```

[ ]:
```python
pred
```

2.1.1 Evaluation of logistic regression

[29]:
```python
from sklearn.metrics import confusion_matrix
conf = confusion_matrix(y_test, pred)
```

[30]:
```python
conf
```

[30]:
```
array([[10,  0,  3, ...,  0,  0,  0],
       [ 0,  0,  0, ...,  0,  0,  0],
       [ 0,  0,  6, ...,  0,  0,  0],
       ...,
       [ 0,  0,  1, ...,  0,  0,  0],
       [ 1,  0,  0, ...,  0,  0,  0],
       [ 1,  0,  0, ...,  0,  0,  0]])
```

We are able to produce a confusion matrix where each row represents an actual class and the column shows predicted class. The full confusion matrix can't be viewed so we will use a classification report to get a measure of how well the model performs.

[31]:
```
from sklearn.metrics import classification_report
```

[32]:
```
class_rep = classification_report(y_test, pred)
print("Logistic Regression: \n", class_rep)
```

```
Logistic Regression:
               precision    recall  f1-score   support

         1.0       0.50      0.62      0.56        16
         3.0       0.00      0.00      0.00         0
         4.0       0.19      0.60      0.29        10
         6.0       0.00      0.00      0.00         1
         9.0       0.00      0.00      0.00         3
        10.0       0.00      0.00      0.00         2
        13.0       0.00      0.00      0.00         1
        14.0       0.00      0.00      0.00         1
        16.0       0.00      0.00      0.00         2
        18.0       0.00      0.00      0.00         1
        20.0       0.00      0.00      0.00         1
        24.0       0.00      0.00      0.00         3
        25.0       0.00      0.00      0.00         3
        31.0       0.00      0.00      0.00         1
        32.0       0.00      0.00      0.00         1
        36.0       0.00      0.00      0.00         0
        39.0       0.00      0.00      0.00         1
        40.0       0.00      0.00      0.00         1
        42.0       0.00      0.00      0.00         1
        43.0       0.00      0.00      0.00         1
        46.0       0.00      0.00      0.00         1
        47.0       0.00      0.00      0.00         1
        49.0       0.00      0.00      0.00         1
        51.0       0.42      0.77      0.54        13
        52.0       0.00      0.00      0.00         3
        53.0       0.00      0.00      0.00         1
        56.0       0.00      0.00      0.00         1
        57.0       0.00      0.00      0.00         1
        60.0       0.50      1.00      0.67         1
        61.0       0.00      0.00      0.00         1
        62.0       0.00      0.00      0.00         3
        63.0       0.00      0.00      0.00         2
        68.0       0.00      0.00      0.00         6
        70.0       0.00      0.00      0.00         0
        80.0       0.00      0.00      0.00         1
        83.0       0.00      0.00      0.00         1
```

```
        85.0       0.00      0.00      0.00         1

    accuracy                           0.31        88
   macro avg       0.04      0.08      0.06        88
weighted avg       0.18      0.31      0.22        88


/Users/Evelyn/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/Evelyn/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning: Recall
and F-score are ill-defined and being set to 0.0 in labels with no true samples.
Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

From the classification report, different values are obtained about the models performace. The overall precision is 0.18, recall 0.27, and f1 score is 0.21. The f1 score is low because both recall and precision scores are also low.

Logistic regression will be used as a baseline to compare more complex methods for classification.

2.2 Decision tree classifier

Decision tree classification will be used in this section to see if there is an improvement to the logistic regression model.

[33]:
```
from sklearn.tree import DecisionTreeClassifier
```

With the remaing model methods, the target variable will not be changed to ensure no information is lost. The methods are also able to handle categorical variables.

[34]:
```
X_train, X_test, y_train, y_test = train_test_split(X,spotify_cat, test_size=0.
↪2, random_state=42)
```

[35]:
```
tree = DecisionTreeClassifier()
tree.fit(X_train,y_train)

pred_tree = tree.predict(X_test)
```

[ ]:
```
pred_tree
```

The model seems to be good at predicting songs that belong to rock and pop sections.

2.2.1 Evaluation of decision tree

[37]:
```
confusion_matrix(y_test, pred_tree)
```

[37]:
```
array([[6, 0, 2, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [1, 0, 4, ..., 0, 0, 0],
       ...,
       [0, 0, 1, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]])
```

[38]:
```
class_rep1 = classification_report(y_test, pred_tree)
print("Decision Tree: \n", class_rep1)
```

```
Decision Tree:
                        precision    recall  f1-score   support

     adult standards       0.40      0.38      0.39        16
             afropop       0.00      0.00      0.00         0
          album rock       0.24      0.40      0.30        10
    alternative rock       0.00      0.00      0.00         1
american folk revival       0.00      0.00      0.00         0
             art pop       0.00      0.00      0.00         0
            art rock       0.00      0.00      0.00         3
         atl hip hop       0.00      0.00      0.00         2
     avant-garde jazz       0.00      0.00      0.00         1
       barbadian pop       0.00      0.00      0.00         1
               bebop       0.00      0.00      0.00         2
         belgian pop       0.00      0.00      0.00         1
               blues       0.00      0.00      0.00         1
            boogaloo       0.00      0.00      0.00         0
            boy band       0.12      0.33      0.18         3
  brill building pop       0.00      0.00      0.00         3
    british invasion       0.00      0.00      0.00         1
        british soul       0.00      0.00      0.00         1
       canadian folk       0.00      0.00      0.00         0
        canadian pop       0.00      0.00      0.00         1
         celtic rock       0.00      0.00      0.00         1
             chanson       0.00      0.00      0.00         0
         chicago rap       0.00      0.00      0.00         1
        chicago soul       0.00      0.00      0.00         1
        classic rock       0.00      0.00      0.00         1
        classic soul       0.00      0.00      0.00         1
      classic uk pop       0.00      0.00      0.00         0
             country       0.00      0.00      0.00         1
           dance pop       0.09      0.08      0.08        13
          dance rock       0.00      0.00      0.00         3
```

```
deep adult standards       1.00      1.00      1.00         1
           deep house       0.00      0.00      0.00         0
                disco       0.00      0.00      0.00         1
          disco house       0.00      0.00      0.00         1
    east coast hip hop       1.00      1.00      1.00         1
            eurodance       0.00      0.00      0.00         1
              europop       0.00      0.00      0.00         3
               g funk       0.00      0.00      0.00         2
            glam rock       0.00      0.00      0.00         6
                latin       0.00      0.00      0.00         0
          mellow gold       0.00      0.00      0.00         0
         new wave pop       0.00      0.00      0.00         0
       permanent wave       0.00      0.00      0.00         0
                  pop       0.00      0.00      0.00         1
            soft rock       0.00      0.00      0.00         1
             yodeling       0.00      0.00      0.00         1

             accuracy                           0.16        88
            macro avg       0.06      0.07      0.06        88
         weighted avg       0.14      0.16      0.15        88

/Users/Evelyn/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/Evelyn/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning: Recall
and F-score are ill-defined and being set to 0.0 in labels with no true samples.
Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

The classification report tells us how well the decision tree method performs. With a precision of 14%, recall of 15% and f1 score of 14%.

2.3 Random forest

Random forest are able to handle categorical values so will be used on the data to build a new model. There are 2 candidate models but random forest is an ensemble method to get a better predictor.

[39]:
```
from sklearn.ensemble import RandomForestClassifier
```

[40]:
```
forest = RandomForestClassifier(
                      min_samples_leaf=40, criterion = 'entropy',
                      n_estimators=15,
                       max_depth = 7,
                      oob_score=True,
```

```
                        n_jobs=-1,
                        random_state=42,
                        max_features='auto')
```

[ ]:
```
forest.fit(X_train, y_train)
```

[42]:
```
forest_tree = forest.predict(X_test)
```

[ ]:
```
forest_tree
```

2.3.1 Evaluation of random forest

[44]:
```
class_rep2 = classification_report(y_test, forest_tree)
print("Random Forest: \n", class_rep2)
```

```
Random Forest:
                        precision    recall  f1-score   support

      adult standards       0.37      0.69      0.48        16
           album rock       0.18      0.70      0.29        10
    alternative rock       0.00      0.00      0.00         1
             art rock       0.00      0.00      0.00         3
           atl hip hop       0.00      0.00      0.00         2
    avant-garde jazz       0.00      0.00      0.00         1
        barbadian pop       0.00      0.00      0.00         1
                bebop       0.00      0.00      0.00         2
          belgian pop       0.00      0.00      0.00         1
                blues       0.00      0.00      0.00         1
             boy band       0.00      0.00      0.00         3
   brill building pop       0.00      0.00      0.00         3
     british invasion       0.00      0.00      0.00         1
         british soul       0.00      0.00      0.00         1
         canadian pop       0.00      0.00      0.00         1
          celtic rock       0.00      0.00      0.00         1
          chicago rap       0.00      0.00      0.00         1
         chicago soul       0.00      0.00      0.00         1
         classic rock       0.00      0.00      0.00         1
         classic soul       0.00      0.00      0.00         1
              country       0.00      0.00      0.00         1
            dance pop       0.21      0.31      0.25        13
           dance rock       0.00      0.00      0.00         3
deep adult standards       0.00      0.00      0.00         1
                disco       0.00      0.00      0.00         1
          disco house       0.00      0.00      0.00         1
    east coast hip hop       0.00      0.00      0.00         1
            eurodance       0.00      0.00      0.00         1
              europop       0.00      0.00      0.00         3
```

```
        g funk       0.00      0.00      0.00         2
     glam rock       0.00      0.00      0.00         6
           pop       0.00      0.00      0.00         1
     soft rock       0.00      0.00      0.00         1
      yodeling       0.00      0.00      0.00         1

      accuracy                           0.25        88
     macro avg       0.02      0.05      0.03        88
  weighted avg       0.12      0.25      0.16        88
```

```
/Users/Evelyn/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

From the classification report, we are able to extract the precision, recall, and f1 score. Random forest method does moderately well with an f1 score of 16%. However, logistic regression still has the best score.

3 Using ensemble classifier to improve model

We will attempt to use a voting classifier. The predictors used so far have an okay level of accuracy but can be improved on by using an ensemble method. This will bring together the predictions of all classifiers and use the class that gets the most votes. In this problem, hard voting is used.

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression

log_reg = LogisticRegression()
rnd_clf = RandomForestClassifier()
tree = DecisionTreeClassifier()
voting_clf = VotingClassifier(
estimators=[('lr', log_reg), ('rf', rnd_clf), ('dc', tree) ], voting='hard')
voting_clf.fit(X_train, y_train)
```

[46]:
```
predict = voting_clf.predict(X_test)
```

[ ]:
```
predict
```

[48]:
```
class_rep4 = classification_report(y_test, predict)
print("Voting Classifier: \n", class_rep4)
```

```
Voting Classifier:
                        precision    recall  f1-score   support
```

adult standards	0.43	0.62	0.51	16
afropop	0.00	0.00	0.00	0
album rock	0.19	0.70	0.30	10
alternative rock	0.00	0.00	0.00	1
art rock	0.00	0.00	0.00	3
atl hip hop	0.00	0.00	0.00	2
avant-garde jazz	0.00	0.00	0.00	1
barbadian pop	0.00	0.00	0.00	1
bebop	0.00	0.00	0.00	2
belgian pop	0.00	0.00	0.00	1
blues	0.00	0.00	0.00	1
boy band	0.00	0.00	0.00	3
brill building pop	0.00	0.00	0.00	3
british invasion	0.00	0.00	0.00	1
british soul	1.00	1.00	1.00	1
bubblegum dance	0.00	0.00	0.00	0
canadian pop	0.00	0.00	0.00	1
celtic rock	0.00	0.00	0.00	1
chicago rap	0.00	0.00	0.00	1
chicago soul	0.00	0.00	0.00	1
classic rock	0.00	0.00	0.00	1
classic soul	0.00	0.00	0.00	1
country	0.00	0.00	0.00	1
dance pop	0.38	0.46	0.41	13
dance rock	0.00	0.00	0.00	3
deep adult standards	0.00	0.00	0.00	1
detroit hip hop	0.00	0.00	0.00	0
disco	0.00	0.00	0.00	1
disco house	0.00	0.00	0.00	1
east coast hip hop	1.00	1.00	1.00	1
eurodance	0.00	0.00	0.00	1
europop	0.00	0.00	0.00	3
g funk	0.00	0.00	0.00	2
glam rock	0.00	0.00	0.00	6
pop	0.00	0.00	0.00	1
soft rock	0.00	0.00	0.00	1
yodeling	0.00	0.00	0.00	1
accuracy			0.28	88
macro avg	0.08	0.10	0.09	88
weighted avg	0.18	0.28	0.21	88

```
/Users/Evelyn/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
/Users/Evelyn/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning: Recall
and F-score are ill-defined and being set to 0.0 in labels with no true samples.
Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

The classification report from the voting classifier shows a good enough performace. The recall is highest at 25% and the precision is 14%. The f1 score is 17%.

4 Evaluation on test set

[49]:
```
Test1 = Test.drop(['Id','title','artist','year','pop'], axis=1)
```

[50]:
```
Test1.head(2)
```

[50]:

	bpm	nrgy	dnce	dB	live	val	dur	acous	spch
0	154	93	65	-3	75	74	213	1	18
1	161	39	30	-15	11	14	292	26	3

[51]:
```
final_predictions = voting_clf.predict(Test1)
```

[ ]:
```
final_predictions
```

5 Converting data to CSV

[53]:
```
submission = pd.DataFrame({"Id":Test["Id"], "top genre": final_predictions})
submission.head(3)
```

[53]:

	Id	top genre
0	454	big room
1	455	album rock
2	456	adult standards

[54]:
```
file = "ClassificationPredictions.csv"

submission.to_csv(file, index = False, header = 1)
```

6 Conclusion

The following model that has been chosen for the classification problem was the best out of all of the tested models/methods. To start with, at the beginning of this report, data cleaning was vital to the successful analysis. Certain columns were removed from the training dataset as they would not be of any use as these factors in hindsight do not contribute to the genre a song belongs in.

The different methods used in this report have all been able to build a successful ML algorithms. A voting classifier algorithm is the final model as it achieves the best recall, f1, and accuracy score. This is successful by combining predictions from different classifiers.

From the Kaggle InClass competition, the final model achieves a score of 0.28571 thus concluding the model built has been successful in predicting the classification of a song. This is a better score than on the training set.