analysis

December 14, 2023

Spotify Song Data Analysis Thursday, December 14th Jack Krebsbach & Eli Edwards

Import all libraries needed for analysis We will use various models to predict song popularity and classify which playlist genre a song came from.

Column Name

Data Type

Description

playlist_genre

character

Playlist genre

playlist_subgenre

character

Playlist subgenre

danceability

double

Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.

energy

double

Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.

key

double

The estimated overall key of the track. Integers map to pitches using standard Pitch Class notation. E.g., 0 = C, 1 = C /D , 2 = D, and so on. If no key was detected, the value is -1.

loudness

double

The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 dB.

mode

double

Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.

speechiness

double

Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g., talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.

acousticness

double

A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.

instrumentalness

double

Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.

liveness

double

Detects the presence of an audience in

Imports Generally we will use `sklearn` for model building. We will use `pandas` to read in the data.

[ ]:
```
# Imports for analysis
import pandas as pd
import itertools
import xgboost as xgb
```

```
import numpy as np
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.model_selection import GridSearchCV
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder
from ISLP import confusion_table
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import (RandomForestRegressor as RF,␣
↪RandomForestClassifier as RFC, GradientBoostingRegressor as GBR)
import sklearn.model_selection as skm
from sklearn.preprocessing import StandardScaler
from matplotlib.pyplot import subplots
import statsmodels.api as sm
from sklearn.tree import ( DecisionTreeRegressor as DTR, plot_tree)
from sklearn.metrics import (accuracy_score,r2_score)
```

Import Data

[ ]:
```
# Read in the CSV
df = pd.read_csv("./clean_data/spotify_songs.csv")

# Transform categorical data
df['playlist_genre'] = df['playlist_genre'].astype('category')
df['key'] = df['key'].astype('category')
df['mode'] = df['mode'].astype('category')

scaler = StandardScaler()
# Standardize numerical data
numeric_cols = df.select_dtypes(include=['number'])
df[numeric_cols.columns] = numeric_cols.astype('float64')
df[numeric_cols.columns] = scaler.fit_transform(numeric_cols)
```

[ ]:
```
# Look at first few columns
df.head()
```

[ ]:
```
                 track_id                                         track_name  \
0  6f807x0ima9a1j3VPbc7VN  I Don't Care (with Justin Bieber) - Loud Luxur…
1  0r7CVbZTWZgbTCYdfa2P31                    Memories - Dillon Francis Remix
2  1z1Hg7Vb0AhHDiEmnDE79l                    All the Time - Don Diablo Remix
3  75FpbthrwQmzHlBJLuGdC7                  Call You Mine - Keanu Silva Remix
4  1e8PAfcKUYoKkxPhrHqw4x            Someone You Loved - Future Humans Remix

       track_artist  track_popularity          track_album_id  \
```

```
0        Ed Sheeran          0.941531  2oCs0DGTsRO98Gh5ZSl2Cx
1          Maroon 5          0.981557  63rPSO264uRjW1X5E6cWv6
2      Zara Larsson          1.101635  1HoSmj2eLcsrR0vE9gThr4
3  The Chainsmokers          0.701374  1nqYsOef1yKKuGOVchbsk6
4     Lewis Capaldi          1.061609  7m7vv9wlQ4i0LFuJiE2zsQ

                                    track_album_name track_album_release_date  \
0  I Don't Care (with Justin Bieber) [Loud Luxury…               2019-06-14
1                    Memories (Dillon Francis Remix)               2019-12-13
2                    All the Time (Don Diablo Remix)               2019-07-05
3                        Call You Mine - The Remixes               2019-07-19
4            Someone You Loved (Future Humans Remix)               2019-03-05

  playlist_name             playlist_id playlist_genre  … key  loudness  \
0     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   6  1.367123
1     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …  11  0.585766
2     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   1  1.100090
3     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   7  0.984309
4     Pop Remix  37i9dQZF1DXcZDD7cfEKhW            pop  …   1  0.685151

   mode speechiness  acousticness instrumentalness  liveness   valence  \
0     1   -0.481362     -0.333898        -0.377953 -0.809230  0.031908
1     1   -0.688642     -0.468670        -0.359177  1.081061  0.782522
2     0   -0.324422     -0.436799        -0.377849 -0.519562  0.439384
3     1   -0.050024     -0.667642        -0.377911  0.089582 -1.001795
4     1   -0.702460     -0.432701        -0.377953 -0.692585  0.919777

      tempo  duration_ms
0  0.042927    -0.518874
1 -0.777198    -1.056268
2  0.116227    -0.822017
3  0.039953    -0.947750
4  0.115037    -0.614172

[5 rows x 23 columns]
```

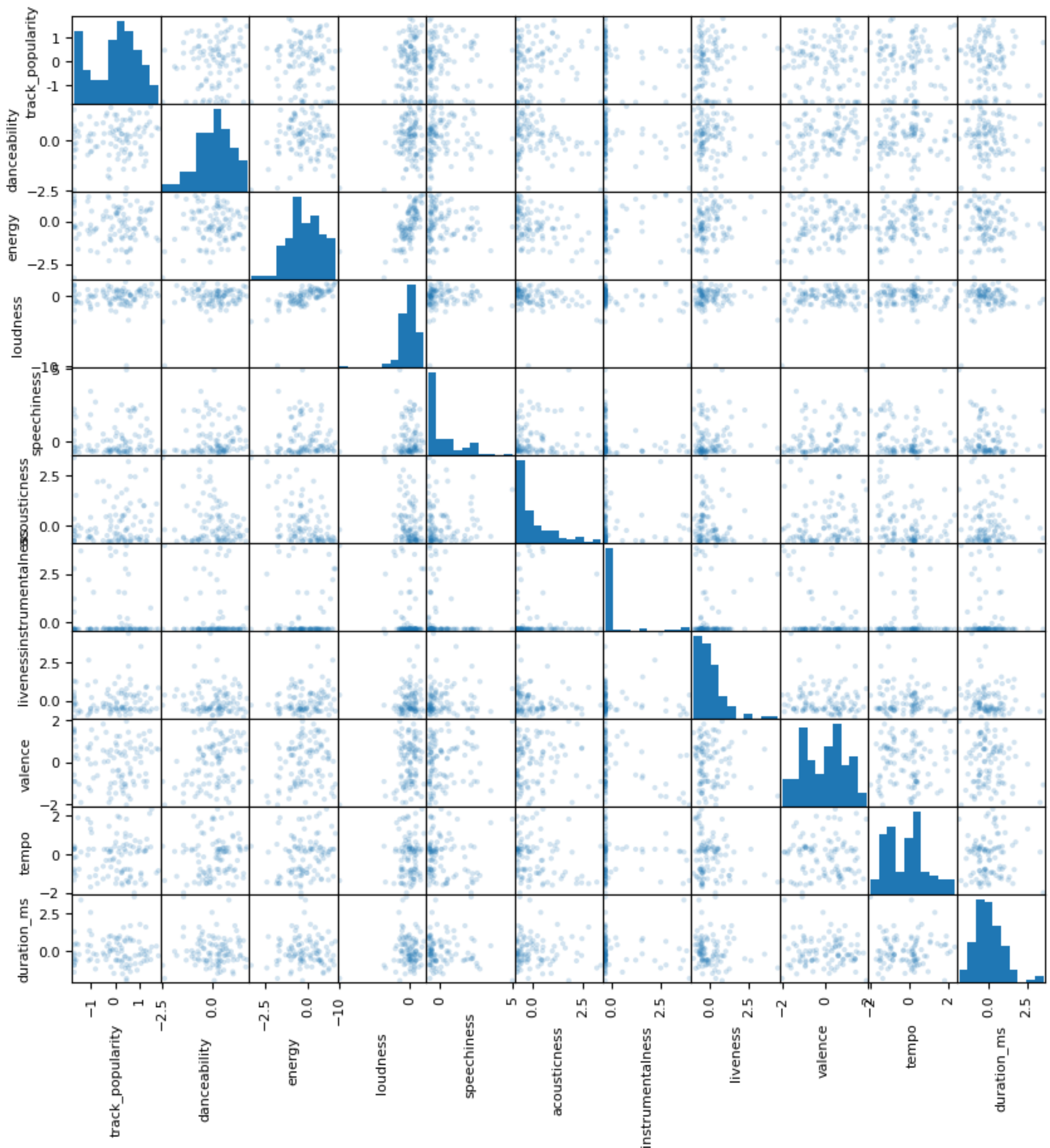
0.0.1 Scatter plot of data

From the scatter plot there is not any clear correlation between the predictors. Livelness, acousticness, and speechiness appear to be skewed to the right, while most of the predictors have a normal distribution.

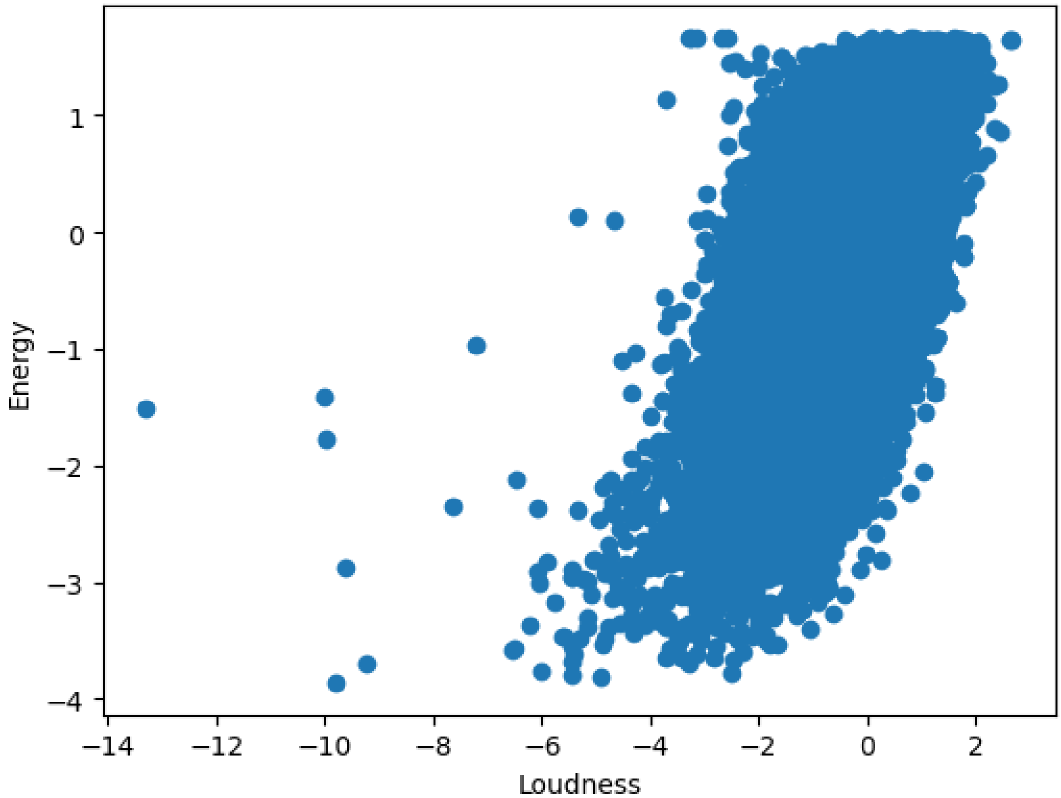
The only correlation we see is between energy and loudness, which makes sense from the description of how these two variables were computed.

[ ]:
```
sampled_df = df[numeric_cols.columns].sample(n=100, random_state=42)

# Create a scatter matrix from the sampled data
```

```
axes = pd.plotting.scatter_matrix(sampled_df, alpha=0.2, figsize=(10, 10))

# Adjust label properties
for ax in axes.flatten():
    ax.xaxis.label.set_rotation(90)
    ax.xaxis.label.set_fontsize(8)
    ax.yaxis.label.set_fontsize(8)
# Display the plot
plt.show()
```



[ ]:
```
plt.scatter(df.loudness, df.energy)
plt.xlabel('Loudness')
plt.ylabel('Energy')
plt.title = 'Loudness vs Energy'
plt.show()
```



Regression Analysis We start out by splitting our data in training and test sets

[ ]:
```
(train, test) = skm.train_test_split(df,
                                     test_size=0.3,
                                     random_state=0)
```

[ ]:
```
# Predictors
cols = [ 'danceability',
        'energy',
        'key',
        'loudness',
        'mode',
        'speechiness',
        'acousticness',
        'instrumentalness',
```

```
        'liveness',
        'valence',
        'tempo',
        'duration_ms' ]
```

Simple Linear Regression We fit a linear model using our training data. While the coefficients appear to be significant (aside from key and mode), the R squared value is 0.072, indicating that our variables don't show much correlation. When testing the model on our test set, its mean squared error values close to 1 - which implies poor prediction because our data was scaled. Looking at a graph of the residuals vs fitted values, the data appears to be resting on a slanted slope. This is irregular and likely means that our selected variables aren't explaining enough.

[ ]:
```
# Training
x_train = train[cols]
x_train = sm.add_constant(x_train)
popularity_train = train.track_popularity
# Testing
x_test = test[cols]
x_test = sm.add_constant(x_test)
popularity_test = test.track_popularity
popularity_train.shape
```

[ ]: (22983,)

[ ]:
```
# Fit the data
reg = sm.OLS(popularity_train, x_train)
results = reg.fit()
results.summary()
```

[ ]:

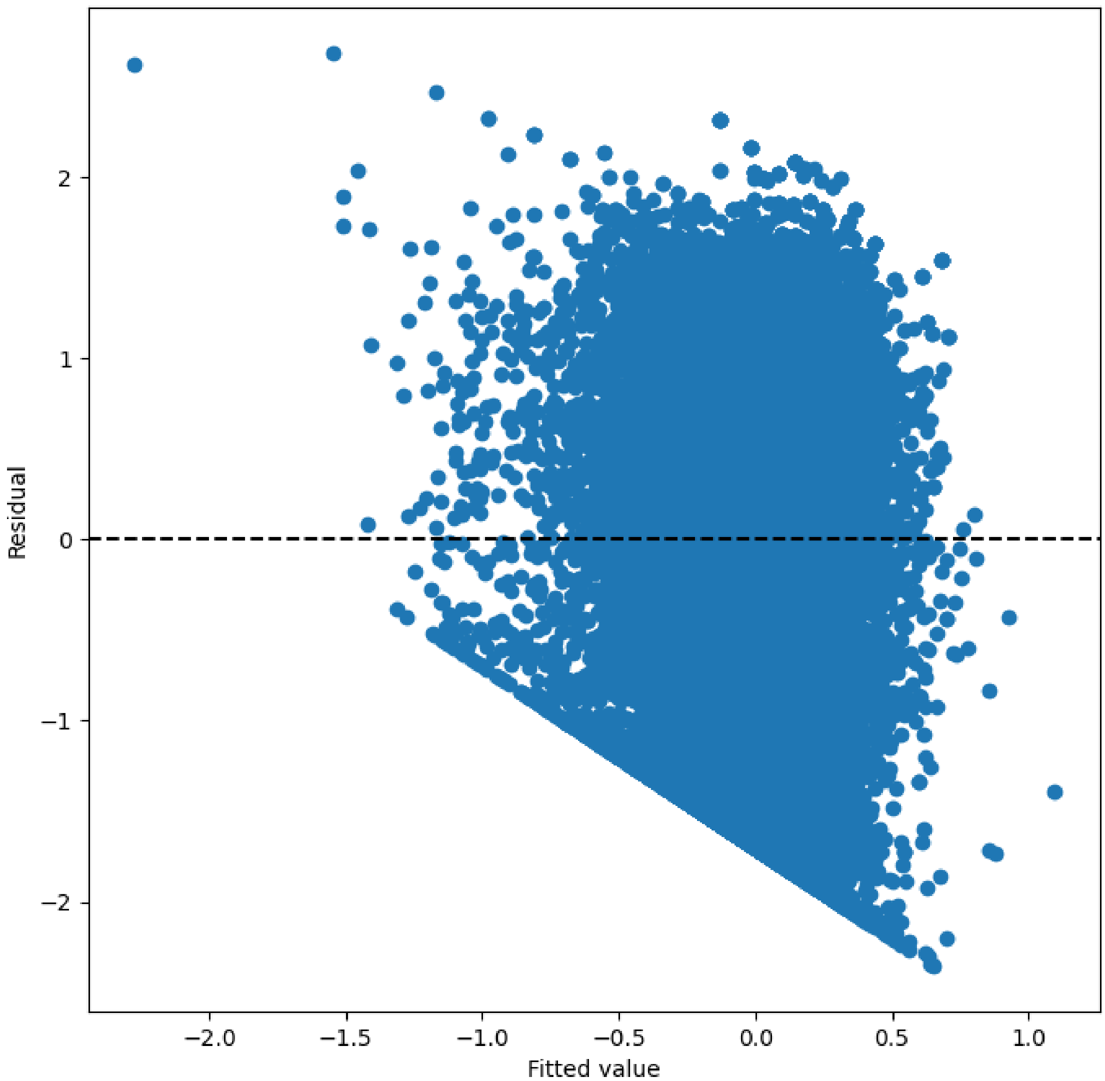
Dep. Variable:	track_popularity	**R-squared:**	0.072
Model:	OLS	**Adj. R-squared:**	0.072
Method:	Least Squares	**F-statistic:**	149.0
Date:	Thu, 14 Dec 2023	**Prob (F-statistic):**	0.00
Time:	11:55:03	**Log-Likelihood:**	-31783.
No. Observations:	22983	**AIC:**	6.359e+04
Df Residuals:	22970	**BIC:**	6.370e+04
Df Model:	12		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	-0.0341	0.015	-2.343	0.019	-0.063	-0.006
danceability	0.0313	0.007	4.291	0.000	0.017	0.046
energy	-0.2028	0.010	-19.564	0.000	-0.223	-0.182
key	0.0018	0.002	1.020	0.308	-0.002	0.005
loudness	0.1806	0.009	19.602	0.000	0.163	0.199
mode	0.0358	0.013	2.732	0.006	0.010	0.061
speechiness	-0.0334	0.007	-5.085	0.000	-0.046	-0.021
acousticness	0.0409	0.008	5.312	0.000	0.026	0.056
instrumentalness	-0.1061	0.007	-15.681	0.000	-0.119	-0.093
liveness	-0.0235	0.007	-3.599	0.000	-0.036	-0.011
valence	0.0208	0.007	2.913	0.004	0.007	0.035
tempo	0.0274	0.007	4.176	0.000	0.015	0.040
duration_ms	-0.1138	0.007	-17.467	0.000	-0.127	-0.101

Omnibus:	2716.932	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1001.369
Skew:	-0.288	**Prob(JB):**	3.59e-218
Kurtosis:	2.156	**Cond. No.**	18.2

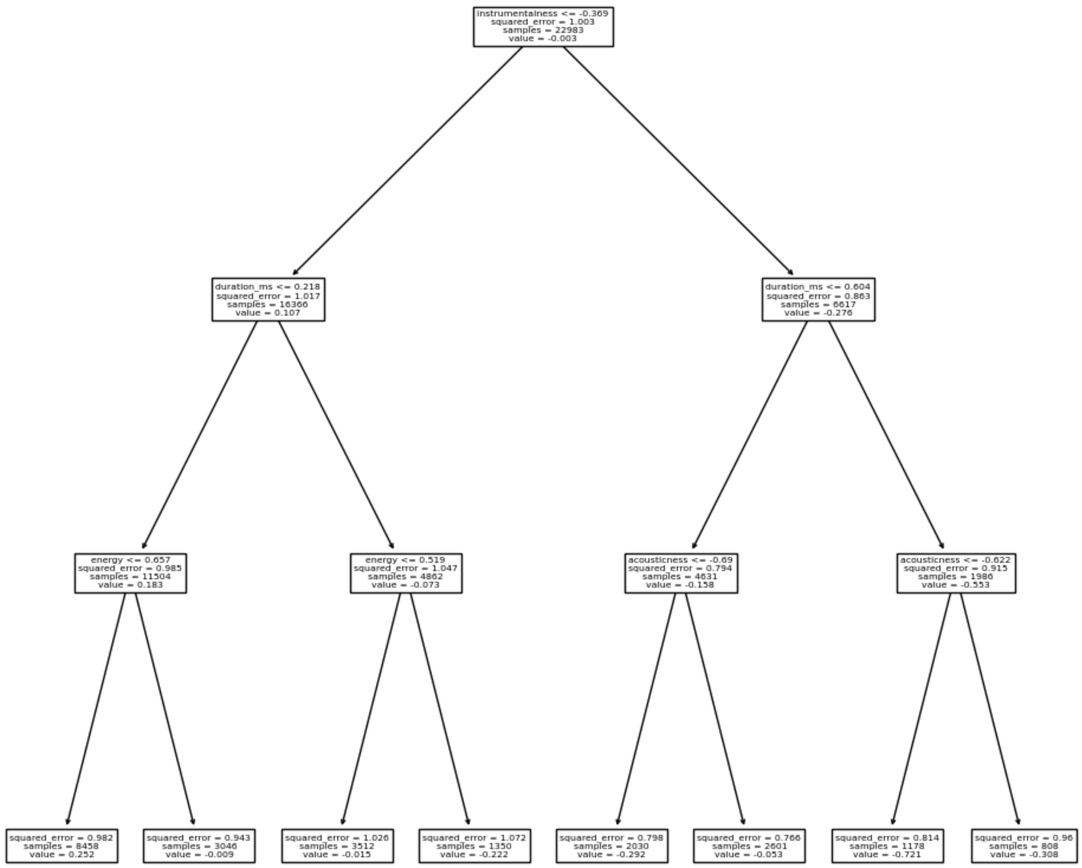
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[ ]:
```
# Plotting residuals vs fitted values
ax = subplots(figsize=(8,8))[1]
ax.scatter(results.fittedvalues , results.resid)
ax.set_xlabel('Fitted value')
ax.set_ylabel('Residual')
ax.axhline(0, c='k', ls='--');
```



Regression Tree Analysis We then fit our data to a regression tree model. We pruned the tree to find the optimal model, which unfortunately did not do a very good job at predicting the data. We fit the data to the test set, and got an even lower R squared value than before. The mean squared error was again close to 1. Getting the importance values, instrumentalness and duration seem to have the most impact on our results, even though they are not very significant.

[ ]:
```
# Creating initial tree
reg = DTR(max_depth=3)
reg.fit(x_train, popularity_train)
ax = subplots(figsize=(12,12))[1]
plot_tree(reg, feature_names=reg.feature_names_in_, ax=ax);
```



[ ]:
```python
# 'Pruning' the tree
ccp_path = reg.cost_complexity_pruning_path(x_train, popularity_train)
kfold = skm.KFold(5,
                  shuffle=True,
                  random_state=10)
grid = skm.GridSearchCV(reg,
                        {'ccp_alpha': ccp_path.ccp_alphas},
                        refit=True,
                        cv=kfold,
                        scoring='neg_mean_squared_error')
G = grid.fit(x_train, popularity_train)
```

```
[ ]: # Fitting our test data
best_ = grid.best_estimator_
predicted = best_.predict(x_test)

# MSE
print(np.mean((popularity_test - best_.predict(x_test))**2))

# R squared
r2_score(popularity_test, predicted)
```

```
0.9443524899017082
```

```
[ ]: 0.049260738158203754
```

```
[ ]: # Importance values of each predictor
print(best_.feature_importances_)
best_.feature_names_in_
```

```
[0.         0.         0.13169085 0.         0.         0.
 0.         0.09989581 0.46945227 0.         0.         0.
 0.29896106]
```

```
[ ]: array(['const', 'danceability', 'energy', 'key', 'loudness', 'mode',
        'speechiness', 'acousticness', 'instrumentalness', 'liveness',
        'valence', 'tempo', 'duration_ms'], dtype=object)
```

Classification Analysis Now we will explore classifying the playlist genre these songs came from.

Overall, the XGBoost classifier had the highest accuracy on the test set. We use k-fold cross validation with 5 folds over a grid of parameters.

XGBoost model - Max Depth: 5 - Number of estimators: 300 - Learning rate: 0.1 - Test set accuracy: 57.4%

Speechiness was the highest importance

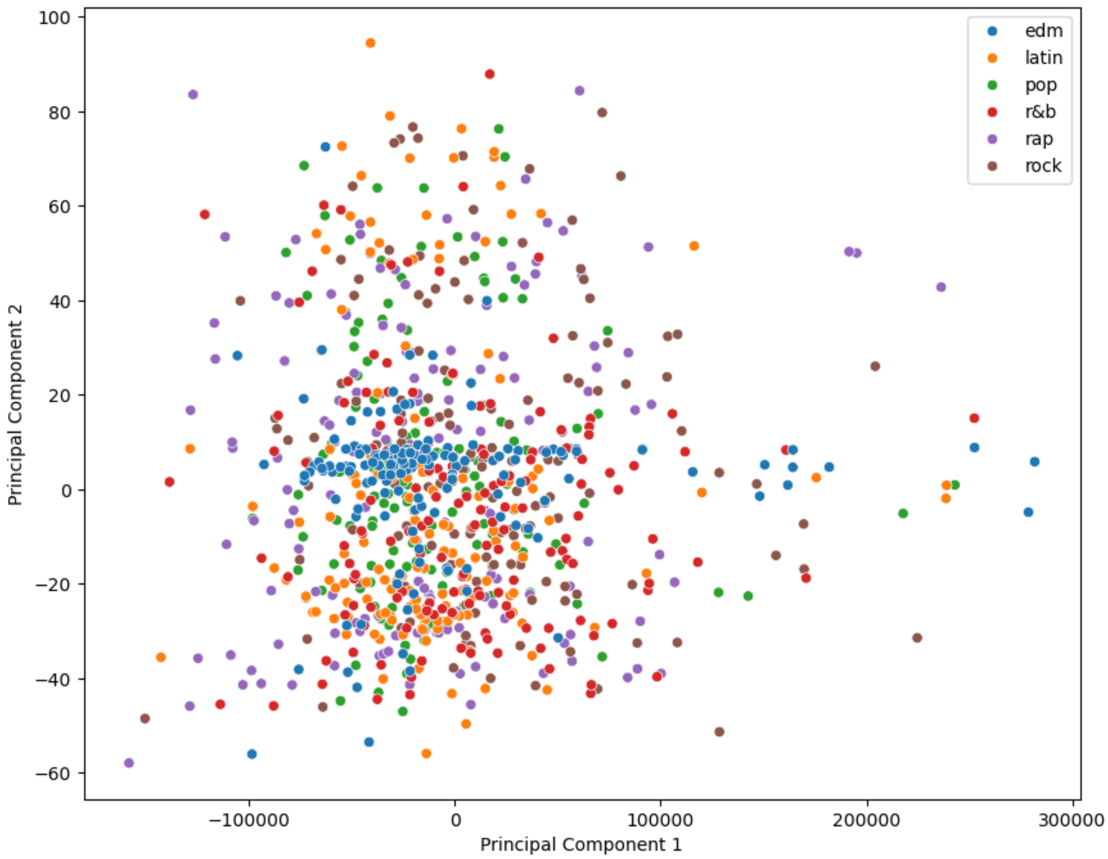
0.0.2 Plot first two principal components of data

To get to know the data first we plot the first two principal components.

Generally the data are scattered across classes. EDM seems to be the most clustered class when plotted on the first two principal components.

```
[ ]: # Get the first two principal components
pca = PCA(n_components=2)
principal_components = pca.fit_transform(numeric_cols)
pca_df = pd.DataFrame(data=principal_components, columns=['PC1', 'PC2'])
pca_df['playlist_genre'] = df['playlist_genre'].values  # Ensure this column␣
 ↪aligns with your PCA data
```

```
# Sample 150 points from each class for plotting
plot_df = pd.DataFrame()
for genre in pca_df['playlist_genre'].unique():
    sampled_genre_df = pca_df[pca_df['playlist_genre'] == genre].sample(n=150,␣
 ↪random_state=42)
    plot_df = pd.concat([plot_df, sampled_genre_df], axis=0)

# Plot the results
plt.figure(figsize=(10, 8))
sns.scatterplot(x='PC1', y='PC2', hue='playlist_genre', data=plot_df)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.show()
```



Create train/test split Because we have so many observations we can afford to only use 10% of the data on testing. We stratify the data be playlist genre to ensure that all classes are included an equal amount in the training and testing data.

```
[ ]: (train, test) = skm.train_test_split(df, test_size=0.10, random_state=0,␣
      ↪stratify=df.playlist_genre)
```

0.0.3 Make model matrix for classification

```
[ ]: # Predictors
     cols = ['track_popularity',
             'danceability',
             'energy',
             'key',
             'loudness',
             'mode',
             'speechiness',
             'acousticness',
             'instrumentalness',
             'liveness',
             'valence',
             'tempo',
             'duration_ms']
```

```
[ ]: # Training
     x_train = train[cols]
     genre_train = train.playlist_genre
```

```
[ ]: # Testing
     x_test = test[cols]
     genre_test = test.playlist_genre
```

0.0.4 K-Nearest Neighbors

For a baseline, we try and fit a K-Nearest-Neighbors model.

```
[ ]: # Use approximately the square root of number of observations
     #k = int(np.floor(np.sqrt(x_train.shape[0])))
     k = 20
     print(f'Using {k} neighbors')
     # Initialize classifier
     knn = KNeighborsClassifier(n_neighbors=k)
     # Fit the model
     knn.fit(x_train, genre_train)
     # Predict on the testing set
     knn_pred = knn.predict(x_test)
     # Get confusion table
     confusion_table(knn_pred, genre_test)
```

```
Using 20 neighbors
```

[ ]:
```
Truth        edm  latin  pop  r&b  rap  rock
Predicted
edm          423     60  118   36   64    70
latin         32    217   75   69   70    15
pop           84     87  193   69   40    69
r&b           18     63   74  225   73    63
rap           20     65   29  101  303     7
rock          27     24   62   43   25   271
```

[ ]:
```python
# Get confusion matrix
np.mean(knn_pred == genre_test)
accuracy_score(genre_test, knn_pred)
```

[ ]:
```
0.49695493300852617
```

Tune KNN Model We will tune the KNN to find the optimal K from 1 to $\lfloor\sqrt{n}\rfloor + 1$ where n is the number of observations in the test set. After about 50 nearest neighbors there is marginal improvement in the training error. The test error holds constant after approximately 25 neighbors.

[ ]:
```python
# Clear plot
plt.clf()
# Range of k to try
k_range = range(1, int(np.floor(np.sqrt(x_train.shape[0]))) + 1)

# Lists to store accuracies
train_error = []
test_error = []
# Loop over different values of k
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(x_train, genre_train)

    # Training accuracy
    train_pred = knn.predict(x_train)
    train_error.append(1- accuracy_score(genre_train, train_pred))

    # Testing accuracy
    test_pred = knn.predict(x_test)
    test_error.append(1- accuracy_score(genre_test, test_pred))

# Plotting
plt.figure(figsize=(10, 6))
plt.plot(k_range, train_error, label='Training Error')
plt.plot(k_range, test_error, label='Testing Error')
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Error')
plt.title('KNN Training and Testing Error')
```

```
plt.legend()
plt.show()
```

<Figure size 640x480 with 0 Axes>

It looks like the best that the KNN classifier can do is around 25%.

LDA Classifier Now we fit a linear discriminant classifier to classify the song genres. There are no hyper parameters to tune. From the confusion matrix, the LDA classifier has the best accuracy when classifying EDM music (65%). This makes sense, as the EDM songs are most clustered compared to other classes in the plot against first two principal components.

[ ]:
```
# Instantiate the LDA model
lda = LinearDiscriminantAnalysis()
# Fit the model
lda.fit(x_train, genre_train)
# Predict on new data
lda_pred = lda.predict(x_test)
# Confusion matrix
cm = confusion_matrix(genre_test, lda_pred)
```

[ ]:
```
# Get genre labels
genre_labels = genre_test.cat.categories.tolist()
```

```
# Coerce into data frame
cm_df = pd.DataFrame(cm, index=genre_labels, columns=genre_labels)
# Plot the DataFrame using matplotlib
fig, ax = plt.subplots(figsize=(5, 5))  # Set figure size
ax.axis('off')

tbl = ax.table(cellText=cm_df.values, colLabels=cm_df.columns, rowLabels=cm_df.index, loc='center', cellLoc='center')
tbl.auto_set_font_size(False)
tbl.set_fontsize(14)
tbl.scale(1.5, 1.5)

# Add labels for True Label and Predicted Label in the appropriate position
ax.text(-0.40, 0.5, 'Truth', va='center', ha='center', rotation='vertical', size=16, transform=ax.transAxes)
ax.text(0, 0.75, 'Predicted',size=16)
print(f'Class Accuracies: {np.diag(cm / np.sum(cm, axis=0))}')
#print(f'Normalized Accuracies: {cm / np.sum(cm, axis=0)}')
```

```
Class Accuracies: [0.55156951 0.37452471 0.36051502 0.44329897 0.50592217
0.54844607]
```

Predicted

Truth	edm	latin	pop	r&b	rap	rock
edm	369	59	89	19	39	29
latin	59	197	65	59	94	42
pop	81	96	168	71	39	96
r&b	29	73	56	215	117	53
rap	78	73	37	61	299	27
rock	53	28	51	60	3	300

[ ]:
```
# Testing Accuracy
accuracy_score(genre_test, lda_pred)
```

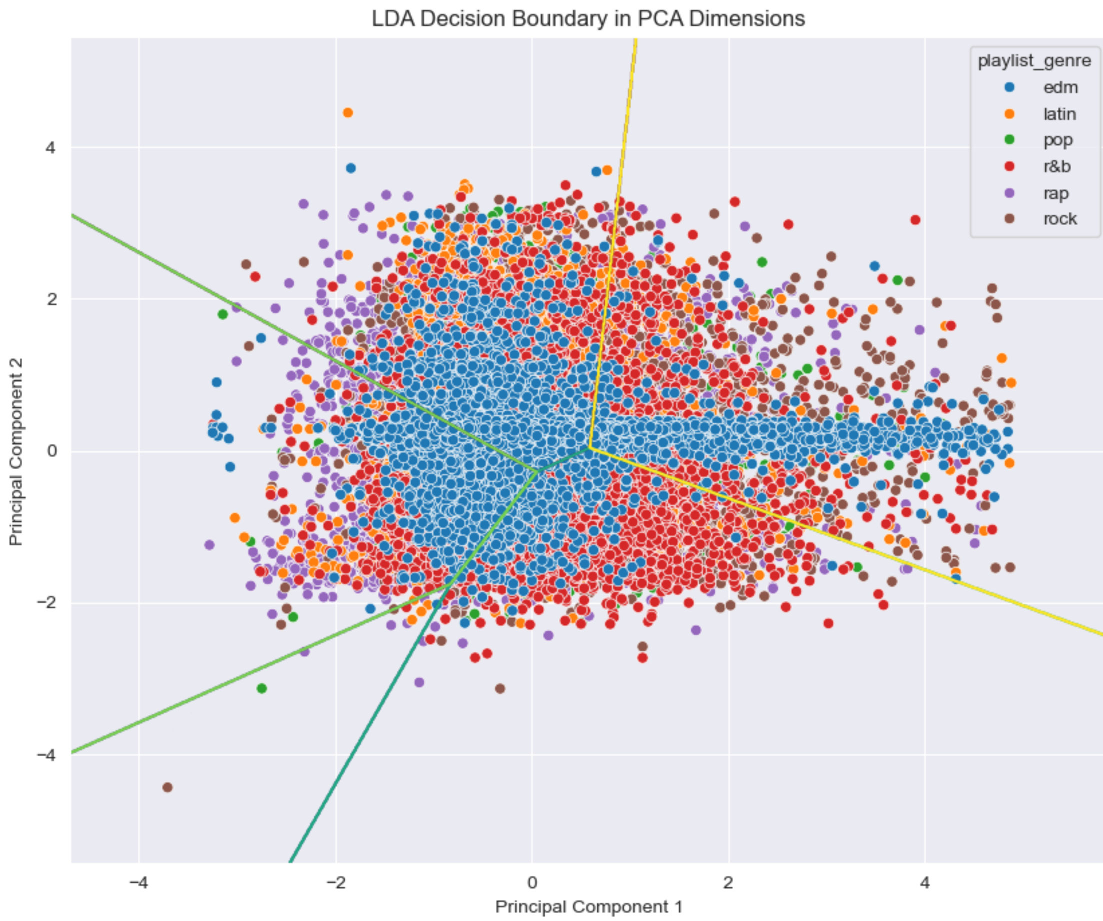
[ ]: 0.4713763702801462

Plot the decision boundary for PCA Data Using the first two principal components we fit the data and plot the decision boundaries.

```
[ ]: # First fit another scaled PCA and predict probabilities
scaler = StandardScaler()
# Fit the scaler to the PCA components and transform the data
# Might have already been done, so we catch the error
try:
    pca_df = pca_df.drop('playlist_genre', axis=1)
except Exception as e:
    print()

pca_df[['PC1', 'PC2']] = scaler.fit_transform(pca_df[['PC1', 'PC2']])

# Instantiate the LDA model for PCA version
lda_pca = LinearDiscriminantAnalysis()

# Fit the model
lda_pca.fit(pca_df[['PC1', 'PC2']], df.playlist_genre)

x_min, x_max = pca_df['PC1'].min() -1 , pca_df['PC1'].max() +1
y_min, y_max = pca_df['PC2'].min() -1 , pca_df['PC2'].max() +1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01), np.arange(y_min, y_max, 0.
 ↪01))

# Create mesh
mesh_points = pd.DataFrame(np.c_[xx.ravel(), yy.ravel()], columns=['PC1','PC2']␣
 ↪)
# Predict the class using LDA for each point on the mesh
Z = lda_pca.predict_proba(mesh_points)
```

```
[ ]: # Plot the PCA-transformed points
plt.figure(figsize=(10, 8))

num_classes = 6
colors = plt.cm.viridis(np.linspace(0, 1, num_classes))

for i in range(num_classes):
    max_prob = np.max(Z, axis=1) == Z[:, i]
    contour = plt.contour(xx, yy, max_prob.reshape(xx.shape),␣
 ↪colors=[colors[i]])

sns.scatterplot(x='PC1', y='PC2', hue=df.playlist_genre, data=pca_df)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
```

```python
plt.title('LDA Decision Boundary in PCA Dimensions')
plt.show()
```



Random Forest We will use Random Forest to classify the songs. With K-fold cross validation we will tune the number of estimators, the max_features used at each split, the max depth of each tree, and the minimum samples in each leaf. We will use 5 folds over the grid. Random Forest does better than the KNN classifier, which had an accuracy of around 25.1%, improving to get an accuracy score of around 54.7% on the test set. The most important features was speechiness. However, danceablility and tempo were nearly just as important.

Top three important features - speechiness 0.176049 - danceability 0.15331 - tempo 0.152939

[ ]:
```python
# Instantiate classifier instance
rfc = RFC(random_state=0)
# Fit the data
rfc.fit(x_train, genre_train)
# Predict on new data
rfc_pred = rfc.predict(x_test)
```

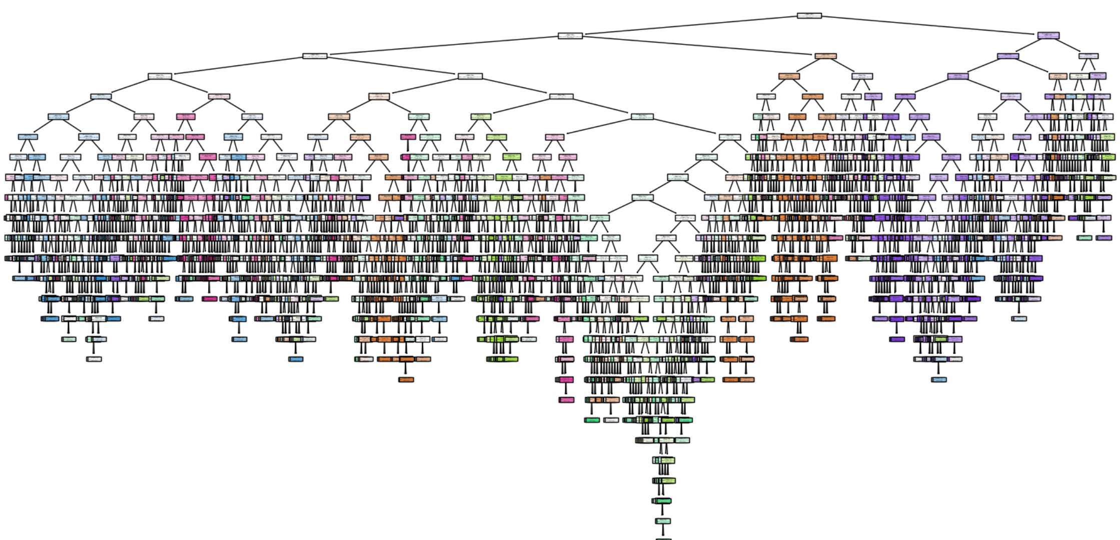
```
# Confusion matrix
cm = confusion_matrix(genre_test, rfc_pred)
cm
```

[ ]:
```
array([[1259,   94,  254,   76,   97,   59],
       [ 156,  609,  270,  196,  242,   70],
       [ 266,  220,  555,  226,  120,  254],
       [  54,  124,  221,  775,  321,  119],
       [  89,  130,   94,  216, 1138,   58],
       [  54,   34,  107,  122,   27, 1144]])
```

[ ]:
```
# Get the accuracy
np.mean(rfc_pred == genre_test)
```

[ ]: 0.5563451776649746

[ ]:
```
# Extract the first tree from the forest
first_tree = rfc.estimators_[0]

# Plot the first tree
plt.figure(figsize=(20,10))
plot_tree(first_tree, filled=True, feature_names=x_train.columns,␣
 ↪class_names=True)
#plt.title("First Tree in the Random Forest")
plt.show()
```



Tune Parameters for Random Forest

[ ]:
```
# Define Grid
param_grid = {
    'n_estimators': [100, 200, 500],
    'max_features': ['sqrt', 'log2'],
    'max_depth': [4, 5, 6, 7, 8],
    'criterion': ['gini',],
    'min_samples_leaf': [1, 2, 4, 10]
}
```

[ ]:
```
rfc = RFC(random_state=0)
CV_rfc = GridSearchCV(estimator=rfc, param_grid=param_grid, cv=5)
CV_rfc.fit(x_train, genre_train)
```

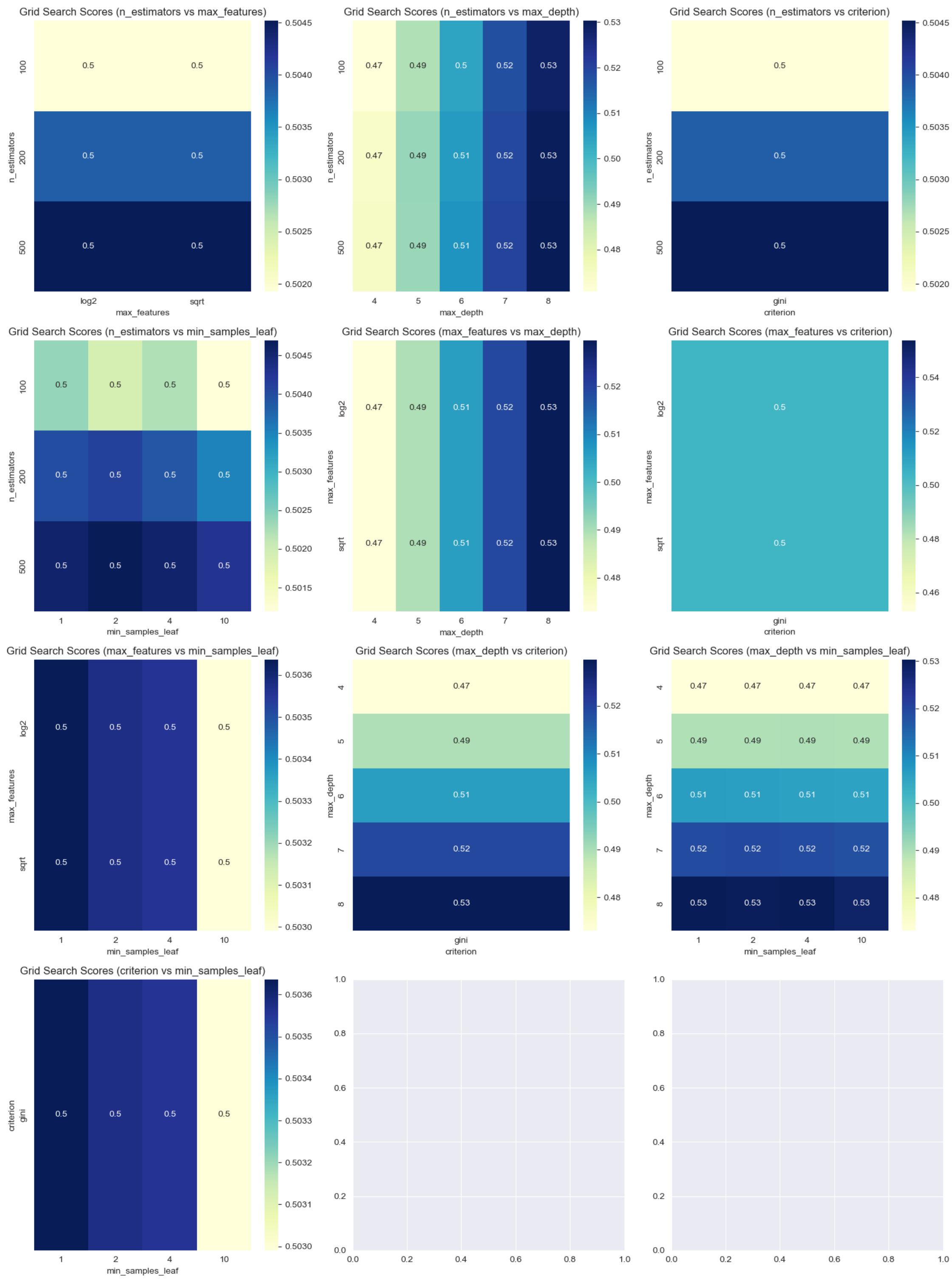
[ ]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=0),
             param_grid={'criterion': ['gini'], 'max_depth': [4, 5, 6, 7, 8],
                         'max_features': ['sqrt', 'log2'],
                         'min_samples_leaf': [1, 2, 4, 10],
                         'n_estimators': [100, 200, 500]})
```

[ ]:
```
print("Best Parameters found by GridSearchCV:")
print(CV_rfc.best_params_)
```

```
Best Parameters found by GridSearchCV:
{'criterion': 'gini', 'max_depth': 8, 'max_features': 'sqrt',
'min_samples_leaf': 4, 'n_estimators': 500}
```

[ ]:
```
# Create plots for different hyperparameter values
param_pairs = list(itertools.combinations(param_grid.keys(), 2))
num_rows = len(param_pairs) // 3 + (len(param_pairs) % 3 > 0)
fig, axs = plt.subplots(num_rows, 3, figsize=(15, 5 * num_rows))
axs = axs.flatten()

# Loop over pairs of parameters
for idx, (param1, param2) in enumerate(param_pairs):
    results = pd.DataFrame(CV_rfc.cv_results_)

    # Aggregate the results
    grouped_results = results.groupby([f"param_{param1}", f"param_{param2}"]).
  ↪mean(numeric_only=True)

    # Create a pivot table for each pair of parameters
    pivot_table = grouped_results["mean_test_score"].unstack()

    # Plotting in the specified subplot
    sns.heatmap(pivot_table, annot=True, cmap="YlGnBu", ax=axs[idx])
    axs[idx].set_title(f"Grid Search Scores ({param1} vs {param2})")
    axs[idx].set_xlabel(param2)
```

```
    axs[idx].set_ylabel(param1)

# Adjust layout
plt.tight_layout()
plt.show()
```



[ ]:
```
rfc_best = CV_rfc.best_estimator_
rfc_pred = rfc_best.predict(x_test)
cm = confusion_matrix(genre_test, rfc_pred)
print(cm)
```

```
[[436  29  68  14  33  24]
 [ 46 198  59  70 110  33]
 [102  76 143  83  49  98]
 [ 23  50  39 261 130  40]
 [ 34  50  26  54 381  30]
 [ 31  14  31  63   8 348]]
```

[ ]:
```
accuracy_score(genre_test, rfc_pred)
```

[ ]:
```
0.5380633373934226
```

[ ]:
```
# Get feature importance for random forest
feature_importances = rfc_best.feature_importances_

# If x_train is a DataFrame, get the feature names
feature_names = x_train.columns

# Coerce to data frame
importances_df = pd.DataFrame({'Feature': feature_names, 'Importance':␣
↪feature_importances})
importances_df = importances_df.sort_values(by='Importance', ascending=False)

# Print the top 3 features and their importances
print("Top 3 Feature Importances:")
print(importances_df.head(3))
```

```
Top 3 Feature Importances:
         Feature  Importance
6    speechiness    0.176049
1   danceability    0.153319
11         tempo    0.152939
```

XGBoost XGBoost produced the highest accuracy on the test set with an accuracy of 57.4%. The feature importance scores were similar with speechiness being the most important feature.

To work with this classifier we first need to encode the data.

[ ]:
```
# Instantiate Label Encoder
pd.options.mode.chained_assignment = None
le_genre = LabelEncoder()
le_key = LabelEncoder()
```

```
# Encode testing set
y_encoded = le_genre.fit_transform(genre_train)
x_train.loc[:,'key'] = le_key.fit_transform(x_train.key)

# Encode training set
y_test_encoded = le_genre.transform(genre_test)
x_test.loc[:,'key'] = le_key.transform(x_test.key)
```

```
/var/folders/gf/bt25hkv172n_bttx0h72_6340000gn/T/ipykernel_71719/1143999346.py:8
: DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will
attempt to set the values inplace instead of always setting a new array. To
retain the old behavior, use either `df[df.columns[i]] = newvals` or, if columns
are non-unique, `df.isetitem(i, newvals)`
  x_train.loc[:,'key'] = le_key.fit_transform(x_train.key)
/var/folders/gf/bt25hkv172n_bttx0h72_6340000gn/T/ipykernel_71719/1143999346.py:1
2: DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will
attempt to set the values inplace instead of always setting a new array. To
retain the old behavior, use either `df[df.columns[i]] = newvals` or, if columns
are non-unique, `df.isetitem(i, newvals)`
  x_test.loc[:,'key'] = le_key.transform(x_test.key)
```

[ ]:
```
# Instantiate the classifier
xg = xgb.XGBClassifier(enable_categorical = True)
# Fit the data
xg.fit(x_train, y_encoded)
```

[ ]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=True, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, objective='multi:softprob', …)
```

[ ]:
```
# Make prediction
xgb_pred = xg.predict(x_test)
#Confusion Matrx
cm = confusion_matrix(y_test_encoded, xgb_pred)
cm
```

[ ]:
```
array([[427,  31,  78,  19,  30,  19],
       [ 32, 219,  90,  70,  81,  24],
```

```
       [ 95,  58, 220,  74,  35,  69],
       [ 18,  58,  65, 261, 100,  41],
       [ 26,  44,  27,  65, 388,  25],
       [ 16,   8,  64,  43,   5, 359]])
```

[ ]:
```
# Get accuracy
np.mean(xgb_pred == y_test_encoded)
```

[ ]:
```
0.5706455542021924
```

Now do a grid search in K-fold cross validation To find the optimal parameters we conduct a grid search with 5 folds along various values for `max_depth`, `n_estimators`, and `learning_rate`.

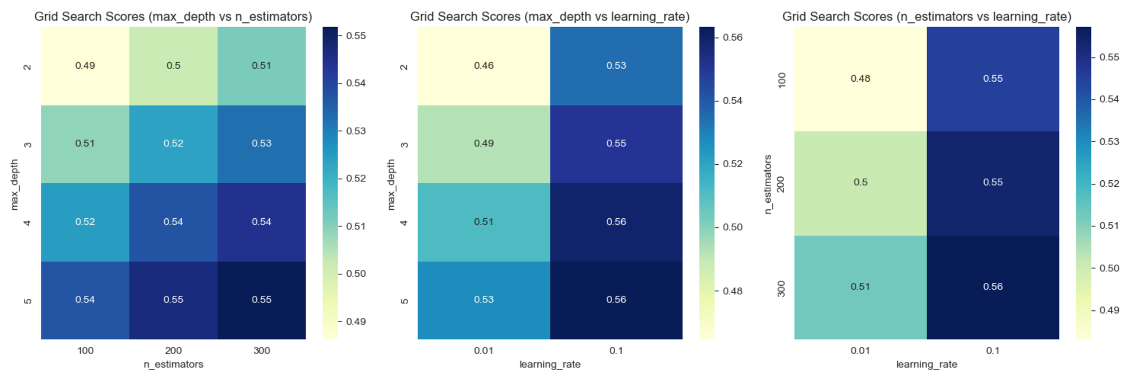
[ ]:
```
# Define the parameter grid
param_grid = {
    'max_depth': [2,3,4, 5],
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1]
}
```

[ ]:
```
# Instantiate an XGBoost classifier
xgb_model = xgb.XGBClassifier(random_state=0,enable_categorical=True,␣
 ↪use_label_encoder=False, eval_metric='mlogloss')
# Create GridSearchCV object
CV_xgb = GridSearchCV(estimator=xgb_model, param_grid=param_grid, cv=5)
# Fit GridSearchCV
CV_xgb.fit(x_train, y_encoded)
# The best estimator after grid search
best_xgb_model = CV_xgb.best_estimator_
```

Plot Grid Search of Best Params

[ ]:
```
# Assuming 'param_grid' and 'CV_xgb.cv_results_' are defined
param_pairs = list(itertools.combinations(param_grid.keys(), 2))

# Calculate the number of rows needed for 3 columns
num_rows = len(param_pairs) // 3 + (len(param_pairs) % 3 > 0)

# Create a figure with subplots
fig, axs = plt.subplots(num_rows, 3, figsize=(15, 5 * num_rows))

# Flatten the array of axes for easy indexing
axs = axs.flatten()

# Loop over pairs of parameters
for idx, (param1, param2) in enumerate(param_pairs):
    results = pd.DataFrame(CV_xgb.cv_results_)
```

```
    # Aggregate the results
    grouped_results = results.groupby([f"param_{param1}", f"param_{param2}"]).
  ↪mean(numeric_only=True)

    # Create a pivot table for each pair of parameters
    pivot_table = grouped_results["mean_test_score"].unstack()

    # Plotting in the specified subplot
    sns.heatmap(pivot_table, annot=True, cmap="YlGnBu", ax=axs[idx])
    axs[idx].set_title(f"Grid Search Scores ({param1} vs {param2})")
    axs[idx].set_xlabel(param2)
    axs[idx].set_ylabel(param1)

# Adjust layout
plt.tight_layout()
plt.show()
```



[ ]:
```
print("Best Parameters found by GridSearchCV:")
print(CV_xgb.best_params_)
```

```
Best Parameters found by GridSearchCV:
{'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 300}
```

[ ]:
```
# Get feature importance for xgboost
best_xgb_model = CV_xgb.best_estimator_
feature_importances = best_xgb_model.feature_importances_
feature_names = x_train.columns
importance_df = pd.DataFrame({'Feature': feature_names, 'Importance':␣
  ↪feature_importances}).sort_values(by='Importance', ascending=False)

# Print the top 3 features and their importance
print("Top 3 Feature Importance:")
print(importance_df.head(3))
```

```
Top 3 Feature Importance:
         Feature  Importance
6    speechiness    0.137885
11         tempo    0.134520
1   danceability    0.123001
```

[ ]:
```python
xgb_best = CV_xgb.best_estimator_
xgb_pred_best = xgb_best.predict(x_test)
cm = confusion_matrix(y_test_encoded, xgb_pred_best)
print(cm)
accuracy_score(y_test_encoded, xgb_pred_best)
```

```
[[429  27  75  22  31  20]
 [ 34 221  80  66  81  34]
 [ 93  63 208  74  37  76]
 [ 21  59  58 270 104  31]
 [ 26  46  28  60 396  19]
 [ 18   6  61  39   8 363]]
```

[ ]: 0.5746041412911084