RF + Boosting Songs

February 11, 2024

0.1 Predicting Song Popularities with RF & XGBoost

For this assignment, we are tasked with building a classification model that can predict a track's popularity into binned categorical variables based on many features.

Here are the steps we followed in this analysis:

- Data Exploration
- Data Processing
- Random Forest model
- XGBoost model

[1]:
```
# import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import seaborn as sns
from scipy import stats
import math
import ast

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import RandomForestClassifier
from sklearn.cluster import KMeans
from sklearn.metrics import roc_auc_score, accuracy_score, f1_score,␣
↪confusion_matrix, classification_report, roc_curve, auc

import xgboost as xgb
from xgboost import XGBClassifier


import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

0.2 Data Exploration

[2]:
```python
songs = pd.read_excel("Songs_2024.xlsx", sheet_name='spotify songs')
songs.head()
```

[2]:
```
   year            track_name  track_popularity  \
0  2000                Yellow                91
1  2000  All The Small Things                84
2  2000               Breathe                69
3  2000            In the End                88
4  2000           Bye Bye Bye                74

                          album  artist_name  \
0                    Parachutes     Coldplay
1           Enema Of The State    blink-182
2                       Breathe   Faith Hill
3  Hybrid Theory (Bonus Edition)  Linkin Park
4           No Strings Attached       *NSYNC

                                     artist_genres  artist_popularity  \
0                         ['permanent wave'; 'pop']                 86
1  ['alternative metal'; 'modern rock'; 'pop punk…                 75
2  ['contemporary country'; 'country'; 'country d…                 61
3  ['alternative metal'; 'nu metal'; 'post-grunge…                 83
4                   ['boy band'; 'dance pop'; 'pop']                 65

   danceability  energy   key  loudness  mode  speechiness  acousticness  \
0         0.429   0.661  11.0      85.0   1.0       0.0281       0.00239
1         0.434   0.897   0.0      69.0   1.0       0.0488       0.01030
2         0.529   0.496   7.0      95.0   1.0       0.0290       0.17300
3         0.556   0.864   3.0      76.0   0.0       0.0584       0.00958
4         0.610   0.926   8.0      68.0   0.0       0.0479       0.03100

   instrumentalness  liveness  valence    tempo  duration_ms
0          0.000121    0.2340    0.285  173.372     266773.0
1          0.000000    0.6120    0.684  148.726     167067.0
2          0.000000    0.2510    0.278  136.859     250547.0
3          0.000000    0.2090    0.400  105.143     216880.0
4          0.001200    0.0821    0.861  172.638     200400.0
```

[3]:
```python
songs.describe()
```

[3]:
```
              year  track_popularity  artist_popularity  danceability  \
count  2300.000000       2300.000000        2300.000000   2299.000000
mean   2011.000000         70.943478          72.869565      0.660116
std       6.634692         12.291526          12.179263      0.141137
min    2000.000000          0.000000          29.000000      0.162000
```

```
25%    2005.000000         66.000000          65.000000      0.572000
50%    2011.000000         72.000000          74.000000      0.671000
75%    2017.000000         79.000000          82.000000      0.759500
max    2022.000000        100.000000         100.000000      0.975000

            energy          key     loudness         mode  speechiness  \
count  2299.000000  2299.000000  2299.000000  2299.000000  2299.000000
mean      0.693047     5.277947    73.006960     0.598521     0.097795
std       0.164838     3.628494    15.643937     0.490304     0.092445
min       0.051900     0.000000   -56.000000     0.000000     0.022500
25%       0.586000     2.000000    63.000000     0.000000     0.038000
50%       0.712000     5.000000    74.000000     1.000000     0.056800
75%       0.820000     8.000000    83.000000     1.000000     0.115500
max       0.999000    11.000000   132.000000     1.000000     0.576000

       acousticness  instrumentalness     liveness      valence        tempo  \
count   2299.000000       2299.000000  2299.000000  2299.000000  2299.000000
mean       0.157689          0.013766     0.172618     0.535110   120.512450
std        0.203844          0.083990     0.131620     0.227821    27.617729
min        0.000013          0.000000     0.021000     0.037700    60.019000
25%        0.016500          0.000000     0.089950     0.360500    98.569500
50%        0.068900          0.000000     0.119000     0.540000   120.000000
75%        0.223000          0.000054     0.220000     0.722000   137.028000
max        0.978000          0.985000     0.843000     0.974000   210.857000

         duration_ms
count    2299.000000
mean   226033.494128
std     42063.678588
min     97393.000000
25%    200179.500000
50%    221653.000000
75%    245950.000000
max    688453.000000
```

[4]:
```
songs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2300 entries, 0 to 2299
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   year               2300 non-null   int64
 1   track_name         2300 non-null   object
 2   track_popularity   2300 non-null   int64
 3   album              2300 non-null   object
 4   artist_name        2300 non-null   object
```

```
 5   artist_genres      2300 non-null   object
 6   artist_popularity  2300 non-null   int64
 7   danceability       2299 non-null   float64
 8   energy             2299 non-null   float64
 9   key                2299 non-null   float64
 10  loudness           2299 non-null   float64
 11  mode               2299 non-null   float64
 12  speechiness        2299 non-null   float64
 13  acousticness       2299 non-null   float64
 14  instrumentalness   2299 non-null   float64
 15  liveness           2299 non-null   float64
 16  valence            2299 non-null   float64
 17  tempo              2299 non-null   float64
 18  duration_ms        2299 non-null   float64
dtypes: float64(12), int64(3), object(4)
memory usage: 341.5+ KB
```

[5]:
```python
#Checking number of unique rows in each feature
songs.nunique().sort_values()
```

[5]:
```
mode                    2
key                    12
year                   23
artist_popularity      62
track_popularity       71
loudness              104
danceability          585
energy                641
artist_genres         698
liveness              807
valence               827
instrumentalness      841
speechiness           860
artist_name           891
acousticness         1322
album                1663
duration_ms          2033
tempo                2074
track_name           2121
dtype: int64
```

[6]:
```python
# visualizing missing rows as numpy array for ease
missing_rows = songs[songs.isnull().any(axis=1)].to_numpy()

# Display the rows with missing values
print(missing_rows)
```

```
[[2004 'These Words' 68 'Unwritten' 'Natasha Bedingfield'
```

"['dance pop'; 'pop'; 'post-teen pop']" 64 nan nan nan nan nan nan nan
nan nan nan nan nan]]

[7]:
```
songs.isnull().sum()
```

[7]:
```
year                  0
track_name            0
track_popularity      0
album                 0
artist_name           0
artist_genres         0
artist_popularity     0
danceability          1
energy                1
key                   1
loudness              1
mode                  1
speechiness           1
acousticness          1
instrumentalness      1
liveness              1
valence               1
tempo                 1
duration_ms           1
dtype: int64
```

[8]:
```
# Dealing with missing values and duplicates
songs = songs.drop_duplicates(subset=['track_name','artist_name']) #Bare in␣
↪mind that we can have songs with the same name but different artists, so we␣
↪are not removing those.


for column in songs.columns:
    if songs[column].isna().any() and songs[column].dtype != 'object':
    # Fill null values with the mean
        songs[column].fillna(songs[column].mean(), inplace=True)
```

[9]:
```
songs.isnull().sum()
```

[9]:
```
year                  0
track_name            0
track_popularity      0
album                 0
artist_name           0
artist_genres         0
artist_popularity     0
danceability          0
```

```
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
tempo               0
duration_ms         0
dtype: int64
```

[10]:

```
# choosing the metric variables to check outlier counts
columns_to_check =␣
↪['year','track_popularity','artist_popularity','danceability','energy','key','loudness','mo

def detect_outliers_iqr(data, column):
    """
    Detects outliers in a dataframe column based on the IQR method.

    Parameters:
    - data: pandas DataFrame.
    - column: String name of the column to check for outliers.

    Returns:
    - DataFrame containing the outliers.
    """
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    # 5 is a high value to check for drastic outliers
    lower_bound = Q1 - 5 * IQR
    upper_bound = Q3 + 5 * IQR
    return data[(data[column] < lower_bound) | (data[column] > upper_bound)]

def detect_outliers_zscore(data, column, threshold=3):
    """
    Detects outliers in a dataframe column based on the Z-score method.

    Parameters:
    - data: pandas DataFrame.
    - column: String name of the column to check for outliers.
    - threshold: Z-score threshold for considering a point as an outlier.

    Returns:
    - DataFrame containing the outliers.
```

```
    """
    z_scores = stats.zscore(data[column])
    return data[abs(z_scores) > threshold]

outliers_count_z = {}
outliers_count_iqr = {}

# Looping through the columns to check for outliers
for column in columns_to_check:
    outliers_iqr = detect_outliers_iqr(songs, column)
    outliers_z = detect_outliers_zscore(songs, column)
    outliers_count_z[column] = len(outliers_iqr)
    outliers_count_iqr[column] = len(outliers_z)

# Creating DataFrames for Z-score and IQR outlier counts
df_outliers_z = pd.DataFrame(list(outliers_count_z.items()), columns=['Column',␣
↪'Outliers_Z'])
df_outliers_iqr = pd.DataFrame(list(outliers_count_iqr.items()),␣
↪columns=['Column', 'Outliers_IQR'])

# Merging the two DataFrames on the 'Column' column
df_outliers = pd.merge(df_outliers_z, df_outliers_iqr, on='Column')

print(df_outliers)
```

```
              Column  Outliers_Z  Outliers_IQR
0               year           0             0
1   track_popularity           0            38
2  artist_popularity           0             7
3       danceability           0             9
4             energy           0            13
5                key           0             0
6           loudness           1            16
7               mode           0             0
8        speechiness           2            40
9       acousticness           0            56
10  instrumentalness         375            36
11          liveness           0            60
12           valence           0             0
13             tempo           0             6
14       duration_ms           3            17
```

[11]:
```
# Replace semicolons with commas in the 'artist_genres' column before applying␣
↪ast.literal_eval
songs['artist_genres'] = songs['artist_genres'].apply(lambda x: x.replace(';',␣
↪',') if isinstance(x, str) else x)
```

```
# Now safely apply ast.literal_eval to convert string representations of lists␣
↪into actual lists
songs['artist_genres'] = songs['artist_genres'].apply(lambda x: ast.
↪literal_eval(x) if isinstance(x, str) else x)

songs = songs.dropna(subset=['artist_genres'])

# Flatten the list of genres from all rows into a single list
all_genres = sum(songs['artist_genres'], [])

# Convert the list to a set to remove duplicates, then count the unique elements
unique_genres = set(all_genres)
number_of_unique_genres = len(unique_genres)

print(f"There are {number_of_unique_genres} unique genres in the dataset.")
```

```
There are 437 unique genres in the dataset.
```

0.2.1 Experimenting with Genre

[12]:
```
# Normalize genre names: lowercase and remove special characters if necessary
songs['artist_genres'] = ["".join(x).lower().replace('[^a-z\s]', '') for x in␣
↪songs['artist_genres']]

# Initialize TF-IDF Vectorizer
tfidf = TfidfVectorizer(max_features=1000)

# Fit and transform the genre names
genre_tfidf = tfidf.fit_transform(songs['artist_genres'])

# Apply K-Means clustering
kmeans = KMeans(n_clusters=10, random_state=42)
songs['genre_cluster'] = kmeans.fit_predict(genre_tfidf)

# Display the number of genres per cluster to check the distribution
print(songs['genre_cluster'].value_counts())
```

```
genre_cluster
2    946
7    260
1    238
8    168
3    154
9    132
0    107
5     89
6     49
```

```
4     38
Name: count, dtype: int64
```

[13]:
```python
# For simplicity, let's see some examples of genres in each cluster
for cluster in sorted(songs['genre_cluster'].unique()):
    print(f"Cluster {cluster}:")
    examples = songs[songs['genre_cluster'] == cluster]['artist_genres'].
↪unique()
    print(examples[:5])  # Print 5 examples per cluster
```

```
Cluster 0:
['detroit hip hophip hoprap'
 'east coast hip hopgangster raphip hoppop raprap'
 'east coast hip hopgangster raphardcore hip hophip hoprap'
 'detroit hip hopgangster raphip hop'
 'dance popeast coast hip hopgangster raphip hophip poppop rapqueens hip
hoprapurban contemporary']
Cluster 1:
['pop rock' 'canadian pop' 'dance pop' 'hip pop' 'pop']
Cluster 2:
['permanent wavepop' 'boy banddance poppop' 'dance rockeuropop'
 'disco housefilter house' 'bouncy houseeurodance']
Cluster 3:
['dance poppop' 'canadian poppop' 'hip poppop' 'poppop r&b'
 'dance poppop danceuk dance']
Cluster 4:
['popsinger-songwriter popuk pop' 'popuk pop' 'popuk danceuk funky']
Cluster 5:
['g funkgangster raphip hoprapwest coast rap' 'comedy rap' 'rap rock'
 'dance popdancehallpoppop rap' 'dance poppoppop rap']
Cluster 6:
['contemporary r&bhip popr&b'
 'dance popr&bsouthern hip hopurban contemporary' 'popr&b'
 'hip popr&bsouthern hip hopurban contemporary'
 'contemporary r&bdirty south raphip popr&bsouthern hip hopurban contemporary']
Cluster 7:
['east coast hip hophardcore hip hop'
 'atl hip hopdirty south raphip hopold school atlanta hip hoprapsouthern hip
hop'
 'atl hip hopcontemporary r&bdance poppopr&brapsouth carolina hip hopurban
contemporary'
 'dance pophip hophip popneo soulpop rapr&brapurban contemporaryvirginia hip
hop'
 'hip popurban contemporary']
Cluster 8:
['contemporary countrycountrycountry dawncountry road'
 'contemporary r&bdirty south raphip popr&burban contemporary'
 'dance popgirl grouppopr&burban contemporary'
```

```
 'contemporary countrycountrycountry road'
 'dance popgangster raphip hoppop raprapst louis rapurban contemporary']
Cluster 9:
['alternative metalmodern rockpop punkpunkrocksocal pop punk'
 'alternative metalnu metalpost-grungerap metalrock'
 'alternative rockfunk metalfunk rockpermanent waverock'
 'alternative metalnu metalpost-grungerock'
 'alternative metalfunk metalnu metalpost-grungerap metalrock']
```

[14]:
```python
cluster_labels = {
    0: 'Urban Hip Hop',
    1: 'Mainstream Pop',
    2: 'Dance/Electronic',
    3: 'Contemporary R&B',
    4: 'UK Pop/Funk',
    5: 'Diverse Hip Hop',
    6: 'Modern R&B',
    7: 'Hip Hop/Rap Fusion',
    8: 'Country',
    9: 'Alt Rock/Metal Fusion'
}
```

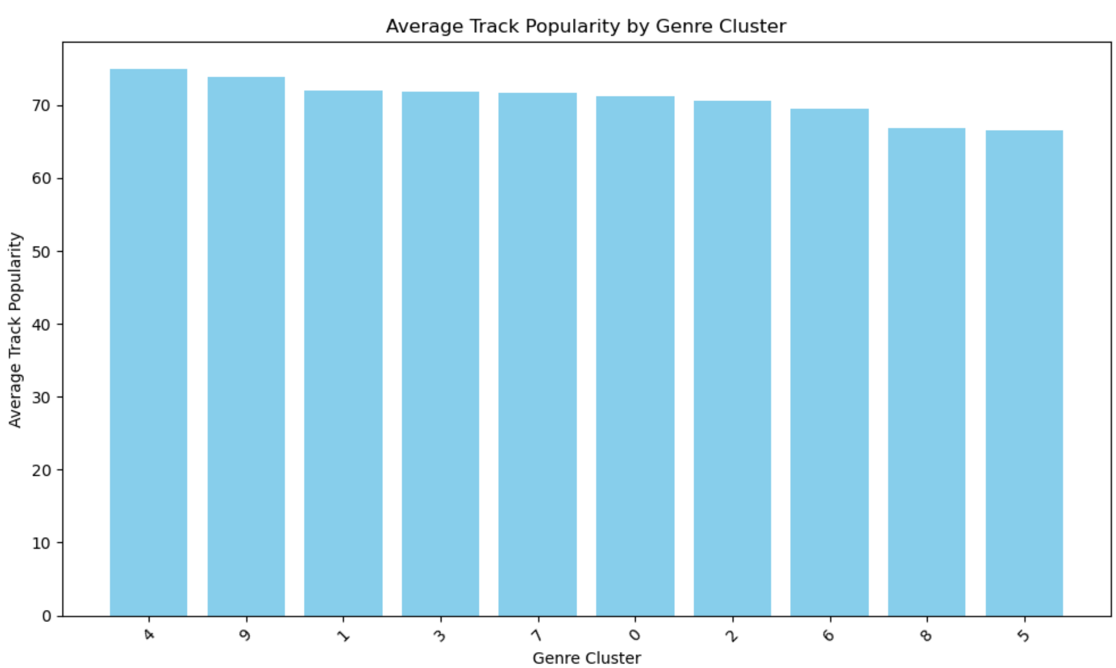
[15]:
```python
# Map the cluster labels to the dataset
songs['genre_label'] = songs['genre_cluster'].map(cluster_labels)
print(songs[['artist_genres', 'genre_cluster', 'genre_label']].head(10))
```

```
                                       artist_genres  genre_cluster  \
0                                      permanent wavepop              2
1  alternative metalmodern rockpop punkpunkrockso…              9
2  contemporary countrycountrycountry dawncountry…              8
3  alternative metalnu metalpost-grungerap metalrock              9
4                                 boy banddance poppop              2
5  contemporary r&bdirty south raphip popr&burban…              8
6                           detroit hip hophip hoprap              0
7                                    dance rockeuropop              2
8        dance popgirl grouppopr&burban contemporary              8
9  alternative rockfunk metalfunk rockpermanent w…              9

             genre_label
0       Dance/Electronic
1  Alt Rock/Metal Fusion
2                Country
3  Alt Rock/Metal Fusion
4       Dance/Electronic
5                Country
6          Urban Hip Hop
7       Dance/Electronic
8                Country
```

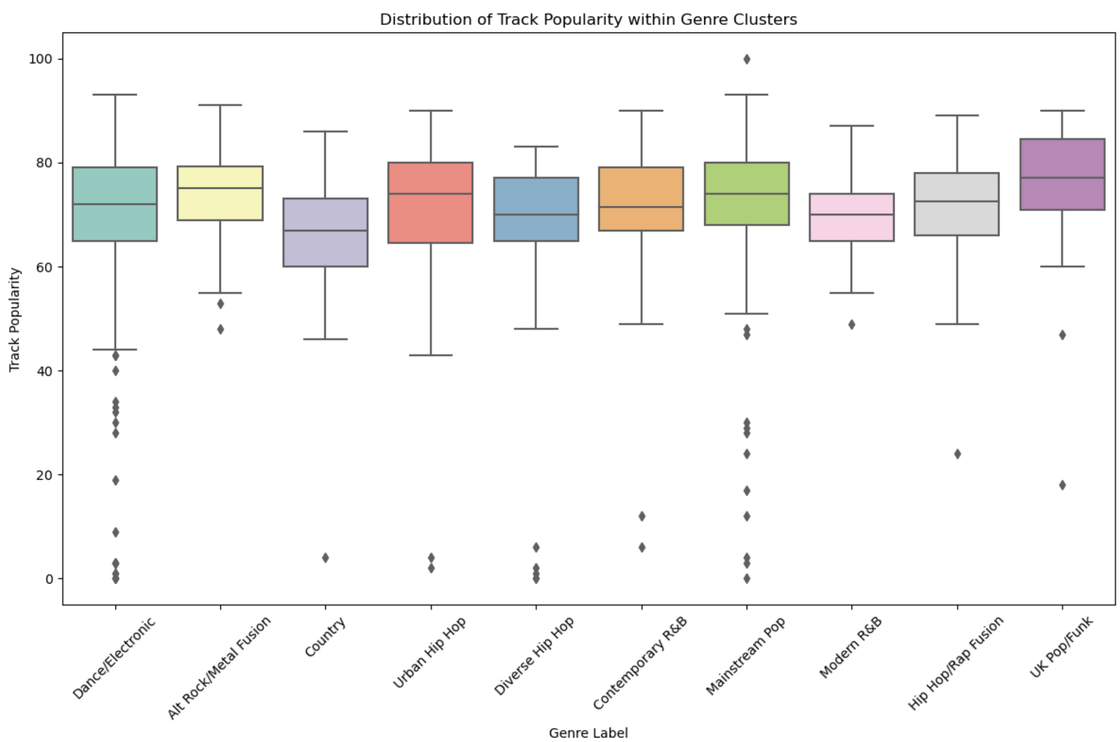
```
9   Alt Rock/Metal Fusion
```

[16]:
```
songs.to_excel('genre_clustered.xlsx', index=False)
```

[17]:
```
# Load the data
songs = pd.read_excel('genre_clustered.xlsx' )

# Calculate average track popularity for each genre cluster
avg_popularity_by_cluster = songs.groupby('genre_cluster')['track_popularity'].
 ↪mean().reset_index()

# Sort the clusters for better visualization
avg_popularity_by_cluster = avg_popularity_by_cluster.
 ↪sort_values(by='track_popularity', ascending=False)

# Plotting
plt.figure(figsize=(10, 6))
plt.bar(avg_popularity_by_cluster['genre_cluster'].astype(str),␣
 ↪avg_popularity_by_cluster['track_popularity'], color='skyblue')
plt.xlabel('Genre Cluster')
plt.ylabel('Average Track Popularity')
plt.title('Average Track Popularity by Genre Cluster')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

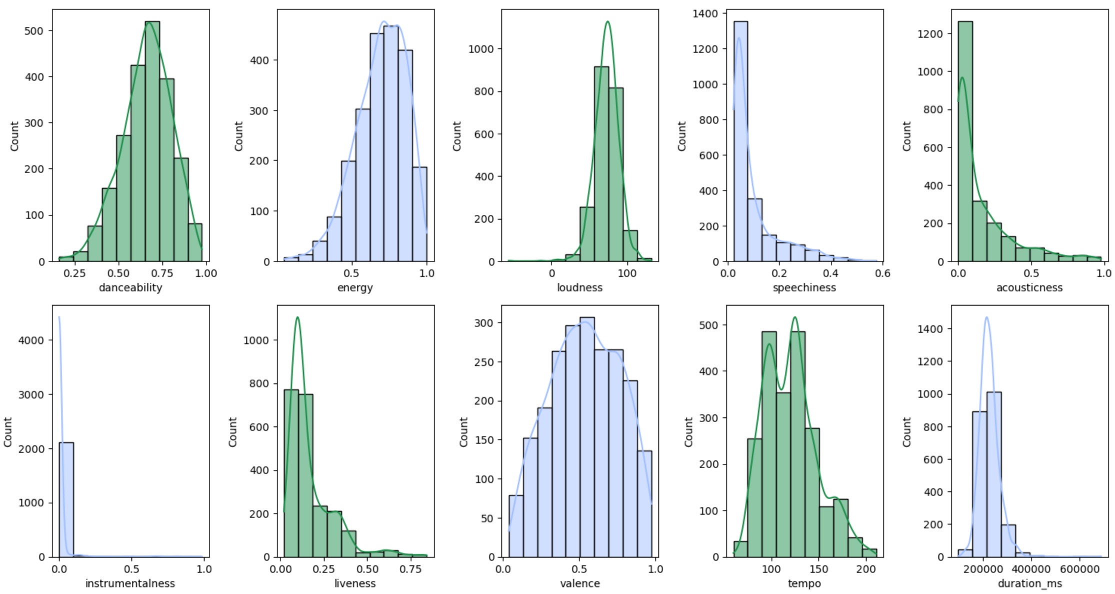


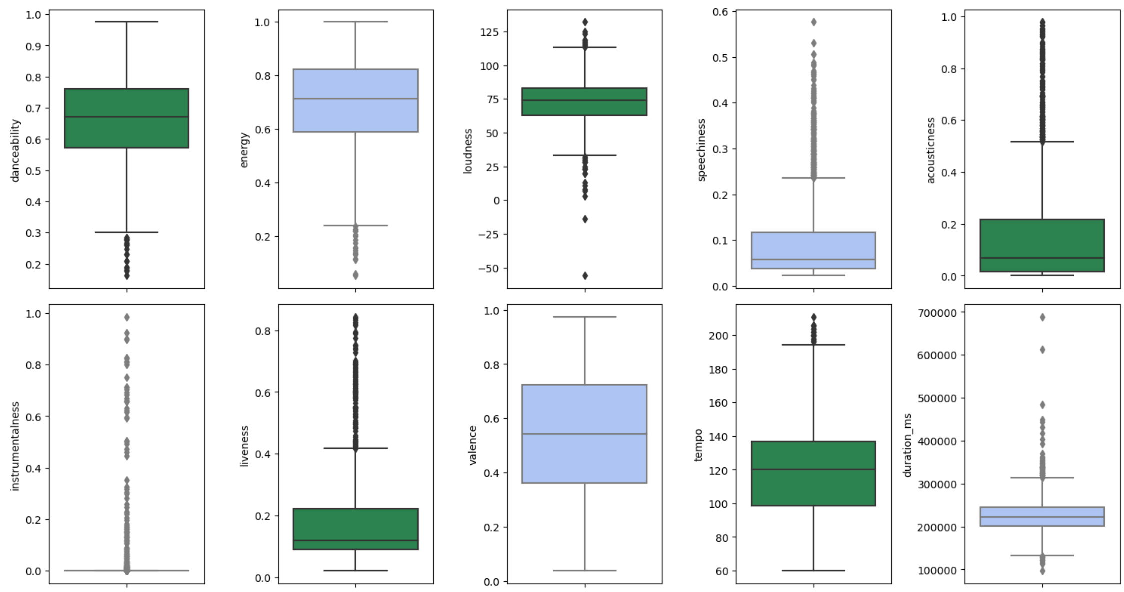
[18]:
```python
# Creating the boxplot
plt.figure(figsize=(12, 8))
sns.boxplot(x='genre_label', y='track_popularity', data=songs, palette="Set3")

plt.title('Distribution of Track Popularity within Genre Clusters')
plt.xlabel('Genre Label')
plt.ylabel('Track Popularity')
plt.xticks(rotation=45)  # Rotates the labels on the x-axis for better␣
↪readability

plt.tight_layout()
plt.show()
```



[19]:
```python
# list of your numerical feature column names
nf = ['danceability', 'energy', 'loudness', 'speechiness', 'acousticness',␣
↪'instrumentalness', 'liveness', 'valence', 'tempo', 'duration_ms']

n = 5  # Columns per row
rows = math.ceil(len(nf)/n)  # Number of rows needed

# Define colors to cycle between green and blue
clr = ['#1E914C', '#A2C1FF']  # using specific hex codes
```

```python
# Distribution plots
plt.figure(figsize=[15, 4*rows])
for i, feature in enumerate(nf):
    plt.subplot(rows, n, i+1)
    sns.histplot(songs[feature], kde=True, color=clr[i % len(clr)], edgecolor="black", bins=10)
plt.tight_layout()
plt.show()

# Box plots
plt.figure(figsize=[15, 4*rows])
for i, feature in enumerate(nf):
    plt.subplot(rows, n, i+1)
    sns.boxplot(y=songs[feature], color=clr[i % len(clr)])
plt.tight_layout()
plt.show()
```





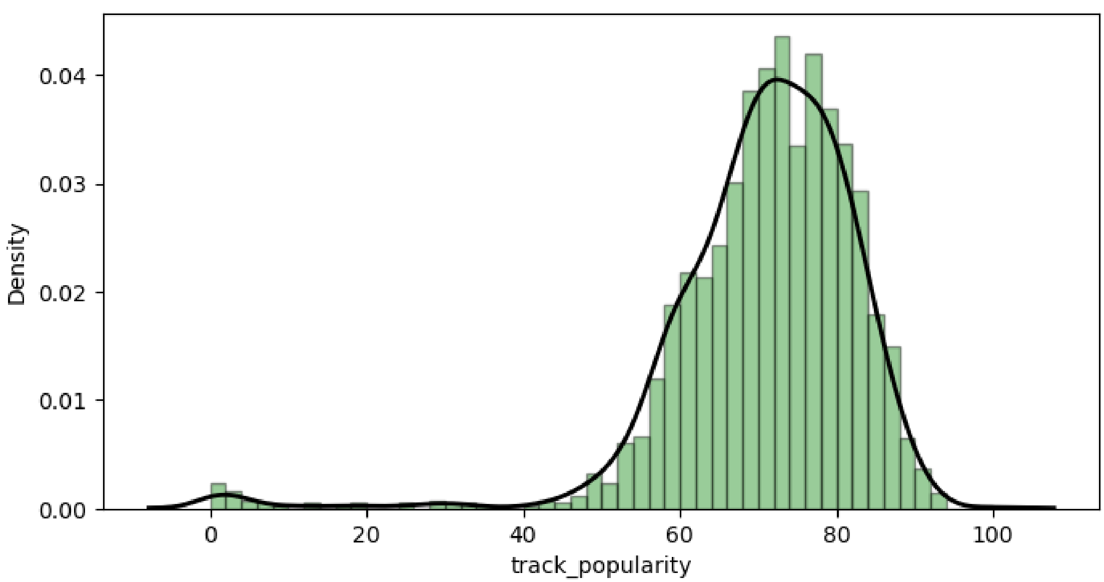
[20]:
```python
# Create a subplot grid: 4 rows, 2 columns, making it more compact
fig = make_subplots(rows=4, cols=2, subplot_titles=(
    'Artist Popularity over Years', 'Artist Popularity vs Track Popularity',
    'Valence vs Danceability', 'Energy vs Valence',
    'Danceability vs Energy', 'Loudness vs Acousticness (Negative Correlation)',
    'Energy vs Acousticness (Negative Correlation)'
))

# Add each scatter plot to the grid, adjust the row and col accordingly
fig.add_trace(go.Scatter(x=songs['year'], y=songs['artist_popularity'], mode='markers', marker=dict(color='#1E914C')), row=1, col=1)
fig.add_trace(go.Scatter(x=songs['artist_popularity'], y=songs['track_popularity'], mode='markers', marker=dict(color='#A2C1FF')), row=1, col=2)
fig.add_trace(go.Scatter(x=songs['valence'], y=songs['danceability'], mode='markers', marker=dict(color='#1E914C')), row=2, col=1)
fig.add_trace(go.Scatter(x=songs['energy'], y=songs['valence'], mode='markers', marker=dict(color='#A2C1FF')), row=2, col=2)
fig.add_trace(go.Scatter(x=songs['danceability'], y=songs['energy'], mode='markers', marker=dict(color='#1E914C')), row=3, col=1)
fig.add_trace(go.Scatter(x=songs['loudness'], y=songs['acousticness'], mode='markers', marker=dict(color='#A2C1FF')), row=3, col=2)
fig.add_trace(go.Scatter(x=songs['energy'], y=songs['acousticness'], mode='markers', marker=dict(color='#1E914C')), row=4, col=1)

# Since we have an odd number of plots, one subplot will be empty
```

```
# Update layout for a cleaner look
fig.update_layout(height=1200, width=800, title_text="Scatter Plots Grid",␣
 ↪showlegend=False)
fig.show()
```

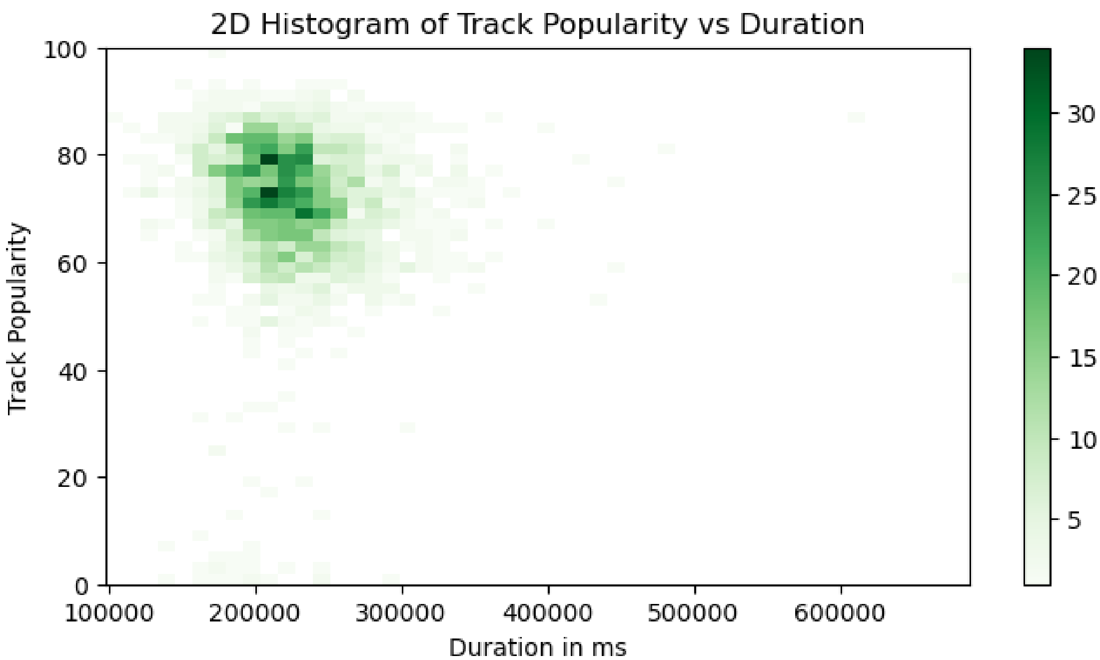
[21]:
```
# Set the figure size
plt.figure(figsize=[8, 4])
# Creating graphic with seaborn using the 'track_popularity' column
sns.distplot(songs['track_popularity'], color='g', kde_kws={"color": "k", "lw":␣
 ↪2}, hist_kws={"edgecolor": "black", "linewidth": 1}, bins=50)
# Establecer el título del gráfico
```

```
/var/folders/r8/9knv8vvj3m98jv1qltst72xr0000gn/T/ipykernel_72994/1722633087.py:4
: UserWarning:



`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

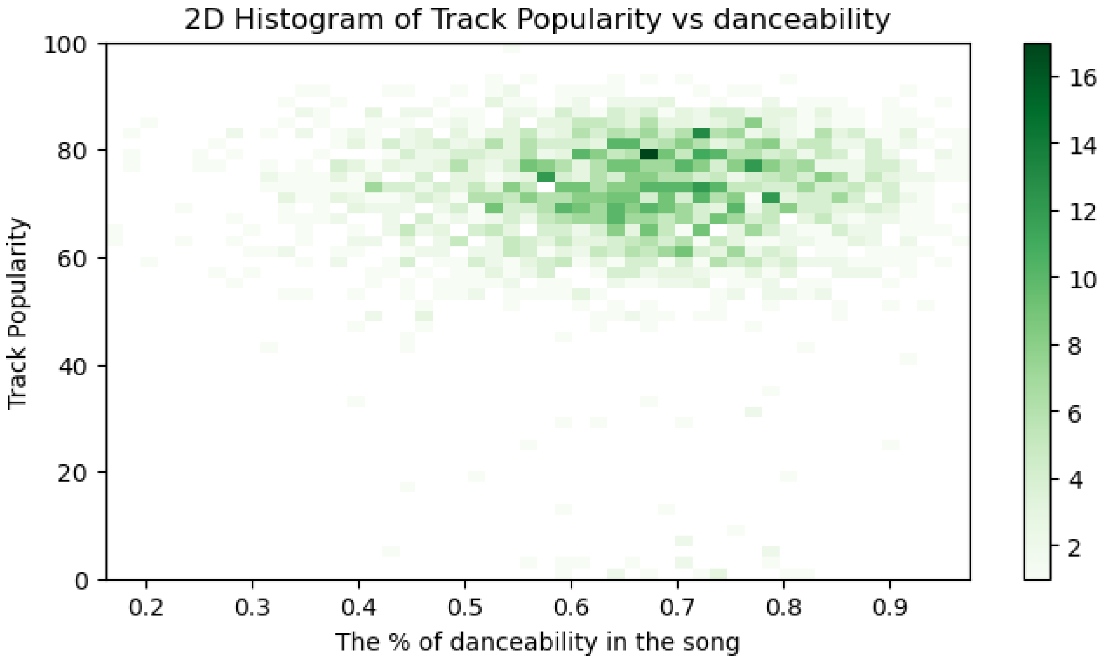
[21]:
```
<Axes: xlabel='track_popularity', ylabel='Density'>
```



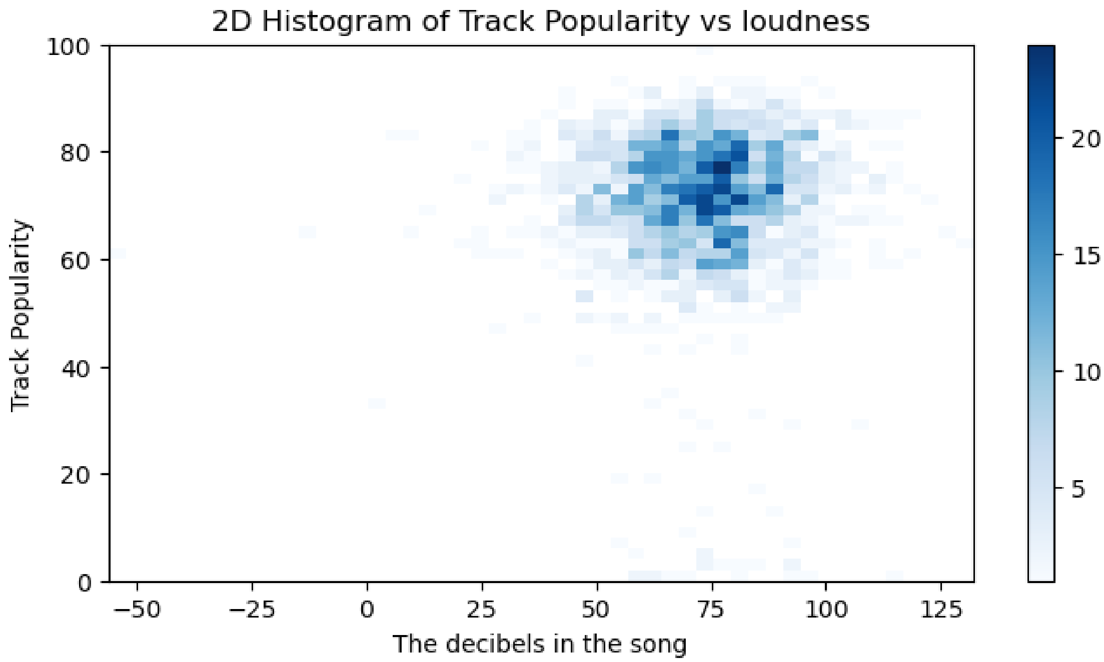
[22]:
```
plt.figure(figsize=[8, 4])
plt.hist2d(songs['duration_ms'], songs['track_popularity'], bins=[50, 50],␣
    ↪cmap='Greens', cmin=1)
plt.xlabel('Duration in ms')
plt.ylabel('Track Popularity')
plt.title('2D Histogram of Track Popularity vs Duration')
plt.colorbar()
plt.show()
```



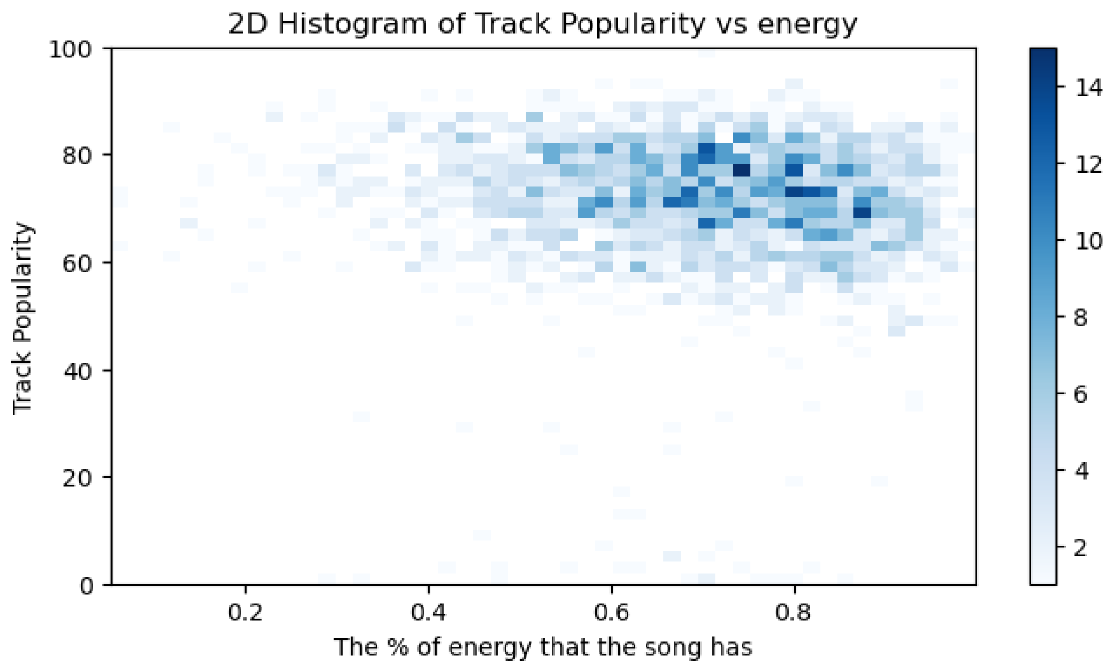
[23]:
```
plt.figure(figsize=[8, 4])
plt.hist2d(songs['danceability'], songs['track_popularity'], bins=[50, 50],␣
    ↪cmap='Greens', cmin=1)
plt.xlabel('The % of danceability in the song')
plt.ylabel('Track Popularity')
plt.title('2D Histogram of Track Popularity vs danceability')
plt.colorbar()
plt.show()
```



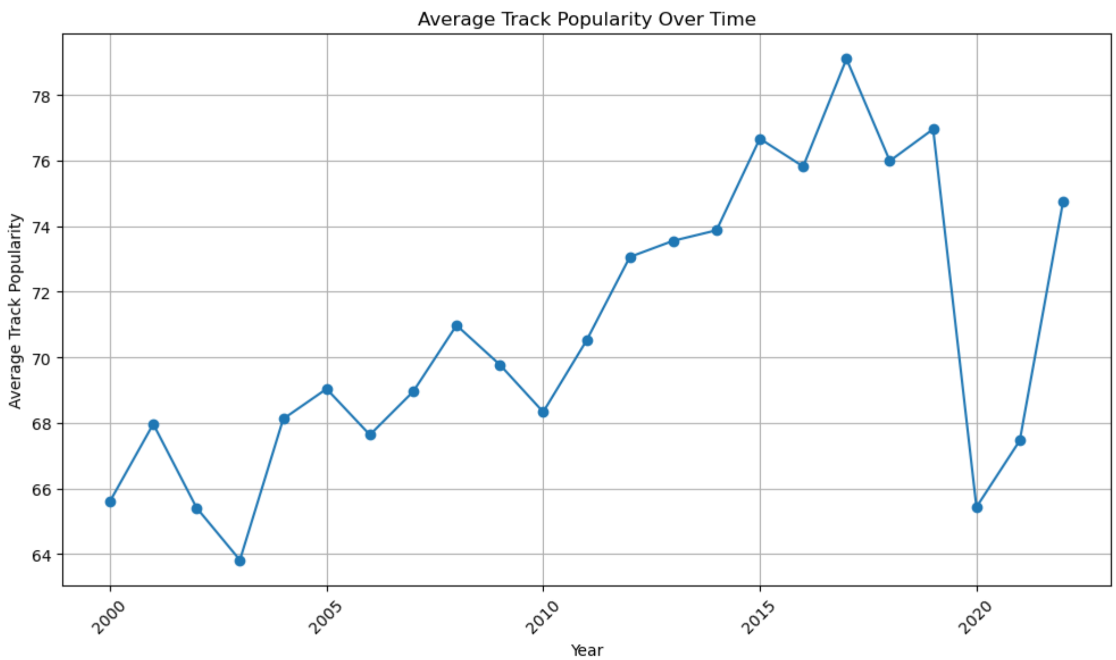
[24]:
```
# Ajustar el tamaño de la figura con matplotlib
plt.figure(figsize=[8, 4])
plt.hist2d(songs['loudness'], songs['track_popularity'], bins=[50, 50],
 ↪cmap='Blues', cmin=1)
plt.xlabel('The decibels in the song')
plt.ylabel('Track Popularity')
plt.title('2D Histogram of Track Popularity vs loudness')
plt.colorbar()
plt.show()
```



[25]:
```
# Ajustar el tamaño de la figura con matplotlib
plt.figure(figsize=[8, 4])


plt.hist2d(songs['energy'], songs['track_popularity'], bins=[50, 50],␣
 ↪cmap='Blues', cmin=1)
plt.xlabel('The % of energy that the song has')
plt.ylabel('Track Popularity')
plt.title('2D Histogram of Track Popularity vs energy')
plt.colorbar()
plt.show()
```



[26]:
```python
# Step 2: Group the data by year and calculate the average track popularity
average_popularity_by_year = songs.groupby('year')['track_popularity'].mean()

# Step 3: Plot the time series
plt.figure(figsize=(10, 6))
average_popularity_by_year.plot(kind='line', marker='o', linestyle='-')
plt.title('Average Track Popularity Over Time')
plt.xlabel('Year')
plt.ylabel('Average Track Popularity')
plt.grid(True)
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.tight_layout()  # Adjust layout to make room for the rotated x-axis labels
plt.show()
```



0.3 Data Processing

We are going to follow the following steps for our data processing: 1. Feature Engineering 2. Binning target variable

0.3.1 Feature Engineering

[27]:
```
# New feature called Melodic Energy that captures the interaction between␣
↪energy and danceability
songs['Melodic Energy'] = songs['energy']*songs['danceability']

# New feature called Emotional Tempo that captures the interaction between␣
↪valence and tempo
songs['Emotional Tempo'] = songs['valence']*songs['tempo']
# weight = 0.5
# songs['Acoustic Instruments'] = (weight * songs['instrumentalness']) +␣
↪(weight * songs['acousticness']) + 1

# songs['Loudness per ms'] = songs['loudness']/songs['duration_ms']

# Dropping the features that were used to create the new features to avoid␣
↪unnecessary multicollinearity
songs.drop(['energy', 'danceability', 'valence', 'tempo'], axis=1, inplace=True)
```

[28]:
```
# Select a subset of popular artists based on a threshold of artist popularity␣
↪for the median
high_popularity_artists = songs[songs['artist_popularity'] >␣
↪songs['artist_popularity'].median()]
# Calculate the median number of songs per popular artist
song_count_popular_artists = high_popularity_artists.groupby('artist_name').
↪size().median()
# Calculate the total number of songs
total_songs_count = len(songs)
# Calculate the ratio of songs by popular artists to total songs
high_popularity_ratio = song_count_popular_artists / total_songs_count

# Calculating individual songs per artist
songs_per_artist = songs.groupby('artist_name').size()
# Calculate artist ratio, handling potential division by zero errors
artist_ratio = songs_per_artist.div(total_songs_count, fill_value=0)
# Map the artist ratio to the original dataset
songs['artist_ratio'] = songs['artist_name'].map(artist_ratio)

# Calculating the difference between the artist ratio and the high popularity␣
↪artist ratio
songs['popularity_difference'] = songs['artist_ratio'] - high_popularity_ratio
# Dropping the artist ratio column to avoid multicollinearity
songs.drop('artist_ratio', axis=1, inplace=True)
```

[29]:
```
# # Creating encoded binary dummy columns for genre_label column
# genre_dummies = pd.get_dummies(songs['genre_label'], drop_first=True)
# # Concatenating the dummy columns to the original dataset
# songs = pd.concat([songs, genre_dummies], axis=1)
```

[30]:
```
# Drop the non-numerical columns where we don't find meaning
songs = songs.drop(columns=['track_name', 'album','artist_name',␣
↪'artist_genres','key','mode', 'genre_cluster', 'genre_label'], axis=1)
```

0.3.2 Binning

We decided to go with a binning approach into 2 bins, splitting on the track popularity of 70. From exploring the data, we saw that 70 provides us a pretty equal split.

[31]:
```
songs['popularity_binned'] = pd.cut(songs['track_popularity'], bins=[0,70,100],␣
↪labels=['Work in Progress','Hit'])
songs['popularity_binned'] = songs['popularity_binned'].
↪fillna(songs['popularity_binned'].mode()[0])
```

[32]:
```
# counting the number of records in our sign category
print(songs['popularity_binned'].value_counts())
```

```
popularity_binned
Hit                  1250
Work in Progress      931
Name: count, dtype: int64
```

[33]:
```
# Export cleaned version of the dataset to an Excel file to save the changes
songs.to_excel('Songs_2024_cleaned.xlsx', index=False)
```

[34]:
```
data=pd.read_excel("Songs_2024_cleaned.xlsx")
data.head()
```

[34]:
```
   year  track_popularity  artist_popularity  loudness  speechiness  \
0  2000                91                 86      85.0       0.0281
1  2000                84                 75      69.0       0.0488
2  2000                69                 61      95.0       0.0290
3  2000                88                 83      76.0       0.0584
4  2000                74                 65      68.0       0.0479

   acousticness  instrumentalness  liveness  duration_ms  Melodic Energy  \
0       0.00239          0.000121    0.2340     266773.0        0.283569
1       0.01030          0.000000    0.6120     167067.0        0.389298
2       0.17300          0.000000    0.2510     250547.0        0.262384
3       0.00958          0.000000    0.2090     216880.0        0.480384
4       0.03100          0.001200    0.0821     200400.0        0.564860

   Emotional Tempo  popularity_difference popularity_binned
0        49.411020               0.005961               Hit
1       101.728584              -0.000459               Hit
2        38.046802              -0.000459  Work in Progress
3        42.057200               0.002751               Hit
4       148.641318               0.000917               Hit
```

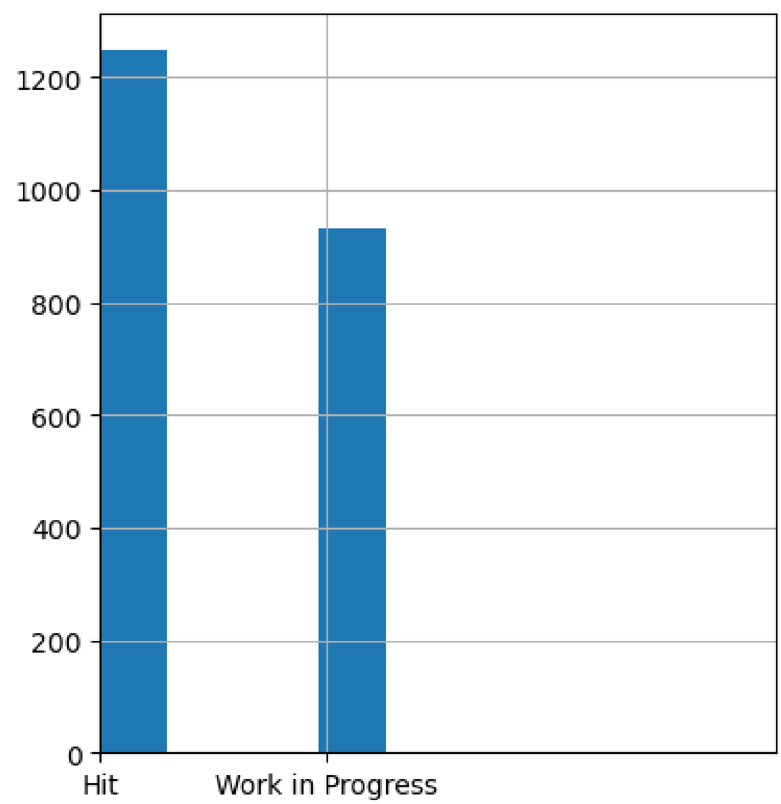
[35]:
```
data.describe()
```

[35]:
```
              year  track_popularity  artist_popularity     loudness  \
count  2181.000000       2181.000000        2181.000000  2181.000000
mean   2010.862907         70.775332          72.696470    72.957339
std       6.632351         12.114627          12.204621    15.709096
min    2000.000000          0.000000          29.000000   -56.000000
25%    2005.000000         65.000000          65.000000    63.000000
50%    2011.000000         72.000000          74.000000    74.000000
75%    2017.000000         78.000000          82.000000    83.000000
max    2022.000000        100.000000         100.000000   132.000000

       speechiness  acousticness  instrumentalness     liveness  \
count  2181.000000   2181.000000       2181.000000  2181.000000
mean      0.098194      0.155747          0.014084     0.173459
```

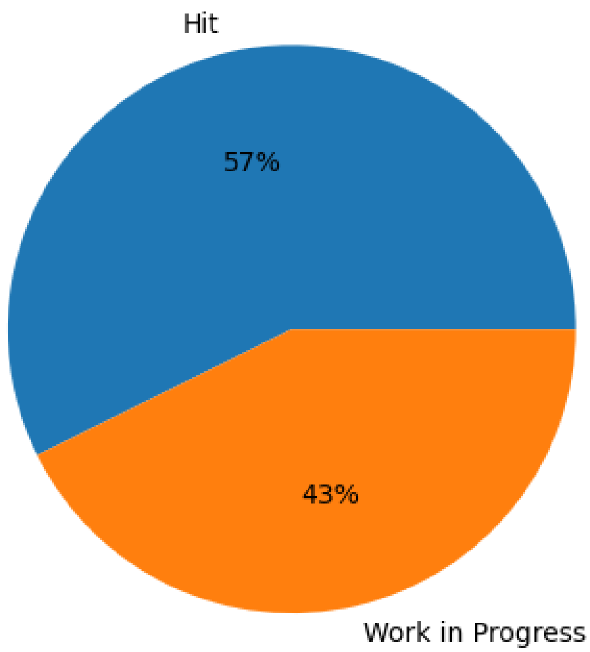
```
std         0.092620      0.202922          0.085464      0.132511
min         0.022500      0.000013          0.000000      0.021000
25%         0.038200      0.016400          0.000000      0.090000
50%         0.057100      0.068500          0.000000      0.120000
75%         0.117000      0.216000          0.000054      0.221000
max         0.576000      0.978000          0.985000      0.843000

         duration_ms  Melodic Energy  Emotional Tempo  popularity_difference
count    2181.000000     2181.000000      2181.000000            2181.000000
mean   226263.307339        0.457684        64.575285               0.001673
std     42192.772559        0.138661        31.459754               0.003133
min     97393.000000        0.020124         3.656558              -0.000917
25%    200360.000000        0.366704        40.797280              -0.000459
50%    221840.000000        0.465010        62.314008               0.000459
75%    245940.000000        0.556206        85.227034               0.002751
max    688453.000000        0.848216       172.636704               0.012380
```

[36]:
```python
# Exploring the binning of the target variable
data['popularity_binned'].hist(bins=30, figsize=(10, 5), width=0.3, ax=plt.
 ↪subplot(1, 2, 1))

plt.xlim(0, 3)
```

[36]:
```
(0.0, 3.0)
```



[37]:
```
unique, counts = np.unique(data["popularity_binned"], return_counts=True)
plt.pie(counts, labels=unique, autopct='%.0f%%');
```

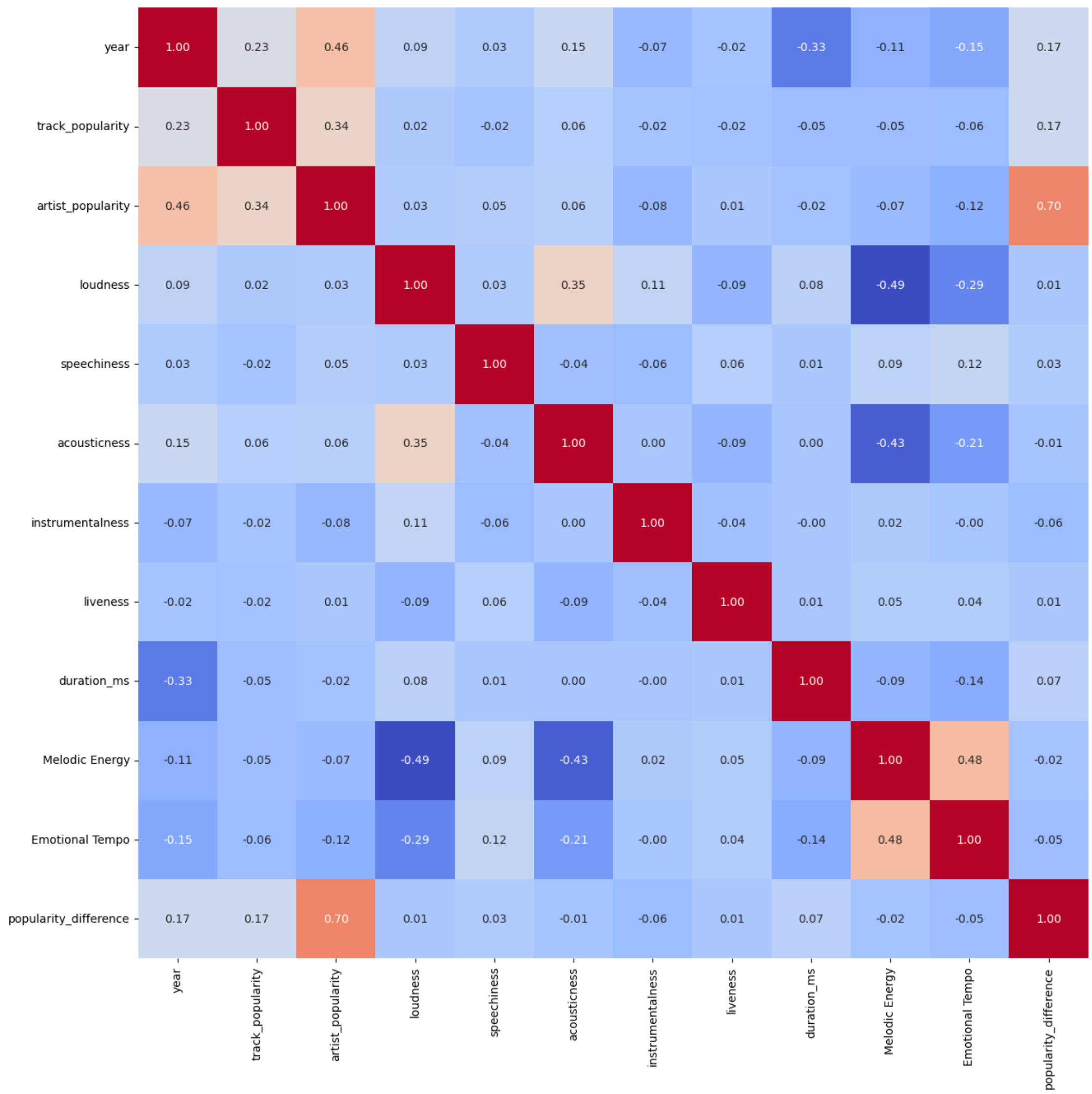


[38]:
```
data.columns
```

[38]:
```
Index(['year', 'track_popularity', 'artist_popularity', 'loudness',
       'speechiness', 'acousticness', 'instrumentalness', 'liveness',
       'duration_ms', 'Melodic Energy', 'Emotional Tempo',
       'popularity_difference', 'popularity_binned'],
      dtype='object')
```

[39]:
```
# Exploring the correlations between all features, both old and engineered new␣
↪ones
plt.figure(figsize=(15, 15))
to_plot_corr = data.drop(['popularity_binned'], axis=1)
sns.heatmap(to_plot_corr.corr(), annot=True, fmt=".2f", cmap='coolwarm',␣
↪cbar=False, square=True)
```

[39]:
```
<Axes: >
```



Splitting the data for models

[40]:
```
# Splitting the data into train and test

# Separate features from response field
X = data.drop(['popularity_binned', 'track_popularity'], axis=1)
y = data['popularity_binned']

# This encodes the target variable, y, into 0 and 1 (1 meaning Hit and 0␣
↪meaning Work in Progress)
encode = LabelEncoder()
y = encode.fit_transform(y)
```

```
# train test split with 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =0.2,␣
↪random_state= 123)
```

[41]:
```
y_train.shape, y_test.shape
```

[41]: ((1744,), (437,))

0.4 Random Forest model

We try first with Random Forest. This model has some features for consideration: - Number of trees (estimators) does not impact overfitting - Max features matters here (just bagging with number of features used for model limited) - Must tune to find best hyperparameters: - 'max_depth': maximum number of levels in each decision tree - 'min_samples_leaf': minimum number of samples required to be at a leaf node - 'max_features': max features considered for each decision tree (we have 11 features total)

Potential scoring metrics: - Accuracy: (TP + TN) / (TP + TN + FP + FN) - f1 score = 2 * (precision * recall) / (precision + recall) - roc_auc = Area under the ROC curve

Given our business model, we will choose the best metric to be the F1 score, given as it captures the interaction between precious and recall quite nicely.

[42]:
```
# Setting the parameter for GridSearchCV to focus on accuracy score optimization
scorer = 'accuracy'
```

[43]:
```
# Instantiate the RF model
rf = RandomForestClassifier(n_estimators=400, oob_score=True, random_state=123)
rf.fit(X_train, y_train)
```

[43]: RandomForestClassifier(n_estimators=400, oob_score=True, random_state=123)

Now we do a grid searching of best hyper parameters for Random Forest.

[44]:
```
# grid search for best RF parameters
rf_params = {
    'max_depth': [4,5,6], # maximum number of levels in each decision tree
    'min_samples_leaf': [1,3,5,7], # minimum number of samples required to be␣
↪at a leaf node
    'max_features': [8,9,10,11] # we have 10 features
    }
# Instantiate the grid search model with the RF model and the parameter grid
grid_rf = GridSearchCV(estimator = rf,
                      param_grid = rf_params,
                      cv=5,
                      scoring=scorer,
                      verbose=2)
# Fit the grid search to the data
```

```
grid_rf.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
[CV] END …max_depth=4, max_features=8, min_samples_leaf=1; total time=   1.5s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=1; total time=   1.6s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=1; total time=   1.6s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=1; total time=   1.6s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=1; total time=   1.6s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=3; total time=   1.6s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=3; total time=   1.4s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=3; total time=   1.3s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=3; total time=   1.3s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=3; total time=   1.7s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=5; total time=   1.5s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=5; total time=   1.7s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=5; total time=   1.5s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=5; total time=   1.6s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=5; total time=   1.5s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=7; total time=   2.0s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=7; total time=   1.6s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=7; total time=   1.9s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=7; total time=   1.7s
[CV] END …max_depth=4, max_features=8, min_samples_leaf=7; total time=   2.1s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=1; total time=   1.7s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=1; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=1; total time=   1.7s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=1; total time=   1.9s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=1; total time=   1.8s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=3; total time=   1.7s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=3; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=3; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=3; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=3; total time=   1.7s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=5; total time=   1.7s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=5; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=5; total time=   1.7s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=5; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=5; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=7; total time=   1.7s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=7; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=7; total time=   1.6s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=7; total time=   1.8s
[CV] END …max_depth=4, max_features=9, min_samples_leaf=7; total time=   1.9s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=1; total time=   1.9s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=1; total time=   1.9s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=1; total time=   1.9s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=1; total time=   1.9s
```

```
[CV] END …max_depth=4, max_features=10, min_samples_leaf=1; total time=   1.8s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=3; total time=   1.9s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=3; total time=   1.8s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=3; total time=   1.8s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=3; total time=   2.1s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=3; total time=   2.0s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=5; total time=   2.2s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=5; total time=   2.1s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=5; total time=   2.1s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=5; total time=   1.9s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=5; total time=   1.9s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=7; total time=   1.8s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=7; total time=   2.1s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=7; total time=   1.7s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=7; total time=   1.8s
[CV] END …max_depth=4, max_features=10, min_samples_leaf=7; total time=   1.6s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=1; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=1; total time=   1.8s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=1; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=1; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=1; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=3; total time=   1.8s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=3; total time=   1.6s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=3; total time=   1.8s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=3; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=3; total time=   1.6s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=5; total time=   1.8s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=5; total time=   1.8s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=5; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=5; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=5; total time=   1.8s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=7; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=7; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=7; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=7; total time=   1.7s
[CV] END …max_depth=4, max_features=11, min_samples_leaf=7; total time=   1.8s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=1; total time=   1.8s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=1; total time=   1.9s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=1; total time=   1.9s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=1; total time=   1.7s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=1; total time=   1.6s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=3; total time=   1.7s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=3; total time=   1.7s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=3; total time=   1.7s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=3; total time=   1.8s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=3; total time=   1.9s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=5; total time=   2.0s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=5; total time=   1.8s
```

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[CV] END …max_depth=5, max_features=8, min_samples_leaf=5; total time=   1.7s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=5; total time=   1.7s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=5; total time=   1.8s
[CV] END …max_depth=5, max_features=8, min_samples_leaf=7; total time=   1.7s
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[CV] END …max_depth=5, max_features=8, min_samples_leaf=7; total time=   1.8s
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[CV] END …max_depth=5, max_features=9, min_samples_leaf=1; total time=   1.9s
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[CV] END …max_depth=5, max_features=11, min_samples_leaf=5; total time=   2.6s
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[CV] END …max_depth=6, max_features=11, min_samples_leaf=5; total time=   2.5s
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[CV] END …max_depth=6, max_features=11, min_samples_leaf=5; total time=   2.4s
[CV] END …max_depth=6, max_features=11, min_samples_leaf=7; total time=   2.5s
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[CV] END …max_depth=6, max_features=11, min_samples_leaf=7; total time=   2.3s
[CV] END …max_depth=6, max_features=11, min_samples_leaf=7; total time=   2.7s
[CV] END …max_depth=6, max_features=11, min_samples_leaf=7; total time=   2.4s
[CV] END …max_depth=6, max_features=11, min_samples_leaf=7; total time=   2.4s
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[44]:
```
GridSearchCV(cv=5,
             estimator=RandomForestClassifier(n_estimators=400, oob_score=True,
                                              random_state=123),
             param_grid={'max_depth': [4, 5, 6], 'max_features': [8, 9, 10, 11],
                         'min_samples_leaf': [1, 3, 5, 7]},
             scoring='accuracy', verbose=2)
```

[45]:
```
# Random Forest model with the best parameters found by GridSearchCV
random_forest_model = RandomForestClassifier(
    n_estimators = 400, random_state=123, #
    max_depth=grid_rf.best_params_['max_depth'], # from our grid search
    max_features=grid_rf.best_params_['max_features'], # from our grid search
    min_samples_leaf=grid_rf.best_params_['min_samples_leaf'], # from our grid␣
 ↪search
    verbose=2) # verbose = 2 means that we want to see the output

# Fit the hyperparameter-tuned model to the training data
random_forest_model.fit(X_train, y_train)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.0s remaining:    0.0s
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building tree 400 of 400

[Parallel(n_jobs=1)]: Done 400 out of 400 | elapsed:    1.7s finished
```

[45]:
```
RandomForestClassifier(max_depth=5, max_features=8, min_samples_leaf=7,
                       n_estimators=400, random_state=123, verbose=2)
```

[46]:
```python
# Predictions for the training and testing sets
rf_test_pred = random_forest_model.predict(X_test)
rf_train_pred = random_forest_model.predict(X_train)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done 400 out of 400 | elapsed:    0.0s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done 400 out of 400 | elapsed:    0.1s finished
```

[47]:
```python
# Accuracy scores for the training and testing sets
acc_rf_train= accuracy_score(y_train, rf_train_pred)
acc_rf_test = accuracy_score(y_test, rf_test_pred)

print("Train set Accuracy: %f " % (acc_rf_train))
print("Test set Accuracy: %f " % (acc_rf_test))

# AUC scores for the training and testing sets
roc_rf_train = roc_auc_score(y_train, rf_train_pred)
roc_rf_test = roc_auc_score(y_test, rf_test_pred)

print("Train set AUC: %f" % (roc_rf_train))
print("Test set AUC: %f" % (roc_rf_test))

# F1 scores for the training and testing sets
f1_rf_train = f1_score(y_train, rf_train_pred, average='macro')
f1_rf_test = f1_score(y_test, rf_test_pred, average='macro')

print("Train set F1: %f" % (f1_rf_train))
print("Test set F1: %f" % (f1_rf_test))
```

```
Train set Accuracy: 0.774656
Test set Accuracy: 0.720824
Train set AUC: 0.756960
Test set AUC: 0.697867
Train set F1: 0.761811
Test set F1: 0.701570
```

[48]:
```python
# Create a DataFrame to store the evaluation results
metrics_rf_df = pd.DataFrame({
    'Train': [acc_rf_train, roc_rf_train, f1_rf_train],
    'Test': [acc_rf_test, roc_rf_test, f1_rf_test]
}, index=['Accuracy', 'AUC', 'F1 Score'])

# Print the DataFrame
print(metrics_rf_df)
```

```
            Train      Test
Accuracy  0.774656  0.720824
AUC       0.756960  0.697867
F1 Score  0.761811  0.701570
```

[49]:
```
# Classification report for the best XGBoost model
print(classification_report(y_test, rf_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.73      0.84      0.78       255
           1       0.71      0.56      0.63       182

    accuracy                           0.72       437
   macro avg       0.72      0.70      0.70       437
weighted avg       0.72      0.72      0.71       437
```

When we run the model without hyperparameter tuning, it does worse. Hyperparameter tuning is essential to ensure our model is making the best choices to avoid overfitting.

We can display the most important features:

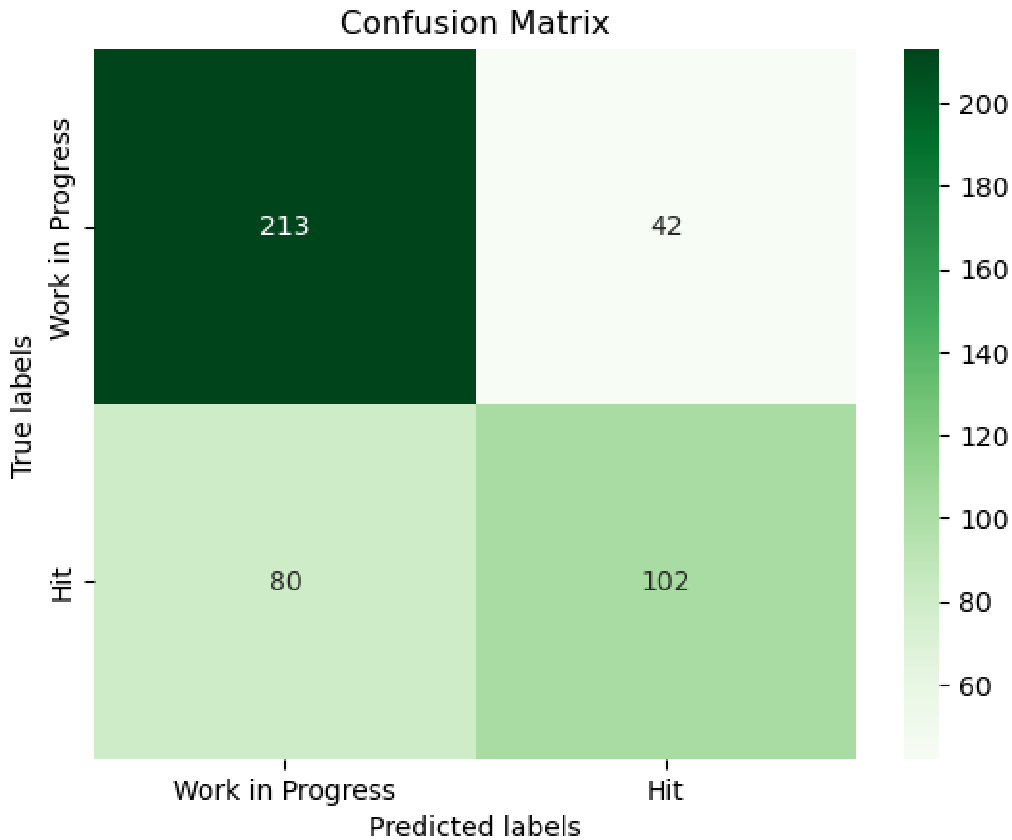
[50]:
```
pd.Series(random_forest_model.feature_importances_, index = X.columns).
 ↪sort_values(ascending = False)
```

[50]:
```
artist_popularity         0.417694
year                      0.306164
popularity_difference     0.044037
acousticness              0.042393
loudness                  0.033851
duration_ms               0.033671
Melodic Energy            0.028978
Emotional Tempo           0.028901
speechiness               0.027978
liveness                  0.026114
instrumentalness          0.010218
dtype: float64
```

[51]:
```
# Initialize the confusion matrix
cm = confusion_matrix(y_test, rf_test_pred)
ax= plt.subplot()
# Create a heatmap of the confusion matrix
sns.heatmap(cm, annot=True, ax = ax, fmt='g', cmap='Greens'); #annot=True to␣
 ↪annotate cells

# Setting labels, title and ticks
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix');
```

```
ax.xaxis.set_ticklabels(['Work in Progress', 'Hit']); ax.yaxis.
↪set_ticklabels(['Work in Progress', 'Hit']);
```



0.5 XGBoost model

Let's attempt an XGBoost Regressor to see if we can get a better performance.

[68]:
```
# Instantiate XGBoost model
model = XGBClassifier(n_estimators=200)
# Fit the model to the training data
model.fit(X_train, y_train)
scorer = 'accuracy'
# Parameters for GridSearchCV for XGBoost
params = {
        'subsample': [0.6, 0.8, 1.0], # the fraction of samples to be used for␣
↪fitting the individual base learners
        'max_depth': [3, 5, 7], # maximum number of levels in each decision tree
        'learning_rate': [0.001, 0.01, 0.1] # step size shrinkage used to␣
↪prevent overfitting
        }
```

```python
# Instantiate the grid search model with the XGBoost model and the parameter␣
↪grid
xgbGrid = GridSearchCV(model, params, cv = 5, scoring='roc_auc', verbose=1)
# Fit the grid search to the data
xgbGrid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
```

[68]:
```
GridSearchCV(cv=5,
             estimator=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=False, eval_metric=None,
                                     feature_types=None, gamma=None,
                                     grow_policy=None, importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=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=200,
                                     n_jobs=None, num_parallel_tree=None,
                                     random_state=None, …),
             param_grid={'learning_rate': [0.001, 0.01, 0.1],
                         'max_depth': [3, 5, 7], 'subsample': [0.6, 0.8, 1.0]},
             scoring='roc_auc', verbose=1)
```

[69]:
```python
# fitting grid search to XGB model
XGB_model = XGBClassifier(n_estimators = 200, random_state=123,
                          subsample=xgbGrid.best_params_['subsample'], # from␣
↪our grid search
                          max_depth=xgbGrid.best_params_['max_depth'], # from␣
↪our grid search
                          learning_rate=xgbGrid.
↪best_params_['learning_rate'], # from our grid search
                          verbose=2) # verbose = 2 means that we want to see␣
↪the output
XGB_model.fit(X_train, y_train)
# pred_train = XGB_model.predict(X_train)
# pred_test = XGB_model.predict(X_test)
```

```
/Users/nataliaclark/anaconda3/lib/python3.11/site-packages/xgboost/core.py:160:
```

```
UserWarning:

[21:38:47] WARNING: /Users/runner/work/xgboost/xgboost/src/learner.cc:742:
Parameters: { "verbose" } are not used.
```

[69]:
```
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=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.01, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=3, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=200, n_jobs=None,
              num_parallel_tree=None, random_state=123, …)
```

[70]:
```python
# Prediction using XGBoost model with the best parameters found by GridSearchCV
pred_train = XGB_model.predict_proba(X_train)[:, 1]
pred_test = XGB_model.predict_proba(X_test)[:, 1]

# Convert predicted probabilities to binary predictions (0 or 1) using a␣
↪threshold of 0.5
pred_train_binary = (pred_train >= 0.5).astype(int)
pred_test_binary = (pred_test >= 0.5).astype(int)
```

[71]:
```python
# Accuracy scores for the training and testing sets
acc_boost_train = accuracy_score(y_train, pred_train_binary)
acc_boost_test = accuracy_score(y_test, pred_test_binary)

print("Attempt 1 Train Accuracy: %f" % (acc_boost_train))
print("Attempt 1 Test Accuracy: %f" % (acc_boost_test))

# AUC scores for the training and testing sets
roc_boost_train = roc_auc_score(y_train, pred_train)
roc_boost_test = roc_auc_score(y_test, pred_test)

print("Train set AUC: %f" % (roc_boost_train))
print("Test set AUC: %f" % (roc_boost_test))

f1_boost_train = f1_score(y_train, pred_train_binary)
f1_boost_test = f1_score(y_test, pred_test_binary)
print("F1 Score Train: ", f1_boost_train)
print("F1 Score Test: ", f1_boost_test)
```

```
Attempt 1 Train Accuracy: 0.749427
```

```
Attempt 1 Test Accuracy: 0.720824
Train set AUC: 0.824440
Test set AUC: 0.760267
F1 Score Train:  0.6630686198920586
F1 Score Test:  0.6139240506329114
```

[72]:

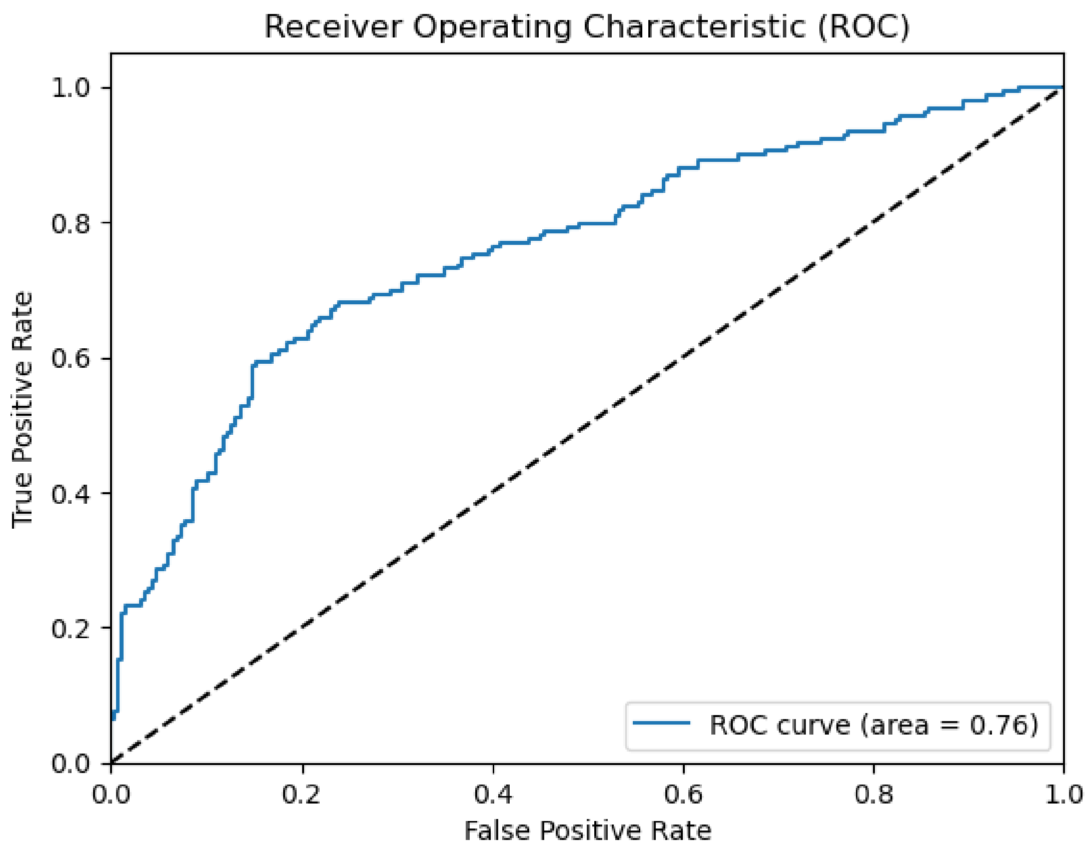
```
# Create a DataFrame to store the evaluation results
metrics_boost_df = pd.DataFrame({
    'Train': [acc_boost_train, roc_boost_train, f1_boost_train],
    'Test': [acc_boost_test, roc_boost_test, f1_boost_test]
}, index=['Accuracy', 'AUC', 'F1'])

# Print the DataFrame
print(metrics_boost_df)
```

```
             Train      Test
Accuracy  0.749427  0.720824
AUC       0.824440  0.760267
F1        0.663069  0.613924
```

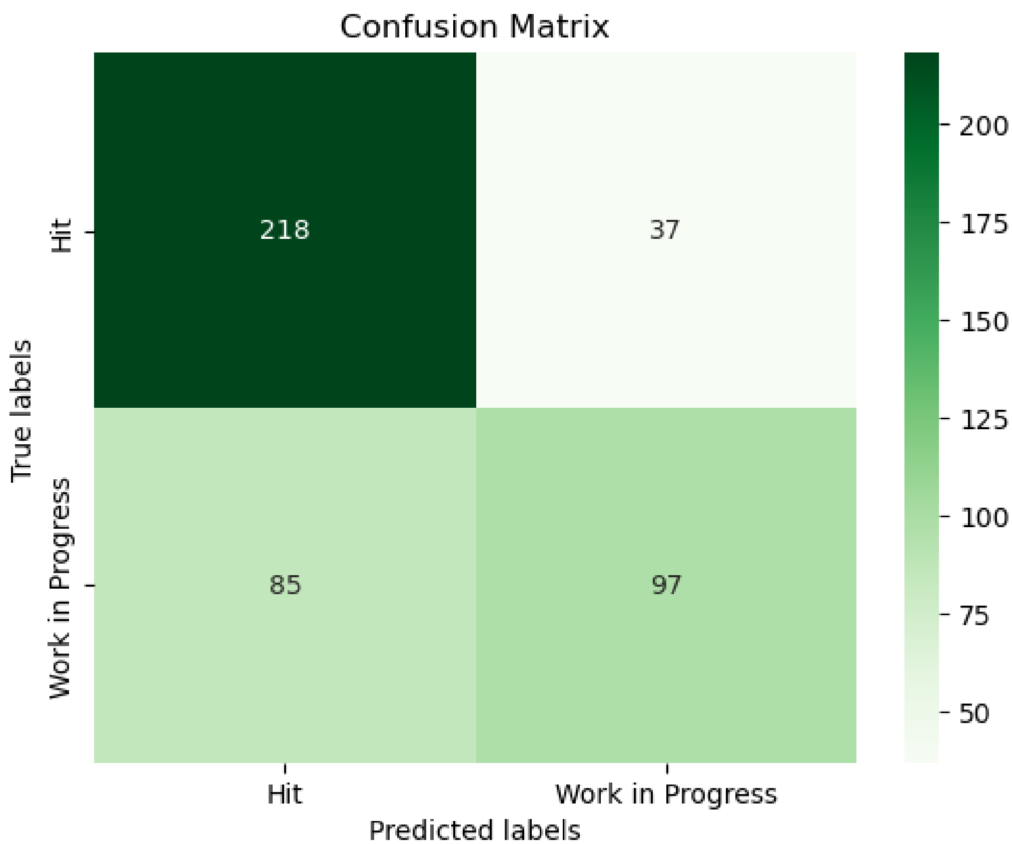
[57]:

```
# Plot the ROC curve
# Initialize the plot
fpr, tpr, thresholds = roc_curve(y_test, pred_test)
# Calculate the AUC
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_boost_test)
# Plot the diagonal line from (0, 1)
plt.plot([0, 1], [0, 1], 'k--')
# Set the limits of the plot for x and y axes
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
# Set the labels and title
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
# Show the legend
plt.legend(loc="lower right")
# Show the plot
plt.show()
```



[58]:
```
# Initialize the confusion matrix
cm = confusion_matrix(y_test, pred_test_binary)
ax= plt.subplot()
# Create a heatmap of the confusion matrix
sns.heatmap(cm, annot=True, ax = ax, fmt='g', cmap='Greens'); #annot=True to␣
↪annotate cells

# Setting labels, title and ticks
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(['Hit', 'Work in Progress']); ax.yaxis.
↪set_ticklabels(['Hit', 'Work in Progress']);
```



[59]:
```
# Finding feature importances from the best XGBoost model
feature_importances = XGB_model.feature_importances_

# Create a Series with feature importances as values and feature names as index
feature_importance_series = pd.Series(feature_importances, index=X.columns)

# Sort the Series by importance values in descending order
feature_importance_series_sorted = feature_importance_series.
 ↪sort_values(ascending=False)

# Show the feature importances
print(feature_importance_series_sorted)
```

```
artist_popularity         0.239313
year                      0.231101
popularity_difference     0.084452
loudness                  0.071111
duration_ms               0.066785
Melodic Energy            0.057306
acousticness              0.054091
```

```
speechiness              0.050549
Emotional Tempo          0.049564
liveness                 0.048824
instrumentalness         0.046905
dtype: float32
```

[60]:
```
# Classification report for the best XGBoost model
print(classification_report(y_test, pred_test_binary))
```

```
              precision    recall  f1-score   support

           0       0.72      0.85      0.78       255
           1       0.72      0.53      0.61       182

    accuracy                           0.72       437
   macro avg       0.72      0.69      0.70       437
weighted avg       0.72      0.72      0.71       437
```

0.5.1 Appendix: Considerations to follow thinking process

- Genre variable: it was referring to the artist, not the track itself. We considered a segmentation of the variable into groups, but when we tried with these variables, they did not add information to our model.
- Choosing a model: our data had outliers and not too many features, made sense to use a tree based model. We tried a simple Decision Tree, Bagging, Random Forest, and Boosting. Boosting seemed to consistently show us the best results, so we decided to use it. We have shown the code here for our 2 most successful models, seeing as we wanted to reduce the complexity of the notebook.
- Feature Engineering: How can we find more information in combinations of variables? We decided that danceability and energy could be multiplied, valence and tempo could be multiplied, and we could come up with a feature for the difference of the percentage of songs made by "popular artists" to the track's artists percentage of songs made. We set this threshold at the 75th percentile.
- What do we do with outliers?: Since we were deciding to use a tree-based model, we knew that outliers are implicitly handled well with these models. We did not worry about clipping them.
- Train/test split: 2300 records is not a lot - we want to have enough training data, but also reserve enough for testing.
- Overfitting: number of trees doesn't impact with most of these models, so we focused on the hyperparameters that would cause our model to overfit for each model and tried to tune on those.
- Computational complexity: considered, which is why we limited grid search parameters using logic and best judgment
- Feature importance: Seems to be artist popularity for all models tested. How can we turn this into a business approach to our problem?
- How do we choose an evaluation metric that best encapsulates our goal? How do we defend the accuracy numbers without undermining our model?