ECS784 - Data Analytics - Coursework 1

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Modeling Song Popularity: The Impact of Audio Features and Streaming Metadata in the Digital Music Landscape

Data Analysis & Machine Learning Implementation

Description:

This notebook explores the relationship between audio features, streaming metadata, and song popularity.

Objective:

- Understand the Dataset & cleanup.
- Build two Machine Learning models to predict the song popularity.
- Evaluate the models & compare their respective scores.

Acknowledgement:

The dataset is referred from Kaggle. It consists mainly with data from Spotify. Dataset Link: https://www.kaggle.com/datasets/priyamchoksi/spotify-dataset-114k-songs/data

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Strractegic Plan of Action

1. Importing the Libraries
2. Loading the Dataset
3. Additional Data Collection
4. Data Pre-processing
5. Exploratory Data Analysis (EDA)
6. Data Manipulation
7. Dataset Splitting
8. Feature Selection/Extraction
9. Data Normalisation
10. Model Training - Evaluation

1 1. Importing the Libraries

[367]:
```
# Essential Libraries
import os
import time
import warnings
import requests
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import display

# Suppress warnings
warnings.filterwarnings('ignore')

# Machine Learning Models
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor

# Data Preprocessing & Feature Engineering
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.feature_selection import RFE
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Model Training & Evaluation
from sklearn.model_selection import train_test_split
from sklearn.metrics import (
    accuracy_score, r2_score, mean_absolute_error, mean_squared_error,
    confusion_matrix, classification_report, roc_curve, auc
)

# Web & API-related Libraries
from flask import Flask, request, redirect
from dotenv import load_dotenv
from concurrent.futures import ThreadPoolExecutor, as_completed
```

---

2 Loading the Dataset

[291]:
```
file_path = '/Users/petros/MSc Computer Science/ECS 784 - Data Analytics/
↪Coursework 1/New_approach/dataset_updated.csv'
df = pd.read_csv(file_path)
display(df.head())
```

```
   Unnamed: 0                track_id       artists  \
0           0  5SuOikwiRyPMVoIQDJUgSV    Gen Hoshino
```

```
1          10  4mzP5mHkRvGxdhdGdAH7EJ  Zack Tabudlo
2          20  3S0OXQeoh0w6AY8WQVckRW    Jason Mraz
3          30  3EQV1ZHtHvq9OnVRYIdbg3    Jason Mraz
4          40  6sp6Vx3sv2l5qxPfbQkcyt  Eddie Vedder

                           album_name           track_name  song_popularity  \
0                              Comedy               Comedy               73
1                             Episode  Give Me Your Forever               74
2  We Sing. We Dance. We Steal Things.             I'm Yours               75
3                     Merry Christmas     Winter Wonderland                0
4            Mega Hits Autumn/Fall 2022             The Haves               0

   duration_ms  explicit  danceability  energy  ...  speechiness  \
0       230666     False         0.676   0.461  ...       0.1430
1       244800     False         0.627   0.363  ...       0.0291
2       242946     False         0.703   0.444  ...       0.0417
3       131760     False         0.620   0.309  ...       0.0495
4       306794     False         0.474   0.519  ...       0.0253

   acousticness  instrumentalness  liveness  valence    tempo  time_signature  \
0        0.0322          0.000001    0.3580    0.715   87.917               4
1        0.2790          0.000000    0.0928    0.301   99.905               4
2        0.5590          0.000000    0.0973    0.712  150.960               4
3        0.7880          0.000000    0.1460    0.664  145.363               4
4        0.2810          0.000000    0.1070    0.326  151.832               4

   track_genre   playcount  listeners
0     acoustic   1612709.0   130314.0
1     acoustic    740989.0    70791.0
2     acoustic  15028381.0  1863538.0
3     acoustic    166496.0    60700.0
4     acoustic     66517.0    17045.0

[5 rows x 23 columns]
```

2.1 Checking the dtypes of all the columns

[294]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 92369 entries, 0 to 92368
Data columns (total 23 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Unnamed: 0        92369 non-null  int64
 1   track_id          92369 non-null  object
 2   artists           92369 non-null  object
 3   album_name        92369 non-null  object
```

```
 4   track_name        92369 non-null  object
 5   song_popularity   92369 non-null  int64
 6   duration_ms       92369 non-null  int64
 7   explicit          92369 non-null  bool
 8   danceability      92369 non-null  float64
 9   energy            92369 non-null  float64
 10  key               92369 non-null  int64
 11  loudness          92369 non-null  float64
 12  mode              92369 non-null  int64
 13  speechiness       92369 non-null  float64
 14  acousticness      92369 non-null  float64
 15  instrumentalness  92369 non-null  float64
 16  liveness          92369 non-null  float64
 17  valence           92369 non-null  float64
 18  tempo             92369 non-null  float64
 19  time_signature    92369 non-null  int64
 20  track_genre       92369 non-null  object
 21  playcount         92369 non-null  float64
 22  listeners         92369 non-null  float64
dtypes: bool(1), float64(11), int64(6), object(5)
memory usage: 15.6+ MB
```

Interpretation: The dataset consists of **92,369** songs and **23 attributes**. It captures a mix of **audio characteristics (e.g., danceability, energy, tempo)** and **streaming metrics (e.g., play count, listeners)**.

With **no missing values** and a structured format, the dataset is well-prepared for statistical analysis and machine learning applications. The diverse range of features allows for a **data-driven exploration of song popularity trends** based on both musical properties and listener engagement.

Note: The dataset have fewer than 100000 records because - as explained in the paper - after fetching the 'listeners' and 'playcount', some records with no data in those columns were being removed.

2.2 Checking number of unique rows in each feature

Helps determine which columns contain categorical vs. continuous data

[298]:
```
df.nunique().sort_values()
```

[298]:
```
explicit               2
mode                   2
time_signature         5
key                   12
song_popularity      101
track_genre          114
danceability        1127
speechiness         1467
liveness            1704
```

```
valence               1751
energy                1948
acousticness          5012
instrumentalness      5290
loudness             17805
artists              19068
listeners            28123
album_name           37569
playcount            40094
tempo                40289
duration_ms          42091
track_name           59064
track_id             72325
Unnamed: 0           92369
dtype: int64
```

2.3 Determine Categorical and Numeric Features

[369]:
```python
# Define features
features = df.columns.tolist()

# Calculate unique values
nu = df[features].nunique().sort_values()
nf = []  # Numerical Features
cf = []  # Categorical Features

# Classify features as numerical or categorical based on unique values
for i in range(df.shape[1]):  # Iterate over all columns
    if nu.values[i] <= 16:
        cf.append(nu.index[i])  # Categorical
    else:
        nf.append(nu.index[i])  # Numerical

# Print numerical & categorical feature count in green
print('\n\033[92mInterpretation:\033[0m The Dataset has {} numerical & {}␣
↪categorical features.'.format(len(nf), len(cf)))

# Print categorical and numerical feature names
print("\nCategorical Features:", cf)
print("\nNumerical Features:", nf)
```

```
Interpretation: The Dataset has 14 numerical & 4 categorical features.

Categorical Features: ['explicit', 'mode', 'time_signature', 'key']

Numerical Features: ['song_popularity', 'track_genre', 'danceability',
'speechiness', 'liveness', 'valence', 'energy', 'acousticness',
```

'instrumentalness', 'loudness', 'listeners', 'playcount', 'tempo',
'duration_ms']

2.4 Checking the stats of all the columns

[307]:
```
display(df.describe())
```

```
          Unnamed: 0  song_popularity   duration_ms  danceability  \
count   92369.000000     92369.000000  9.236900e+04  92369.000000
mean    56945.604489        33.408871  2.265400e+05      0.561857
std     32995.467348        22.530959  1.054532e+05      0.170716
min         0.000000         0.000000  1.338600e+04      0.000000
25%     28588.000000        17.000000  1.743550e+05      0.452000
50%     57426.000000        34.000000  2.128120e+05      0.574000
75%     85752.000000        50.000000  2.591050e+05      0.687000
max    113999.000000       100.000000  5.237295e+06      0.985000

             energy           key      loudness          mode  speechiness  \
count  92369.000000  92369.000000  92369.000000  92369.000000  92369.000000
mean       0.647695      5.300913     -8.141625      0.647068      0.083301
std        0.249009      3.558513      4.826038      0.477884      0.108154
min        0.000020      0.000000    -49.531000      0.000000      0.000000
25%        0.477000      2.000000     -9.953000      0.000000      0.035300
50%        0.690000      5.000000     -6.960000      1.000000      0.048200
75%        0.859000      8.000000     -4.987000      1.000000      0.081900
max        1.000000     11.000000      4.532000      1.000000      0.965000

       acousticness  instrumentalness      liveness       valence  \
count  92369.000000      92369.000000  92369.000000  92369.000000
mean       0.307672          0.153213      0.213835      0.479284
std        0.328803          0.307420      0.190553      0.259129
min        0.000000          0.000000      0.009250      0.000000
25%        0.014300          0.000000      0.098200      0.266000
50%        0.160000          0.000040      0.132000      0.469000
75%        0.585000          0.043200      0.274000      0.688000
max        0.996000          1.000000      0.997000      0.995000

              tempo  time_signature     playcount     listeners
count  92369.000000    92369.000000  9.236900e+04  9.236900e+04
mean     122.370046        3.905033  7.813009e+05  9.369392e+04
std       30.082062        0.419681  3.010490e+06  2.653359e+05
min        0.000000        0.000000  0.000000e+00  0.000000e+00
25%       99.088000        4.000000  1.758000e+03  4.840000e+02
50%      122.008000        4.000000  2.136100e+04  4.845000e+03
75%      140.569000        4.000000  2.172130e+05  4.012600e+04
max      243.372000        5.000000  1.347577e+08  3.472457e+06
```

Interpretation: The stats appear to be within a reasonable range; however, further analysis will be conducted to verify for any potential outliers and ensure data consistency.

---

3 Additional Data Collection

Interpretation: Fetching the 'playcount' and 'listeners' features from Last.fm API

3.1 Load environment variables from .env file

[49]:
```
load_dotenv()
```

[49]: True

3.2 Collecting the additional features

[ ]:
```
LASTFM_API_KEY = "LASTFM_API_KEY"
LASTFM_API_URL = "http://ws.audioscrobbler.com/2.0/"

def normalize_string(text):
    """Normalize artist and track names for better API matching."""
    return text.strip().lower().replace("&", "and").replace("'", "").
 ↪replace("-", "")

def get_lastfm_track_info(artist, track, retries=3):
    """Fetch playcount and listeners from Last.fm with retries."""
    normalized_artist = normalize_string(artist)
    normalized_track = normalize_string(track)

    params = {
        "method": "track.getInfo",
        "api_key": LASTFM_API_KEY,
        "artist": normalized_artist,
        "track": normalized_track,
        "format": "json"
    }

    for attempt in range(retries):
        try:
            response = requests.get(LASTFM_API_URL, params=params, timeout=5)

            if response.status_code == 200:
                data = response.json()
                if "track" in data:
                    return {
                        "playcount": int(data["track"].get("playcount", 0)),
                        "listeners": int(data["track"].get("listeners", 0))
```

```python
                    }

            # If no valid data, wait & retry
            time.sleep(1 + attempt)

        except requests.RequestException as e:
            print(f"Error fetching {track} by {artist}: {e}")

    return {"playcount": 0, "listeners": 0}  # Return 0 if all attempts fail

# Ensure "playcount" and "listeners" columns exist
if "playcount" not in df.columns:
    df["playcount"] = 0
if "listeners" not in df.columns:
    df["listeners"] = 0

# Filter only missing data to reduce API calls
df_to_fetch = df[(df["playcount"] == 0) & (df["listeners"] == 0)]
print(f"Fetching data for {len(df_to_fetch)} songs (Skipping already fetched␣
↪songs)")

# Process dataset with increased threading
MAX_THREADS = 50  # Increase for speed
batch_size = 1000  # Save progress more frequently

with ThreadPoolExecutor(max_workers=MAX_THREADS) as executor:
    futures = {executor.submit(get_lastfm_track_info, row["artists"],␣
↪row["track_name"]): index for index, row in df_to_fetch.iterrows()}

    for count, future in enumerate(as_completed(futures), 1):
        index = futures[future]
        result = future.result()

        # Update the dataframe with fetched data
        df.at[index, "playcount"] = result["playcount"]
        df.at[index, "listeners"] = result["listeners"]

        # Print progress every 500 records
        if count % 500 == 0:
            print(f"Processed {count}/{len(df_to_fetch)} records...")

        # Save intermediate results every 1000 records
        if count % batch_size == 0:
            temp_output = f"./Temp_Music_Info_LastFM_{count}.csv"
            df.to_csv(temp_output, index=False)
            print(f" Saved progress at {count} records: {temp_output}")
```

```
# Final save of the complete dataset
output_file = "./Music_Info_LastFM_Optimized.csv"
df.to_csv(output_file, index=False)

print(f"\n Full dataset saved: {output_file}")
```

---

4 Data Pre-processing

4.1 Remove Unecessary Features

[309]:
```
df.drop(columns=['Unnamed: 0', 'track_id', 'artists', 'album_name',␣
↪'track_name'], inplace=True)
```

[309]:
```
song_popularity     0
duration_ms         0
explicit            0
danceability        0
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
tempo               0
time_signature      0
track_genre         0
playcount           0
listeners           0
dtype: int64
```

Interpretation: The columns 'Unnamed: 0', 'track_id', 'artists', 'album_name', 'track_name' were removed because they do not offer anything to the model training.

4.2 Check for empty elements

[312]:
```
nvc = pd.DataFrame(df.isnull().sum().sort_values(), columns=['Total Null␣
↪Values'])
nvc['Percentage'] = round(nvc['Total Null Values']/df.shape[0],3)*100
print(nvc)
```

```
                   Total Null Values  Percentage
song_popularity                    0         0.0
track_genre                        0         0.0
time_signature                     0         0.0
tempo                              0         0.0
valence                            0         0.0
liveness                           0         0.0
instrumentalness                   0         0.0
acousticness                       0         0.0
speechiness                        0         0.0
mode                               0         0.0
loudness                           0         0.0
key                                0         0.0
energy                             0         0.0
danceability                       0         0.0
explicit                           0         0.0
duration_ms                        0         0.0
playcount                          0         0.0
listeners                          0         0.0
```

4.3 Removal of any Duplicate rows (if any)

[235]:
```
counter = 0
# Store the original dataset shape (number of rows and columns)
rs,cs = original_df.shape

# Remove duplicate rows from the dataset
df.drop_duplicates(inplace=True)

if df.shape == (rs, cs):
    print('\n\033[92mInterpretation:\033[0m The dataset doesn\'t have any␣
 ↪duplicates')
else:
    print(f'\n\033[92mInterpretation:\033[0m Number of duplicates dropped --->␣
 ↪{rs - df.shape[0]}')
```

```
Interpretation: Number of duplicates dropped ---> 6065
```

4.4 Defining Target Variable - Song Popularity

[314]:
```
# Define the target variable for prediction
target = 'song_popularity'

# Select all features except the target variable
features = [i for i in df.columns if i not in [target]]

# Create a deep copy of the original dataset to preserve the raw data
```

```
original_df = df.copy(deep=True)
```

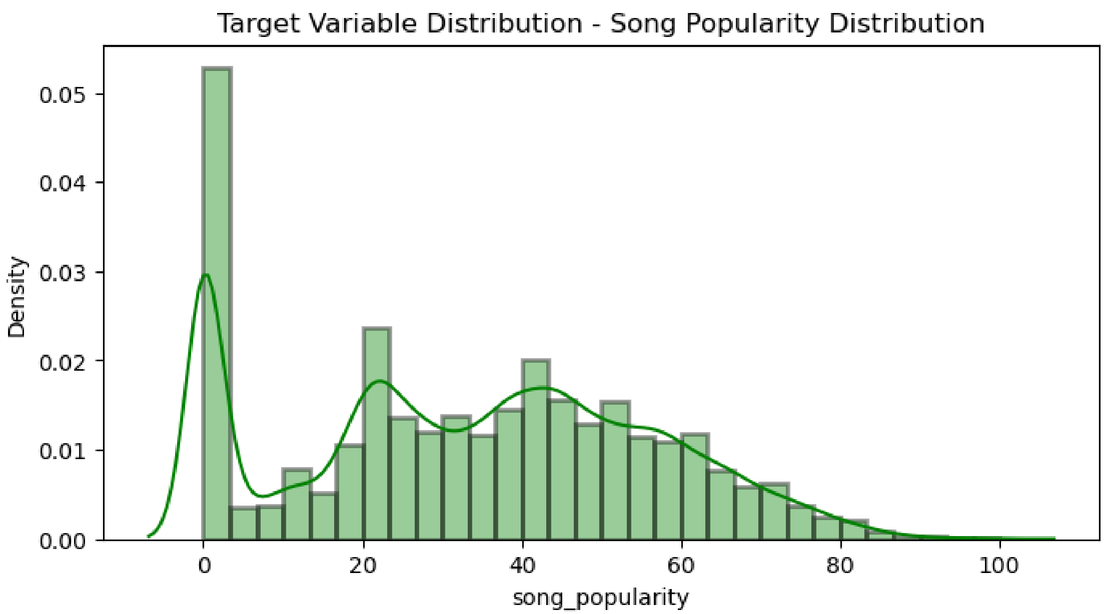
Interpretation: 'song_popularity' was set as the dependent variable (y)

5 Exploratory Data Analysis (EDA)

5.1 Analysing the distribution of the target variable

Interpretation: Detailed analysis for the following visualisation is included in the paper

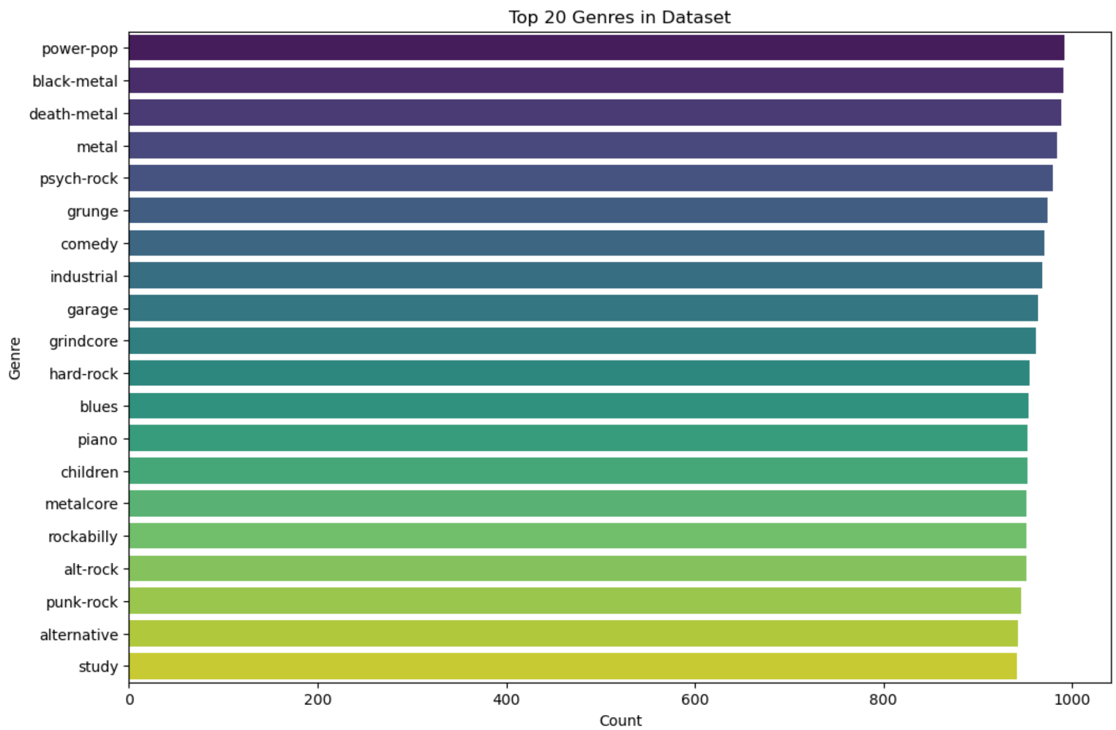
[318]:
```
plt.figure(figsize=[8,4])
sns.distplot(df[target], color='g',hist_kws=dict(edgecolor="black",␣
↪linewidth=2), bins=30)
plt.title('Target Variable Distribution - Song Popularity Distribution')
plt.show()
```



5.2 Visualising the 'track_genre' feature

[249]:
```
# Define the column name explicitly
genre_column = "track_genre"  # Ensure this is the correct column name

# Select top 20 genres only
top_20_genres = df[genre_column].value_counts().head(20)

# Set figure size
plt.figure(figsize=(12, 8))
```

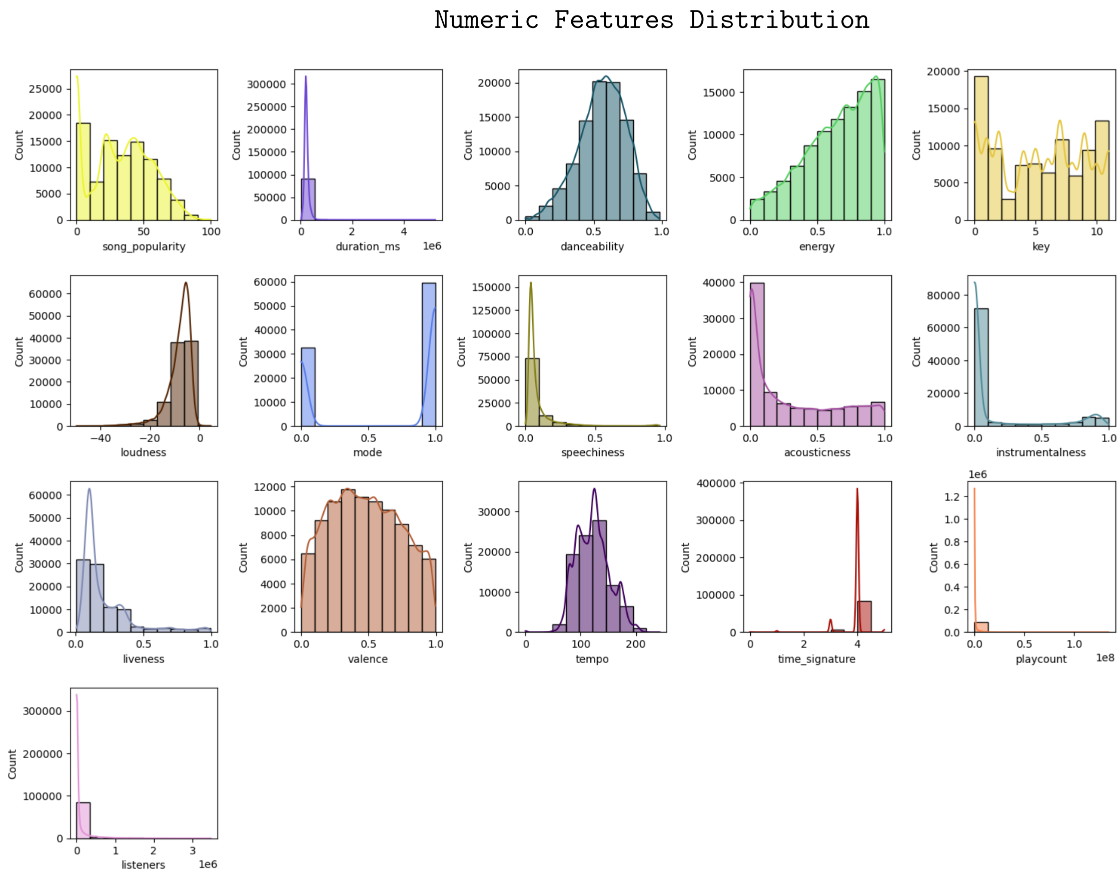
```
# Plot Bar Chart
sns.barplot(y=top_20_genres.index, x=top_20_genres.values, palette="viridis")

plt.xlabel("Count")
plt.ylabel("Genre")
plt.title("Top 20 Genres in Dataset")

plt.show()
```

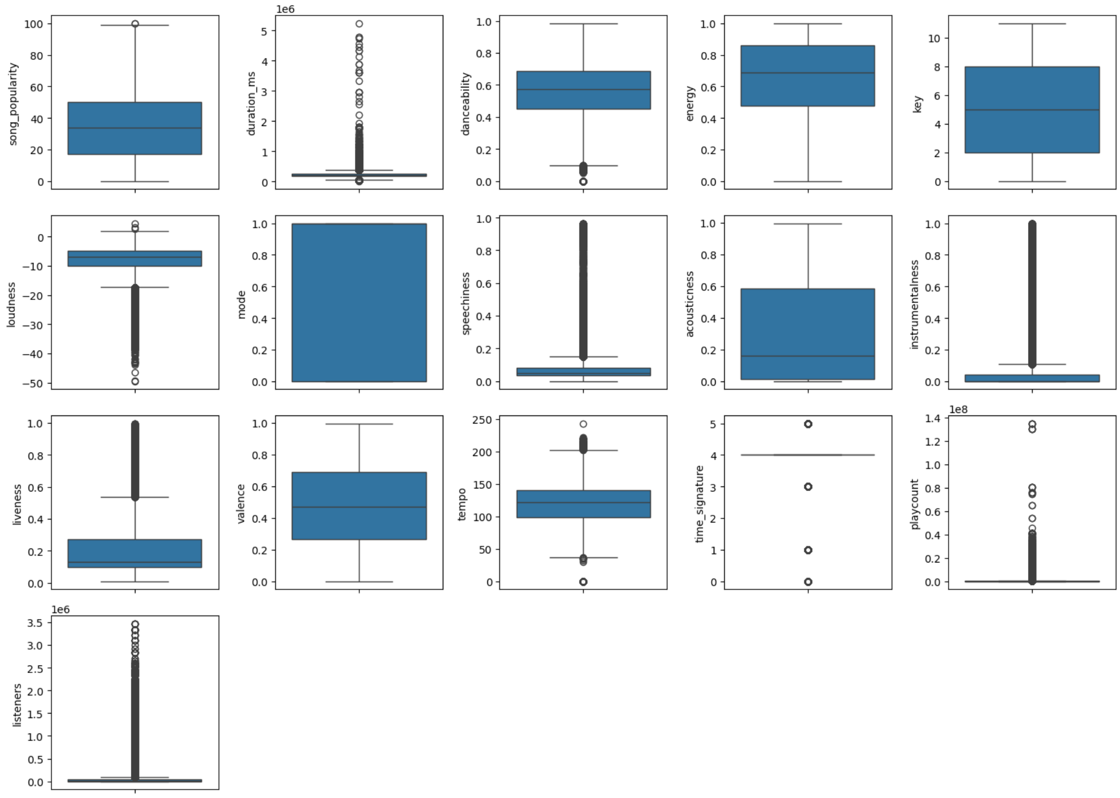


5.3 Visualising the numerical features

[112]:
```
# Ensure nf contains only numeric columns (int64, float64)
nf = df.select_dtypes(include=['int64', 'float64']).columns.tolist()

# Visualizing numeric features
print('\033[1mNumeric Features Distribution'.center(100))

n = 5

plt.figure(figsize=[15, 4 * math.ceil(len(nf) / n)])
for i in range(len(nf)):
    plt.subplot(math.ceil(len(nf) / 3), n, i + 1)
```

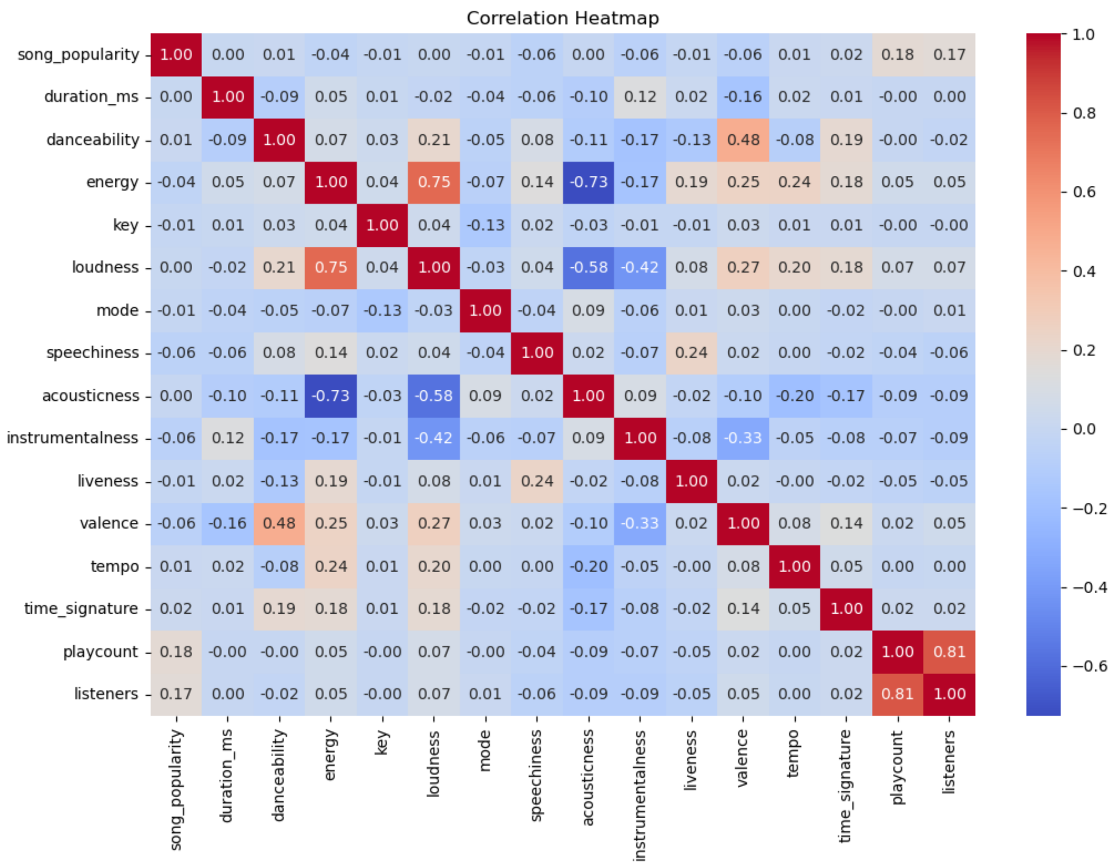
```
    sns.histplot(df[nf[i]], bins=10, kde=True, color=np.random.rand(3,))
plt.tight_layout()
plt.show()

# Boxplot for numeric features
plt.figure(figsize=[15, 4 * math.ceil(len(nf) / n)])
for i in range(len(nf)):
    plt.subplot(math.ceil(len(nf) / 3), n, i + 1)
    sns.boxplot(y=df[nf[i]])
plt.tight_layout()
plt.show()
```





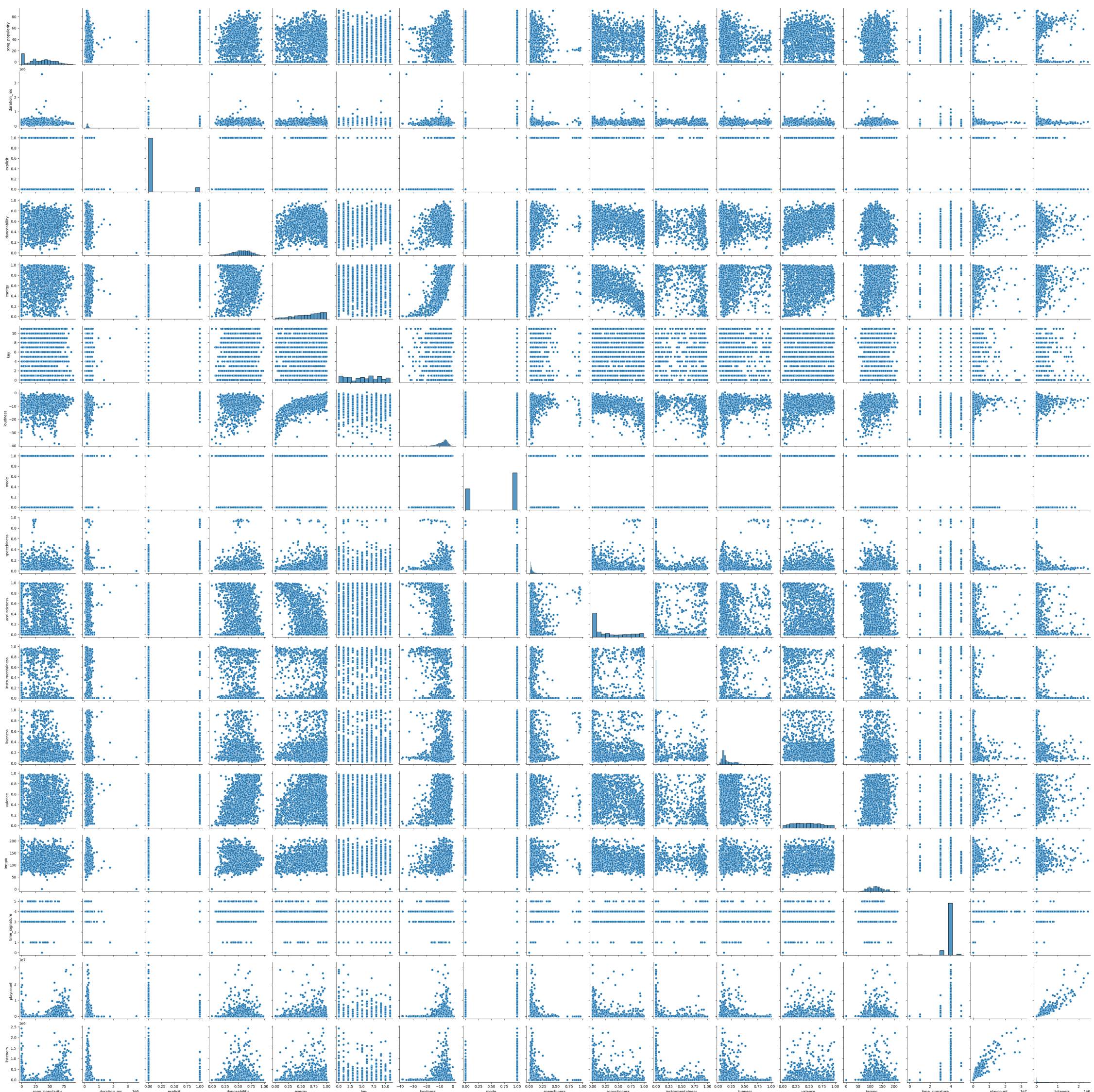
5.4 Correlation Heatmap

[251]:
```
# Select only numeric columns for correlation heatmap
numeric_df = df.select_dtypes(include=[np.number])

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



5.5 Pairplot of Sampled Features

[117]:
```
df_sample = df.sample(2000, random_state=42)
sns.pairplot(df_sample)
plt.show()
```



Interpretation: The pairplot provides a visual representation of relationships between numerical features in the dataset. It helps identify correlations, trends, and potential outliers. The scatter plots reveal that play count and listeners are strongly correlated with song popularity, while audio features exhibit weaker relationships. This suggests that streaming metadata plays a more significant role in determining a song's success.

---

6 Data Manipulation

6.1 Convert categorical features to numerical using One-Hot Encoding

[320]:
```
# Detect categorical columns (non-numeric columns)
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()

# Apply One-Hot Encoding to categorical columns
df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=True)  #␣
↪drop_first=True to avoid multicollinearity

# Display the new dataframe with encoded columns
print(f"Categorical columns converted to numeric: {categorical_cols}")
print(df_encoded.head())
```

```
Categorical columns converted to numeric: ['track_genre']
   song_popularity  duration_ms  explicit  danceability  energy  key  \
0               73       230666     False         0.676   0.461    1
1               74       244800     False         0.627   0.363    8
2               75       242946     False         0.703   0.444   11
3                0       131760     False         0.620   0.309    5
4                0       306794     False         0.474   0.519    7

   loudness  mode  speechiness  acousticness  ...  track_genre_spanish  \
0    -6.746     0       0.1430        0.0322  ...                False
1    -8.127     1       0.0291        0.2790  ...                False
2    -9.331     1       0.0417        0.5590  ...                False
3    -9.209     1       0.0495        0.7880  ...                False
4    -5.291     1       0.0253        0.2810  ...                False

   track_genre_study  track_genre_swedish  track_genre_synth-pop  \
0              False                False                  False
1              False                False                  False
2              False                False                  False
3              False                False                  False
4              False                False                  False

   track_genre_tango  track_genre_techno  track_genre_trance  \
0              False               False               False
1              False               False               False
2              False               False               False
3              False               False               False
4              False               False               False

   track_genre_trip-hop  track_genre_turkish  track_genre_world-music
0                 False                False                    False
1                 False                False                    False
2                 False                False                    False
```

```
3                  False                   False                        False
4                  False                   False                        False

[5 rows x 130 columns]
```

[322]:
```
print("Categorical columns converted to numeric:", [col for col in df_encoded.
 ↪columns if col not in df.columns])
```

```
Categorical columns converted to numeric: ['track_genre_afrobeat',
'track_genre_alt-rock', 'track_genre_alternative', 'track_genre_ambient',
'track_genre_anime', 'track_genre_black-metal', 'track_genre_bluegrass',
'track_genre_blues', 'track_genre_brazil', 'track_genre_breakbeat',
'track_genre_british', 'track_genre_cantopop', 'track_genre_chicago-house',
'track_genre_children', 'track_genre_chill', 'track_genre_classical',
'track_genre_club', 'track_genre_comedy', 'track_genre_country',
'track_genre_dance', 'track_genre_dancehall', 'track_genre_death-metal',
'track_genre_deep-house', 'track_genre_detroit-techno', 'track_genre_disco',
'track_genre_disney', 'track_genre_drum-and-bass', 'track_genre_dub',
'track_genre_dubstep', 'track_genre_edm', 'track_genre_electro',
'track_genre_electronic', 'track_genre_emo', 'track_genre_folk',
'track_genre_forro', 'track_genre_french', 'track_genre_funk',
'track_genre_garage', 'track_genre_german', 'track_genre_gospel',
'track_genre_goth', 'track_genre_grindcore', 'track_genre_groove',
'track_genre_grunge', 'track_genre_guitar', 'track_genre_happy',
'track_genre_hard-rock', 'track_genre_hardcore', 'track_genre_hardstyle',
'track_genre_heavy-metal', 'track_genre_hip-hop', 'track_genre_honky-tonk',
'track_genre_house', 'track_genre_idm', 'track_genre_indian',
'track_genre_indie', 'track_genre_indie-pop', 'track_genre_industrial',
'track_genre_iranian', 'track_genre_j-dance', 'track_genre_j-idol',
'track_genre_j-pop', 'track_genre_j-rock', 'track_genre_jazz', 'track_genre_k-
pop', 'track_genre_kids', 'track_genre_latin', 'track_genre_latino',
'track_genre_malay', 'track_genre_mandopop', 'track_genre_metal',
'track_genre_metalcore', 'track_genre_minimal-techno', 'track_genre_mpb',
'track_genre_new-age', 'track_genre_opera', 'track_genre_pagode',
'track_genre_party', 'track_genre_piano', 'track_genre_pop', 'track_genre_pop-
film', 'track_genre_power-pop', 'track_genre_progressive-house',
'track_genre_psych-rock', 'track_genre_punk', 'track_genre_punk-rock',
'track_genre_r-n-b', 'track_genre_reggae', 'track_genre_reggaeton',
'track_genre_rock', 'track_genre_rock-n-roll', 'track_genre_rockabilly',
'track_genre_romance', 'track_genre_sad', 'track_genre_salsa',
'track_genre_samba', 'track_genre_sertanejo', 'track_genre_show-tunes',
'track_genre_singer-songwriter', 'track_genre_ska', 'track_genre_sleep',
'track_genre_songwriter', 'track_genre_soul', 'track_genre_spanish',
'track_genre_study', 'track_genre_swedish', 'track_genre_synth-pop',
'track_genre_tango', 'track_genre_techno', 'track_genre_trance',
'track_genre_trip-hop', 'track_genre_turkish', 'track_genre_world-music']
```

---

7 Dataset Splitting

[324]:
```
# Define features (X) and target (y)
X = df_encoded.drop(columns=['song_popularity'], errors='ignore')  # Drop target␣
↪column
y = df_encoded['song_popularity']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

print(f"Training Set Size: {X_train.shape[0]} samples")
print(f"Testing Set Size: {X_test.shape[0]} samples")
```

```
Training Set Size: 73895 samples
Testing Set Size: 18474 samples
```

8 Feature Selection

8.1 Random Forest Feature Importance (RF Importance)

[326]:
```
def get_rfi(X_train, y_train, top_n=15):
    """
    Trains a Random Forest Classifier and extracts the top N most important␣
↪features.

    Parameters:
        X_train (DataFrame): Training feature set.
        y_train (Series): Target variable.
        top_n (int): Number of top features to select (default is 15).

    Returns:
        list: Top N selected features based on importance.
        DataFrame: Full feature importance ranking.
    """
    # Initialize and train the Random Forest model
    rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
    rf_model.fit(X_train, y_train)

    # Compute feature importance
    feature_importance = pd.DataFrame({
        "Feature": X_train.columns,
        "Importance": rf_model.feature_importances_
    }).sort_values(by="Importance", ascending=False)

    # Select top N features
    selected_features = feature_importance.head(top_n)["Feature"].tolist()
```

```
    print(f"Top {top_n} Features using Random Forest Importance:",␣
↪selected_features)

    return selected_features, feature_importance

# Apply RFI Feature Selection
selected_features_rf, feature_importance_df = get_rfi(X_train, y_train)
```

```
Top 15 Features using Random Forest Importance: ['playcount', 'listeners',
'duration_ms', 'acousticness', 'loudness', 'danceability', 'valence', 'tempo',
'speechiness', 'energy', 'liveness', 'instrumentalness', 'key', 'mode',
'time_signature']
```

8.2 Variance Inflation Factor (VIF)

[329]:
```
def calculate_vif(df, threshold=10):
    """
    Removes features with high multicollinearity using Variance Inflation Factor␣
↪(VIF).

    Parameters:
    - df: DataFrame containing only numerical features.
    - threshold: VIF threshold (default = 10). Features with VIF > threshold are␣
↪removed.

    Returns:
    - selected_features_vif: List of selected features after removing high VIF␣
↪ones.
    """
    X = df.copy()  # Copy dataset to avoid modifying original
    dropped = True  # Flag to track feature removal

    while dropped:
        dropped = False
        vif_data = pd.DataFrame()
        vif_data["Feature"] = X.columns
        vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in␣
↪range(X.shape[1])]

        max_vif = vif_data["VIF"].max()
        if max_vif > threshold:
            drop_feature = vif_data.sort_values(by="VIF", ascending=False).
↪iloc[0]["Feature"]
            X.drop(columns=[drop_feature], inplace=True)
            dropped = True  # Set flag to True to continue iteration
```

```
    selected_features_vif = X.columns.tolist()
    return selected_features_vif

# Ensure dataset only contains numerical features
numerical_features = df_encoded.select_dtypes(include=[np.number]).
 ↪drop(columns=['song_popularity'], errors='ignore')

# Apply VFI Feature Selection
selected_features_vif = calculate_vif(numerical_features, threshold=10)
print("Selected Features using Variance Inflation Factor (VFI):",␣
 ↪selected_features_vif)
```

```
Selected Features using Variance Inflation Factor (VFI): ['duration_ms', 'key',
'loudness', 'mode', 'speechiness', 'acousticness', 'instrumentalness',
'liveness', 'valence', 'playcount', 'listeners']
```

8.3 LASSO (Least Absolute Shrinkage and Selection Operator)

[332]:
```
def select_features_lasso(X, y, alpha=0.01):
    """
    Performs feature selection using LASSO (L1 Regularization).

    Parameters:
    - X: Feature matrix (only numerical values).
    - y: Target variable.
    - alpha: Regularization strength (default = 0.01).

    Returns:
    - selected_features_lasso: List of selected features.
    """
    # Standardize the data (LASSO is sensitive to scale)
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)

    # Apply LASSO model
    lasso = Lasso(alpha=alpha)
    lasso.fit(X_scaled, y)

    # Select features with non-zero coefficients
    selected_features_lasso = X.columns[lasso.coef_ != 0].tolist()
    return selected_features_lasso

# Ensure dataset only contains numerical features
numerical_features = df_encoded.select_dtypes(include=['number']).
 ↪drop(columns=['song_popularity'], errors='ignore')

# Apply LASSO Feature Selection
```

```
selected_features_lasso = select_features_lasso(numerical_features,␣
↪df_encoded['song_popularity'], alpha=0.01)
print("Selected Features using LASSO (L1 Regularization):",␣
↪selected_features_lasso)
```

```
Selected Features using LASSO (L1 Regularization): ['duration_ms',
'danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',
'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
'time_signature', 'playcount', 'listeners']
```

---

9 Data Normalisation

[336]:
```
def standardize_data(X_train, X_test):
    """
    Standardizes the numerical features of the dataset.
    - Fits StandardScaler on training data.
    - Transforms both training and testing data.
    - Prints summary statistics before and after standardization.
    - Returns DataFrames with standardized values.
    """
    # Initialize StandardScaler
    scaler = StandardScaler()

    # Apply Standardization
    X_train_std = scaler.fit_transform(X_train)
    X_test_std = scaler.transform(X_test)

    # Convert back to DataFrame
    X_train_std_df = pd.DataFrame(X_train_std, columns=X_train.columns)
    X_test_std_df = pd.DataFrame(X_test_std, columns=X_test.columns)

    # Print transformed data statistics after standardization
    print("\nAfter Standardization:".center(120))
    print("Training Set (Standardized):")
    display(X_train_std_df.describe())
    print("\nTesting Set (Standardized):")
    display(X_test_std_df.describe())

    return X_train_std_df, X_test_std_df
```

[338]:
```
X_train_std, X_test_std = standardize_data(X_train, X_test)
```

```
After Standardization:
Training Set (Standardized):
```

```
       duration_ms      explicit  danceability        energy           key  \
count  7.389500e+04  7.389500e+04  7.389500e+04  7.389500e+04  7.389500e+04
mean  -1.159999e-16 -3.813176e-17 -2.312545e-17  3.942385e-18 -8.735748e-17
std    1.000007e+00  1.000007e+00  1.000007e+00  1.000007e+00  1.000007e+00
min   -2.048806e+00 -3.027937e-01 -3.282853e+00 -2.601604e+00 -1.488577e+00
25%   -5.002000e-01 -3.027937e-01 -6.389100e-01 -6.854820e-01 -9.262948e-01
50%   -1.309664e-01 -3.027937e-01  6.887133e-02  1.661635e-01 -8.287182e-02
75%    3.141024e-01 -3.027937e-01  7.357066e-01  8.490867e-01  7.605512e-01
max    4.386997e+01  3.302579e+00  2.478838e+00  1.415511e+00  1.603974e+00

          loudness          mode   speechiness  acousticness  \
count  7.389500e+04  7.389500e+04  7.389500e+04  7.389500e+04
mean   1.989943e-16  1.096175e-17  7.889577e-17 -1.078386e-16
std    1.000007e+00  1.000007e+00  1.000007e+00  1.000007e+00
min   -8.575363e+00 -1.351786e+00 -7.685284e-01 -9.358708e-01
25%   -3.748189e-01 -1.351786e+00 -4.429975e-01 -8.930140e-01
50%    2.455697e-01  7.397619e-01 -3.249580e-01 -4.495531e-01
75%    6.522562e-01  7.397619e-01 -1.325983e-02  8.452678e-01
max    2.625193e+00  7.397619e-01  8.130545e+00  2.091457e+00

       instrumentalness  ...  track_genre_spanish  track_genre_study  \
count      7.389500e+04  ...         7.389500e+04       7.389500e+04
mean      -2.620244e-17  ...        -2.418317e-17       7.247738e-17
std        1.000007e+00  ...         1.000007e+00       1.000007e+00
min       -4.990712e-01  ...        -9.507702e-02      -1.020076e-01
25%       -4.990712e-01  ...        -9.507702e-02      -1.020076e-01
50%       -4.989382e-01  ...        -9.507702e-02      -1.020076e-01
75%       -3.560513e-01  ...        -9.507702e-02      -1.020076e-01
max        2.751380e+00  ...         1.051779e+01       9.803188e+00

       track_genre_swedish  track_genre_synth-pop  track_genre_tango  \
count         7.389500e+04           7.389500e+04       7.389500e+04
mean         -3.569781e-17          -6.109494e-17       5.043368e-17
std           1.000007e+00           1.000007e+00       1.000007e+00
min          -9.701442e-02          -9.912430e-02      -8.393872e-02
25%          -9.701442e-02          -9.912430e-02      -8.393872e-02
50%          -9.701442e-02          -9.912430e-02      -8.393872e-02
75%          -9.701442e-02          -9.912430e-02      -8.393872e-02
max           1.030775e+01           1.008834e+01       1.191345e+01

       track_genre_techno  track_genre_trance  track_genre_trip-hop  \
count        7.389500e+04        7.389500e+04          7.389500e+04
mean        -4.522925e-17       -1.935134e-17         -2.312545e-17
std          1.000007e+00        1.000007e+00          1.000007e+00
min         -9.009620e-02       -8.077415e-02         -9.637279e-02
25%         -9.009620e-02       -8.077415e-02         -9.637279e-02
50%         -9.009620e-02       -8.077415e-02         -9.637279e-02
75%         -9.009620e-02       -8.077415e-02         -9.637279e-02
```

```
max          1.109925e+01        1.238020e+01          1.037637e+01

       track_genre_turkish  track_genre_world-music
count         7.389500e+04             7.389500e+04
mean          4.257295e-17             2.586589e-17
std           1.000007e+00             1.000007e+00
min          -9.665846e-02            -8.754240e-02
25%          -9.665846e-02            -8.754240e-02
50%          -9.665846e-02            -8.754240e-02
75%          -9.665846e-02            -8.754240e-02
max           1.034571e+01             1.142304e+01

[8 rows x 129 columns]


Testing Set (Standardized):
        duration_ms      explicit  danceability        energy           key  \
count  18474.000000  18474.000000  18474.000000  18474.000000  18474.000000
mean       0.003571     -0.011811      0.018454      0.001167      0.008635
std        1.067948      0.982080      0.992799      1.001589      1.002187
min       -1.973289     -0.302794     -3.282853     -2.601604     -1.488577
25%       -0.502900     -0.302794     -0.621362     -0.685482     -0.926295
50%       -0.132365     -0.302794      0.080570      0.182232     -0.082872
75%        0.312290     -0.302794      0.741556      0.849087      0.760551
max       48.180170      3.302579      2.455440      1.415511      1.603974

           loudness          mode   speechiness  acousticness  \
count  18474.000000  18474.000000  18474.000000  18474.000000
mean      -0.002388      0.007935     -0.001690     -0.003535
std        0.999194      0.997564      0.986842      0.996944
min       -7.231827     -1.351786     -0.768528     -0.935871
25%       -0.378807     -1.351786     -0.441153     -0.890810
50%        0.240183      0.739762     -0.323114     -0.443474
75%        0.656969      0.739762     -0.013490      0.827031
max        2.219543      0.739762      8.112102      2.091457

       instrumentalness  ...  track_genre_spanish  track_genre_study  \
count      18474.000000  ...         18474.000000       18474.000000
mean          -0.005306  ...             0.010627          -0.005497
std            0.996246  ...             1.053900           0.972981
min           -0.499071  ...            -0.095077          -0.102008
25%           -0.499071  ...            -0.095077          -0.102008
50%           -0.498954  ...            -0.095077          -0.102008
75%           -0.371410  ...            -0.095077          -0.102008
max            2.751380  ...            10.517788           9.803188

       track_genre_swedish  track_genre_synth-pop  track_genre_tango  \
count         18474.000000           18474.000000       18474.000000
```

```
mean            -0.012533              -0.004275             0.003084
std              0.933767               0.978432             1.018098
min             -0.097014              -0.099124            -0.083939
25%             -0.097014              -0.099124            -0.083939
50%             -0.097014              -0.099124            -0.083939
75%             -0.097014              -0.099124            -0.083939
max             10.307746              10.088344            11.913453

       track_genre_techno  track_genre_trance  track_genre_trip-hop  \
count        18474.000000        18474.000000          18474.000000
mean            -0.010752           -0.009950              0.009636
std              0.938915            0.936785              1.048343
min             -0.090096           -0.080774             -0.096373
25%             -0.090096           -0.080774             -0.096373
50%             -0.090096           -0.080774             -0.096373
75%             -0.090096           -0.080774             -0.096373
max             11.099247           12.380198             10.376373

       track_genre_turkish  track_genre_world-music
count         18474.000000             18474.000000
mean             -0.002828                -0.010282
std               0.985426                 0.939890
min              -0.096658                -0.087542
25%              -0.096658                -0.087542
50%              -0.096658                -0.087542
75%              -0.096658                -0.087542
max              10.345706                11.423037

[8 rows x 129 columns]
```

10 Model Training - Evaluation

10.1 Random Forest Classifier

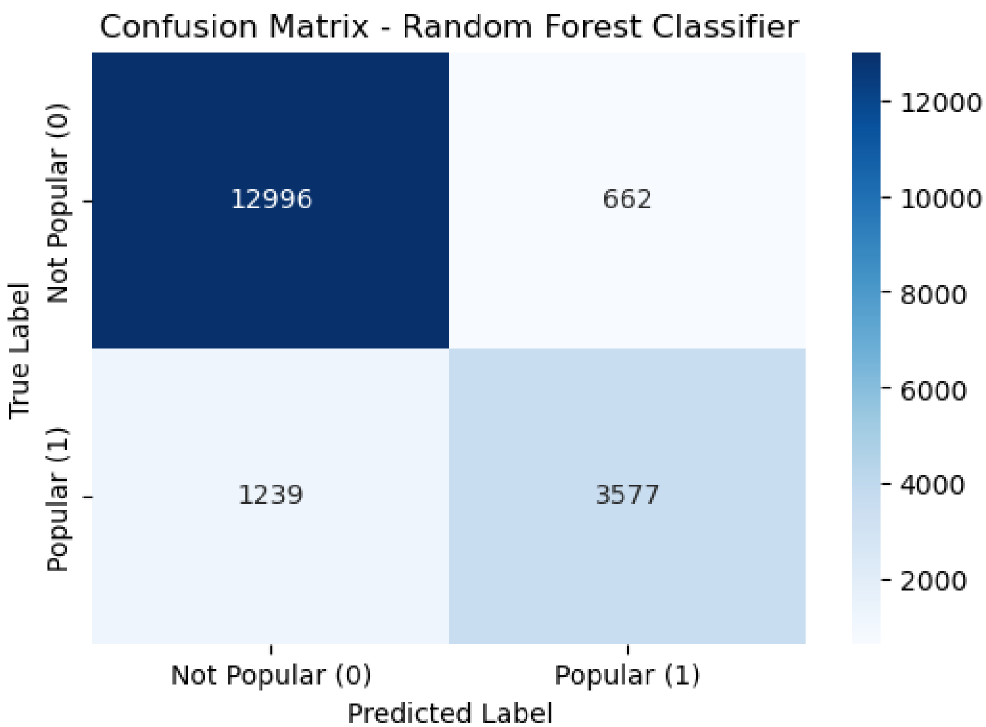
[356]:
```
# Set this flag to True to use standardized data, or False to use original data
use_standardized = False  # Change this as needed

# Select feature selection method: "rfi", "vif", "lasso", or "combined"
feature_selection_method = "combined"

# Ensure categorical features are identified
categorical_features = df.select_dtypes(include=['object']).columns.tolist()
categorical_columns = df_encoded.columns[df_encoded.columns.str.
 ↪startswith(tuple(categorical_features))].tolist()

# Choose selected features based on feature selection method
feature_selection_dict = {
```

```python
    "rfi": selected_features_rf,
    "vif": selected_features_vif,
    "lasso": selected_features_lasso,
    "combined": list(set(selected_features_rf + selected_features_vif +␣
 ↪selected_features_lasso))
}

if feature_selection_method not in feature_selection_dict:
    raise ValueError("Invalid feature selection method. Choose from 'rfi',␣
 ↪'vif', 'lasso', or 'combined'.")

selected_features = feature_selection_dict[feature_selection_method]

# Choose between Standardized or Original Numerical Data
if use_standardized:
    Train_X_num_df = X_train_std[selected_features].reset_index(drop=True)
    Test_X_num_df = X_test_std[selected_features].reset_index(drop=True)
    print("\nUsing Standardized Numerical Features")
else:
    Train_X_num_df = X_train[selected_features].reset_index(drop=True)
    Test_X_num_df = X_test[selected_features].reset_index(drop=True)
    print("\nUsing Original (Non-Standardized) Numerical Features")

# Extract categorical features for training and testing sets
X_train_categorical = X_train[categorical_columns].reset_index(drop=True)
X_test_categorical = X_test[categorical_columns].reset_index(drop=True)

# Combine numerical and categorical features
X_train_final = pd.concat([Train_X_num_df, X_train_categorical], axis=1)
X_test_final = pd.concat([Test_X_num_df, X_test_categorical], axis=1)

# Initialize and train the Random Forest Classifier
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train_final, y_train)

# Make predictions
y_pred = clf.predict(X_test_final)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)

# Print accuracy and final features used
print(f"Model Accuracy: {accuracy:.4f}")
```

```
Using Original (Non-Standardized) Numerical Features
Model Accuracy: 0.8971
```

10.2 Generate the confusion matrix

[359]:
```
cm = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix as a heatmap
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Popular␣
↪(0)', 'Popular (1)'], yticklabels=['Not Popular (0)', 'Popular (1)'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix - Random Forest Classifier')
plt.show()

# Print classification report with 4 decimal places
print("Classification Report:")
print(classification_report(y_test, y_pred, digits=4))
```



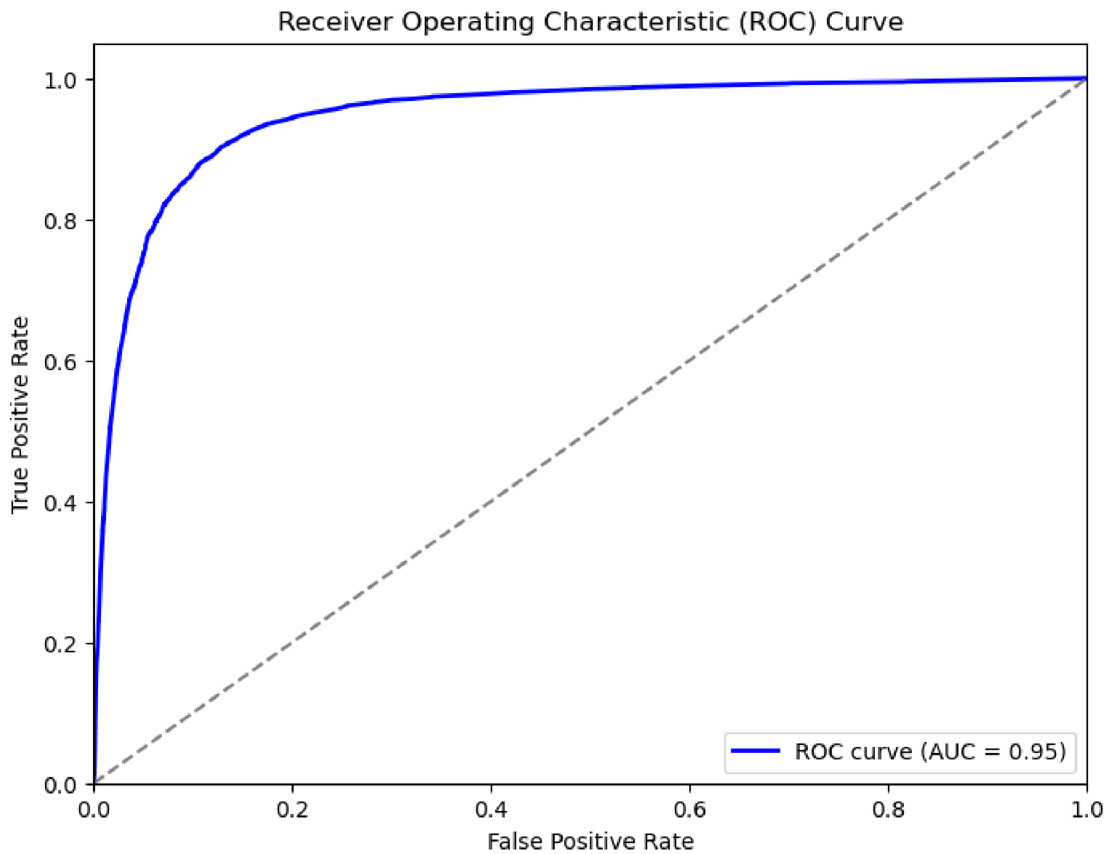

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9130    0.9515    0.9318     13658
           1     0.8438    0.7427    0.7901      4816

    accuracy                         0.8971     18474
```

macro avg	0.8784	0.8471	0.8610	18474
weighted avg	0.8949	0.8971	0.8949	18474

10.3 ROC Curve

[350]:

```
# Get prediction probabilities for the positive class (1)
y_probs = clf.predict_proba(X_test_final)[:, 1]

# Compute ROC curve and AUC
fpr, tpr, _ = roc_curve(y_test, y_probs)
roc_auc = auc(fpr, tpr)

# Plot ROC Curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')  # Diagonal line (random␣
↪model)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

# Print AUC Score
print(f"AUC Score: {roc_auc:.4f}")
```




```
AUC Score: 0.9477
```

10.4 Random Forest Regressor

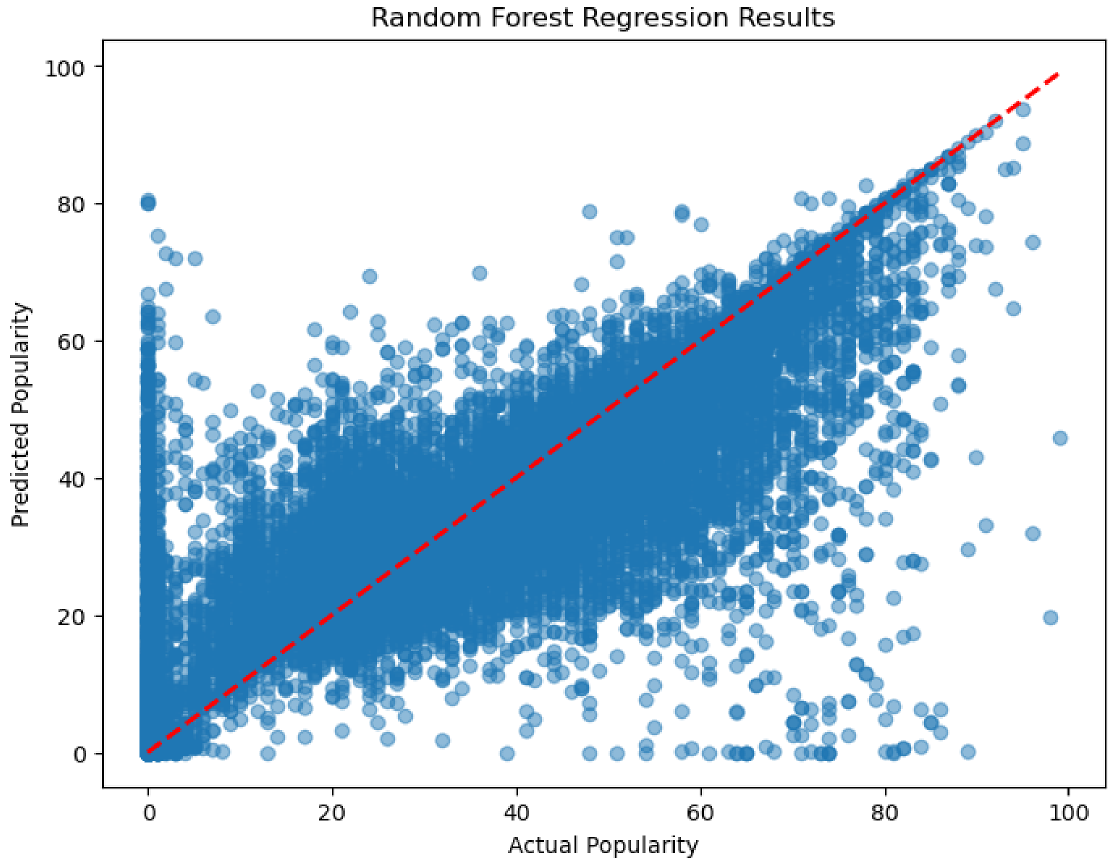
[272]:

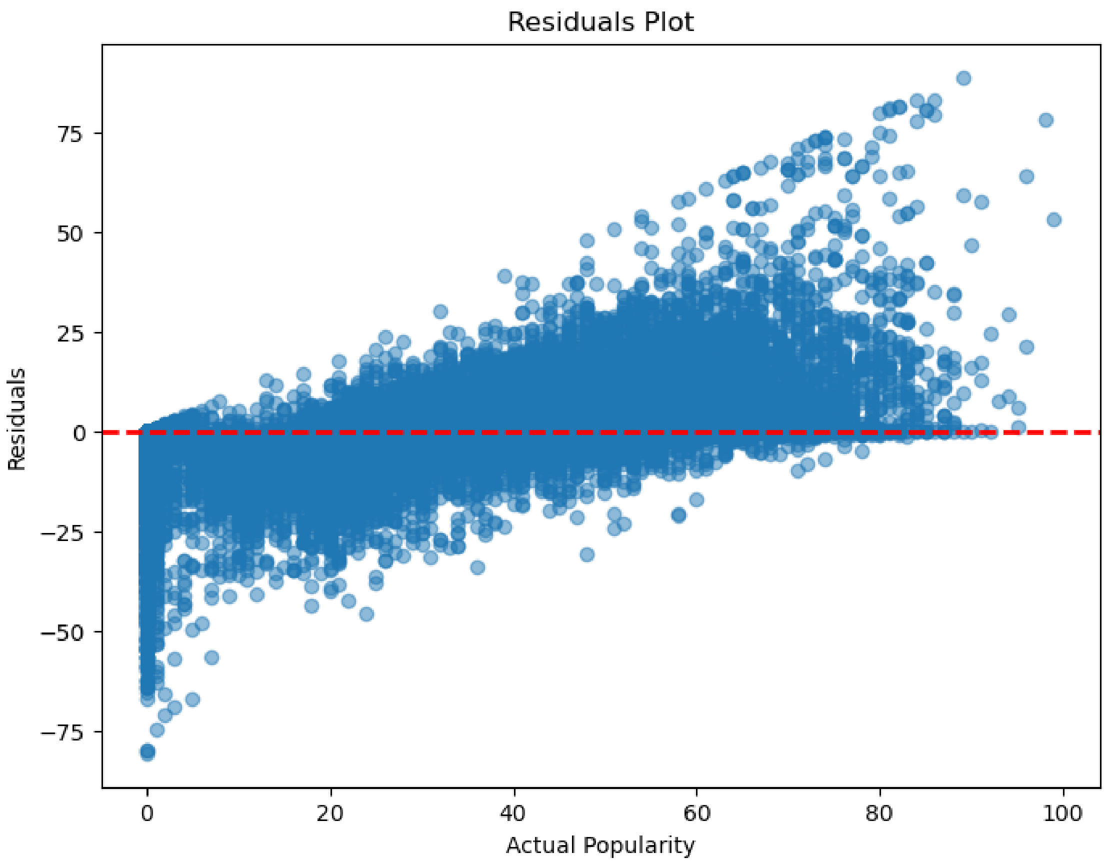
```
# Set this flag to True to use standardized data, or False to use original data
use_standardized = False  # Change this to True or False as needed

# Choose feature selection method: "rfi", "vif", "lasso", or "combined"
feature_selection_method = "rfi"  # Change as needed

# Define target variable
y = df_encoded['song_popularity']

# Select features based on feature selection method
if feature_selection_method == "rfi":
    selected_features = selected_features_rf
elif feature_selection_method == "vif":
    selected_features = selected_features_vif
elif feature_selection_method == "lasso":
    selected_features = selected_features_lasso
```

```
elif feature_selection_method == "combined":
    selected_features = list(set(selected_features_rf + selected_features_vif +␣
↪selected_features_lasso))  # Merge all
else:
    raise ValueError("Invalid feature selection method. Choose from 'rfi',␣
↪'vif', 'lasso', or 'combined'.")

# Choose between Standardized or Original Numerical Data
if use_standardized:
    # Use Standardized Data
    Train_X_num_df = X_train_std[selected_features].copy()
    Test_X_num_df = X_test_std[selected_features].copy()
    print("\nUsing Standardized Numerical Features")
else:
    # Use Original Data (No Standardization)
    Train_X_num_df = X_train[selected_features].reset_index(drop=True)
    Test_X_num_df = X_test[selected_features].reset_index(drop=True)
    print("\nUsing Original (Non-Standardized) Numerical Features")

# Train Random Forest Regressor
regressor = RandomForestRegressor(n_estimators=10, random_state=42)
regressor.fit(Train_X_num_df, y_train)

# Make predictions
y_pred = regressor.predict(Test_X_num_df)

# Evaluate model performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"R² Score: {r2:.4f}")

# Visualization (Scatter & Residual Plots)
def plot_results(y_test, y_pred, title="Model Performance"):
    """
    Creates scatter and residual plots for regression results.
    """
    # Scatter Plot
    plt.figure(figsize=(8, 6))
    plt.scatter(y_test, y_pred, alpha=0.5)
    plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], '--r',␣
↪linewidth=2)
    plt.xlabel("Actual Popularity")
    plt.ylabel("Predicted Popularity")
```

```
    plt.title(title)
    plt.show()

    # Residual Plot
    residuals = y_test - y_pred
    plt.figure(figsize=(8, 6))
    plt.scatter(y_test, residuals, alpha=0.5)
    plt.axhline(y=0, color='r', linestyle='--', linewidth=2)
    plt.xlabel("Actual Popularity")
    plt.ylabel("Residuals")
    plt.title("Residuals Plot")
    plt.show()

plot_results(y_test, y_pred, title="Random Forest Regression Results")
```

```
Using Original (Non-Standardized) Numerical Features
Mean Squared Error (MSE): 178.45
Mean Absolute Error (MAE): 8.70
R² Score: 0.6523
```





10.4.1 Additional Comment for Both Models

Standardization was tested but did not improve model performance, so the final models were trained using the original numerical features.