African Music Popularity Prediction

Introduction and Objectives

This project focuses on the top 7 African music industries with the primary aim of conducting a detailed analysis of regions that wield significant influence within the continent's musical landscape. The selected countries, consistently identified as key players by reputable sources, have been chosen strategically to align with the objectives of our machine learning analysis. The goal of the machine learning model is to predict the popularity of songs and understand the factors contributing to their popularity.

In machine learning, the inclusion of too many diverse and potentially noisy datasets could hinder the precision and interpretability of the model. By narrowing our focus to the top 7 African music industries, we seek to streamline the dataset to include only the most influential and impactful regions. This deliberate selection enhances the model's ability to discern patterns, trends, and features relevant to predicting the popularity of songs.

The criteria employed to identify the top music industries encompassed key factors like market size, cultural influence, export/import dynamics of musical content, and the overall impact on the global music landscape. Two independent articles (https://www.boomplay.com/buzz/3520053 and https://www.schooldrillers.com/biggest-music-industry-in-africa/) were reviewed, ensuring reliability and consistency. This dual-source analysis produced a harmonious list, confirming the top 7 African music industries. Notably, the sources shared a uniform methodology, further enhancing the credibility of the selected regions. The countries selected includes Nigeria, South Africa, Ghana, Kenya, Tanzania, DR Congo, and Benin Republic.

We exclusively examine songs by *top* and *popular* artists hailing from the selected countries (using google search), and intriguingly, the artists listed in Forbes list of the 20 biggest African artists in 2022 are from the countries selected. Note that the term *top* and *popular* maybe subjective.

In [1]:

```
# Top African artist according to forbes:
# https://www.forbesafrica.com/cover-story/2022/08/19/the-playlist-africas-top-20-musicia
ns/
forbes = ['Angelique Kidjo', 'Burna Boy', 'Tiwa Savage', 'Davido',
           'Wizkid', 'Master KG', 'Major League Djz', 'Diamond Platnumz',
           'Nasty C', 'Mr Eazi', 'Lebo M.', 'Black Coffee', '2Baba',
           'Cassper Nyovest', 'Yvonne Chaka Chaka', 'KDDO', 'Rayvanny',
           'Fally Ipupa', 'DJ Maphorisa', 'Lira'
          ]

# Biggest Music Industries In Africa:
# https://www.boomplay.com/buzz/3520053
# https://www.schooldrillers.com/biggest-music-industry-in-africa/

NGA = ["Burna Boy", "Davido", "Wizkid", "Olamide", "Tiwa Savage", "Fireboy DML",
       "Joeboy", "Rema", "Patoranking", "Tekno", "Mr Eazi", "Falz", "Blaqbonez",
       "Adekunle Gold", "Mayorkun", "Oxlade", "Peruzzi", "Tems", "Naira Marley",
       "Simi", "Ajebo Hustlers", "Bella Shmurda", "Ruger", "Bnxn", "Terri", "Fela Kuti",
       "Mohbad", "Asake", "CKay", "Victony", "Omah Lay", "Zinoleesky", "Lyta",
      ]


GHA = ['Sarkodie', 'Shatta Wale', 'Stonebwoy', 'KiDi', 'Black Sherif',
       'Gyakie', 'Amerado', 'Kwesi Arthur', 'Kofi Kinaata', 'Efya',
       'Adina Thembi', 'Medikal', 'Wendy Shay', 'King Promise', 'Becca',
       'MzVee', 'Kelvyn Boy', 'Cina Soul', 'DarkoVibes', 'Joey B',
       'Kuami Eugene', 'Camidoh', 'Fameye', 'Akwaboah', 'Mzbel',
       'R2Bees', 'Guru', 'A.B. Crentsil', 'Daddy Lumba', 'Castro',
      ]

ZAF = ["Nasty C", "DJ Maphorisa", "Kabza De Small", "Sho Madjozi", "Blxckie",
```

```
        "Busiswa", "Shekhinah", "YoungstaCPT", "Kwesta", "Black Motion","Mi Casa",
        "Moonchild Sanelly", "Msaki", "Locnville", "Die Antwoord", "TRESOR",
        "Berita", "The Soil", "Mafikizolo", "Brenda Fassie", "Johnny Clegg",
        "Thandiswa", "Hugh Masekela", "Miriam Makeba", "Lucky Dube", "Lady Zamar",
        "Black Coffee", 'Cassper Nyovest', 'AKA', 'Sho Madjozi', 'Prince Kaybee', "ANATII"
       ]

KEN = ["Sauti Sol", "Nyashinski", "Khaligraph Jones", "ETHIC",
        "Nikita Kering'", "Rekles", "Mr Seed", "Masauti", "Ethic Entertainment",
        "Willy Paul", "Akothee", "Avril", "Kagwe Mungai", "Sanaipei Tande",
        "Fena Gitu", "Mejja", "Eko Dydda", "Teddy Afro", "MOG",
        'Nameless', 'Victoria Kimani', "Kristoff",
       ]

TZA = ["Diamond Platnumz", "Nandy", "Harmonize", "Rayvanny", "Zuchu",
        "Alikiba", "Marioo", "Baba Levo", "B-Boy", " Mr Nice",
        "Mzee Bwax", "Queen Darleen", "Dulla Makabila", "Chege Chege",
        "Ben Pol", "Alikiba", "Linah Sanga",
        "Nikki Mbishi", "Afande Sele", "Rosa Ree",
       ]

DRC = ["Papa Wemba", "Fally Ipupa", "Yxng Bane", "Koffi Olomide", "Werrason",
        "JB Mpiana", "Dadju", "Luciana de Paula", "Gims", "Atele", "Koffi Olomide",
        "Mbilia Bel", "Celeo Scram", "Ferre Gola", "Deplick Pomba", "Werrason", 'Awilo Lo
gomba',
        "Cindy Le Coeur", "Robinio Mundibu", "Fabregas le Métis Noir", "Barbara Kanam"
       ]

BEN = ["Gangbé Brass Band", "T.P. Orchestre Poly-Rythmo", "Gnonnas Pedro",
        "Gabo Brown", "Lokonon Andre", "Les Volcans", "Tcheba",
        "Angelique Kidjo", "Sessimè", "Adje", "Virgul",
       ]

all_artists = list(set(forbes + NGA + GHA + ZAF  + KEN + TZA + DRC + BEN))
len(all_artists)
```

Out[1]:

172

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
pd.set_option("display.max_columns", None)
```

In [3]:

```
data = pd.read_csv("data/african_tracks.csv")
data.head()
```

Out[3]:

	track_name	track_id	genre	album_name	artist_name	release_date	duration_ms	popularity	da
0	بسبوسة - لايف	4WGJd3fF7E3ckfUJ6HVk5r	arab pop,classic arab pop,egyptian pop	بسبوسة (لايف)	Angham	2024-01-16	273461.0	17.0	
1	الركن البعيد الهادى - لايف	68HMt4igjymgwwujfnaG5S	arab pop,classic arab pop,egyptian pop	بسبوسة (لايف)	Angham	2024-01-16	500715.0	12.0	
2	الركن البعيد الهادي - لايف	00CNApfgvYR76i5ZYvUssm	arab pop,classic arab pop,egyptian	بسبوسة (لايف)	Angham	2024-01-16	505637.0	13.0	

	track_name	track_id	genre	album_name	artist_name	release_date	duration_ms	popularity	da
3	هوى المصايف - لايف	1AZ3hNhHlrQYwtVWaQkJ49	arab pop,classic arab pop,egyptian pop	يسبوسة (لايف)	Angham	2024-01-16	514297.0	13.0	
4	لايق - لايف	7yBGhl4nLP84Ew0Flo4Rf8	arab pop,classic arab pop,egyptian pop	يسبوسة (لايف)	Angham	2024-01-16	506009.0	7.0	

In [4]:

```
data.shape
```

Out[4]:

```
(20959, 20)
```

In [5]:

```
# Filter out songs not from the selected artists
data = data[data['artist_name'].isin(all_artists)]
data.reset_index(drop=True, inplace=True)
```

In [6]:

```
len(data)
```

Out[6]:

```
9130
```

In [7]:

```
validation_pct = 0.15  # Remove 15% of the data

np.random.seed(0)    # For Reproducability

# Randomly select index for the validation set
valid_idx = np.random.choice(a=range(len(data)),
                              size=int(validation_pct * len(data)),
                              replace=False
                             )

# Apply the index to filter the dataset
validation = data.loc[valid_idx]
validation.reset_index(drop=True, inplace=True)

# Remove the the validation data from the entire data
df = data.drop(valid_idx).reset_index(drop=True)
```

In [8]:

```
len(validation)
```

Out[8]:

```
1369
```

In [9]:

```
len(df)
```

Out[9]:

```
7761
```

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA)

In [10]:

```
## Looking at the stats of different columns
df.describe()
```

Out[10]:

	duration_ms	popularity	danceability	key	acousticness	mode	energy	instrumentalness	li
count	7.761000e+03	7761.000000	7761.000000	7761.000000	7761.000000	7761.000000	7761.000000	7761.000000	7761.
mean	2.846125e+05	17.400206	0.659105	5.287978	0.337017	0.616931	0.671804	0.063985	0.
std	1.662459e+05	15.326082	0.143368	3.671031	0.276628	0.486166	0.187413	0.190288	0.
min	4.937000e+03	0.000000	0.000000	0.000000	0.000012	0.000000	0.000101	0.000000	0.
25%	1.944660e+05	4.000000	0.554000	2.000000	0.091500	0.000000	0.565000	0.000000	0.
50%	2.487430e+05	14.000000	0.676000	5.000000	0.275000	1.000000	0.700000	0.000013	0.
75%	3.437730e+05	27.000000	0.770000	9.000000	0.546000	1.000000	0.813000	0.003010	0.
max	4.851037e+06	81.000000	0.985000	11.000000	0.994000	1.000000	0.999000	0.998000	0.

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7761 entries, 0 to 7760
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   track_name        7761 non-null   object 
 1   track_id          7761 non-null   object 
 2   genre             7503 non-null   object 
 3   album_name        7761 non-null   object 
 4   artist_name       7761 non-null   object 
 5   release_date      7761 non-null   object 
 6   duration_ms       7761 non-null   float64
 7   popularity        7761 non-null   float64
 8   danceability      7761 non-null   float64
 9   key               7761 non-null   float64
 10  acousticness      7761 non-null   float64
 11  mode              7761 non-null   float64
 12  energy            7761 non-null   float64
 13  instrumentalness  7761 non-null   float64
 14  liveness          7761 non-null   float64
 15  loudness          7761 non-null   float64
 16  speechiness       7761 non-null   float64
 17  tempo             7761 non-null   float64
 18  time_signature    7761 non-null   float64
 19  valence           7761 non-null   float64
dtypes: float64(14), object(6)
memory usage: 1.2+ MB
```

We once again see that we have 7761 tracks for training and testing with both categorical and numerical columns. In order to use the information from the categorical columns (`genre`, `artist_name`, `track_name`, `album_name`, `track_id`, `key`, `mode`, `time_signature`) we will either need to represent them numerically by feature engineering or drop them to be able to train the models.

In [12]:

```
# Looking at different values contained within columns
for col in df.columns:
    print(f"Column: {col}")
    print(df[col].value_counts())
    print("--------------------")
```

```
Column: track_name
track_name
Bandana              1
Selection            1
Frigo F.N.M.A        1
Ah quelle flamme     1
Choc d'amour         1
                    ..
Ba lobi              1
Toucher et jouer     1
Bébé Bouchou         1
La foi - Liyebo      1
Sugarcane - Remix    1
Name: count, Length: 7761, dtype: int64
--------------------
Column: track_id
track_id
2qWwuCVeMjF9mUT0S5Iqvl    1
0cjnORDDZDWDgKhGyXdMWi    1
4Y1zYWulI8ZjgfoV2zdi5h    1
6HSsvr1k4oBesZnwGwk4Td    1
3wJ4EBF7DrBnjNMCQjvdvK    1
                         ..
2aXEPEO1pZkGnyCTqDenN1    1
2F5Of9riitaU9ezUmr6wIw    1
3SS1dAtglMNIZByr6Ojl6N    1
1y7t2zoMMWwJ5XdtmBqrm2    1
6NuG2JgERZZXvvjmtjOFix    1
Name: count, Length: 7761, dtype: int64
--------------------
Column: genre
genre
afropop,south african jazz,world,xhosa                            524
azontobeats,ndombolo,rumba congolaise,soukous,zilizopendwa    402
afropop,rumba congolaise,soukous,zilizopendwa                     364
afropop,jazz trumpet,kwaito,south african jazz                    258
azonto,hiplife                                                    237
                                                                 ...
motown                                                              1
afro house,south african deep house                                 1
funk carioca,funk rj                                                1
r&b francais                                                        1
organic electronic                                                  1
Name: count, Length: 131, dtype: int64
--------------------
Column: album_name
album_name
Miriam Makeba (Five Original Albums)         58
The Healers: The Last Chapter                36
Highlife: Jazz and Afro- Soul (1963-1969)    32
Answers (The Hybrid)                         28
Control                                      27
                                             ..
The Click Song                                1
Miriam Makeba the Best                        1
Township Grooves                              1
Kalakuta Show                                 1
Opposite People                               1
Name: count, Length: 863, dtype: int64
--------------------
Column: artist_name
artist_name
Miriam Makeba      536
Koffi Olomide      410
Papa Wemba         374
Hugh Masekela      264
Lucky Dube         227
                  ...
Victony              5
Robinio Mundibu      5
Nikita Kering'       5
Cina Soul            5
```

```
Lyta                    4
Name: count, Length: 130, dtype: int64
--------------------
Column: release_date
release_date
2014-01-01    144
2009-01-01     79
2011-01-01     74
2013-01-01     69
2017-12-06     57
             ...
2012-06-01      1
1977-01-01      1
2020-04-10      1
2013-08-23      1
2013-03-26      1
Name: count, Length: 637, dtype: int64
--------------------
Column: duration_ms
duration_ms
240000.0    9
160000.0    7
190000.0    7
165000.0    6
216000.0    6
           ..
236170.0    1
230737.0    1
229372.0    1
260058.0    1
251147.0    1
Name: count, Length: 7117, dtype: int64
--------------------
Column: popularity
popularity
0.0     631
1.0     481
2.0     359
3.0     345
4.0     297
       ...
75.0      2
77.0      2
81.0      1
73.0      1
74.0      1
Name: count, Length: 77, dtype: int64
--------------------
Column: danceability
danceability
0.759    36
0.803    31
0.728    31
0.809    30
0.804    30
         ..
0.243     1
0.183     1
0.216     1
0.261     1
0.960     1
Name: count, Length: 700, dtype: int64
--------------------
Column: key
key
0.0     1054
7.0      868
1.0      778
9.0      753
2.0      697
5.0      662
11.0     642
```

```
10.0     614
6.0      528
8.0      475
4.0      465
3.0      225
Name: count, dtype: int64
--------------------
Column: acousticness
acousticness
0.118000    27
0.117000    18
0.106000    18
0.114000    17
0.202000    16
            ..
0.000962     1
0.000362     1
0.000097     1
0.001140     1
0.088400     1
Name: count, Length: 2034, dtype: int64
--------------------
Column: mode
mode
1.0    4788
0.0    2973
Name: count, dtype: int64
--------------------
Column: energy
energy
0.7390    31
0.6690    28
0.8330    26
0.7640    26
0.7130    25
          ..
0.3250     1
0.1820     1
0.0268     1
0.1230     1
0.2150     1
Name: count, Length: 901, dtype: int64
--------------------
Column: instrumentalness
instrumentalness
0.000000    2920
0.000014       9
0.104000       8
0.000107       8
0.000020       7
            ...
0.096000       1
0.170000       1
0.000713       1
0.000540       1
0.000004       1
Name: count, Length: 2798, dtype: int64
--------------------
Column: liveness
liveness
0.1030    71
0.1090    70
0.1040    69
0.1110    65
0.1080    64
          ..
0.0413     1
0.5320     1
0.5760     1
0.5530     1
0.8350     1
Name: count, Length: 1403, dtype: int64
```

```
--------------------
Column: loudness
loudness
-6.044     6
-7.893     6
-5.078     5
-5.861     5
-4.857     5
          ..
-5.595     1
-13.095    1
-6.656     1
-8.219     1
-5.533     1
Name: count, Length: 5591, dtype: int64
--------------------
Column: speechiness
speechiness
0.1110    33
0.1190    26
0.1090    26
0.1020    26
0.1080    25
          ..
0.0274     1
0.0801     1
0.7940     1
0.0953     1
0.7110     1
Name: count, Length: 1213, dtype: int64
--------------------
Column: tempo
tempo
112.999    9
113.005    9
113.001    9
113.002    8
113.013    8
          ..
125.052    1
104.985    1
103.020    1
170.122    1
202.034    1
Name: count, Length: 6548, dtype: int64
--------------------
Column: time_signature
time_signature
4.0    6947
3.0     483
5.0     282
1.0      40
0.0       9
Name: count, dtype: int64
--------------------
Column: valence
valence
0.9610    57
0.9620    36
0.9650    30
0.9640    29
0.8380    28
          ..
0.0380     1
0.0502     1
0.2280     1
0.0656     1
0.0948     1
Name: count, Length: 935, dtype: int64
--------------------
```

Data Preprocessing

Missing Values

In [13]:

```
#checking for missing values
df.isna().sum()
```

Out[13]:

```
track_name            0
track_id              0
genre               258
album_name            0
artist_name           0
release_date          0
duration_ms           0
popularity            0
danceability          0
key                   0
acousticness          0
mode                  0
energy                0
instrumentalness      0
liveness              0
loudness              0
speechiness           0
tempo                 0
time_signature        0
valence               0
dtype: int64
```

We have 206 missing values in the `'genre'` column

In [14]:

```
df[df['genre'].isna()]
```

Out[14]:

	track_name	track_id	genre	album_name	artist_name	release_date	duration_ms	popularity	dan
108	Dada	7gOiZ1yDVv3teExIKt6O5c	NaN	Karibu	Barbara Kanam	2009	168253.0	5.0	
485	Par amour	0XG1u0KC2lG7qFlY0LAFt4	NaN	Techno malewa sans cesse, Vol. 1	Werrason	2009-01-01	531773.0	21.0	
641	Afro Beat Blues	4xclRUqjOM5HMzDZQyRaPo	NaN	The Chisa Years 1965-1975 (Rare and Unreleased)	Hugh Masekela	2006-03-13	408106.0	44.0	
644	Joala	2ZFywHbfQDiTLJLzk5wj9U	NaN	The Chisa Years 1965-1975 (Rare and Unreleased)	Hugh Masekela	2006-03-13	122946.0	17.0	
646	Za Labalaba	4iw3PchnWTNJFaqeEFVsf1	NaN	The Chisa Years 1965-1975 (Rare and Unreleased)	Hugh Masekela	2006-03-13	187160.0	13.0	
...	...	...	...	...	...	...	...	...	...
	Animation			Le zénith de papa					

	track_name	track_id	genre	album_name	artist_name	release_date	duration_ms	popularity	dan
6602	... pour les fioti-fioti - Live	3CVjzMBmyDxy897G[illegible]	NaN	... papa wemba, vol. 1 (Esprit de fêtes)	Papa Wemba	1999-12-17	[illegible]	0.0	
6609	Présentation de Zimbabwe par Rouf Mbuta Nganga...	6bHJkPp54xMpcKDxdtlbEc	NaN	Le zénith de papa wemba, vol. 1 (Esprit de fêtes)	Papa Wemba	1999-12-17	25208.0	0.0	
6611	Présentation des fioti-fioti par Rouf Mbuta Ng...	594Q8xWo0spLm5wEdlhdOF	NaN	Le zénith de papa wemba, vol. 1 (Esprit de fêtes)	Papa Wemba	1999-12-17	6025.0	0.0	
6674	Allah	5PwcufFyTYhOhVLDFMPSzG	NaN	Merveilles du passé (1977-1985)	Papa Wemba	1997-04-21	408986.0	1.0	
7289	Inyakanyaka (feat. S.C Gorna & Khandu Cash)	3WuQZRMIWXH6yY2A5d4xfs	NaN	Blaqboy Music Presents Gqom Wave	DJ Maphorisa	2017-11-17	325320.0	10.0	

258 rows × 20 columns

We shall drop all rows with missing genres from the dataset

In [15]:

```
df = df.dropna()
df.shape
```

Out[15]:

```
(7503, 20)
```

In [16]:

```
df.isna().sum()
```

Out[16]:

```
track_name          0
track_id            0
genre               0
album_name          0
artist_name         0
release_date        0
duration_ms         0
popularity          0
danceability        0
key                 0
acousticness        0
mode                0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
time_signature      0
valence             0
dtype: int64
```

In [17]:

```
# Check for duplicated tracks by using their unique id numbers.
df[df['track_id'].duplicated()]
```

Out[17]:

track_name	track_id	genre	album_name	artist_name	release_date	duration_ms	popularity	danceability	key	acousticnes

We do not have any duplicated track.

Multiple genres are associated with each track because the genres of the track is based on the genre which the artist belong for this dataset. What makes the most sense in this case would be to create different columns with the genre names and display with binary values whether a song belongs to that genre or not. Before we do this, we need to address some few key issues.

First, we have both 'afrobeat' and 'afrobeats' listed as genres. Also 'azonto' and 'azontobeats' should be listed as same genre. To ensure consistency and accurate categorization, these terms should be treated as synonymous:

In [18]:

```
import re
```

In [19]:

```
# Check genres that contains afrobeat
pattern = fr'\bafrobeat\b'
pattern = re.compile(pattern, flags=re.IGNORECASE)
df[df['genre'].apply(lambda x: bool(pattern.search(x)))].shape[0]
```

Out[19]:

109

In [20]:

```
# Check genres that contains afrobeats
pattern = fr'\bafrobeats\b'
pattern = re.compile(pattern, flags=re.IGNORECASE)
df[df['genre'].apply(lambda x: bool(pattern.search(x)))].shape[0]
```

Out[20]:

1714

We have 111 genres with 'afrobeat' (without 's') and 1724 genres with 'afrobeats' (with 's')

In [21]:

```
# Replace all 'afrobeat' with 'afrobeats'
pattern = r'\bafrobeat\b'
df['genre'] = df['genre'].apply(lambda x: re.sub(pattern, 'afrobeats', x))
```

Recheck to see if the issue has been resolved

In [22]:

```
pattern = r'\bafrobeat\b'
pattern = re.compile(pattern, flags=re.IGNORECASE)
df[df['genre'].apply(lambda x: bool(pattern.search(x)))].shape[0]
```

Out[22]:

0

In [23]:

```
pattern = r'\bafrobeats\b'
pattern = re.compile(pattern, flags=re.IGNORECASE)
df[df['genre'].apply(lambda x: bool(pattern.search(x)))].shape[0]
```

Out[23]:

1823

We'll perform the same operation for azonto, azontobeat and azontobeats

In [24]:

```
pattern = r'(\bazonto\b)|(\bazontobeat\b)'
pattern = re.compile(pattern, flags=re.IGNORECASE)
df[df['genre'].apply(lambda x: bool(pattern.search(x)))].shape[0]
```

Out[24]:

745

In [25]:

```
pattern = r'\bazontobeats\b'
pattern = re.compile(pattern, flags=re.IGNORECASE)
df[df['genre'].apply(lambda x: bool(pattern.search(x)))].shape[0]
```

Out[25]:

1420

In [26]:

```
# Replace 'azonto' and 'azontobeat' with 'azontobeats'
pattern = r'\bazonto\b'
df['genre'] = df['genre'].apply(lambda x: re.sub(pattern, 'azontobeats', x))
```

In [27]:

```
pattern = r'(\bazonto\b)|(\bazontobeat\b)'
pattern = re.compile(pattern, flags=re.IGNORECASE)
df[df['genre'].apply(lambda x: bool(pattern.search(x)))].shape[0]
```

Out[27]:

0

In [28]:

```
pattern = r'\bazontobeats\b'
pattern = re.compile(pattern, flags=re.IGNORECASE)
df[df['genre'].apply(lambda x: bool(pattern.search(x)))].shape[0]
```

Out[28]:

2019

Secondly, in the `genre` column, we observe various subgenres, including 'south african pop', ghanian pop', nigerian pop' which all fall under the broader category of pop music. Similarly, 'south african hip hop', 'nigerian hip hop,' and 'christian hip hop' are subgenres falling within the hip hop music category. To streamline our machine learning process, we will group these subgenres together under their respective main genres for effective model training and classification.

In [29]:

```
def genres_from_string(series):
    all_genres = set()     # Remove duplicates
    genres = series.str.split(',')
    for item in genres:
        all_genres.update(item)
    return list(all_genres)
```

In [30]:

```
# generating a list with the genre names
genre_list = genres_from_string(df['genre'])
```

In [31]:

```
len(genre_list)
```

Out[31]:

```
88
```

In [32]:

```
genre_list
```

Out[32]:

```
['dancehall',
 'r&b francais',
 'motown',
 'south african house',
 'gengetone',
 'ghanaian pop',
 'kwaito',
 'barcadi',
 'melodic techno',
 'afroswing',
 'afro soul',
 'south african hip hop',
 'old school highlife',
 'christian afrobeats',
 'swiss house',
 'xhosa hip hop',
 'organic electronic',
 'uk dancehall',
 'amharic pop',
 'belgian techno',
 'zilizopendwa',
 'kasi rap',
 'minimal tech house',
 'house argentino',
 'afrobeats',
 'world',
 'alte',
 'xitsonga pop',
 'south african pop',
 'south african trap',
 'ghanaian alternative',
 'portuguese pop',
 'south african deep house',
 'afro r&b',
 'south african pop dance',
 'afrikaans hip hop',
 'nigerian pop',
 'israeli techno',
 'organic house',
 'french hip hop',
 'pop urbaine',
 'microhouse',
 'bolobedu house',
 'african rock',
 'azontobeats',
 'xhosa',
 'cape town indie',
 'funk carioca',
 'grime',
 'uk hip hop',
 'brass band',
 'funky house',
 'soukous',
 'south african alternative',
 'swedish dancehall',
 'ndombolo',
 'beninese pop',
 'kenyan r&b',
```

```
 'deep deep house',
 'sda a cappella',
 'rumba congolaise',
 'eritrean pop',
 'hiplife',
 'minimal techno',
 'ghanaian hip hop',
 'afropop',
 'dutch hip hop',
 'south african jazz',
 'movie tunes',
 'asakaa',
 'funk rj',
 'melodic house',
 'nigerian hip hop',
 'tanzanian hip hop',
 'musique urbaine kinshasa',
 'amapiano',
 'german house',
 'kenyan pop',
 'afro house',
 'ethiopian pop',
 'south african soulful deep house',
 'jazz trumpet',
 'gqom',
 'tanzanian pop',
 'kenyan hip hop',
 'south african choral',
 'bongo flava',
 'african reggae']
```

In [33]:

```
main_genres = ['hip hop', 'pop', 'rock', 'rap', 'r&b', 'jazz', 'trap',
               'afrobeat', 'alternative', 'soul', 'blues', 'techno', 'amapiano',
               'reggae', 'highlife', 'house', 'dancehall', 'funk']
```

In [34]:

```
new_genres = genre_list.copy()
```

In [35]:

```
for genre in main_genres:
    pattern = fr'\b{genre}\b'
    pattern = re.compile(pattern, flags=re.IGNORECASE)
    for i, sub_genre in enumerate(new_genres):
        if pattern.search(sub_genre):
            new_genres[i] = genre
```

The code above turns every subgenres in new_genres into its main genres

In [36]:

```
genre_list[:8]
```

Out[36]:

```
['dancehall',
 'r&b francais',
 'motown',
 'south african house',
 'gengetone',
 'ghanaian pop',
 'kwaito',
 'barcadi']
```

In [37]:

```
new_genres[:8]
```

Out[37]:

```
['dancehall',
 'r&b',
 'motown',
 'house',
 'gengetone',
 'pop',
 'kwaito',
 'barcadi']
```

In [38]:

```
# remove duplicates genres
new_genres = list(set(new_genres))
```

In [39]:

```
len(new_genres)
```

Out[39]:

```
45
```

In [40]:

```
new_genres
```

Out[40]:

```
['dancehall',
 'zilizopendwa',
 'hiplife',
 'xhosa',
 'afrobeats',
 'house',
 'soul',
 'motown',
 'afropop',
 'world',
 'gengetone',
 'alte',
 'kwaito',
 'alternative',
 'barcadi',
 'south african choral',
 'cape town indie',
 'trap',
 'grime',
 'funk',
 'movie tunes',
 'asakaa',
 'brass band',
 'afroswing',
 'rock',
 'soukous',
 'musique urbaine kinshasa',
 'reggae',
 'amapiano',
 'hip hop',
 'christian afrobeats',
 'jazz',
 'ndombolo',
 'azontobeats',
 'microhouse',
 'organic electronic',
 'techno',
 'gqom',
 'pop',
 'r&b',
 'sda a cappella',
 'highlife',
 'rap',
```

```
 'rap',
 'bongo flava',
 'rumba congolaise']
```

As we focus on popular music, we'll exclude genres that are either unpopular or infrequent (with a low count or appearance) in our dataset. This involves counting each genre and eliminating those that constitute less than 5 percent of the total dataset.

In [41]:

```python
genre_counts = {}
for genre in new_genres:
    pattern = re.compile(fr'\b{genre}\b')
    count = df['genre'].apply(lambda x: bool(pattern.search(x))).sum()
    genre_counts[genre] = count

genre_counts
```

Out[41]:

```
{'dancehall': 238,
 'zilizopendwa': 874,
 'hiplife': 407,
 'xhosa': 579,
 'afrobeats': 1823,
 'house': 409,
 'soul': 882,
 'motown': 1,
 'afropop': 2672,
 'world': 811,
 'gengetone': 157,
 'alte': 100,
 'kwaito': 816,
 'alternative': 209,
 'barcadi': 53,
 'south african choral': 38,
 'cape town indie': 133,
 'trap': 270,
 'grime': 17,
 'funk': 1,
 'movie tunes': 7,
 'asakaa': 84,
 'brass band': 34,
 'afroswing': 30,
 'rock': 209,
 'soukous': 1113,
 'musique urbaine kinshasa': 257,
 'reggae': 227,
 'amapiano': 256,
 'hip hop': 1720,
 'christian afrobeats': 18,
 'jazz': 1061,
 'ndombolo': 735,
 'azontobeats': 2019,
 'microhouse': 1,
 'organic electronic': 3,
 'techno': 4,
 'gqom': 19,
 'pop': 3556,
 'r&b': 362,
 'sda a cappella': 38,
 'highlife': 44,
 'rap': 165,
 'bongo flava': 264,
 'rumba congolaise': 1245}
```

In [42]:

```python
0.05 * len(df)
```

Out[42]:

```
375.15000000000003
```

In [43]:

```python
new_genres = [genre for genre in genre_counts if genre_counts[genre] >= 0.05 * len(df)]
new_genres
```

Out[43]:

```
['zilizopendwa',
 'hiplife',
 'xhosa',
 'afrobeats',
 'house',
 'soul',
 'afropop',
 'world',
 'kwaito',
 'soukous',
 'hip hop',
 'jazz',
 'ndombolo',
 'azontobeats',
 'pop',
 'rumba congolaise']
```

To refine our dataset for analysis, genres were binarized, transforming them into distinct binary columns. This process involved assigning a '1' to indicate the presence of a genre and '0' for absence. Notably, only genres above 5%, determined based on their prevalence within the dataset, were retained for further investigation. This selective approach ensures that our analysis focuses on the most influential genres, allowing for a more concentrated examination of the predominant musical styles in our dataset.

In [44]:

```python
df
```

Out[44]:

	track_name	track_id	genre	album_name	artist_name	release_date	duration_ms
0	Bandana	2qWwuCVeMjF9mUT0S5lqvl	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	178225.0
1	All Of Us (Ashawo)	6459gZKddpOoPlH8PAcCwS	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	183349.0
2	Playboy	2gGAyatRqjjx3DOmLGI12W	azontobeats,hiplife	Play Boy	Daddy Lumba	1992-10-05	316440.0
3	Adore (feat. euro)	3ouP8HFixJmafK7hd1wJ0q	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	201826.0
4	Sofri	6S5XNauc7v8FLJWElk0z2c	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	179246.0
...	...	...	...	...	...	...	...
7756	Odo Dede	5JB0EcpkbUsyaU9EvzK3bw	afro r&b,afrobeats,ghanaian pop	L.I.T.A (Deluxe Edition)	Camidoh	2023-06-23	236202.0
7757	Save My Soul	0dXCiV6LK9YkpBP5lbFiD4	afro r&b,afrobeats,ghanaian pop	L.I.T.A (Deluxe Edition)	Camidoh	2023-06-23	139080.0
7758	Decisions	2U5vPEm0m58dY8DCmKx1hr	afro r&b,afrobeats,ghanaian pop	L.I.T.A	Camidoh	2023-06-02	197041.0
7759	Sugarcane	2HfK1KumDffDWPZga46Hmw	afro r&b,afrobeats,ghanaian pop	L.I.T.A	Camidoh	2023-06-02	156781.0
7760	Sugarcane - Remix	6NuG2JgERZZXvvjmtjOFix	afro r&b,afrobeats,ghanaian pop	L.I.T.A	Camidoh	2023-06-02	251147.0

track_name	track_id	genre	album_name	artist_name	release_date	duration_ms

7503 rows × 20 columns

In [45]:

```
# Creating columns for each genre in the new_genres list
for genre in new_genres:
    pattern = re.compile(fr'\b{genre}\b')
    df[genre] = (df['genre'].apply(lambda x: bool(pattern.search(x)))).astype('int')
```

In [46]:

```
# View all rows where 'pop' is included as a genre
df[df['pop']==1]
```

Out[46]:

	track_name	track_id	genre	album_name	artist_name	release_date	duration_ms
0	Bandana	2qWwuCVeMjF9mUT0S5lqvl	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	178225.(
1	All Of Us (Ashawo)	6459gZKddpOoPIH8PAcCwS	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	183349.(
3	Adore (feat. euro)	3ouP8HFixJmafK7hd1wJ0q	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	201826.(
4	Sofri	6S5XNauc7v8FLJWEIk0z2c	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	179246.(
6	Compromise (feat. Rema)	2dG1cXdbEPKEOyUq96R9xz	afrobeats,nigerian pop	Playboy	Fireboy DML	2022-08-04	195939.(
...	...	...	...	...	...	...	..
7756	Odo Dede	5JB0EcpkbUsyaU9EvzK3bw	afro r&b,afrobeats,ghanaian pop	L.I.T.A (Deluxe Edition)	Camidoh	2023-06-23	236202.(
7757	Save My Soul	0dXCiV6LK9YkpBP5lbFiD4	afro r&b,afrobeats,ghanaian pop	L.I.T.A (Deluxe Edition)	Camidoh	2023-06-23	139080.(
7758	Decisions	2U5vPEm0m58dY8DCmKx1hr	afro r&b,afrobeats,ghanaian pop	L.I.T.A	Camidoh	2023-06-02	197041.(
7759	Sugarcane	2HfK1KumDffDWPZga46Hmw	afro r&b,afrobeats,ghanaian pop	L.I.T.A	Camidoh	2023-06-02	156781.(
7760	Sugarcane - Remix	6NuG2JgERZZXvvjmtjOFix	afro r&b,afrobeats,ghanaian pop	L.I.T.A	Camidoh	2023-06-02	251147.(

3556 rows × 36 columns

In [47]:

```
# View all rows where 'azontobeats' is included as a genre
df[df['azontobeats']==1]
```

Out[47]:

	track_name	track_id	genre	album_name	artist_name	relea
2	Playboy	2gGAyatRqjjx3DOmLGI12W	azontobeats,hiplife	Play Boy	Daddy Lumba	19
10	Glory	5KLFqxmGAZKj3HpGzExiZR	afrobeats,afropop,azontobeats,ghanaian hip hop	Highest	Sarkodie	20

	track_name	track_id	genre	album_name	artist_name	relea
21	Vibration	1G9vMHSCONlfAJpr43dXLp	afrobeats,azontobeats,azontobeats,hiplife	inVeencible	MzVee	202
59	Superwoman	2N0CQeerTwRs3qHicCma4J	azontobeats,bongo flava,tanzanian pop	Flamingo	Ben Pol	202
62	Beat It	3rL8A5P8pMH6E3KdK1xG3n	afrobeats,afropop,alte,azontobeats,nigerian pop	Oga Ju	Simi	201
...	...	...	...	...	...	
7743	Designer	12h07KUjxVo51jvtBcTPkR	afrobeats,afropop,azontobeats,nigerian hip hop...	Old Romance	Tekno	202
7744	Neighbour	0nmNi1EhdLOSwTntGieWzs	afrobeats,afropop,azontobeats,nigerian hip hop...	Old Romance	Tekno	202
7745	Armageddon	7zvjLlVmJ6r3g2EiSWpJ4W	afrobeats,afropop,azontobeats,nigerian hip hop...	Old Romance	Tekno	202
7746	Dana	5D3MhUkeFoOHmdGG8uOVTX	afrobeats,afropop,azontobeats,nigerian hip hop...	Old Romance	Tekno	202
7747	Ugly Parade	4H8dMbq5ffZHI5oNjuq1S5	afrobeats,afropop,azontobeats,nigerian hip hop...	Old Romance	Tekno	202

2019 rows × 36 columns

In [48]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7503 entries, 0 to 7760
Data columns (total 36 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   track_name         7503 non-null   object 
 1   track_id           7503 non-null   object 
 2   genre              7503 non-null   object 
 3   album_name         7503 non-null   object 
 4   artist_name        7503 non-null   object 
 5   release_date       7503 non-null   object 
 6   duration_ms        7503 non-null   float64
 7   popularity         7503 non-null   float64
 8   danceability       7503 non-null   float64
 9   key                7503 non-null   float64
 10  acousticness       7503 non-null   float64
 11  mode               7503 non-null   float64
 12  energy             7503 non-null   float64
 13  instrumentalness   7503 non-null   float64
 14  liveness           7503 non-null   float64
 15  loudness           7503 non-null   float64
 16  speechiness        7503 non-null   float64
 17  tempo              7503 non-null   float64
 18  time_signature     7503 non-null   float64
 19  valence            7503 non-null   float64
 20  zilizopendwa       7503 non-null   int64  
 21  hiplife            7503 non-null   int64  
 22  xhosa              7503 non-null   int64  
 23  afrobeats          7503 non-null   int64  
 24  house              7503 non-null   int64  
 25  soul               7503 non-null   int64  
 26  afropop            7503 non-null   int64  
 27  world              7503 non-null   int64  
 28  kwaito             7503 non-null   int64  
 29  soukous            7503 non-null   int64  
 30  hip hop            7503 non-null   int64  
 31  jazz               7503 non-null   int64  
 32  ndombolo           7503 non-null   int64  
 33  azontobeats        7503 non-null   int64  
 34  pop                7503 non-null   int64  
 35  rumba congolaise   7503 non-null   int64  
dtypes: float64(14), int64(16), object(6)
memory usage: 2.1+ MB
```

In [49]:

```
# Removing the redundant genre column
df.drop('genre', axis=1, inplace=True)
df.head()
```

Out[49]:

	track_name	track_id	album_name	artist_name	release_date	duration_ms	popularity	danceability	ke
0	Bandana	2qWwuCVeMjF9mUT0S5Iqvl	Playboy	Fireboy DML	2022-08-04	178225.0	73.0	0.818	1
1	All Of Us (Ashawo)	6459gZKddpOoPIH8PAcCwS	Playboy	Fireboy DML	2022-08-04	183349.0	62.0	0.605	11
2	Playboy	2gGAyatRqjjx3DOmLGI12W	Play Boy	Daddy Lumba	1992-10-05	316440.0	16.0	0.732	11
3	Adore (feat. euro)	3ouP8HFixJmafK7hd1wJ0q	Playboy	Fireboy DML	2022-08-04	201826.0	42.0	0.709	0
4	Sofri	6S5XNauc7v8FLJWEIk0z2c	Playboy	Fireboy DML	2022-08-04	179246.0	47.0	0.745	6

Feature Engineering

Creating `is_popular` Feature

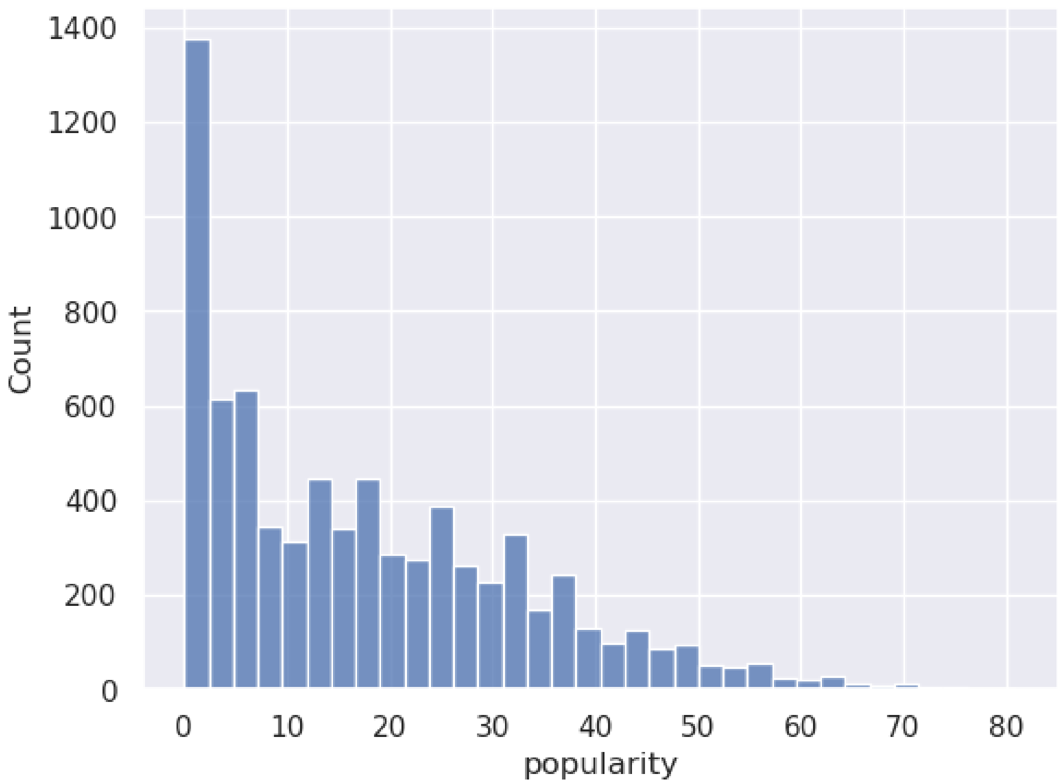
Since our goal is to be able to identify which tracks will be popular, we need to feature engineer a new column by binarizing the popularity column. To be able to do this, we need to decide on a cut-off point of popularity score which if a song stays above this cut-off point it will be considered "popular" and if it stays below it will be considered "not popular". We can start off by taking a look at the distribution of the popularity score distribution.

In [51]:

```
#creating a histogram to see distribution of popularity scores in the dataset.
sns.histplot(df['popularity'], bins='auto')
```

Out[51]:

```
<Axes: xlabel='popularity', ylabel='Count'>
```



Top 100 Songs

In order to better decide what's popular, we can take a look at the Top 100 songs' popularity scores from a playlist that contains top 100 popular songs by african artist created by a spotify user.

In [52]:

```
df_100 = pd.read_csv('data/top_100_african_hits.csv')
```

In [53]:

```
df_100['popularity'].describe()
```

Out[53]:

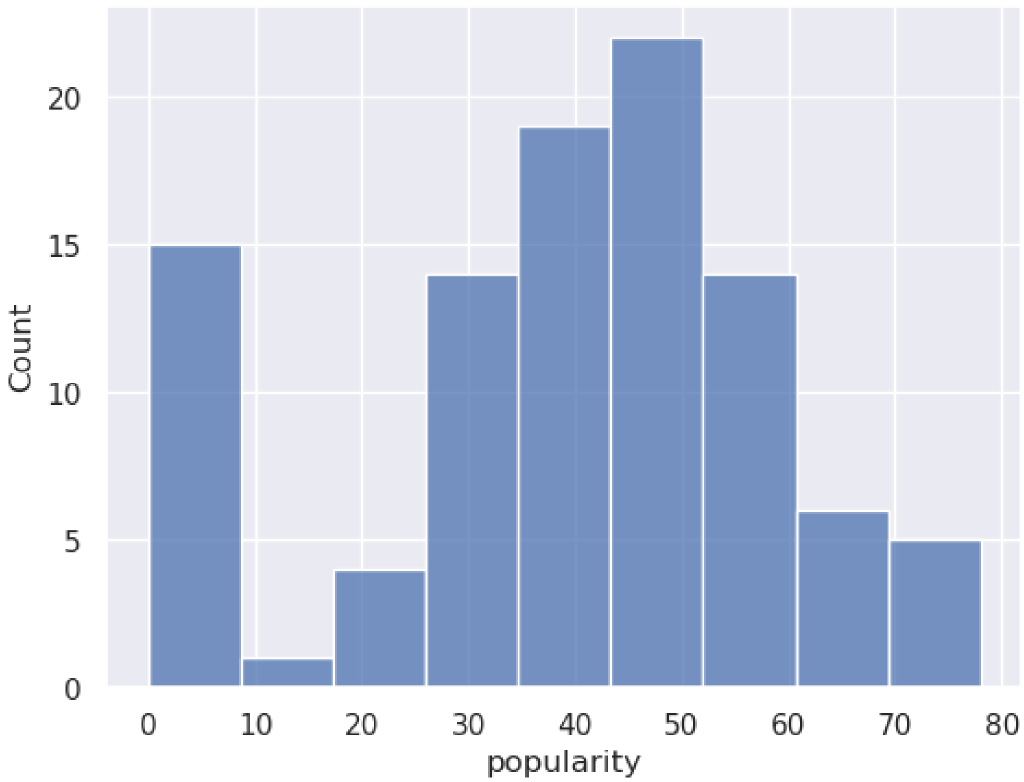
```
count    100.000000
mean      38.860000
std       20.584892
min        0.000000
25%       30.500000
50%       42.500000
75%       51.250000
max       78.000000
Name: popularity, dtype: float64
```

In [54]:

```
fig, ax = plt.subplots()
sns.histplot(df_100['popularity'], bins='auto', ax=ax)
```

Out[54]:

```
<Axes: xlabel='popularity', ylabel='Count'>
```



From the above histogram we see that we have a bimodal distribution. One of the peaks is around 5, and the other one seems to be around 45.

In [55]:

```
df_100['popularity'].describe()['50%']        # Median value
```

Out[55]:

42.5

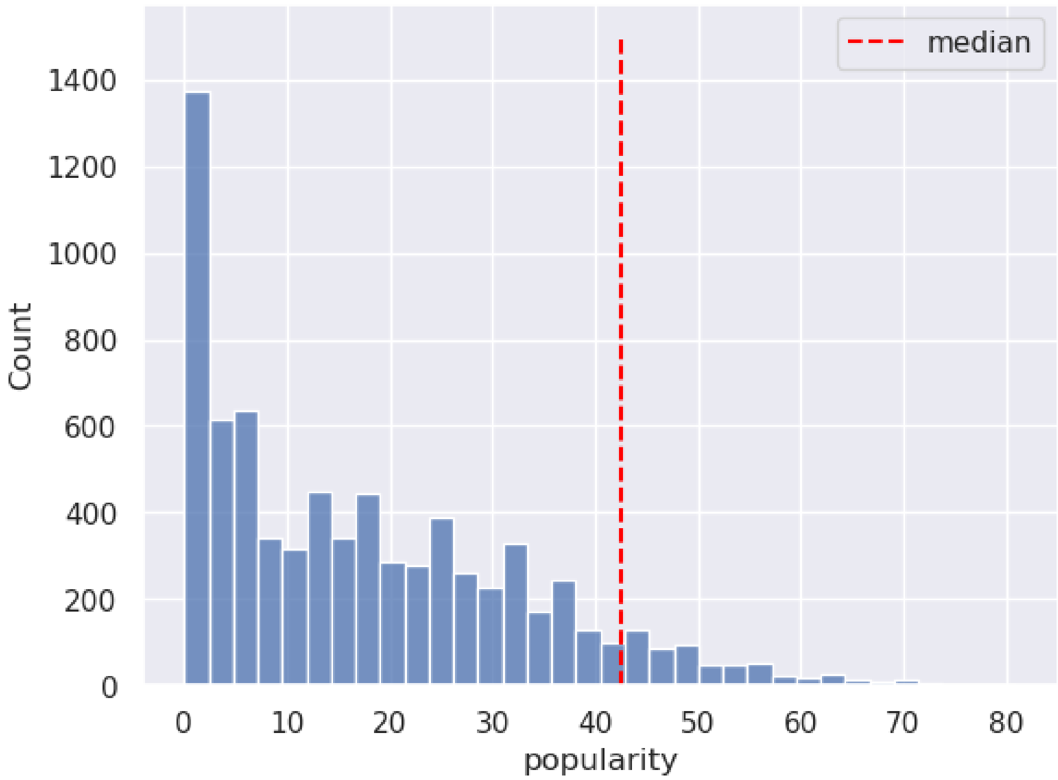
We will be defining a song being popular as being African Top 100 worthy and therefore we will establish our cutoff point at the median value (42.5)

In [56]:

```
# Visualizing the meadian popularity scores on the overall dataset histogram
fig, ax = plt.subplots()
sns.histplot(df['popularity'], bins='auto', ax=ax)
ax.vlines(x=df_100['popularity'].describe()['50%'], ymin=0, ymax=1500, linestyles='dashed', colors='red', label='median')
plt.legend()
```

Out[56]:

<matplotlib.legend.Legend at 0x7feefa72a050>



In [57]:

```
#creating is_popular column with our cutoff point
df['is_popular']=(df['popularity']>=42.5).astype('int')
df.head()
```

Out[57]:

	track_name	track_id	album_name	artist_name	release_date	duration_ms	popularity	danceability	ke
0	Bandana	2qWwuCVeMjF9mUT0S5lqvl	Playboy	Fireboy DML	2022-08-04	178225.0	73.0	0.818	1
1	All Of Us (Ashawo)	6459gZKddpOoPIH8PAcCwS	Playboy	Fireboy DML	2022-08-04	183349.0	62.0	0.605	11
2	Playboy	2gGAyatRqjjx3DOmLGI12W	Play Boy	Daddy Lumba	1992-10-05	316440.0	16.0	0.732	11
3	Adore (feat. euro)	3ouP8HFixJmafK7hd1wJ0q	Playboy	Fireboy DML	2022-08-04	201826.0	42.0	0.709	0
4	Sofri	6S5XNauc7v8FLJWElk0z2c	Playboy	Fireboy DML	2022-08-04	179246.0	47.0	0.745	6

In [58]:

```
#dropping popularity score column since we will not be using it
df.drop(['popularity', 'artist_name', 'track_name', 'album_name', 'release_date'], axis=
1, inplace=True)
df.set_index('track_id', inplace=True)     # Set the 'track_id' column as the index
df.head()
```

Out[58]:

	duration_ms	danceability	key	acousticness	mode	energy	instrumentalness	liveness	loudnes
track_id									
2qWwuCVeMjF9mUT0S5lqvl	178225.0	0.818	1.0	0.293	1.0	0.605	0.011600	0.0696	-7.12
6459gZKddpOoPIH8PAcCwS	183349.0	0.605	11.0	0.304	1.0	0.813	0.003300	0.1320	-6.41
2gGAyatRqjjx3DOmLGI12W	316440.0	0.732	11.0	0.225	1.0	0.797	0.138000	0.2650	-10.20
3ouP8HFixJmafK7hd1wJ0q	201826.0	0.709	0.0	0.108	1.0	0.511	0.000019	0.1410	-6.97
6S5XNauc7v8FLJWEIk0z2c	179246.0	0.745	6.0	0.341	1.0	0.580	0.002610	0.1270	-5.59

We dropped popularity scores since we already binarized that column, but additionally we are dropping `'artist_name'`, `'track_name'`, `'album_name'`, and `'release_date'` since we are looking at the anatomy of a song and not who sings it, what it's called or when it was released. The goal is to identify songs that will become popular without being affected by the artist's name since we would also like to find songs from up-and-coming artists.

One Hot Encoding the Categorical Columns

We still have categorical columns that need one hot encoding. Namely, these columns are `key`, `mode` and `time_signature`.

In [59]:

```
# Check to see how many more columns we will be creating by OHE the cat_cols.
df.nunique()
```

Out[59]:

```
duration_ms         6891
danceability         700
key                   12
acousticness        2023
mode                   2
energy               899
instrumentalness    2769
liveness            1392
loudness            5447
speechiness         1207
tempo               6342
time_signature         5
valence              934
zilizopendwa           2
hiplife                2
xhosa                  2
afrobeats              2
house                  2
soul                   2
afropop                2
world                  2
kwaito                 2
soukous                2
hip hop                2
jazz                   2
ndombolo               2
azontobeats            2
```

```
pop                   2
rumba congolaise      2
is_popular            2
dtype: int64
```

In [60]:

```python
df.nunique()['mode']
```

Out[60]:

```
2
```

In [61]:

```python
df.nunique()['time_signature']
```

Out[61]:

```
5
```

In [62]:

```python
df.nunique()['key']
```

Out[62]:

```
12
```

We will be creating additional 16 columns ---> 2 (mode) + 5 (time_signature) + 12 (key) - 3 (We'll drop first column of each encoded category)

In [63]:

```python
# Define categorical columns
cat_cols = ['key', 'mode', 'time_signature']
```

In [64]:

```python
# One hot encoding the dataframes
from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder(sparse_output=False, drop='first')

df_ohe = encoder.fit_transform(df[cat_cols])
df_ohe = pd.DataFrame(df_ohe, columns=encoder.get_feature_names_out(cat_cols), index=df.
index)
df_ohe.head()
```

Out[64]:

	key_1.0	key_2.0	key_3.0	key_4.0	key_5.0	key_6.0	key_7.0	key_8.0	key_9.0	key_10.0	key_11.(
track_id											
2qWwuCVeMjF9mUT0S5lqvl	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
6459gZKddpOoPIH8PAcCwS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.(
2gGAyatRqjjx3DOmLGI12W	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.(
3ouP8HFixJmafK7hd1wJ0q	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
6S5XNauc7v8FLJWEIk0z2c	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.(

In [65]:

```python
df_ohe.shape
```

Out[65]:

```
(7503, 16)
```

In [66]:

```
# Merging OHE columns with numerical columns
df = pd.concat([df.drop(cat_cols, axis=1), df_ohe], axis=1)
df.tail()
```

Out[66]:

	duration_ms	danceability	acousticness	energy	instrumentalness	liveness	loudness	speechin
track_id								
5JB0EcpkbUsyaU9EvzK3bw	236202.0	0.651	0.112	0.707	0.000000	0.0894	-4.835	0.1
0dXCiV6LK9YkpBP5lbFiD4	139080.0	0.529	0.672	0.526	0.000000	0.4190	-7.153	0.1
2U5vPEm0m58dY8DCmKx1hr	197041.0	0.835	0.466	0.590	0.001660	0.1690	-8.347	0.0
2HfK1KumDffDWPZga46Hmw	156781.0	0.519	0.415	0.713	0.000507	0.1230	-5.497	0.2
6NuG2JgERZZXvvjmtjOFix	251147.0	0.838	0.347	0.707	0.000029	0.1130	-5.533	0.0

In [67]:

```
df.columns
```

Out[67]:

```
Index(['duration_ms', 'danceability', 'acousticness', 'energy',
       'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo',
       'valence', 'zilizopendwa', 'hiplife', 'xhosa', 'afrobeats', 'house',
       'soul', 'afropop', 'world', 'kwaito', 'soukous', 'hip hop', 'jazz',
       'ndombolo', 'azontobeats', 'pop', 'rumba congolaise', 'is_popular',
       'key_1.0', 'key_2.0', 'key_3.0', 'key_4.0', 'key_5.0', 'key_6.0',
       'key_7.0', 'key_8.0', 'key_9.0', 'key_10.0', 'key_11.0', 'mode_1.0',
       'time_signature_1.0', 'time_signature_3.0', 'time_signature_4.0',
       'time_signature_5.0'],
      dtype='object')
```

Train Test Split

In [68]:

```
df.shape
```

Out[68]:

```
(7503, 43)
```

In [69]:

```
# Splitting the data to training and test sets in order to be able to measure performance
from sklearn.model_selection import train_test_split
y=df['is_popular']
X=df.drop('is_popular', axis=1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, random_state=4
2)
```

With both the X_train and X_test dataframes cleaned and one hot encoded we can move onto the modelling process.

Models

The first model we will be generating is a dummy classifier. We will be comparing our models' success to each other but also to this baseline model.

Model 0 - Baseline - Dummy Classifier

In [70]:

```
from sklearn.dummy import DummyClassifier

clf_dummy = DummyClassifier(random_state=42)
clf_dummy.fit(X_train, y_train)
y_pred = clf_dummy.predict(X_test)
```

We need a function that will show us the classification report, the confusion matrix as well as the ROC curve to be able to evaluate our models.

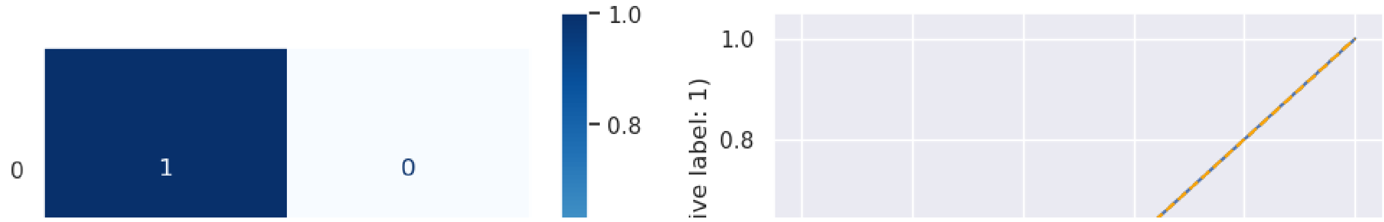
In [71]:

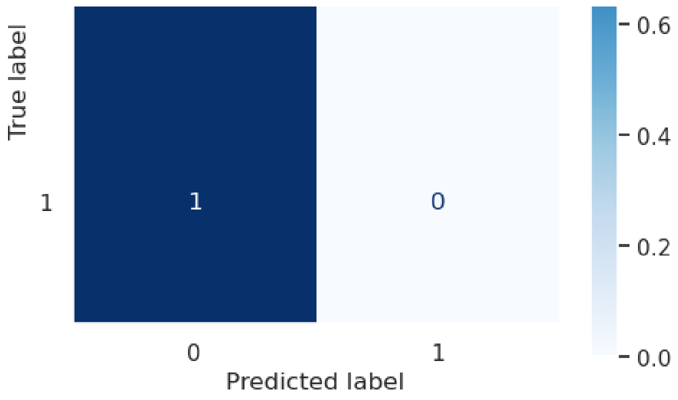
```
from sklearn.metrics import classification_report, ConfusionMatrixDisplay, RocCurveDispla
y

def classification(y_true, y_pred, X, clf):
    """This function shows the classification report,
    the confusion matrix as well as the ROC curve for evaluation of model quality.

    y_true: Correct y values, typically y_test that comes from the train_test_split perfo
rmed at the beginning of model development.
    y_pred: Predicted y values by the model.
    clf: classifier model that was fit to training data.
    X: X_test values"""

    #Classification report
    print("CLASSIFICATION REPORT")
    print("-------------------------------------------")
    print(classification_report(y_true=y_true, y_pred=y_pred, zero_division=0))

    #Creating a figure/axes for confusion matrix and ROC curve
    fig, ax = plt.subplots(ncols=2, figsize=(12, 5))

    #Plotting the normalized confusion matrix
    ConfusionMatrixDisplay.from_estimator(estimator=clf, X=X, y=y_true, cmap='Blues', no
rmalize='true', ax=ax[0])
    ax[0].grid(False)

    # Plotting the ROC curve
    RocCurveDisplay.from_estimator(estimator=clf, X=X, y=y_true, ax=ax[1])

    #Plotting the 50-50 guessing plot for reference
    ax[1].plot([0,1], [0,1], ls='--', color='orange',)
```

In [72]:

```
classification(y_test, y_pred, X_test, clf_dummy)
```

```
CLASSIFICATION REPORT
-------------------------------------------
              precision    recall  f1-score   support

           0       0.92      1.00      0.96      1038
           1       0.00      0.00      0.00        88

    accuracy                           0.92      1126
   macro avg       0.46      0.50      0.48      1126
weighted avg       0.85      0.92      0.88      1126
```





This plot above consists of two key visualizations evaluating a Dummy Classifier in a classification task:

1. **Confusion Matrix (Left Plot): The model predicts only one class (label 0) for all instances, completely ignoring label 1. This suggests a non-informative model.**
2. **ROC Curve (Right Plot): The diagonal line indicates random guessing, with an AUC (Area Under Curve) of 0.50, which confirms that the Dummy Classifier has no predictive power.**

Addressing Class Imbalance with SMOTENC

In [73]:

```
# Class imbalance percentages
y_train.value_counts(normalize=True)
```

Out[73]:

```
is_popular
0    0.923475
1    0.076525
Name: proportion, dtype: float64
```

We clearly have a class imbalance problem where approximately 93% of our data is not popular and only about 7% of it is. To address this we can SMOTE the training data and see if training a model with this method would improve our results.

In [74]:

```
X.head()
```

Out[74]:

	duration_ms	danceability	acousticness	energy	instrumentalness	liveness	loudness	speechine
track_id								
2qWwuCVeMjF9mUT0S5lqvl	178225.0	0.818	0.293	0.605	0.011600	0.0696	-7.121	0.03
6459gZKddpOoPIH8PAcCwS	183349.0	0.605	0.304	0.813	0.003300	0.1320	-6.416	0.09
2gGAyatRqjjx3DOmLGI12W	316440.0	0.732	0.225	0.797	0.138000	0.2650	-10.205	0.06
3ouP8HFixJmafK7hd1wJ0q	201826.0	0.709	0.108	0.511	0.000019	0.1410	-6.972	0.14
6S5XNauc7v8FLJWEIk0z2c	179246.0	0.745	0.341	0.580	0.002610	0.1270	-5.596	0.07

In [75]:

```
# Looking at column names to determine the position of the categorical/binarized columns
and extract the column indices for SMOTENC
X_train.columns
```

Out[75]:

```
Index(['duration_ms', 'danceability', 'acousticness', 'energy',
       'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo',
       'valence', 'zilizopendwa', 'hiplife', 'xhosa', 'afrobeats', 'house',
       'soul', 'afropop', 'world', 'kwaito', 'soukous', 'hip hop', 'jazz',
       'ndombolo', 'azontobeats', 'pop', 'rumba congolaise', 'key_1.0',
       'key_2.0', 'key_3.0', 'key_4.0', 'key_5.0', 'key_6.0', 'key_7.0',
       'key_8.0', 'key_9.0', 'key_10.0', 'key_11.0', 'mode_1.0',
       'time_signature_1.0', 'time_signature_3.0', 'time_signature_4.0',
       'time_signature_5.0'],
      dtype='object')
```

In [76]:

```
# creating a list of categorical column indices
cat_cols = list(range(10, len(X_train.columns)))
X_train.columns[cat_cols]
```

Out[76]:

```
Index(['zilizopendwa', 'hiplife', 'xhosa', 'afrobeats', 'house', 'soul',
       'afropop', 'world', 'kwaito', 'soukous', 'hip hop', 'jazz', 'ndombolo',
       'azontobeats', 'pop', 'rumba congolaise', 'key_1.0', 'key_2.0',
       'key_3.0', 'key_4.0', 'key_5.0', 'key_6.0', 'key_7.0', 'key_8.0',
       'key_9.0', 'key_10.0', 'key_11.0', 'mode_1.0', 'time_signature_1.0',
       'time_signature_3.0', 'time_signature_4.0', 'time_signature_5.0'],
      dtype='object')
```

In [77]:

```
# pip install imblearn --user
```

In [78]:

```
import imblearn
```

In [79]:

```
# Using SMOTENC to address class imbalance. We are not using SMOTE since we have categori
cal columns.
from imblearn.over_sampling import SMOTENC

sm = SMOTENC(categorical_features=cat_cols, random_state=42)

X_train_sm, y_train_sm = sm.fit_resample(X_train, y_train)
y_train_sm.value_counts(normalize=True)
```

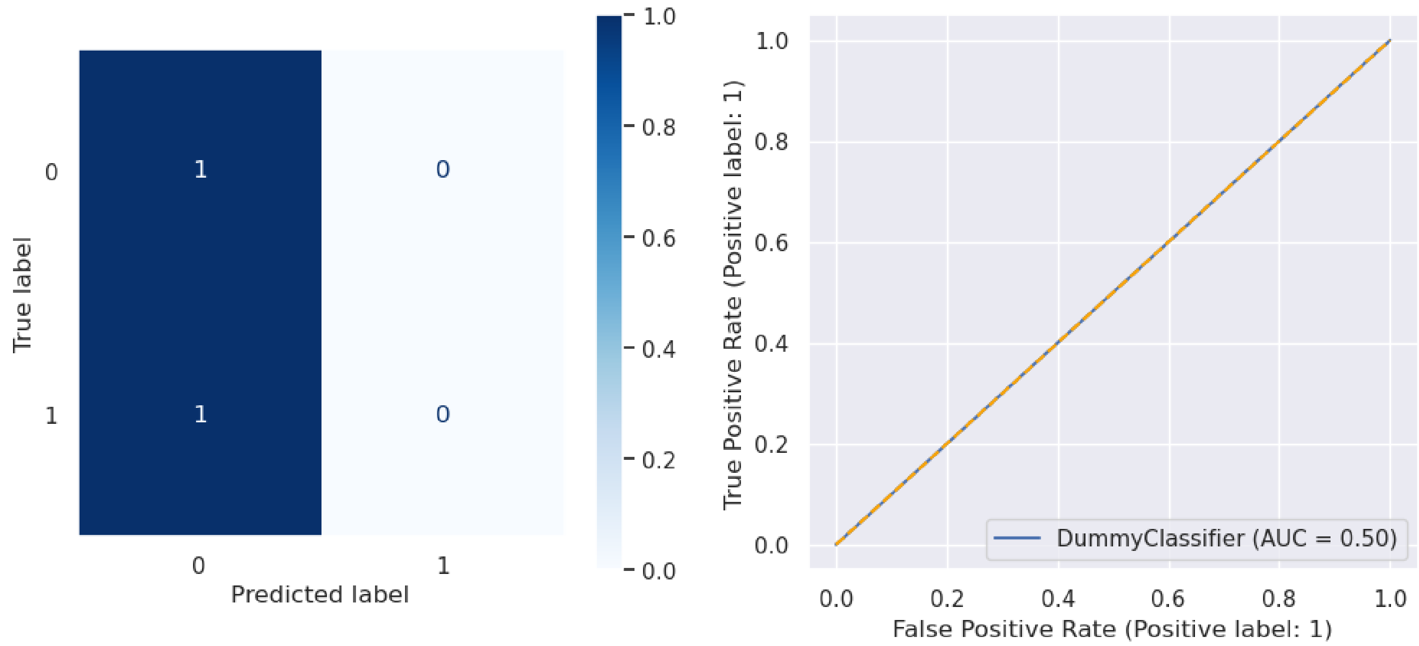
Out[79]:

```
is_popular
0    0.5
1    0.5
Name: proportion, dtype: float64
```

In [80]:

```
# Re-fitting the Dummy Classifier without the class imbalance problem
clf_dummy_sm = DummyClassifier(random_state=42)
clf_dummy_sm.fit(X_train_sm, y_train_sm)
y_pred = clf_dummy_sm.predict(X_test)
classification(y_test, y_pred, X_test, clf_dummy_sm)
```

```
CLASSIFICATION REPORT
------------------------------------------
              precision    recall  f1-score   support

           0       0.92      1.00      0.96      1038
           1       0.00      0.00      0.00        88

    accuracy                           0.92      1126
   macro avg       0.46      0.50      0.48      1126
weighted avg       0.85      0.92      0.88      1126
```



The Dummy Classifier provides a baseline for comparison by making simple predictions, often based on class distribution. Here, it fails to distinguish between classes, achieving an AUC of 0.50, meaning it performs no better than random chance.

In [81]:

```
from sklearn.metrics import recall_score

df_results = pd.DataFrame(columns=['Model Name', 'Recall Score'])

def add_results(df, model_name, model, X_test, y_test):
    """
    Adds recall score to df_results for a given model.

    Parameters:
    - model_name: Name of the model (string).
    - model: Trained model object.
    - X_test: Test features.
    - y_test: True labels.
    - df: DataFrame to store results.

    Returns:
    - Updated DataFrame with new recall score.
    """
    # Get predictions from the model
    if hasattr(model, "predict_proba"):  # Check if model supports probability predictio
ns
        y_pred = (model.predict_proba(X_test)[:, 1] > 0.5).astype(int)
    else:
        y_pred = model.predict(X_test)

    # Compute recall score
    recall = round(recall_score(y_test, y_pred), 2)

    # Add results to DataFrame
    # Check if model name is already exist and update
    if model_name in df["Model Name"].array:
        ind = df["Model Name"].index[df["Model Name"] == model_name][0] # Get the index
of the existing model name
        print(f"Model name '{model_name}' already exist, updating value...")
        df.loc[ind] = [model_name, recall]
    else:
        df.loc[len(df)] = [model_name, recall]

    return df
```

In [82]:

```
df_results = add_results(df_results, 'Dummy Classifier', clf_dummy_sm, X_test, y_test)
df_results.head()
```

Out[82]:

	Model Name	Recall Score
0	Dummy Classifier	0.0

Model 1 - Random Forest Classifier

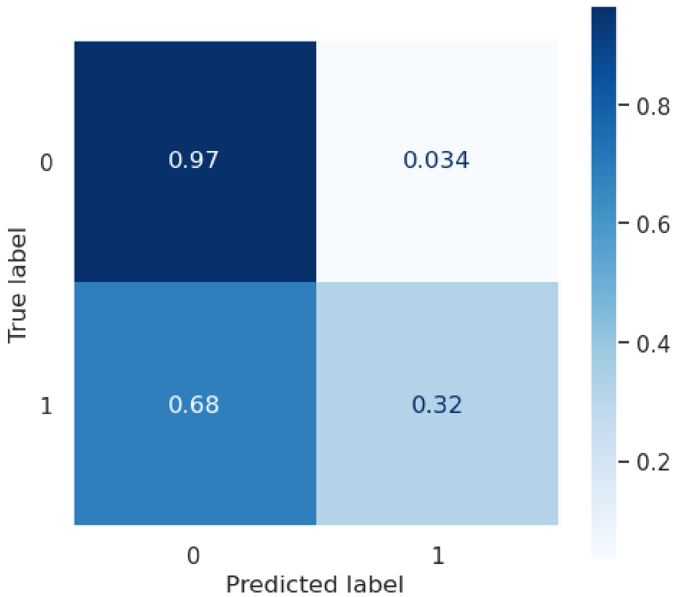
The first model we will be developing is the Random Forest classifier.

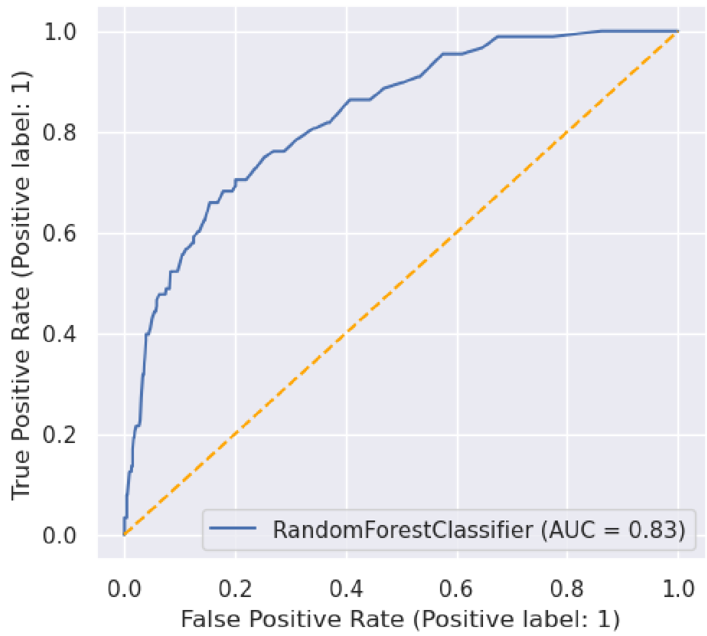
Initial Model

In [83]:

```
# Fitting RF Classifier to SMOTE'ed data
from sklearn.ensemble import RandomForestClassifier

clf_rf = RandomForestClassifier(random_state=42)
clf_rf.fit(X_train_sm, y_train_sm)

#Making predictions and evaluation.
y_pred = clf_rf.predict(X_test)
classification(y_test, y_pred, X_test, clf_rf)
```

```
CLASSIFICATION REPORT
------------------------------------------
              precision    recall  f1-score   support

           0       0.94      0.97      0.95      1038
           1       0.44      0.32      0.37        88

    accuracy                           0.92      1126
   macro avg       0.69      0.64      0.66      1126
weighted avg       0.90      0.92      0.91      1126
```





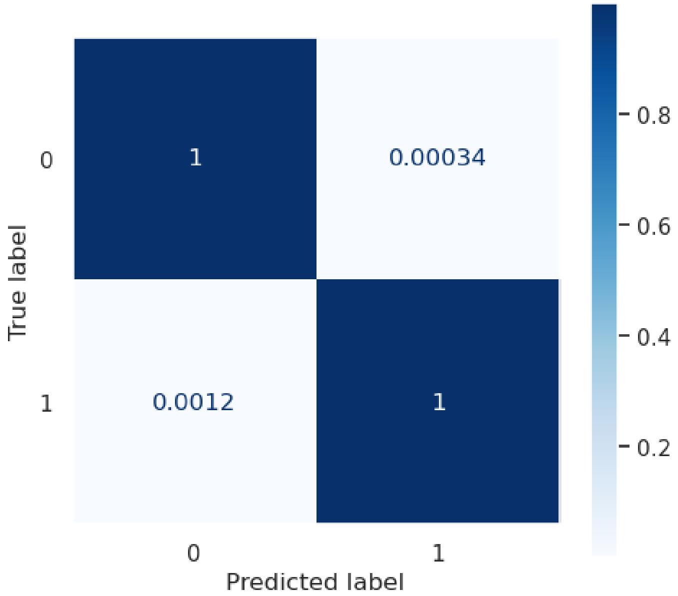
The model may be underfitting, so to confirm we will look at the performance of the model with the training data.

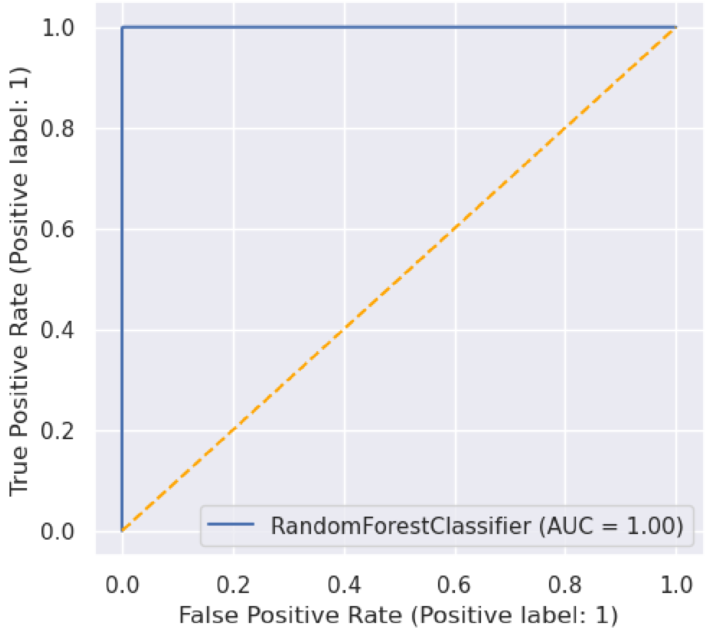
In [84]:

```
# Evaluating the model performance for the training data
y_pred = clf_rf.predict(X_train_sm)
```

```
classification(y_train_sm, y_pred, X_train_sm, clf_rf)
```

```
CLASSIFICATION REPORT
------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      5889
           1       1.00      1.00      1.00      5889

    accuracy                           1.00     11778
   macro avg       1.00      1.00      1.00     11778
weighted avg       1.00      1.00      1.00     11778
```





Our model is performing perfectly on the training data but not so much on the test data since it is overfitting to the training set. We need to tune our model to get more accurate results on unseen data. We will be using a grid search to optimize for the recall score. We are optimizing recall instead of other scores since we primarily care about correctly identifying a song that will be popular and we don't mind if we pick a few songs that don't end up becoming popular.

Hyperparameter Tuning

In [85]:

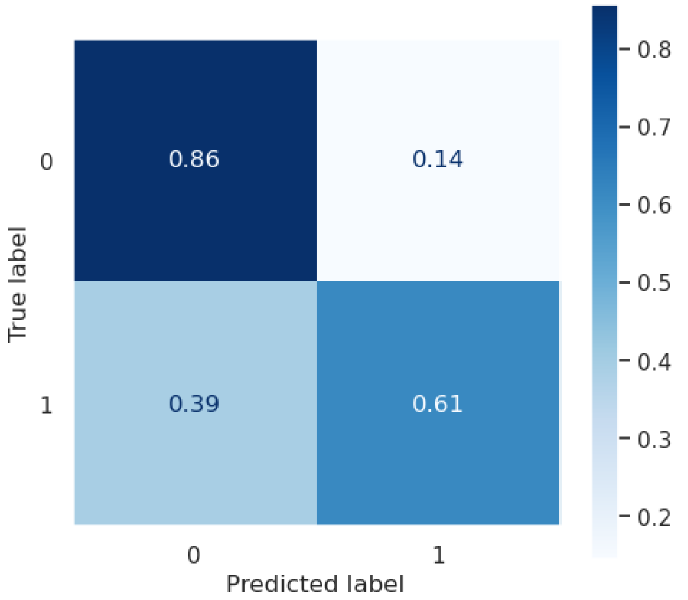
```
# from sklearn.model_selection import GridSearchCV

# clf = RandomForestClassifier()
# grid = {'criterion': ['gini', 'entropy'],
#         'max_depth': [4, 5, 6],
#         'min_samples_leaf': [3, 4, 5, 6, 7]
#        }

# gridsearch = GridSearchCV(estimator=clf, param_grid=grid, scoring='recall', n_jobs=-1,
verbose=2)

# gridsearch.fit(X_train_sm,  y_train_sm)
# gridsearch.best_params_
# #Results: {'criterion': 'gini', 'max_depth': 6, 'min_samples_leaf': 3}
```

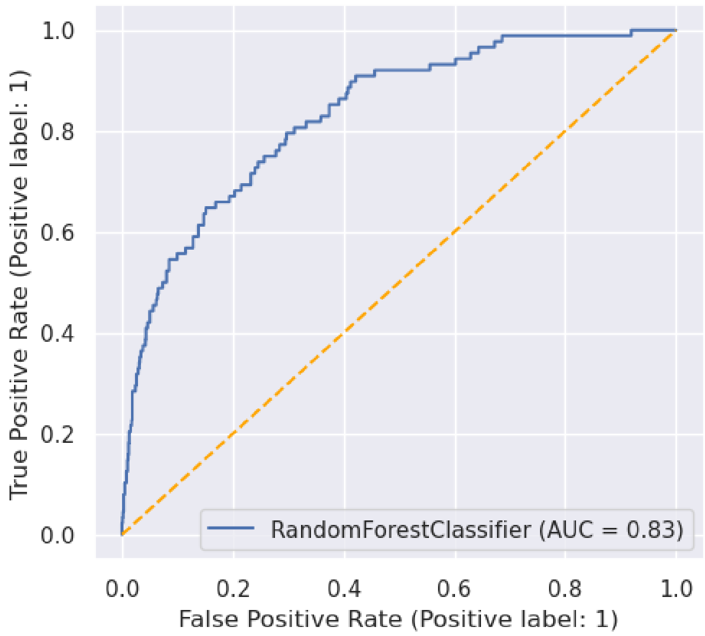
In [86]:

```
clf_rf_tuned = RandomForestClassifier(criterion='gini', max_depth=6,
                                      min_samples_leaf=3, class_weight='balanced',
                                      random_state=42
                                     )

clf_rf_tuned.fit(X_train_sm, y_train_sm)
```

```
y_pred = clf_rf_tuned.predict(X_test)
classification(y_test, y_pred, X_test, clf_rf_tuned)
```

```
CLASSIFICATION REPORT
------------------------------------------
              precision    recall  f1-score   support

           0       0.96      0.86      0.91      1038
           1       0.27      0.61      0.37        88

    accuracy                           0.84      1126
   macro avg       0.61      0.74      0.64      1126
weighted avg       0.91      0.84      0.86      1126
```





In [87]:

```
# Appending the recall score to the results dataframe
df_results = add_results(df_results, 'Random Forest', clf_rf_tuned, X_test, y_test)
df_results.head()
```

Out[87]:

	Model Name	Recall Score
0	Dummy Classifier	0.00
1	Random Forest	0.61

Model 2 - LogisticRegressionCV

Since Logistic Regression models are potentially sensitive to outliers and need scaled data we will need to process our data one more time to remove outliers and scale it.

Removing Outliers

In [88]:

```
#separating out the numerical columns for outlier removal
num_cols = ['acousticness', 'danceability', 'duration_ms', 'energy', 'instrumentalness',
            'liveness', 'loudness', 'speechiness', 'tempo', 'valence']
num_cols
```

Out[88]:

```
['acousticness',
 'danceability',
```

```
 'duration_ms',
 'energy',
 'instrumentalness',
 'liveness',
 'loudness',
 'speechiness',
 'tempo',
 'valence']
```

In [89]:

```
# Concatenating the training and testing sets together for outlier removal
df_train = pd.concat([X_train, y_train], axis=1)
df_test = pd.concat([X_test, y_test], axis=1)
```

In [90]:

```
#Outlier Removal with the IQR method

def find_outliers_IQR(data, return_limits = False):
    """Use Tukey's Method of outlier removal AKA InterQuartile-Range Rule
    and return boolean series where True indicates it is an outlier.
    - Calculates the range between the 75% and 25% quartiles
    - Outliers fall outside upper and lower limits, using a treshold of 1.5*IQR the 75% a
nd 25% quartiles.

    IQR Range Calculation:
        res = df.describe()
        IQR = res['75%'] -  res['25%']
        lower_limit = res['25%'] - 1.5*IQR
        upper_limit = res['75%'] + 1.5*IQR

    Args:
        data (Series, or ndarray): data to test for outliers.

    Returns:
        [boolean Series]: A True/False for each row use to slice outliers.

    Adapted from Flatiron School Phase #2 Py Files.
    URL = https://github.com/flatiron-school/Online-DS-FT-022221-Cohort-Notes/blob/master
/py_files/functions_SG.py

    """
    df_b = data.copy()
    res= df_b.describe()

    IQR = res['75%'] -  res['25%']
    lower_limit = res['25%'] - 1.5*IQR
    upper_limit = res['75%'] + 1.5*IQR

    if return_limits:
        return lower_limit, upper_limit

    else:
        idx_outs = (df_b > upper_limit) | (df_b < lower_limit)
        return idx_outs
```

In [91]:

```
#finding and removing outliers based on X_train (df_train) to avoid data leakage

original_length_train = len(df_train)
original_length_test = len(df_test)

for col in num_cols:

    lower_limit, upper_limit = find_outliers_IQR(df_train[col], return_limits=True)

    df_train = df_train[(df_train[col] >= lower_limit) & (df_train[col] <= upper_limit)]
    df_test = df_test[(df_test[col] >= lower_limit) & (df_test[col] <= upper_limit)]
```

```
print(f'{original_length_train - len(df_train)} outliers removed from training set')
print(f'{original_length_test - len(df_test)} outliers removed from test set')
```

```
2406 outliers removed from training set
417 outliers removed from test set
```

In [92]:

```
# Separating out the X and y values for training and test sets
y_train = df_train['is_popular']
X_train = df_train.drop('is_popular', axis=1)

y_test = df_test['is_popular']
X_test = df_test.drop('is_popular', axis=1)
```

Addressing Class Imbalance with SMOTENC

In [93]:

```
y_train.value_counts(normalize=True)
```

Out[93]:

```
is_popular
0    0.910854
1    0.089146
Name: proportion, dtype: float64
```

Once again our data has a class imbalance issue so we will be using SMOTENC to address this.

In [94]:

```
X_train.columns
```

Out[94]:

```
Index(['duration_ms', 'danceability', 'acousticness', 'energy',
       'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo',
       'valence', 'zilizopendwa', 'hiplife', 'xhosa', 'afrobeats', 'house',
       'soul', 'afropop', 'world', 'kwaito', 'soukous', 'hip hop', 'jazz',
       'ndombolo', 'azontobeats', 'pop', 'rumba congolaise', 'key_1.0',
       'key_2.0', 'key_3.0', 'key_4.0', 'key_5.0', 'key_6.0', 'key_7.0',
       'key_8.0', 'key_9.0', 'key_10.0', 'key_11.0', 'mode_1.0',
       'time_signature_1.0', 'time_signature_3.0', 'time_signature_4.0',
       'time_signature_5.0'],
      dtype='object')
```

In [95]:

```
cat_cols = list(range(10, len(X_train.columns)))
```

In [96]:

```
sm = SMOTENC(categorical_features=cat_cols, random_state=42)

X_train_sm, y_train_sm = sm.fit_resample(X_train, y_train)
y_train_sm.value_counts(normalize=True)
```

Out[96]:

```
is_popular
0    0.5
1    0.5
Name: proportion, dtype: float64
```

Scaling the Data

In [97]:

```
# Using Standard Scaler to scale the smote'd data
```

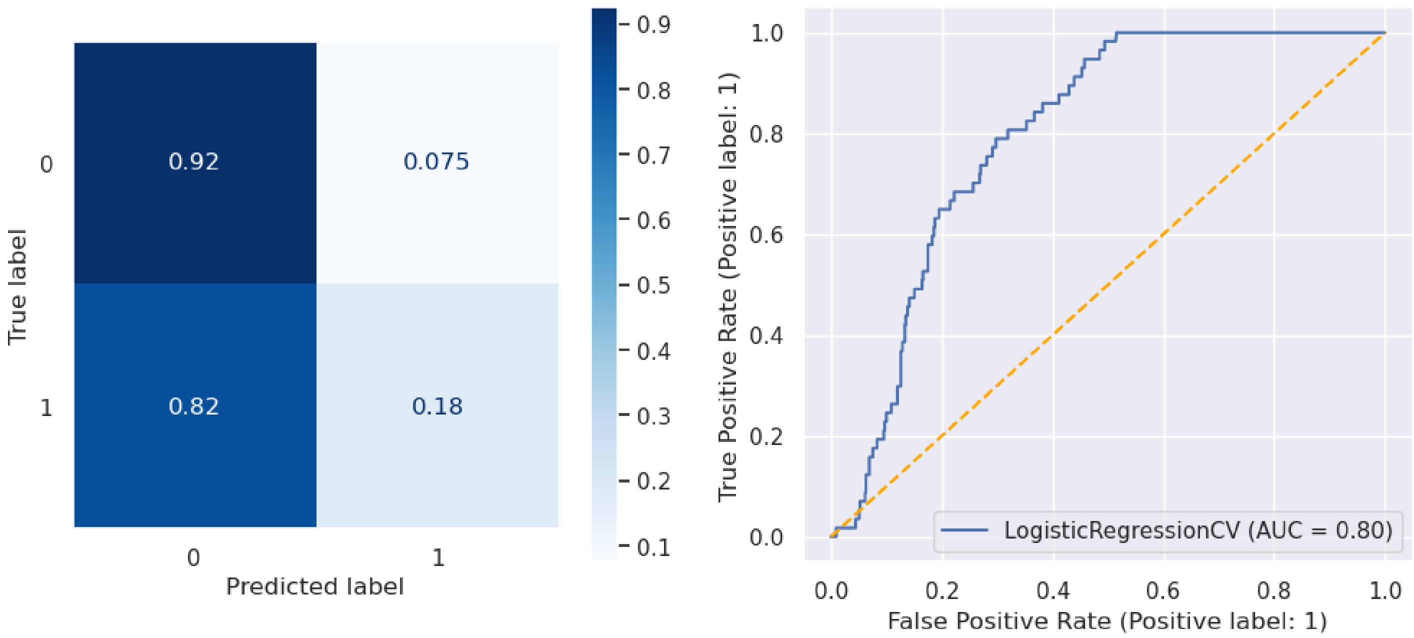
```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train_sm_sc = scaler.fit_transform(X_train_sm)
X_test_sc = scaler.transform(X_test)
```

Initial Model

In [98]:

```python
from sklearn.linear_model import LogisticRegressionCV
clf_logregcv = LogisticRegressionCV(cv=5, max_iter=500, random_state=42)
clf_logregcv.fit(X_train_sm_sc,  y_train_sm)
y_pred = clf_logregcv.predict(X_test_sc)
classification(y_test, y_pred, X_test_sc, clf_logregcv)
```

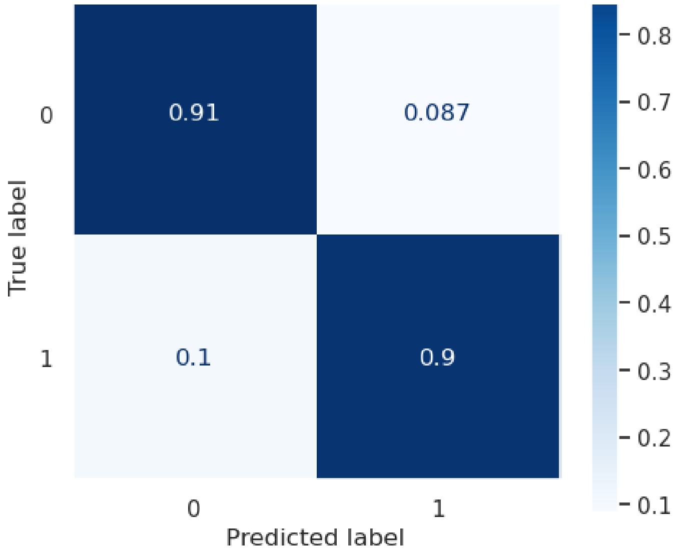
```
CLASSIFICATION REPORT
------------------------------------------
              precision    recall  f1-score   support

           0       0.93      0.92      0.93       652
           1       0.17      0.18      0.17        57

    accuracy                           0.86       709
   macro avg       0.55      0.55      0.55       709
weighted avg       0.87      0.86      0.87       709
```

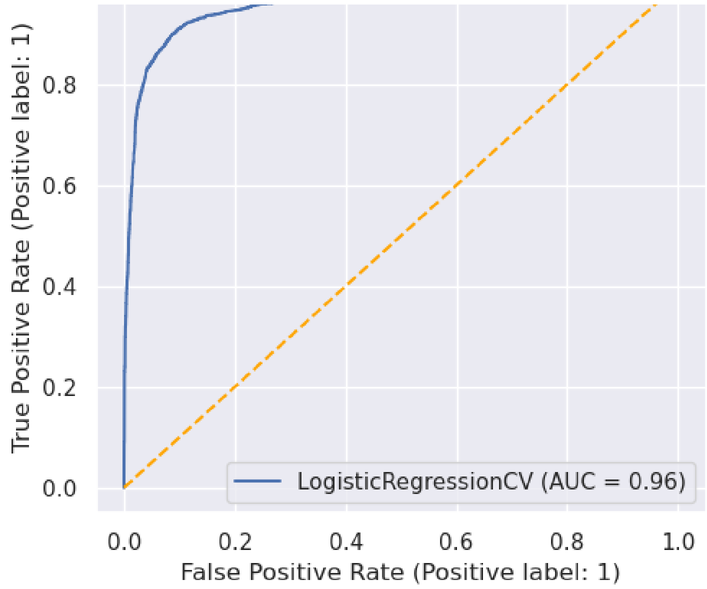


In [99]:

```python
#Evaluating the model performance for the training data
y_pred = clf_logregcv.predict(X_train_sm_sc)
classification(y_train_sm, y_pred, X_train_sm_sc, clf_logregcv)
```

```
CLASSIFICATION REPORT
------------------------------------------
              precision    recall  f1-score   support

           0       0.90      0.91      0.91      3617
           1       0.91      0.90      0.91      3617

    accuracy                           0.91      7234
   macro avg       0.91      0.91      0.91      7234
weighted avg       0.91      0.91      0.91      7234
```





Our model is once again overfitting to the training data and performing very well on it but the model's performance drops significantly when we test it with the test data. In order to address this, we can once again perform a grid search and try to tune the model.

Hyperparameter Tuning

In [100]:

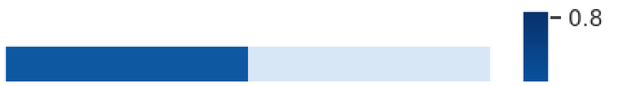
```
# clf = LogisticRegressionCV(cv=5)
# grid = {'class_weight': ['balanced', None],
#          'penalty':['l1', 'l2'],
#          'solver':['liblinear'],
#          'Cs': [10, 1]
#        }

# gridsearch = GridSearchCV(estimator=clf, param_grid = grid, scoring='recall', n_jobs=-1
, verbose=2)

# gridsearch.fit(X_train_sm_sc,  y_train_sm)
# gridsearch.best_params_
# # {'Cs': 1, 'class_weight': 'balanced', 'penalty': 'l2', 'solver': 'liblinear'}
```

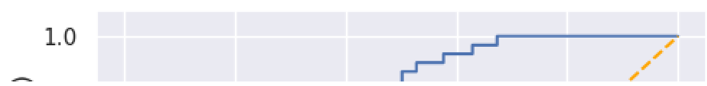
The grid search returned 'l2' as the regularization method which is the Ridge regularization as well as a C value of 1. We will use these parameters on a new model to see if the recall score improves.

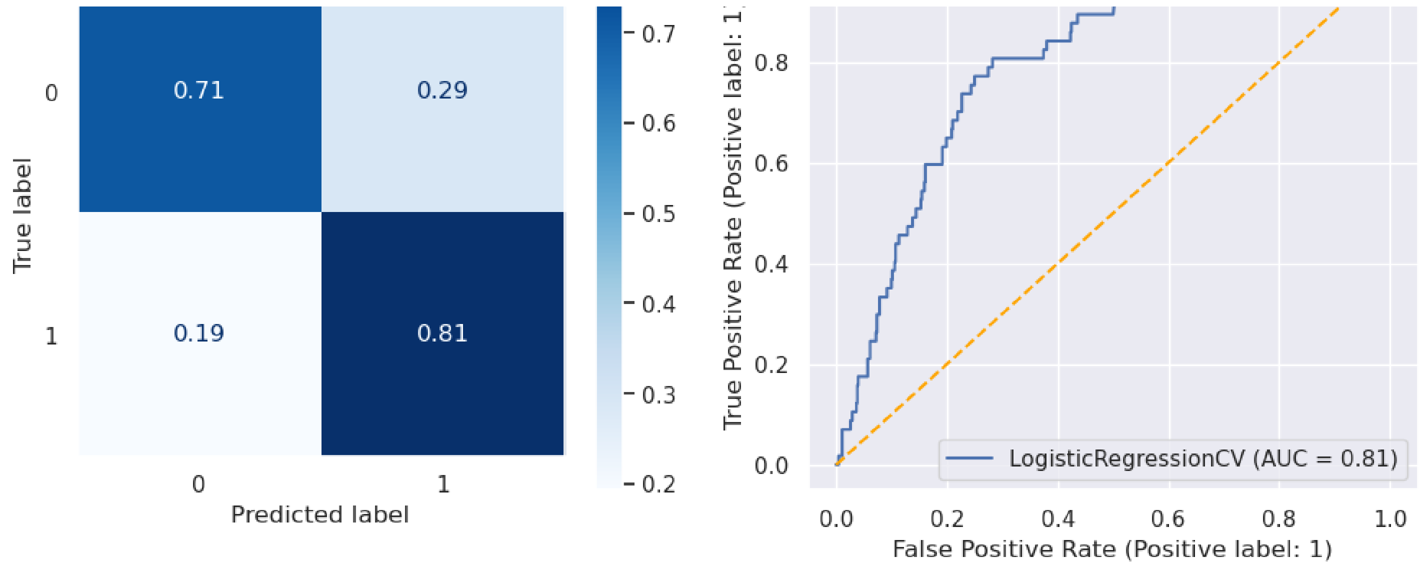
In [101]:

```
clf_logregcv_tuned = LogisticRegressionCV(cv=5, class_weight='balanced', Cs=1,
                                          penalty='l2', solver='liblinear',
                                          max_iter=500, random_state=42)
clf_logregcv_tuned.fit(X_train_sm_sc,  y_train_sm)
y_pred = clf_logregcv_tuned.predict(X_test_sc)
classification(y_test, y_pred, X_test_sc, clf_logregcv_tuned)
```

```
CLASSIFICATION REPORT
------------------------------------------
              precision    recall  f1-score   support

           0       0.98      0.71      0.82       652
           1       0.20      0.81      0.32        57

    accuracy                           0.72       709
   macro avg       0.59      0.76      0.57       709
weighted avg       0.91      0.72      0.78       709
```







In [102]:

```
# Appending the recall score to the results dataframe
df_results = add_results(df_results, 'Logistic Regression', clf_logregcv_tuned, X_test=X_test_sc, y_test=y_test)
df_results.head()
```

Out[102]:

	Model Name	Recall Score
0	Dummy Classifier	0.00
1	Random Forest	0.61
2	Logistic Regression	0.81

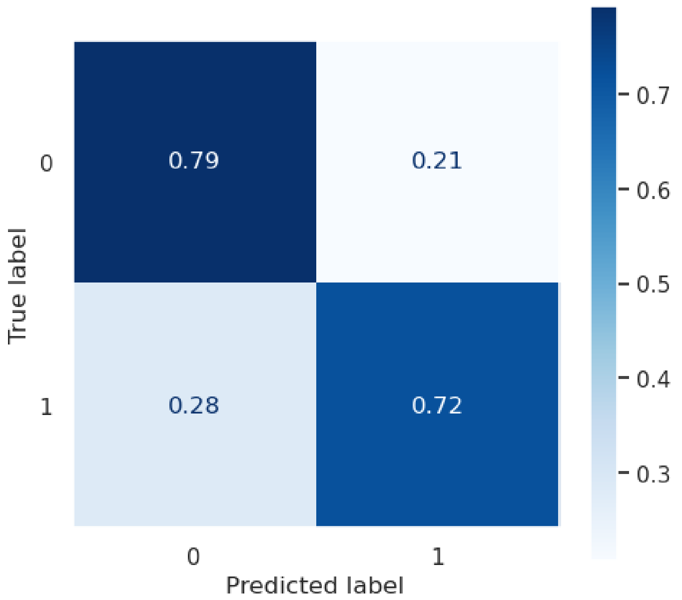
Model 3 - XGBOost

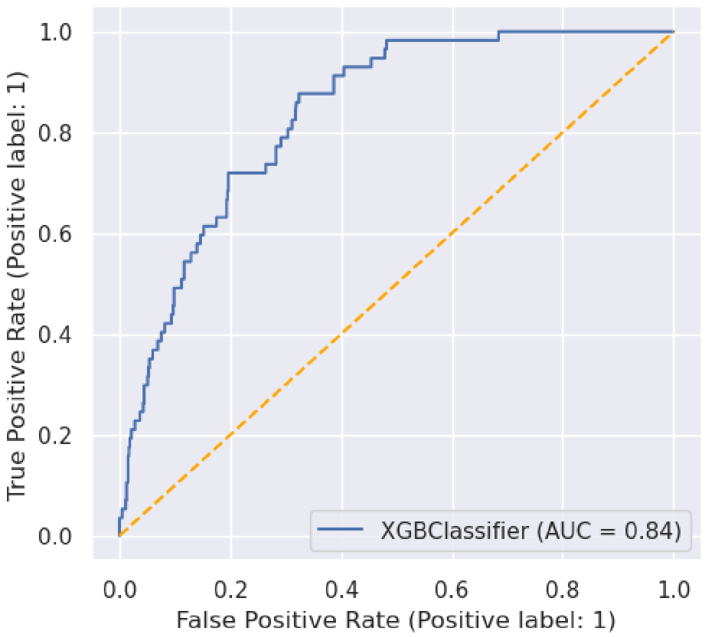
In [103]:

```
from sklearn.model_selection import RandomizedSearchCV
import xgboost as xgb

# Parameter grid
param_grid = {
    "learning_rate": [0.001, 0.005, 0.01, 0.05, 0.1],
    "n_estimators": [50, 100, 200, 500],
    "max_depth": [3, 4, 5],
    "subsample": [0.7, 0.8, 0.9],
    "colsample_bytree": [0.7, 0.8, 0.9],
    "scale_pos_weight": [10, 12, 15],
}

#  Model
xgb_model = xgb.XGBClassifier(
    objective="binary:logistic",
    eval_metric="aucpr"
)
# RandomizedSearchCV tuning
random_search = RandomizedSearchCV(
    xgb_model,
    param_distributions=param_grid,
    n_iter=10,  # Try 10 random combinations
    scoring="roc_auc",
    cv=5,  # 3-fold cross-validation
    verbose=1,
    n_jobs=-1,  # Use all processors
    random_state=42
)
```

```python
# Fit the model
random_search.fit(X_train, y_train)

# Best parameters
print("Best Parameters:", random_search.best_params_)

# Predict on test set
xgb_tuned = random_search.best_estimator_
y_pred = xgb_tuned.predict(X_test)

#  Final evaluation
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix

classification(y_test, y_pred, X_test, xgb_tuned)
```

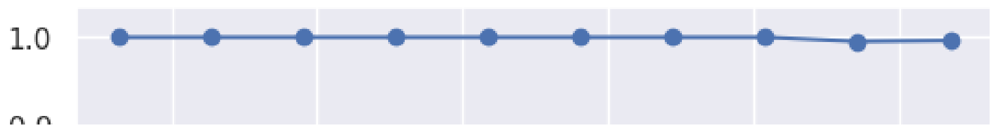
```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Best Parameters: {'subsample': 0.9, 'scale_pos_weight': 12, 'n_estimators': 500, 'max_dep
th': 5, 'learning_rate': 0.01, 'colsample_bytree': 0.8}
CLASSIFICATION REPORT
-------------------------------------------
              precision    recall  f1-score   support

           0       0.97      0.79      0.87       652
           1       0.23      0.72      0.35        57

    accuracy                           0.79       709
   macro avg       0.60      0.76      0.61       709
weighted avg       0.91      0.79      0.83       709
```

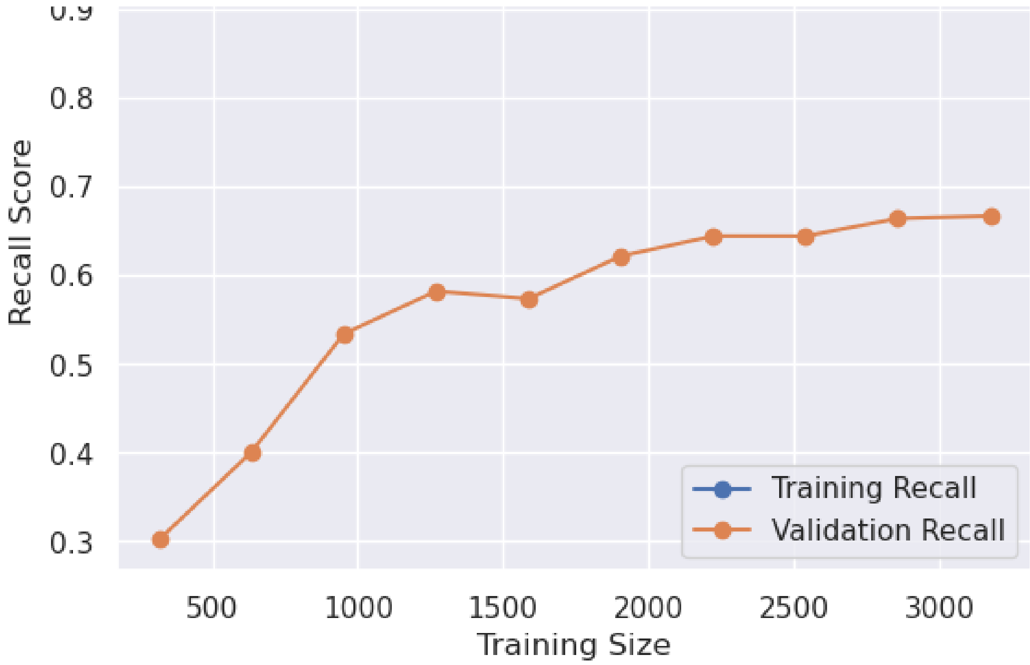




In [104]:

```python
from sklearn.model_selection import learning_curve

train_sizes, train_scores, test_scores = learning_curve(
    xgb_tuned, X_train, y_train, cv=5, scoring="recall", train_sizes=np.linspace(0.1, 1.
0, 10)
)

plt.plot(train_sizes, train_scores.mean(axis=1), 'o-', label="Training Recall")
plt.plot(train_sizes, test_scores.mean(axis=1), 'o-', label="Validation Recall")
plt.xlabel("Training Size")
plt.ylabel("Recall Score")
plt.legend()
plt.show()
```





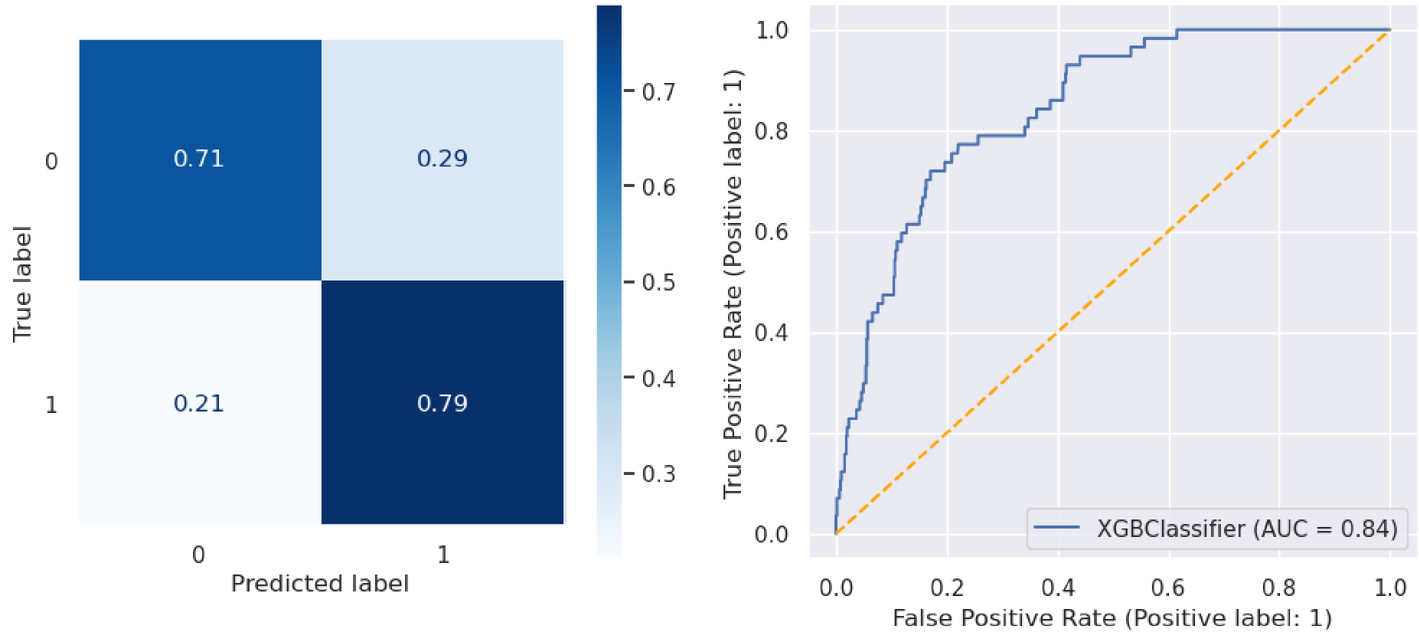
The initial tuning with `RandomizedSearchCV` showed overfitting, with a large gap between training and validation recall. To reduce overfitting, we will manually adjust `scale_pos_weight`, `learning_rate`, `max_depth`, `n_estmators`, `min_child_weight`, and `subsample`. The goal is to increase validation recall while narrowing the training-validation recall gap.

In [105]:

```
import xgboost as xgb
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix, preci
sion_recall_curve

# Compute class imbalance ratio
scale_pos_weight = sum(y_train == 0) / sum(y_train == 1)  # Increase weight for popular
songs

# Define the XGBoost model with recall-focused settings
xgb_model = xgb.XGBClassifier(
    objective='binary:logistic',
    scale_pos_weight=scale_pos_weight,
    learning_rate=0.005,  # Lower for better generalization
    n_estimators=500,  # More trees to improve learning
    max_depth=3,   # Slightly shallower to avoid overfitting
    min_child_weight=5,
    subsample=0.8,  # Keep training diverse
    colsample_bytree=0.8,  # More features per tree
    random_state=42,
    eval_metric='logloss'
)

# Train the model
xgb_model.fit(X_train, y_train)

# Predict probabilities on the test set
y_pred = xgb_model.predict(X_test)

# Print performance metrics
classification(y_test, y_pred, X_test, xgb_model)
```

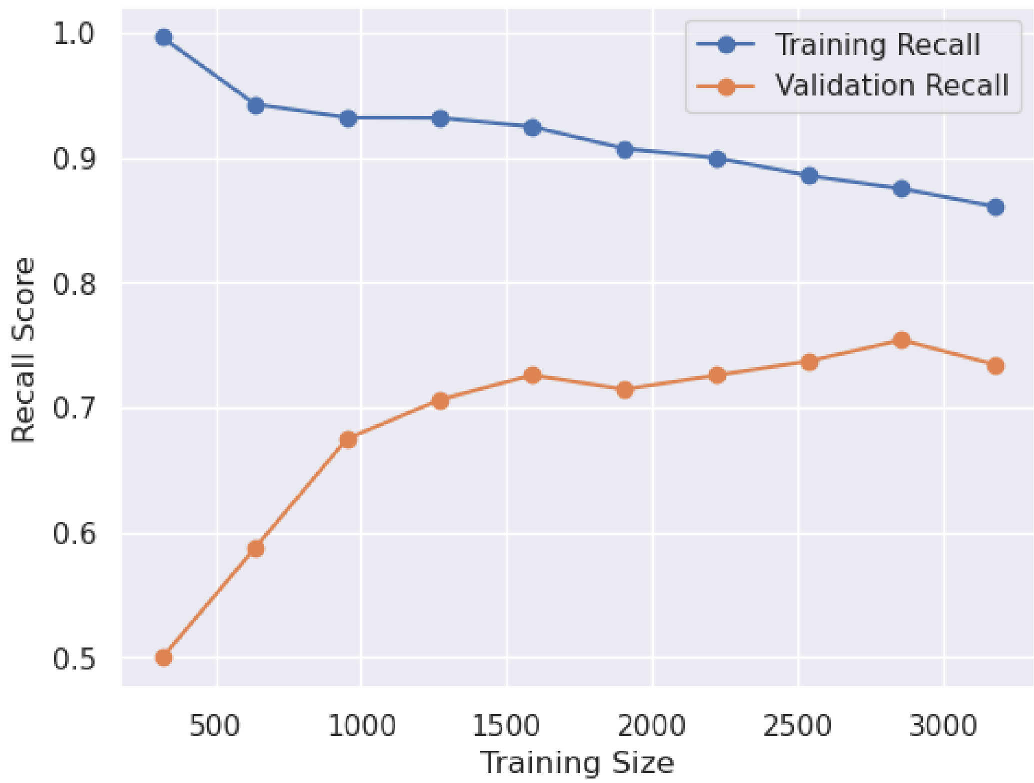
```
CLASSIFICATION REPORT
------------------------------------------
              precision    recall  f1-score   support

           0       0.97      0.71      0.82       652
           1       0.19      0.79      0.31        57

    accuracy                           0.71       709
   macro avg       0.58      0.75      0.56       709
weighted avg       0.91      0.71      0.78       709
```

```
weighted avg       0.91      0.71      0.78       709
```



In [106]:

```python
train_sizes, train_scores, test_scores = learning_curve(
    xgb_model, X_train, y_train, cv=5, scoring="recall", train_sizes=np.linspace(0.1, 1.
0, 10)
)

plt.plot(train_sizes, train_scores.mean(axis=1), 'o-', label="Training Recall")
plt.plot(train_sizes, test_scores.mean(axis=1), 'o-', label="Validation Recall")
plt.xlabel("Training Size")
plt.ylabel("Recall Score")
plt.legend()
plt.show()
```



The training and validation recall curve are closer compared to earlier

In [107]:

```python
# Appending the recall score to the results dataframe
```

```
df_results = add_results(df_results, 'xgb', xgb_model, X_test, y_test)
df_results.head()
```

Out[107]:

	Model Name	Recall Score
0	Dummy Classifier	0.00
1	Random Forest	0.61
2	Logistic Regression	0.81
3	xgb	0.79

Understanding Model Decision Patterns

With three optimized models at our disposal, the next step is to uncover the reasoning behind their predictions. By analyzing feature importances, we can determine which attributes played a crucial role in classifying songs as popular or unpopular. Comparing these insights across models will help identify shared influential factors, providing a deeper understanding of the key elements driving song popularity. This analysis can also highlight differences in how each model prioritizes features, offering valuable insights into their decision-making processes.

Feature Importances

Random Forest

In [108]:

```
# Accessing feature importance values of the tuned random forest model and sorting them
rf_importances_df = pd.Series(clf_rf_tuned.feature_importances_, index=X_train.columns).
sort_values(ascending=False)

# Parsing the series to a dataframe
rf_importances_df = rf_importances_df.reset_index()
rf_importances_df.columns = ['RF-Attribute', 'RF-Importance']
rf_importances_df
```

Out[108]:

	RF-Attribute	RF-Importance
0	afrobeats	0.235356
1	duration_ms	0.078874
2	pop	0.062613
3	afropop	0.057019
4	rumba congolaise	0.054605
5	acousticness	0.047414
6	jazz	0.046208
7	energy	0.045351
8	danceability	0.039230
9	soukous	0.034644
10	instrumentalness	0.031420
11	world	0.026048
12	speechiness	0.021196
13	valence	0.020636
14	hiplife	0.016551
15	zilizopendwa	0.016300

	RF-Attribute	RF-Importance
16	kwaito	0.014467
17	key_1.0	0.013011
18	soul	0.012835
19	key_7.0	0.012171
20	key_5.0	0.011456
21	azontobeats	0.010641
22	loudness	0.009788
23	xhosa	0.009480
24	key_9.0	0.009370
25	liveness	0.008719
26	ndombolo	0.007982
27	key_11.0	0.007776
28	hip hop	0.007712
29	mode_1.0	0.006445
30	tempo	0.005369
31	house	0.005198
32	key_10.0	0.004484
33	key_2.0	0.003073
34	time_signature_4.0	0.002064
35	time_signature_3.0	0.001418
36	key_8.0	0.001089
37	key_6.0	0.000986
38	time_signature_5.0	0.000849
39	key_4.0	0.000130
40	key_3.0	0.000020
41	time_signature_1.0	0.000000

Logistic Regresson

In [109]:

```
#accessing feature importance values of the tuned logistic regression model and sorting t
hem
logregcv_importances_df = pd.Series(clf_logregcv_tuned.coef_[0], index=X_train.columns).
sort_values(ascending=False)
#parsing the series to a dataframe
logregcv_importances_df = logregcv_importances_df.reset_index()
logregcv_importances_df.columns = ['LogReg-Attribute', 'LogReg-Importance']
logregcv_importances_df
```

Out[109]:

	LogReg-Attribute	LogReg-Importance
0	afrobeats	0.096934
1	pop	0.077400
2	danceability	0.055383
3	hip hop	0.053179
4	time_signature_4.0	0.026080
5	instrumentalness	0.011555
6	speechiness	0.011142

	LogReg-Attribute	LogReg-Importance
7	loudness	0.000128
8	azontobeats	-0.009186
9	time_signature_1.0	-0.011865
10	tempo	-0.013315
11	time_signature_5.0	-0.017168
12	liveness	-0.018946
13	house	-0.025012
14	acousticness	-0.025946
15	valence	-0.027863
16	key_3.0	-0.029161
17	time_signature_3.0	-0.032124
18	ndombolo	-0.033468
19	key_6.0	-0.033998
20	xhosa	-0.034974
21	key_8.0	-0.038696
22	kwaito	-0.039121
23	energy	-0.040011
24	key_4.0	-0.040471
25	world	-0.046953
26	key_10.0	-0.046984
27	zilizopendwa	-0.048370
28	jazz	-0.048449
29	key_1.0	-0.048712
30	mode_1.0	-0.048871
31	key_2.0	-0.048967
32	duration_ms	-0.049519
33	key_9.0	-0.049785
34	key_11.0	-0.050750
35	key_5.0	-0.051795
36	afropop	-0.051824
37	soukous	-0.052192
38	hiplife	-0.053151
39	rumba congolaise	-0.056030
40	soul	-0.056096
41	key_7.0	-0.059423

XGBoost

In [110]:

```
# Accessing feature importance values of the tuned random forest model and sorting them
xgb_importances_df = pd.Series(xgb_model.feature_importances_, index=X_train.columns).so
rt_values(ascending=False)

# Parsing the series to a dataframe
xgb_importances_df = xgb_importances_df.reset_index()
xgb_importances_df.columns = ['XGB-Attribute', 'XGB-Importance']
xgb_importances_df
```

Out[110]:

Out[110]:

	XGB-Attribute	XGB-Importance
0	afrobeats	0.156353
1	soukous	0.055920
2	jazz	0.053715
3	world	0.050915
4	duration_ms	0.045947
5	hip hop	0.044887
6	energy	0.041057
7	hiplife	0.041020
8	afropop	0.039293
9	danceability	0.034772
10	acousticness	0.032162
11	mode_1.0	0.030616
12	zilizopendwa	0.030590
13	soul	0.029514
14	instrumentalness	0.028665
15	pop	0.026268
16	valence	0.024950
17	azontobeats	0.023853
18	speechiness	0.022686
19	loudness	0.020979
20	ndombolo	0.019182
21	time_signature_4.0	0.017931
22	liveness	0.015950
23	key_7.0	0.014730
24	tempo	0.014709
25	kwaito	0.013823
26	key_4.0	0.013266
27	key_1.0	0.012164
28	key_2.0	0.009855
29	key_9.0	0.009438
30	key_5.0	0.009279
31	key_10.0	0.008795
32	time_signature_3.0	0.006716
33	key_3.0	0.000000
34	key_6.0	0.000000
35	house	0.000000
36	key_8.0	0.000000
37	key_11.0	0.000000
38	xhosa	0.000000
39	time_signature_1.0	0.000000
40	rumba congolaise	0.000000
41	time_signature_5.0	0.000000

In [111]:

```
#Concatenating feature importances into a single dataframe
importances_df = pd.concat([rf_importances_df, logregcv_importances_df, xgb_importances_
df], axis=1)
importances_df
```

Out[111]:

	RF-Attribute	RF-Importance	LogReg-Attribute	LogReg-Importance	XGB-Attribute	XGB-Importance
0	afrobeats	0.235356	afrobeats	0.096934	afrobeats	0.156353
1	duration_ms	0.078874	pop	0.077400	soukous	0.055920
2	pop	0.062613	danceability	0.055383	jazz	0.053715
3	afropop	0.057019	hip hop	0.053179	world	0.050915
4	rumba congolaise	0.054605	time_signature_4.0	0.026080	duration_ms	0.045947
5	acousticness	0.047414	instrumentalness	0.011555	hip hop	0.044887
6	jazz	0.046208	speechiness	0.011142	energy	0.041057
7	energy	0.045351	loudness	0.000128	hiplife	0.041020
8	danceability	0.039230	azontobeats	-0.009186	afropop	0.039293
9	soukous	0.034644	time_signature_1.0	-0.011865	danceability	0.034772
10	instrumentalness	0.031420	tempo	-0.013315	acousticness	0.032162
11	world	0.026048	time_signature_5.0	-0.017168	mode_1.0	0.030616
12	speechiness	0.021196	liveness	-0.018946	zilizopendwa	0.030590
13	valence	0.020636	house	-0.025012	soul	0.029514
14	hiplife	0.016551	acousticness	-0.025946	instrumentalness	0.028665
15	zilizopendwa	0.016300	valence	-0.027863	pop	0.026268
16	kwaito	0.014467	key_3.0	-0.029161	valence	0.024950
17	key_1.0	0.013011	time_signature_3.0	-0.032124	azontobeats	0.023853
18	soul	0.012835	ndombolo	-0.033468	speechiness	0.022686
19	key_7.0	0.012171	key_6.0	-0.033998	loudness	0.020979
20	key_5.0	0.011456	xhosa	-0.034974	ndombolo	0.019182
21	azontobeats	0.010641	key_8.0	-0.038696	time_signature_4.0	0.017931
22	loudness	0.009788	kwaito	-0.039121	liveness	0.015950
23	xhosa	0.009480	energy	-0.040011	key_7.0	0.014730
24	key_9.0	0.009370	key_4.0	-0.040471	tempo	0.014709
25	liveness	0.008719	world	-0.046953	kwaito	0.013823
26	ndombolo	0.007982	key_10.0	-0.046984	key_4.0	0.013266
27	key_11.0	0.007776	zilizopendwa	-0.048370	key_1.0	0.012164
28	hip hop	0.007712	jazz	-0.048449	key_2.0	0.009855
29	mode_1.0	0.006445	key_1.0	-0.048712	key_9.0	0.009438
30	tempo	0.005369	mode_1.0	-0.048871	key_5.0	0.009279
31	house	0.005198	key_2.0	-0.048967	key_10.0	0.008795
32	key_10.0	0.004484	duration_ms	-0.049519	time_signature_3.0	0.006716
33	key_2.0	0.003073	key_9.0	-0.049785	key_3.0	0.000000
34	time_signature_4.0	0.002064	key_11.0	-0.050750	key_6.0	0.000000
35	time_signature_3.0	0.001418	key_5.0	-0.051795	house	0.000000
36	key_8.0	0.001089	afropop	-0.051824	key_8.0	0.000000
37	key_6.0	0.000986	soukous	-0.052192	key_11.0	0.000000

	RF-Attribute	RF-Importance	LogReg-Attribute	LogReg-Importance	XGB-Attribute	XGB-Importance
38	time_signature_5.0	0.000849	hiplife	-0.053151	xhosa	0.000000
39	key_4.0	0.000130	rumba congolaise	-0.056030	time_signature_1.0	0.000000
40	key_3.0	0.000020	soul	-0.056096	rumba congolaise	0.000000
41	time_signature_1.0	0.000000	key_7.0	-0.059423	time_signature_5.0	0.000000

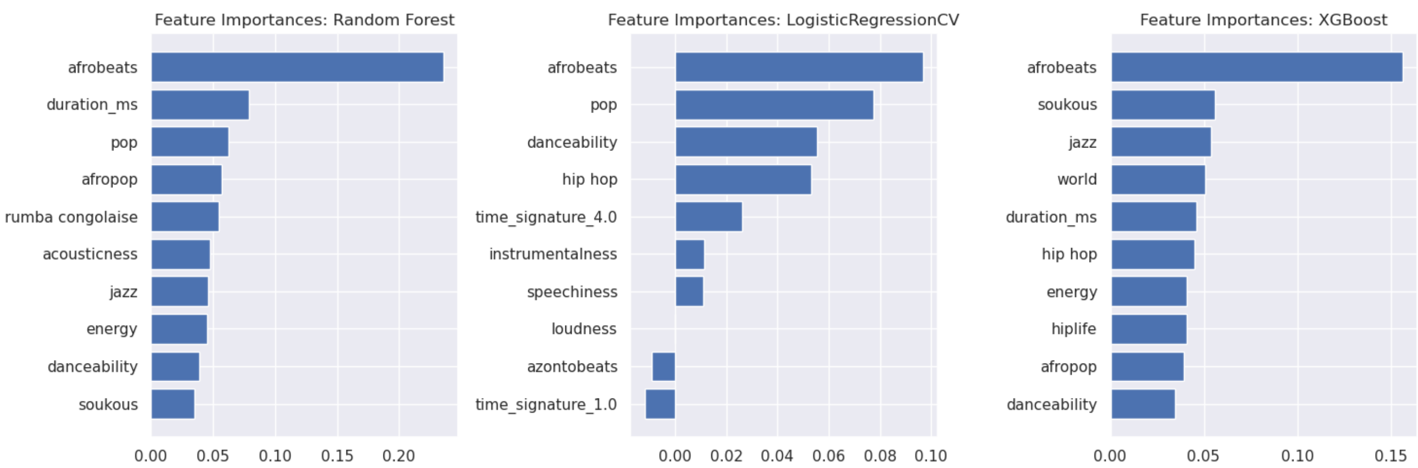
Feature Importance Comparison

In [112]:

```
# Plotting feature importances for all models for comparison

fig, ax = plt.subplots(ncols=3, figsize=(15,5))

rf_importances_df = rf_importances_df.sort_values(by='RF-Importance', ascending=True).ta
il(10)
ax[0].barh(rf_importances_df['RF-Attribute'], rf_importances_df['RF-Importance'])
ax[0].set_title('Feature Importances: Random Forest')

logregcv_importances_df = logregcv_importances_df.sort_values(by='LogReg-Importance', asc
ending=True).tail(10)
ax[1].barh(logregcv_importances_df['LogReg-Attribute'], logregcv_importances_df['LogReg-I
mportance'])
ax[1].set_title('Feature Importances: LogisticRegressionCV')
plt.tight_layout()

xgb_importances_df = xgb_importances_df.sort_values(by='XGB-Importance', ascending=True).
tail(10)
ax[2].barh(xgb_importances_df['XGB-Attribute'], xgb_importances_df['XGB-Importance'])
ax[2].set_title('Feature Importances: XGBoost')
```

Out[112]:

```
Text(0.5, 1.0, 'Feature Importances: XGBoost')
```



The feature importance analysis shows that all three models prioritize "afrobeats" as the most influential feature. However, Logistic Regression incorporates additional musical characteristics like "danceability", "time signature", "speechiness", "instrumentalness" and "loudness", suggesting a broader reliance on both genre and musical properties. In contrast, Random Forest and XGBoost focus more on genre-based features such as "pop," "rumba congolaise," "soukous," and "jazz." This distinction implies that Logistic Regression may be more sensitive to subtle audio characteristics, while tree-based models emphasize categorical influences. The variation in feature importance suggests that different models interpret the dataset differently, which can impact their predictive performance and generalization. Ultimately, the choice between models depends on whether genre or broader musical attributes better capture the patterns in the data.

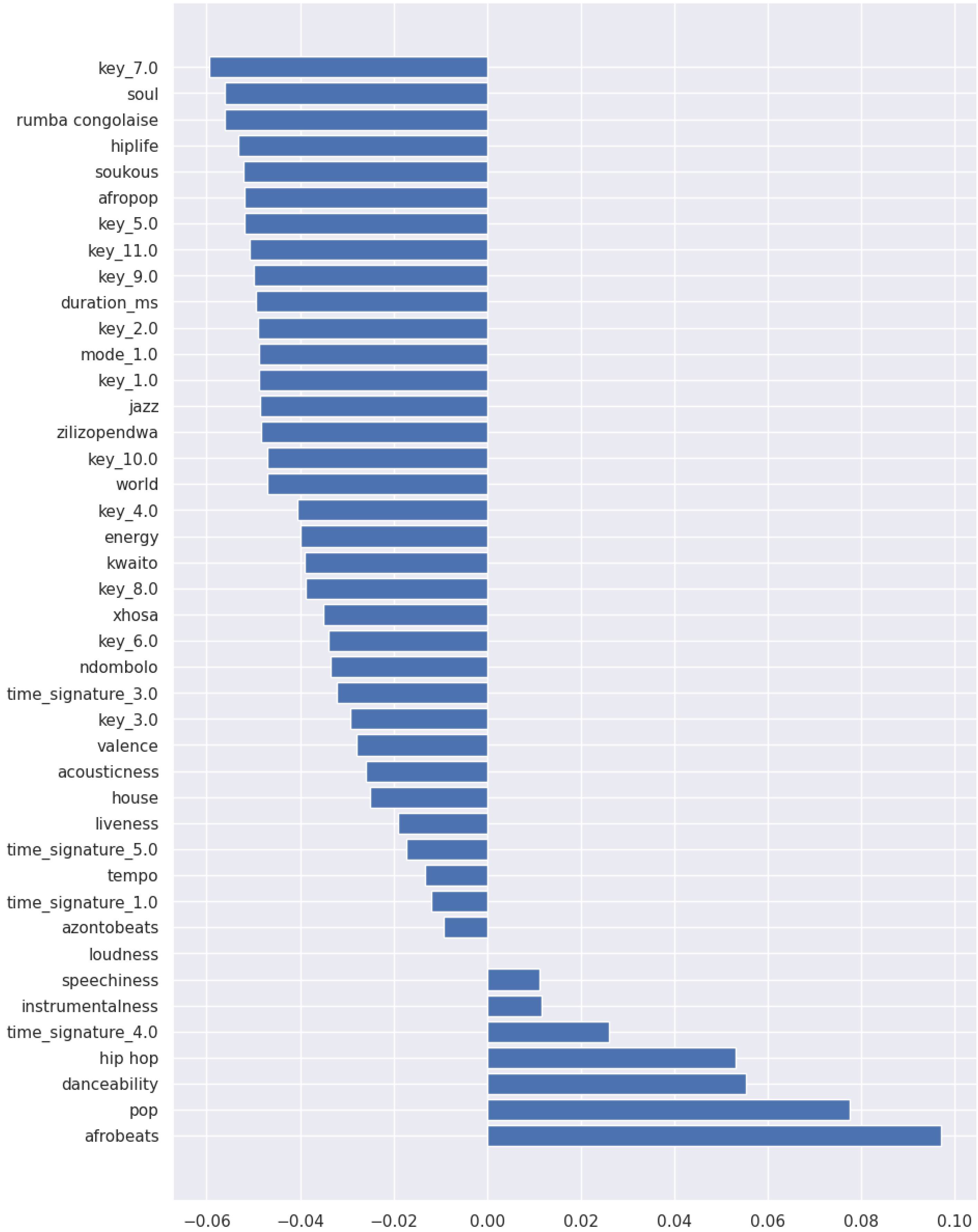
In [113]:

```
logregcv_importances_df = pd.Series(clf_logregcv_tuned.coef_[0], index=X_train.columns).
sort_values(ascending=False)

# Parsing the series to a dataframe
```

```
logregcv_importances_df = logregcv_importances_df.reset_index()
logregcv_importances_df.columns = ['Attribute', 'Importance']

fig, ax = plt.subplots(figsize=(10,15))
ax.barh(logregcv_importances_df['Attribute'], logregcv_importances_df['Importance'])
```

Out[113]:

```
<BarContainer object of 42 artists>
```



We can see here that while certain features like 'afrobeats', 'pop', and 'danceability' positively affected the prediction, other features such as 'rumba congolaise', 'soul' and 'key_11 (or Key_B)' negatively affected it in the

case of logistic regression. Next we can dive into our processed dataframe and explore some of these attributes for popular and unpopular songs to come to conclusions.

Exploring Track Features and Popularity

In this section, we examine how track features such as `'danceability'`, `'speechiness'`, and `'instrumentalness'` influence popularity, independent of genre classifications with reference to the definitions provided in the Spotify documentation.

Danceability

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

In [114]:

```
# Separating popular and unpopular songs to two dfs
popular_songs_df = df[df['is_popular'] == 1]
unpopular_songs_df = df[df['is_popular']==0]
```

In [115]:

```
# Removing outliers from danceability scores and separating them to Series for popular an
d unpopular songs
popular_dance_clean = popular_songs_df[find_outliers_IQR(popular_songs_df['danceability']
)==False]
print(popular_dance_clean['danceability'].describe())

unpopular_dance_clean = unpopular_songs_df[find_outliers_IQR(unpopular_songs_df['danceabi
lity'])==False]
print(unpopular_dance_clean['danceability'].describe())
```

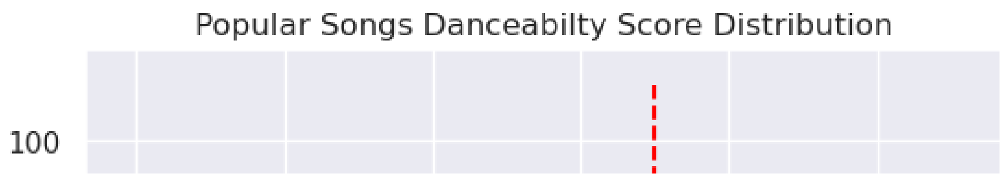
```
count    574.000000
mean       0.729172
std        0.117489
min        0.394000
25%        0.647250
50%        0.750000
75%        0.820000
max        0.956000
Name: danceability, dtype: float64
count    6912.000000
mean        0.656242
std         0.141828
min         0.231000
25%         0.550000
50%         0.672000
75%         0.766000
max         0.985000
Name: danceability, dtype: float64
```

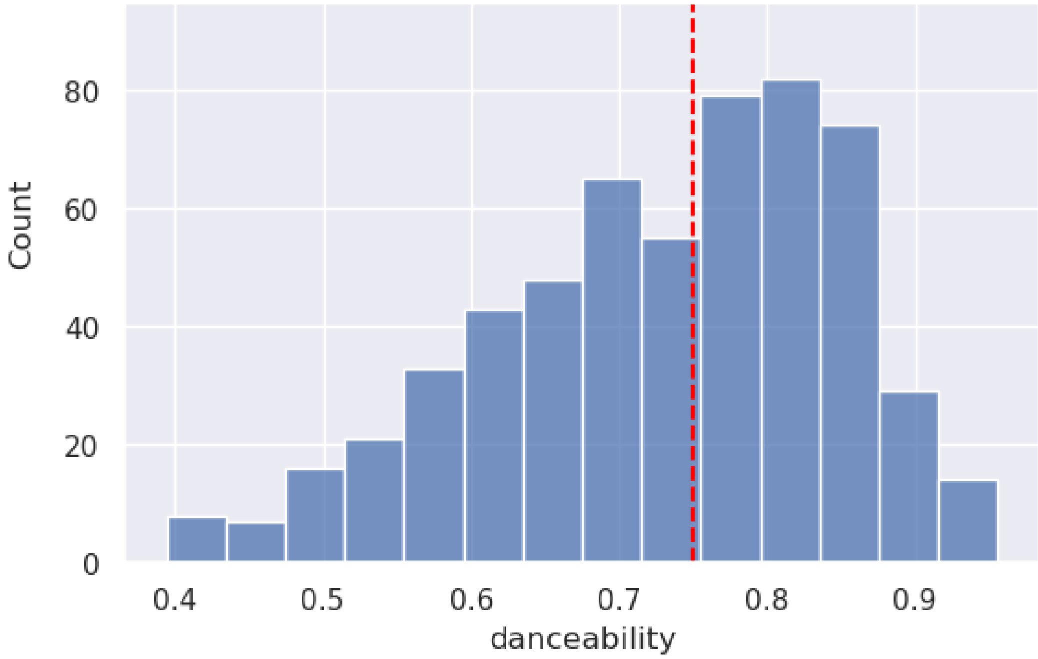
In [116]:

```
sns.histplot(data=popular_dance_clean, x='danceability', bins='auto')
plt.title('Popular Songs Danceabilty Score Distribution')
plt.vlines(x=popular_dance_clean['danceability'].median(), ymin=0, ymax=110, color='red',
ls='--')
```

Out[116]:

```
&lt;matplotlib.collections.LineCollection at 0x7feeeebf4dd0&gt;
```



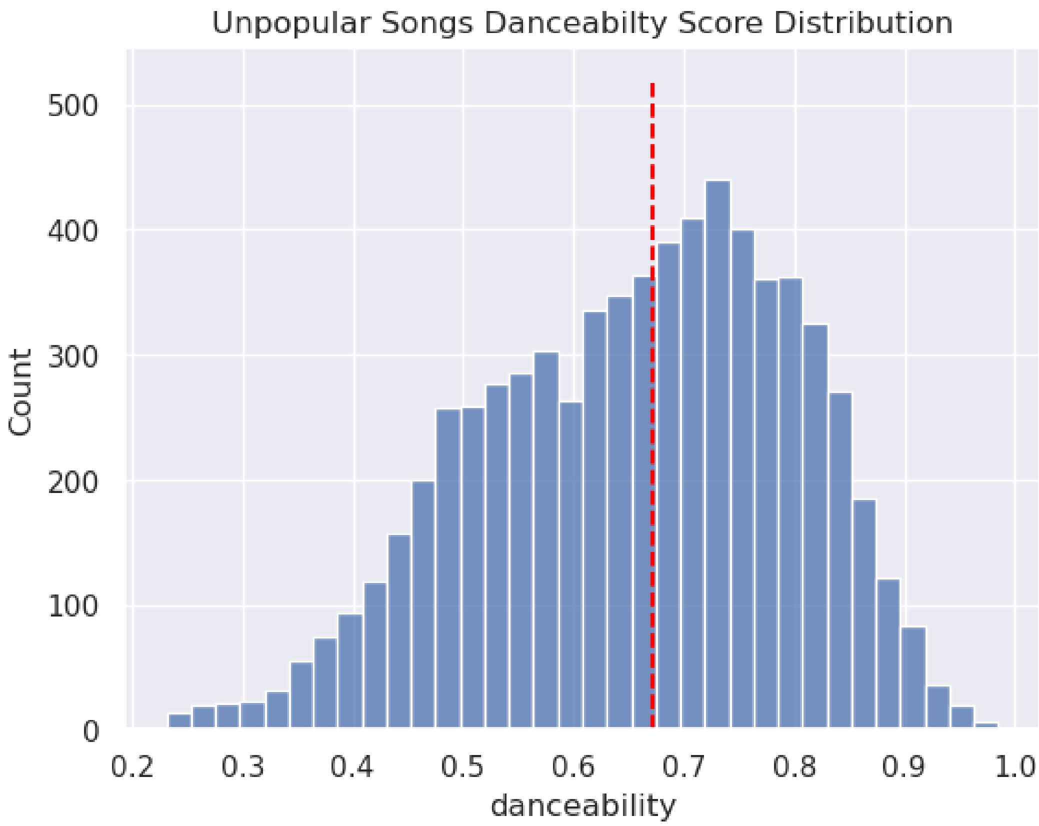


In [117]:

```
sns.histplot(data=unpopular_dance_clean, x='danceability', bins='auto')
plt.title('Unpopular Songs Danceabilty Score Distribution')
plt.vlines(x=unpopular_dance_clean['danceability'].median(), ymin=0, ymax=520, color='red
', ls='--')
```

Out[117]:

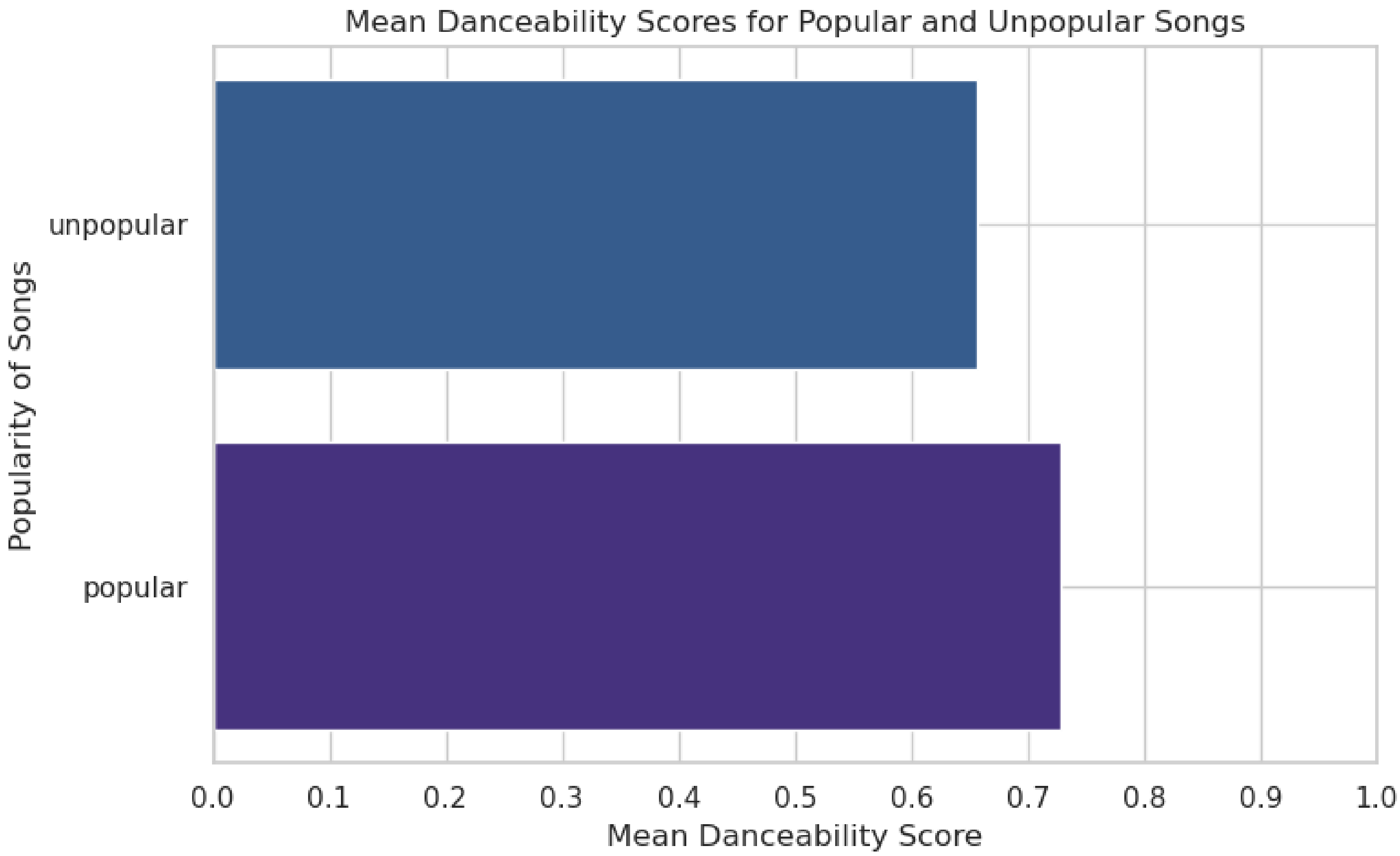
```
<matplotlib.collections.LineCollection at 0x7feeeeb90f10>
```



In [118]:

```
# Storing mean danceability scores in dict
mean_danceability = {'popular': popular_dance_clean['danceability'].mean(),
                     'unpopular': unpopular_dance_clean['danceability'].mean()}

#visualizing mean scores
with sns.axes_style("whitegrid"):
    fig, ax = plt.subplots(figsize=(8,5))
    ax.barh(y=list(mean_danceability.keys()),
```

```
            width=list(mean_danceability.values()),
            color=[sns.color_palette('viridis')[0],sns.color_palette('viridis')[1]])
    ax.set_xlim(0, 1)
    ax.set_xticks(np.arange(0,1.1,0.1))
    ax.set_ylabel('Popularity of Songs')
    ax.set_xlabel('Mean Danceability Score')
    ax.set_title('Mean Danceability Scores for Popular and Unpopular Songs')
    plt.tight_layout()
```



Above, it is clear that the popular songs tends to have a higher danceability score compared to unpopular songs.

Speechiness

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

In [119]:

```
# Removing outliers from danceability scores and separating them to Series for popular an
d unpopular songs
# The `find_outliers_IQR` function  returns boolean series where True represent an outlie
r
popular_speechiness_clean = popular_songs_df[~find_outliers_IQR(popular_songs_df['speechi
ness'])]
print(popular_speechiness_clean['speechiness'].describe())

unpopular_speechiness_clean = unpopular_songs_df[~find_outliers_IQR(unpopular_songs_df['s
peechiness'])]
print(unpopular_speechiness_clean['speechiness'].describe())
```

```
count    554.000000
mean       0.130499
std        0.094864
min        0.026100
25%        0.056550
50%        0.091250
```

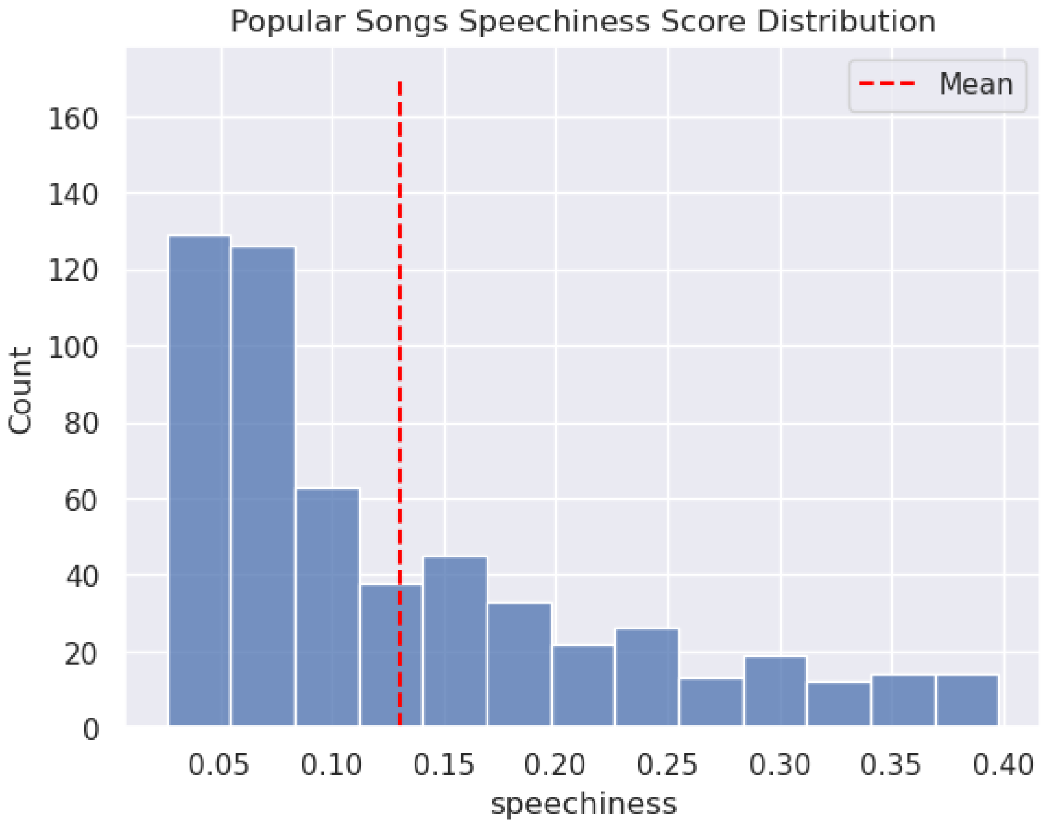
```
75%          0.182750
max          0.398000
Name: speechiness, dtype: float64
count     6427.000000
mean         0.101813
std          0.079037
min          0.000000
25%          0.044800
50%          0.067500
75%          0.134000
max          0.346000
Name: speechiness, dtype: float64
```

In [120]:

```
sns.histplot(data = popular_speechiness_clean, x='speechiness', bins='auto')
plt.title('Popular Songs Speechiness Score Distribution')
plt.vlines(x=popular_speechiness_clean['speechiness'].mean(), ymin=0, ymax=170, color='re
d', ls='--', label='Mean')
plt.legend()
```

Out[120]:

```
<matplotlib.legend.Legend at 0x7feeee8e7090>
```

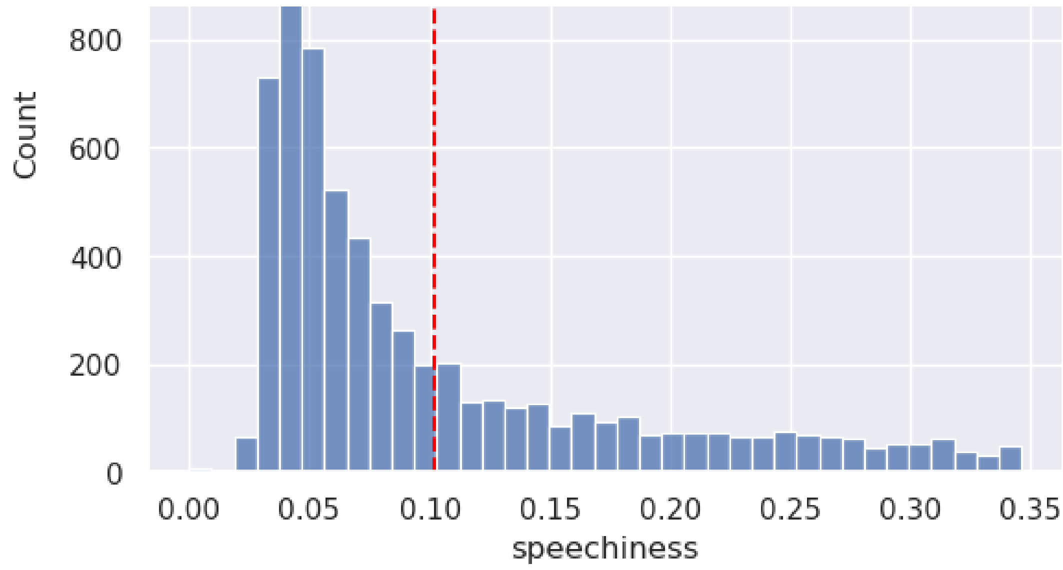


In [121]:

```
sns.histplot(data=unpopular_speechiness_clean, x='speechiness', bins='auto')
plt.title('Unpopular Songs Speechiness Score Distribution')
plt.vlines(x=unpopular_speechiness_clean['speechiness'].mean(), ymin=0, ymax=1200, color=
'red', ls='--', label='median')
```

Out[121]:

```
<matplotlib.collections.LineCollection at 0x7feeef531790>
```



In [122]:

```
# Save mean acousticness scores in dict
mean_speechiness = {'popular': popular_speechiness_clean['speechiness'].mean(),
                    'unpopular': unpopular_speechiness_clean['speechiness'].mean()
                   }

# Visualizing mean scores
with sns.axes_style("whitegrid"):
    fig, ax = plt.subplots(figsize=(8,5))
    ax.barh(y=list(mean_speechiness.keys()),
            width=list(mean_speechiness.values()),
            color=[sns.color_palette('viridis')[2],sns.color_palette('viridis')[3]])
    ax.set_xlim(0, 0.2)
    ax.set_ylabel('Popularity of Songs')
    ax.set_xlabel('Mean Speechiness Score')
    ax.set_title('Mean Speechiness Scores for Popular and Unpopular Songs')
    plt.tight_layout()
```

Similar to danceability scores, we see that the popular songs tends to have a higher speechiness score.

Instrumentalness

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

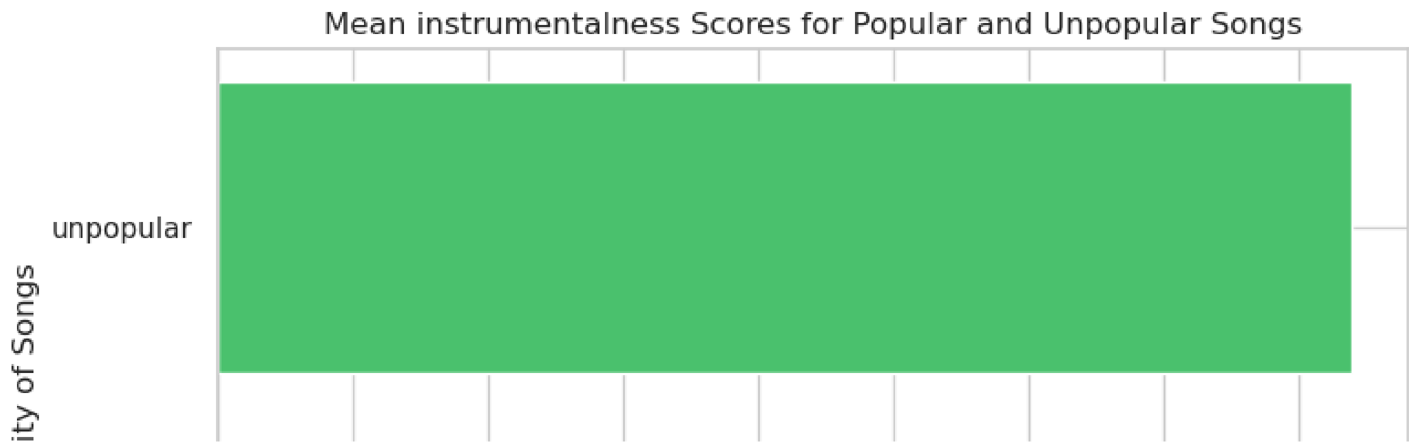
In [123]:

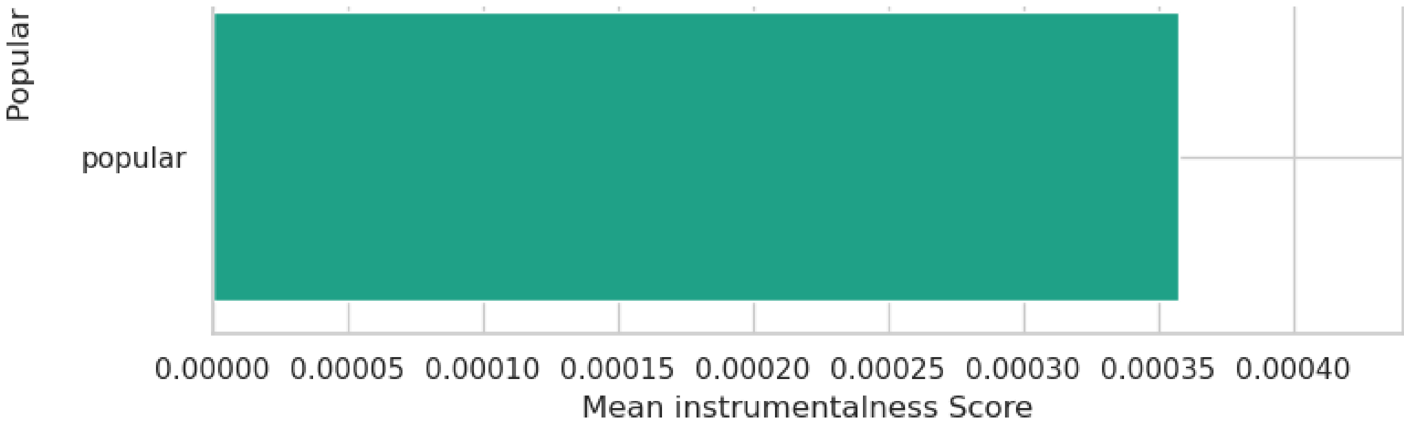
```
# Removing outliers from instrumentalness scores and separating them to Series for popula
r and unpopular songs
popular_instrumentalness_clean = popular_songs_df[~find_outliers_IQR(popular_songs_df['in
strumentalness'])]
print(popular_instrumentalness_clean['instrumentalness'].describe())

unpopular_instrumentalness_clean = unpopular_songs_df[~find_outliers_IQR(unpopular_songs_
df['instrumentalness'])]
print(unpopular_instrumentalness_clean['instrumentalness'].describe())
```

```
count    459.000000
mean       0.000358
std        0.000970
min        0.000000
25%        0.000000
50%        0.000002
75%        0.000092
max        0.005920
Name: instrumentalness, dtype: float64
count    5441.000000
mean        0.000420
std         0.001251
min         0.000000
25%         0.000000
50%         0.000002
75%         0.000077
max         0.008460
Name: instrumentalness, dtype: float64
```

In [124]:

```
# Save mean instrumentalness scores in dict
mean_instrumentalness = {'popular':popular_instrumentalness_clean['instrumentalness'].mea
n(),
                         'unpopular':unpopular_instrumentalness_clean['instrumentalness'
].mean()
                        }
# Visualizing mean scores
with sns.axes_style("whitegrid"):
    fig, ax = plt.subplots(figsize=(8,5))
    ax.barh(y=list(mean_instrumentalness.keys()),
            width=list(mean_instrumentalness.values()),
            color=[sns.color_palette('viridis')[3],sns.color_palette('viridis')[4]])
    ax.set_ylabel('Popularity of Songs')
    ax.set_xlabel('Mean instrumentalness Score')
    ax.set_title('Mean instrumentalness Scores for Popular and Unpopular Songs')
    plt.tight_layout()
```





As can be seen above, the popular songs tends to be more vocal (low instrumentalness score) compare to unpopular songs.

Prediction and Evaluation

In this section, I employ each model to predict the popularity of songs and assess their performance on a new dataset. This dataset comprises track features obtained from Spotify for songs by artists not included in either the training or test data. By utilizing this unseen dataset, I can evaluate how well the models perform on entirely new data that was not previously encountered during the training or testing phases.

In [125]:

```
# !pip install spotipy
```

In [126]:

```
import spotipy
from spotipy.oauth2 import SpotifyClientCredentials
import pandas as pd
from credentials import SPOTIPY_CLIENT_ID, SPOTIPY_CLIENT_SECRET

client_credentials_manager = SpotifyClientCredentials(SPOTIPY_CLIENT_ID, SPOTIPY_CLIENT_S
ECRET)
spotify = spotipy.Spotify(client_credentials_manager=client_credentials_manager)
```

New Data

In [127]:

```
# The code below (modified), used to get track features and properties, was adapted from
# https://www.kaggle.com/code/worlaalex/top-50-afrobeats-data-extraction-from-spotify

def TrackFeatures(track_id):
    meta = spotify.track(track_id)
    artist = spotify.artist(meta["artists"][0]["external_urls"]["spotify"])

    features = spotify.audio_features(track_id)
    genres = artist["genres"]
    # metadata
    track_name = meta['name']
    album_name = meta['album']['name']
    artist_name = meta['album']['artists'][0]['name']
    release_date = meta['album']['release_date']
    duration_ms = meta['duration_ms']
    popularity = meta['popularity']

    # specific feartures
    if features[0]:
        acousticness = features[0]['acousticness']
        danceability = features[0]['danceability']
        energy = features[0]['energy']
```

```
        instrumentalness = features[0]['instrumentalness']
        liveness = features[0]['liveness']
        loudness = features[0]['loudness']
        speechiness = features[0]['speechiness']
        tempo = features[0]['tempo']
        time_signature = features[0]['time_signature']
        key = features[0]['key']
        mode = features[0]['mode']
        valence = features[0]['valence']

        track = [track_name, track_id, ",".join(genres), album_name, artist_name, releas
e_date, duration_ms,
                 popularity, danceability, key, acousticness, mode, energy, instrumental
ness, liveness,
                 loudness, speechiness, tempo, time_signature, valence,
                ]
    else:
        track = [np.nan] * 20
    return track
```

In [128]:

```
def get_features(track_ids):
    if isinstance(track_ids, list):
        tracks = [TrackFeatures(track_id) for track_id in track_ids]
        columns = ['track_name', 'track_id', 'genre', 'album_name', 'artist_name', 'rele
ase_date', 'duration_ms',
                   'popularity', 'danceability', 'key', 'acousticness', 'mode', 'energy'
, 'instrumentalness',
                   'liveness', 'loudness', 'speechiness', 'tempo', 'time_signature', 'va
lence',
                  ]
        df = pd.DataFrame(tracks, columns=columns)
        return df

    else:
        print("Track ids must be surplied as a list")
```

In [129]:

```
def predict(df, model='logreg'):
    import re
    df_new = df.dropna()
    df_new['key'] = df_new['key'].astype('float')
    df_new['mode'] = df_new['mode'].astype('float')
    df_new['time_signature'] = df_new['time_signature'].astype('float')

    # Replace all 'afrobeat' with 'afrobeats'
    pattern = r'\bafrobeat\b'
    df['genre'] = df['genre'].apply(lambda x: re.sub(pattern, 'afrobeats', x))

    # Replace 'azonto' and 'azotobeat' with 'azontobeats'
    pattern = r'(\bazonto\b)|(\bazontobeat\b)'
    df_new['genre'] = df_new['genre'].apply(lambda x: re.sub(pattern, 'azontobeats', x))

    #creating columns for each genre in the new_genres list
    for genre in new_genres:
        pattern = re.compile(fr'\b{genre}\b')
        df_new[genre] = (df_new['genre'].apply(lambda x: bool(pattern.search(x)))).astyp
e('int')

    #removing the redundant genre column
    df_new.drop('genre', axis=1, inplace=True)

    #dropping 'artist_name', 'track_name', 'album_name', and 'release_date' columns.
    df_new.drop(['artist_name', 'track_name', 'album_name', 'release_date'],
            axis=1, inplace=True, errors='ignore',
           )
    df_new.set_index('track_id', inplace=True)     # Set the 'track_id' column as the ind
ex
```

```
    #define categorical columns
    cat_cols = ['key', 'mode', 'time_signature']

    #One hot encoding the dataframes
    from sklearn.preprocessing import OneHotEncoder

    encoder = OneHotEncoder(sparse_output=False, drop='first')
    data_ohe = encoder.fit_transform(df_new[cat_cols])
    df_ohe = pd.DataFrame(data_ohe, columns=encoder.get_feature_names_out(cat_cols), ind
ex=df_new.index)

    #merging OHE columns with numerical columns
    df_new = pd.concat([df_new.drop(cat_cols, axis=1), df_ohe], axis=1)

    # The test set must have the same columns as the training set, therefore
    # we'll create the missing columns in the test set and fill with zeros
    missing_cols = X_train.columns.difference(df_new.columns)
    if any(missing_cols):
        for cols in missing_cols:
            df_new[cols] = 0
    df_new = df_new[X_train.columns]

    # PREDICT
    if model == 'rf':
        y_pred = clf_rf_tuned.predict(df_new)
    elif model == 'xgb':
        y_pred = xgb_model.predict(df_new)
    elif model == 'logreg':
        if len(df_new) > 1:
            from sklearn.preprocessing import StandardScaler
            scaler = StandardScaler()
            df_new_sc = scaler.fit_transform(df_new)
            y_pred = clf_logregcv_tuned.predict(df_new_sc)
        elif len(df_new) == 1:
            y_pred = clf_logregcv_tuned.predict(df_new.values)

    return y_pred
```

In [130]:

```
# # This ids are track ids from artist not in the original data set
# ids = ['2khv04F26pnJr4989Maowi', '1rrqJ9QkOBYJlsZgqqwxgB', '1IMRi5UVOV77PsAgdWDvzh', '5
FHwYRqxv08eyWWw7ARzJj',
#         '7f3xivnGz4HU0UigVxvlEe', '3cRYXW7xZ6GJttdlPhBb1k', '54KmblozuEemR23n9a4Grt', '4
vb777iaycnlFxVkJMmtfd',
#         '5aIVCx5tnk0ntmdiinnYvw', "7lu6f7znGvbUpjFKvdqC8B", '3eWpfsYgd5OL2QdwcVcF6Q', '4
YAd7QqSKHz6dS2MCnq4mO',
#         '7xzMrUmlooPa1Fmp88hlYc', '6gfdkLXXBzNUkCsf31PVYm', '24qQClclS8CCjiCZKM8d9m', '5
aNRjr4RchxYx1tT8z6CWa',
#       ]
# df_new = get_features(ids)
# df_new
```

Since the Auidio features end point of the Spotify API is deprecated, we will rely on our validation set to perform the prediction

Validation Data

In [131]:

```
validation.shape
```

Out[131]:

```
(1369, 20)
```

In [132]:

```
validation.isna().sum()
```

Out[132]:

```
track_name           0
track_id             0
genre               46
album_name           0
artist_name          0
release_date         0
duration_ms          0
popularity           0
danceability         0
key                  0
acousticness         0
mode                 0
energy               0
instrumentalness     0
liveness             0
loudness             0
speechiness          0
tempo                0
time_signature       0
valence              0
dtype: int64
```

In [133]:

```
validation = validation.dropna()
validation.isna().sum()
```

Out[133]:

```
track_name          0
track_id            0
genre               0
album_name          0
artist_name         0
release_date        0
duration_ms         0
popularity          0
danceability        0
key                 0
acousticness        0
mode                0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
time_signature      0
valence             0
dtype: int64
```

In [134]:

```
validation.shape
```

Out[134]:

```
(1323, 20)
```

In [135]:

```
valid_popular = validation[validation['popularity'] >= 42.5]
valid_popular.shape
```

Out[135]:

```
(100, 20)
```

In [136]:

```
valid_unpopular = validation[validation['popularity'] < 42.5]
```

```
valid_unpopular.shape
```

Out[136]:

```
(1223, 20)
```

In [137]:

```
df_new = validation.copy()
df_new
```

Out[137]:

	track_name	track_id	genre	album_name	artist_name	release_date	dura
0	Phaseur (Live)	7riMewdeFzlouweIXf04O4	azontobeats,ndombolo,rumba congolaise,soukous,...	100% tcha tcho, Vol. 2 (Live)	Koffi Olomide	2009-01-01	4
1	I Do	3pzAmz9wv1xkzxWWcDh0QR	afrobeats,nigerian pop	Sorry I'm Late	Bnxn	2021-10-27	1
2	Aben Wo Aha	1sw1Ahq16MtmeFlwEgXxKm	azonto,hiplife	Aben Wo Aha	Daddy Lumba	1998-03-27	3
3	Trésor public	3vElmpLOPvbjP2SG1Zn3Fq	azontobeats,ndombolo,rumba congolaise,soukous,...	Légende Ed. Diamond	Koffi Olomide	2022-11-25	4
4	No More Cryin	4w3Kz4PP3tuEdC20LI9SpJ	afropop,jazz trumpet,kwaito,south african jazz	Notes of Life	Hugh Masekela	1996-11-02	2
...	...	...	...	...	...	...	...
1364	The Break Up	4gDJDDNiL6e1TmqjhVfhvS	afro soul,kwaito,sda a cappella,south african ...	Echoes Of Kofifi	The Soil	2016-10-21	2
1365	Heartbreaker (feat. Nasty C)	28qXHN4aeQ3D2asjK0Vouz	afrobeats,nigerian hip hop,nigerian pop	Sex Over Love	Blaqbonez	2021-04-30	1
1366	Steppin' Out	3oQZ4ss7H33riju34UaVW0	afropop,jazz trumpet,kwaito,south african jazz	Beatin' Aroun De Bush	Hugh Masekela	1992-04-04	2
1367	Ngibambe	65vVCIdceUiRTnRtG10LNz	afro soul,south african house,south african pop	Highly Flavoured	Busiswa	2017-01-01	2
1368	Wokyire Mea	7i6vFb8jEKx11nriltfTGV	old school highlife	Sweet Talks	A.B. Crentsil	2000-02-07	3

1323 rows × 20 columns

Random Forest Prediction

In [138]:

```
import numpy as np

# Predict using Random Forest model
prediction_rf = predict(df_new.drop('popularity', axis=1, errors='ignore'), model='rf')

# Prepare dataframe for evaluation
df_pred_rf = df_new.loc[:, ['track_name', 'artist_name', 'popularity']].copy()

# Assign true labels based on popularity threshold
df_pred_rf['true_value'] = df_pred_rf['popularity'].apply(lambda x: 'popular' if x >= 42
.5 else 'unpopular')

# Assign predicted labels
df_pred_rf['prediction'] = np.where(np.array(prediction_rf) == 1, 'popular', 'unpopular'
)

# Compute classification counts
```

```
total_samples = len(df_pred_rf)
correct = (df_pred_rf['true_value'] == df_pred_rf['prediction']).sum()
misclassified = total_samples - correct

# Count subclass predictions
popular_total = (df_pred_rf['true_value'] == 'popular').sum()
popular_correct = ((df_pred_rf['true_value'] == 'popular') & (df_pred_rf['prediction'] =
= 'popular')).sum()
popular_misclassified = popular_total - popular_correct

unpopular_total = (df_pred_rf['true_value'] == 'unpopular').sum()
unpopular_correct = ((df_pred_rf['true_value'] == 'unpopular') & (df_pred_rf['prediction
'] == 'unpopular')).sum()
unpopular_misclassified = unpopular_total - unpopular_correct

# Calculate percentages
accuracy = (correct / total_samples) * 100
popular_accuracy = (popular_correct / popular_total) * 100 if popular_total > 0 else 0
unpopular_accuracy = (unpopular_correct / unpopular_total) * 100 if unpopular_total > 0
else 0
popular_misclassification_rate = (popular_misclassified / popular_total) * 100 if popula
r_total > 0 else 0
unpopular_misclassification_rate = (unpopular_misclassified / unpopular_total) * 100 if
unpopular_total > 0 else 0

# Print results
print(f'Correctly classified: {correct} ({accuracy:.2f}%)')
print(f'Misclassified: {misclassified} ({100 - accuracy:.2f}%)')
print(f'Popular songs correctly classified: {popular_correct} ({popular_accuracy:.2f}%)')
print(f'Popular songs misclassified as unpopular: {popular_misclassified} ({popular_miscl
assification_rate:.2f}%)')
print(f'Unpopular songs correctly classified: {unpopular_correct} ({unpopular_accuracy:.2
f}%)')
print(f'Unpopular songs misclassified as popular: {unpopular_misclassified} ({unpopular_m
isclassification_rate:.2f}%)')

# Display predictions
df_pred_rf
```

```
Correctly classified: 1088 (82.24%)
Misclassified: 235 (17.76%)
Popular songs correctly classified: 63 (63.00%)
Popular songs misclassified as unpopular: 37 (37.00%)
Unpopular songs correctly classified: 1025 (83.81%)
Unpopular songs misclassified as popular: 198 (16.19%)
```

Out[138]:

	track_name	artist_name	popularity	true_value	prediction
0	Phaseur (Live)	Koffi Olomide	2.0	unpopular	unpopular
1	I Do	Bnxn	46.0	popular	popular
2	Aben Wo Aha	Daddy Lumba	42.0	unpopular	unpopular
3	Trésor public	Koffi Olomide	20.0	unpopular	unpopular
4	No More Cryin	Hugh Masekela	1.0	unpopular	unpopular
...	...	...	...	...	...
1364	The Break Up	The Soil	37.0	unpopular	unpopular
1365	Heartbreaker (feat. Nasty C)	Blaqbonez	28.0	unpopular	popular
1366	Steppin' Out	Hugh Masekela	2.0	unpopular	unpopular
1367	Ngibambe	Busiswa	8.0	unpopular	unpopular
1368	Wokyire Mea	A.B. Crentsil	4.0	unpopular	unpopular

1323 rows × 5 columns

Logistic Regression Prediction

Logistic Regression Prediction

In [139]:

```python
import numpy as np

# Predict using Logistic Regression model
prediction_logreg = predict(df_new.drop('popularity', axis=1, errors='ignore'), model='logreg')

# Prepare dataframe for evaluation
df_pred_logreg = df_new.loc[:, ['track_name', 'artist_name', 'popularity']].copy()

# Assign true labels based on popularity threshold
df_pred_logreg['true_value'] = df_pred_logreg['popularity'].apply(lambda x: 'popular' if x >= 42.5 else 'unpopular')

# Assign predicted labels
df_pred_logreg['prediction'] = np.where(np.array(prediction_logreg) == 1, 'popular', 'unpopular')

# Compute classification counts
total_samples = len(df_pred_logreg)
correct = (df_pred_logreg['true_value'] == df_pred_logreg['prediction']).sum()
misclassified = total_samples - correct

# Count subclass predictions
popular_total = (df_pred_logreg['true_value'] == 'popular').sum()
popular_correct = ((df_pred_logreg['true_value'] == 'popular') & (df_pred_logreg['prediction'] == 'popular')).sum()
popular_misclassified = popular_total - popular_correct

unpopular_total = (df_pred_logreg['true_value'] == 'unpopular').sum()
unpopular_correct = ((df_pred_logreg['true_value'] == 'unpopular') & (df_pred_logreg['prediction'] == 'unpopular')).sum()
unpopular_misclassified = unpopular_total - unpopular_correct

# Calculate percentages
accuracy = (correct / total_samples) * 100
popular_accuracy = (popular_correct / popular_total) * 100 if popular_total > 0 else 0
unpopular_accuracy = (unpopular_correct / unpopular_total) * 100 if unpopular_total > 0 else 0
popular_misclassification_rate = (popular_misclassified / popular_total) * 100 if popular_total > 0 else 0
unpopular_misclassification_rate = (unpopular_misclassified / unpopular_total) * 100 if unpopular_total > 0 else 0

# Print results
print(f'Correctly classified: {correct} ({accuracy:.2f}%)')
print(f'Misclassified: {misclassified} ({100 - accuracy:.2f}%)')
print(f'Popular songs correctly classified: {popular_correct} ({popular_accuracy:.2f}%)')
print(f'Popular songs misclassified as unpopular: {popular_misclassified} ({popular_misclassification_rate:.2f}%)')
print(f'Unpopular songs correctly classified: {unpopular_correct} ({unpopular_accuracy:.2f}%)')
print(f'Unpopular songs misclassified as popular: {unpopular_misclassified} ({unpopular_misclassification_rate:.2f}%)')

# Display predictions
df_pred_logreg
```

```
Correctly classified: 695 (52.53%)
Misclassified: 628 (47.47%)
Popular songs correctly classified: 97 (97.00%)
Popular songs misclassified as unpopular: 3 (3.00%)
Unpopular songs correctly classified: 598 (48.90%)
Unpopular songs misclassified as popular: 625 (51.10%)
```

Out[139]:

	track_name	artist_name	popularity	true_value	prediction
0	Phaseur (Live)	Koffi Olomide	2.0	unpopular	unpopular

	track_name	artist_name	popularity	true_value	prediction
1	I Do	Bnxn	46.0	popular	popular
2	Aben Wo Aha	Daddy Lumba	42.0	unpopular	unpopular
3	Trésor public	Koffi Olomide	20.0	unpopular	unpopular
4	No More Cryin	Hugh Masekela	1.0	unpopular	unpopular
...	...	...	...	...	...
1364	The Break Up	The Soil	37.0	unpopular	unpopular
1365	Heartbreaker (feat. Nasty C)	Blaqbonez	28.0	unpopular	popular
1366	Steppin' Out	Hugh Masekela	2.0	unpopular	unpopular
1367	Ngibambe	Busiswa	8.0	unpopular	popular
1368	Wokyire Mea	A.B. Crentsil	4.0	unpopular	unpopular

1323 rows × 5 columns

XGBoost Prediction

In [140]:

```
import numpy as np

# Predict using XGBoost model
prediction_xgb = predict(df_new.drop('popularity', axis=1, errors='ignore'), model='xgb'
)

# Prepare dataframe for evaluation
df_pred_xgb = df_new.loc[:, ['track_name', 'artist_name', 'popularity']].copy()

# Assign true labels based on popularity threshold
df_pred_xgb['true_value'] = df_pred_xgb['popularity'].apply(lambda x: 'popular' if x >=
42.5 else 'unpopular')

# Assign predicted labels
df_pred_xgb['prediction'] = np.where(np.array(prediction_xgb) == 1, 'popular', 'unpopula
r')

# Compute classification counts
total_samples = len(df_pred_xgb)
correct = (df_pred_xgb['true_value'] == df_pred_xgb['prediction']).sum()
misclassified = total_samples - correct

# Count subclass predictions
popular_total = (df_pred_xgb['true_value'] == 'popular').sum()
popular_correct = ((df_pred_xgb['true_value'] == 'popular') & (df_pred_xgb['prediction']
== 'popular')).sum()
popular_misclassified = popular_total - popular_correct

unpopular_total = (df_pred_xgb['true_value'] == 'unpopular').sum()
unpopular_correct = ((df_pred_xgb['true_value'] == 'unpopular') & (df_pred_xgb['predicti
on'] == 'unpopular')).sum()
unpopular_misclassified = unpopular_total - unpopular_correct

# Calculate percentages
accuracy = (correct / total_samples) * 100
popular_accuracy = (popular_correct / popular_total) * 100 if popular_total > 0 else 0
unpopular_accuracy = (unpopular_correct / unpopular_total) * 100 if unpopular_total > 0
else 0
popular_misclassification_rate = (popular_misclassified / popular_total) * 100 if popula
r_total > 0 else 0
unpopular_misclassification_rate = (unpopular_misclassified / unpopular_total) * 100 if
unpopular_total > 0 else 0

# Print results
print(f'Correctly classified: {correct} ({accuracy:.2f}%)')
print(f'Misclassified: {misclassified} ({100 - accuracy:.2f}%)')
print(f'Popular songs correctly classified: {popular_correct} ({popular_accuracy:.2f}%)')
```

```
print(f'Popular songs misclassified as unpopular: {popular_misclassified} ({popular_misclassification_rate:.2f}%)')
print(f'Unpopular songs correctly classified: {unpopular_correct} ({unpopular_accuracy:.2f}%)')
print(f'Unpopular songs misclassified as popular: {unpopular_misclassified} ({unpopular_misclassification_rate:.2f}%)')

# Display predictions
df_pred_xgb
```

```
Correctly classified: 984 (74.38%)
Misclassified: 339 (25.62%)
Popular songs correctly classified: 78 (78.00%)
Popular songs misclassified as unpopular: 22 (22.00%)
Unpopular songs correctly classified: 906 (74.08%)
Unpopular songs misclassified as popular: 317 (25.92%)
```

Out[140]:

	track_name	artist_name	popularity	true_value	prediction
0	Phaseur (Live)	Koffi Olomide	2.0	unpopular	unpopular
1	I Do	Bnxn	46.0	popular	popular
2	Aben Wo Aha	Daddy Lumba	42.0	unpopular	unpopular
3	Trésor public	Koffi Olomide	20.0	unpopular	unpopular
4	No More Cryin	Hugh Masekela	1.0	unpopular	unpopular
...	...	...	...	...	...
1364	The Break Up	The Soil	37.0	unpopular	unpopular
1365	Heartbreaker (feat. Nasty C)	Blaqbonez	28.0	unpopular	popular
1366	Steppin' Out	Hugh Masekela	2.0	unpopular	unpopular
1367	Ngibambe	Busiswa	8.0	unpopular	unpopular
1368	Wokyire Mea	A.B. Crentsil	4.0	unpopular	unpopular

1323 rows × 5 columns

In [141]:

```
df_pred_all_model = df_new.loc[:, ['track_name', 'artist_name', 'popularity']]
df_pred_all_model['true_value'] = df_pred_all_model['popularity'].apply(lambda x: 'popular' if x>=42.5 else 'unpopular')
df_pred_all_model['Random Forest Prediction'] = df_pred_rf['prediction']
df_pred_all_model['Logistic Regrssion Prediction'] = df_pred_xgb['prediction']
df_pred_all_model['XGBoost Prediction'] = df_pred_xgb['prediction']
df_pred_all_model.head(10)
```

Out[141]:

	track_name	artist_name	popularity	true_value	Random Forest Prediction	Logistic Regrssion Prediction	XGBoost Prediction
0	Phaseur (Live)	Koffi Olomide	2.0	unpopular	unpopular	unpopular	unpopular
1	I Do	Bnxn	46.0	popular	popular	popular	popular
2	Aben Wo Aha	Daddy Lumba	42.0	unpopular	unpopular	unpopular	unpopular
3	Trésor public	Koffi Olomide	20.0	unpopular	unpopular	unpopular	unpopular
4	No More Cryin	Hugh Masekela	1.0	unpopular	unpopular	unpopular	unpopular
5	Evil Boy	Die Antwoord	29.0	unpopular	unpopular	unpopular	unpopular
6	Liwa Wechi - Congolese Lament. The Wife Bids H...	Miriam Makeba	0.0	unpopular	unpopular	unpopular	unpopular

	track_name	artist_name	popularity	true_value	Random Forest Prediction	Logistic Regrssion Prediction	XGBoost Prediction
	The Wife Bids H...	Makeba					
7	BASE - Skit	Adje	0.0	unpopular	unpopular	unpopular	unpopular
8	Kelele	Angelique Kidjo	10.0	unpopular	unpopular	unpopular	unpopular
9	Child Of The Earth	Hugh Masekela	10.0	unpopular	unpopular	unpopular	unpopular

Random Forest achieved the highest overall accuracy at 82.24%, correctly classifying most songs. However, it struggled with identifying popular songs, misclassifying 37 as unpopular, leading to a lower performance in this category. Logistic Regression, on the other hand, excelled at detecting popular songs with 97% accuracy but performed poorly overall, with a low 52.53% accuracy due to frequent misclassification of unpopular songs. XGBoost provided a more balanced performance, achieving 74% accuracy while correctly classifying 78% of popular songs. **Although Random Forest had the best overall classification, XGBoost appears to be the more reliable choice due to its better handling of both categories (popular and unpopular).**

In [ ]:

```
# df_pred_all_model.to_csv("Prediction_result.csv", index=False)
```