Popular Audio Features Analysis

- Student name: Myrna Grace Calip
- Student pace: Part-Time
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- Instructor name: Claude Fried
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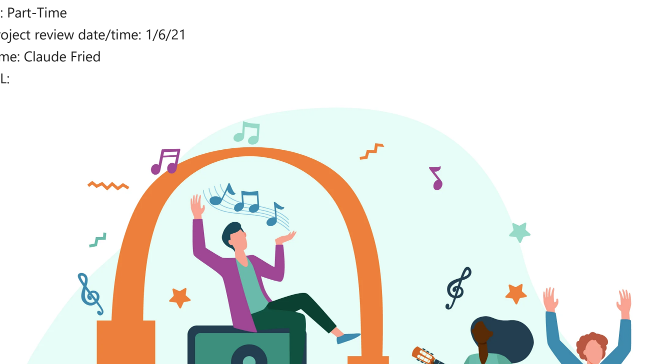


Business Problem

Popular music streaming platforms such as Youtube, Spotify, and SoundCloud has made it easier for musicians of all types to upload music content and share it instantly with audiences world wide. Yet, as a musician it is hard to get your music heard let alone become a top hit. Our analysis offers record labels, artists, and producers determine what qualities they should consider when releasing music on streaming platforms based on Spotify's audio features provided from the given Data.

Our goal is to answer the following questions:

- Which audio features makes an impact on a song's popularity?
- What genre should a record label prioritize when finding an artist?
- Does music theory features contribute to their popularity?

In [132…

```
# import libraries

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

import datetime
import os

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder, LabelEncoder, MinMaxScaler
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import (VotingClassifier,
                              RandomForestClassifier,
                              AdaBoostClassifier,
                              GradientBoostingClassifier,
                              AdaBoostClassifier,
                              BaggingClassifier
                             )
from imblearn.pipeline import Pipeline as imbPipeline
from sklearn.pipeline import FeatureUnion
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.model_selection import cross_val_score, cross_validate
from imblearn.over_sampling import SMOTENC
from imblearn.under_sampling import ClusterCentroids
from sklearn.metrics import (accuracy_score,
                             f1_score,
                             recall_score,
                             precision_score,
                             precision_recall_curve,
                             make_scorer,
                             confusion_matrix,
                             plot_confusion_matrix,
                             plot_roc_curve,
                             classification_report,
                             roc_curve,
                             auc,
                             plot_precision_recall_curve,
                             roc_auc_score,
                             log_loss

)
# For plotting the tree.
from sklearn.tree import export_graphviz, plot_tree
from pydotplus import graph_from_dot_data
from IPython.display import Image
from sklearn import tree

import warnings
warnings.filterwarnings('ignore')

import joblib
import xgboost as xgb
from xgboost import plot_importance
```

Helper Functions

In [2]:

```
def get_value_counts(data):
    for count in data.columns:
        print(count)
        print(data[count].value_counts())
        print('                                                       ')
    return count

def unique_values(data):
    for col in data.columns:
        print(col)
        print(data[col].unique())
        print('                                                        ')

def convert_dtype(data,dtype):
    data = data.astype(dtype)
    return data

def make_plot_count(col, data, order = None):
    sns.countplot(x = col, data = data, palette = 'icefire_r', order = order)
    plt.title(f'Frequency in {col}')
    plt.show()

def test_train_split(data, TARGET, random_state = 100):

    data = data.copy()

    # Separate independant variables from dependant variable.
    X = data.drop(columns=[TARGET], axis = 1)
    y = data[TARGET]

    X_train, X_test, y_train, y_test = train_test_split(X,y, random_state=random_state)

    X_train.reset_index(drop=True, inplace=True)
    X_test.reset_index(drop=True, inplace=True)
    y_train.reset_index(drop=True, inplace=True)
    y_test.reset_index(drop=True, inplace=True)

    return X_train, X_test, y_train, y_test
```

Data Understanding

In [3]:

```
# Importing the dataframe
# Checking the amount of columns & rows

df = pd.read_csv("data/music_genre.csv")
df.shape
```

Out[3]:

```
(50005, 18)
```

In [4]:

```
# Checking the datatypes & column names
# 5 rows have missing information

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50005 entries, 0 to 50004
Data columns (total 18 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   instance_id       50000 non-null  float64
 1   artist_name       50000 non-null  object
 2   track_name        50000 non-null  object
 3   popularity        50000 non-null  float64
 4   acousticness      50000 non-null  float64
 5   danceability      50000 non-null  float64
 6   duration_ms       50000 non-null  float64
 7   energy            50000 non-null  float64
 8   instrumentalness  50000 non-null  float64
 9   key               50000 non-null  object
 10  liveness          50000 non-null  float64
 11  loudness          50000 non-null  float64
 12  mode              50000 non-null  object
 13  speechiness       50000 non-null  float64
 14  tempo             50000 non-null  object
 15  obtained_date     50000 non-null  object
 16  valence           50000 non-null  float64
 17  music_genre       50000 non-null  object
dtypes: float64(11), object(7)
memory usage: 6.9+ MB
```

Spotify's Audio Features

Below are the meaning behind Spotify's Audio Features based on their Web API audio features reference.

- **popularity**: The popularity of the track. The value will be between 0 and 100, with 100 being the most popular. The popularity of a track is a value between 0 and 100, with 100 being the most popular. The popularity is calculated by algorithm and is based, in the most part, on the total number of plays the track has had and how recent those plays are. Generally speaking, songs that are being played a lot now will have a higher popularity than songs that were played a lot in the past. Duplicate tracks (e.g. the same track from a single and an album) are rated independently. Artist and album popularity is derived mathematically from track popularity.
- **acousticness**: A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
- **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.
- **duration_ms**: The duration of the track in milliseconds.
- **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.
- **key**: The key the track is in. Integers map to pitches using standard Pitch Class notation. E.g. 0 = C, 1 = C♯/D♭, 2 = D, and so on. If no key was detected, the value is -1.
- **liveness**: Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.
- **loudness**: The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 db.
- **mode**: Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.
- **speechiness**: 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.
- **tempo**: The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.
- **valence**: A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).
- **music_genre**: .

In [5]:

```
df
```

Out[5]:

	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loud
0	32894.0	Röyksopp	Röyksopp's Night Out	27.0	0.00468	0.652	-1.0	0.941	0.79200	A#	0.115	-5
1	46652.0	Thievery Corporation	The Shining Path	31.0	0.01270	0.622	218293.0	0.890	0.95000	D	0.124	-7
2	30097.0	Dillon Francis	Hurricane	28.0	0.00306	0.620	215613.0	0.755	0.01180	G#	0.534	-4
3	62177.0	Dubloadz	Nitro	34.0	0.02540	0.774	166875.0	0.700	0.00253	C#	0.157	-4
4	24907.0	What So Not	Divide & Conquer	32.0	0.00465	0.638	222369.0	0.587	0.90900	F#	0.157	-6
...	...	...	...	...	...	...	...	...	...	...	...	
50000	58878.0	BEXEY	GO GETTA	59.0	0.03340	0.913	-1.0	0.574	0.00000	C#	0.119	-7
50001	43557.0	Roy Woods	Drama (feat. Drake)	72.0	0.15700	0.709	251860.0	0.362	0.00000	B	0.109	-9
50002	39767.0	Berner	Lovin' Me (feat. Smiggz)	51.0	0.00597	0.693	189483.0	0.763	0.00000	D	0.143	-5
50003	57944.0	The-Dream	Shawty Is Da Shit	65.0	0.08310	0.782	262773.0	0.472	0.00000	G	0.106	-5
50004	63470.0	Naughty By Nature	Hip Hop Hooray	67.0	0.10200	0.862	267267.0	0.642	0.00000	F#	0.272	-13

50005 rows × 18 columns

In [6]:

```
# check the stats for the dataset

df.describe()
```

Out[6]:

	instance_id	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	liveness	loudness	sp
count	50000.000000	50000.000000	50000.000000	50000.000000	5.000000e+04	50000.000000	50000.000000	50000.000000	50000.000000	500
mean	55888.396360	44.220420	0.306383	0.558241	2.212526e+05	0.599755	0.181601	0.193896	-9.133761	
std	20725.256253	15.542008	0.341340	0.178632	1.286720e+05	0.264559	0.325409	0.161637	6.162990	
min	20002.000000	0.000000	0.000000	0.059600	-1.000000e+00	0.000792	0.000000	0.009670	-47.046000	
25%	37973.500000	34.000000	0.020000	0.442000	1.748000e+05	0.433000	0.000000	0.096900	-10.860000	
50%	55913.500000	45.000000	0.144000	0.568000	2.192810e+05	0.643000	0.000158	0.126000	-7.276500	
75%	73863.250000	56.000000	0.552000	0.687000	2.686122e+05	0.815000	0.155000	0.244000	-5.173000	
max	91759.000000	99.000000	0.996000	0.986000	4.830606e+06	0.999000	0.996000	1.000000	3.744000	

In [7]:

```
# look at all the columns value counts
# 2489 entries with an empty_field as a artist name
# 2980 entries with '?' for tempo
get_value_counts(df)
```

```
instance_id
69127.0    1
54606.0    1
77158.0    1
28359.0    1
90011.0    1
          ..
67931.0    1
47596.0    1
70990.0    1
33535.0    1
53248.0    1
Name: instance_id, Length: 50000, dtype: int64

artist_name
empty_field                2489
Nobuo Uematsu               429
Wolfgang Amadeus Mozart     402
Ludwig van Beethoven        317
Johann Sebastian Bach       314
                           ...
Black Diamond Heavies         1
Steeve Laffont                1
Fat Pat                       1
Cult To Follow                1
Bryan Ferry                   1
Name: artist_name, Length: 6863, dtype: int64

track_name
Home                                                                     16
Forever                                                                  15
Without You                                                              14
Wake Up                                                                  13
Summertime                                                               13
                                                                         ..
Second Suite in F Major, Op. 28 No. 2, H. 106: IV. Fantasia on the Dargason    1
仮面ライダークウガ! - RIDER CHIPS Ver.                                          1
Aimai                                                                     1
God Love The Rain                                                         1
Reconcile (feat. Liz)                                                     1
Name: track_name, Length: 41699, dtype: int64

popularity
52.0    1316
54.0    1295
53.0    1286
50.0    1265
55.0    1250
        ...
93.0       2
94.0       1
92.0       1
99.0       1
97.0       1
Name: popularity, Length: 99, dtype: int64

acousticness
0.995000    278
0.994000    240
0.992000    215
0.993000    198
0.990000    158
           ...
0.000071      1
0.000005      1
0.000078      1
0.000485      1
0.000079      1
Name: acousticness, Length: 4193, dtype: int64

danceability
0.5290    143
0.6570    139
0.6100    134
0.5540    133
0.4990    130
         ...
0.0839      1
0.0962      1
0.0827      1
0.0772      1
0.0744      1
Name: danceability, Length: 1088, dtype: int64

duration_ms
-1.0         4939
 240000.0      33
 192000.0      32
 180000.0      28
 216000.0      20
             ...
 189531.0       1
 172290.0       1
 311813.0       1
 202824.0       1
 343032.0       1
Name: duration_ms, Length: 26028, dtype: int64

energy
0.80500    103
0.67500    103
0.72000     99
0.85900     98
0.83000     96
          ...
0.00872      1
0.01770      1
0.00603      1
0.06600      1
0.09310      1
Name: energy, Length: 2085, dtype: int64

instrumentalness
0.000000    15001
0.898000       70
0.902000       69
0.897000       66
0.912000       66
            ...
0.000009        1
0.000071        1
0.065100        1
0.063600        1
0.009330        1
Name: instrumentalness, Length: 5131, dtype: int64

key
G     5727
C     5522
C#    5405
D     5265
A     4825
F     4341
B     3789
E     3760
A#    3356
G#    3319
F#    3101
D#    1590
Name: key, dtype: int64

liveness
0.1100    625
0.1080    610
0.1110    609
0.1090    552
0.1070    542
         ...
0.0307      1
0.7750      1
0.9960      1
0.0173      1
0.0214      1
Name: liveness, Length: 1646, dtype: int64

loudness
-5.443     19
-5.133     17
-7.066     17
-5.606     16
-5.982     16
           ..
-17.872     1
-16.376     1
-22.772     1
-3.190      1
-22.557     1
Name: loudness, Length: 17247, dtype: int64

mode
Major    32099
Minor    17901
Name: mode, dtype: int64

speechiness
0.0332    173
0.0337    155
0.0315    153
0.0329    152
0.0362    148
         ...
0.6980      1
0.6080      1
0.9270      1
0.5060      1
0.8770      1
Name: speechiness, Length: 1337, dtype: int64

tempo
?                     4980
120.0                   17
140.007                 17
100.00299999999999      16
100.014                 15
                      ...
94.906                   1
114.06700000000001       1
66.745                   1
173.0                    1
112.285                  1
Name: tempo, Length: 29394, dtype: int64

obtained_date
4-Apr    44748
3-Apr     4067
5-Apr      784
1-Apr      400
0/4          1
Name: obtained_date, dtype: int64

valence
0.3380    100
0.3240     95
0.3320     93
0.3510     91
0.3700     87
         ...
0.9810      1
0.0592      1
0.0957      1
0.0301      1
0.0576      1
Name: valence, Length: 1615, dtype: int64

music_genre
Country        5000
Alternative    5000
Rap            5000
Electronic     5000
Jazz           5000
Rock           5000
Hip-Hop        5000
Anime          5000
Blues          5000
Classical      5000
Name: music_genre, dtype: int64
```

Out[7]:

```
'music_genre'
```

Data Preparation

Before runnning our models, we preprocess our data to see if there is any necessary data cleaning and feature engineering needed to be processed.

In [8]:

```
# get the unique values from each column

unique_values(df)
```

```
instance_id
[32894. 46652. 30097. ... 39767. 57944. 63470.]

artist_name
['Röyksopp' 'Thievery Corporation' 'Dillon Francis' ... 'Darshan Raval'
 'Powers Pleasant' 'Millonario']

track_name
["Röyksopp's Night Out" 'The Shining Path' 'Hurricane' ...
 'Drama (feat. Drake)' "Lovin' Me (feat. Smiggz)" 'Hip Hop Hooray']

popularity
[27. 31. 28. 34. 32. 47. 46. 43. 39. 22. 30. 50. 59. 29. 35. 44. 33. 56.
 21. 48. 45. 53. 63. 25. 36. 37. 51. 55. 49. 41. 38. 52. 24. 42. 26. 96.
 40. 23. 61. 54. 66. 70. 67. 60. 58. 65. 69. 72. 64. 62. 57.  0. 76. 20.
 74. 71. 84. 68. 18. 82.  3. 11. 17. 15. 12. 10. 13. 16. 14.  9. 19.  8.
  7.  4.  2.  1.  5.  6. nan 79. 73. 75. 78. 83. 81. 80. 77. 85. 97. 88.
 87. 86. 99. 89. 93. 90. 94. 91. 95. 92.]

acousticness
[4.68e-03 1.27e-02 3.06e-03 ... 8.79e-04 5.20e-05 2.98e-04]

danceability
[0.652 0.622 0.62  ... 0.974 0.98  0.966]

duration_ms
[-1.00000e+00  2.18293e+05  2.15613e+05 ...  1.97923e+05  2.51860e+05
  1.89483e+05]

energy
[0.941   0.89    0.755   ... 0.0191  0.00226 0.0776 ]

instrumentalness
[7.92e-01 9.50e-01 1.18e-02 ... 8.63e-04 9.14e-02 9.26e-04]

key
['A#' 'D' 'G#' 'C#' 'F#' 'B' 'G' 'F' 'A' 'C' 'E' 'D#' nan]

liveness
[0.115  0.124  0.534  ... 0.0352 0.803  0.0196]

loudness
[ -5.201  -7.043  -4.617 ...  -8.326  -7.706 -13.652]

mode
['Minor' 'Major' nan]

speechiness
[0.0748 0.03   0.0345 ... 0.675  0.704  0.855 ]

tempo
['100.889' '115.00200000000001' '127.994' ... '112.97' '167.655'
 '99.20100000000001']

obtained_date
['4-Apr' '3-Apr' '5-Apr' '1-Apr' nan '0/4']

valence
[0.759  0.531  0.333  ... 0.0273 0.0296 0.0292]

music_genre
['Electronic' 'Anime' nan 'Jazz' 'Alternative' 'Country' 'Rap' 'Blues'
 'Rock' 'Classical' 'Hip-Hop']
```

In [9]:

```
# Check the number of duplicates in this dataset
df.duplicated().value_counts()
```

Out[9]:

```
False    50001
True         4
dtype: int64
```

In [10]:

```
# looks like the duplicates are mostly missing values
df[df.duplicated()]
```

Out[10]:

	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness
10001	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10002	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10003	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10004	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [11]:

```
# drop all the rows that have missing information
df.dropna(axis=0, inplace= True)
```

In [12]:

```
# sanity check on duplicates and missing values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 50000 entries, 0 to 50004
Data columns (total 18 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   instance_id       50000 non-null  float64
 1   artist_name       50000 non-null  object
 2   track_name        50000 non-null  object
 3   popularity        50000 non-null  float64
 4   acousticness      50000 non-null  float64
 5   danceability      50000 non-null  float64
 6   duration_ms       50000 non-null  float64
 7   energy            50000 non-null  float64
 8   instrumentalness  50000 non-null  float64
 9   key               50000 non-null  object
 10  liveness          50000 non-null  float64
 11  loudness          50000 non-null  float64
 12  mode              50000 non-null  object
 13  speechiness       50000 non-null  float64
 14  tempo             50000 non-null  object
 15  obtained_date     50000 non-null  object
 16  valence           50000 non-null  float64
 17  music_genre       50000 non-null  object
dtypes: float64(11), object(7)
memory usage: 7.2+ MB
```

In [13]:

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

Out[13]:

```
instance_id         0
artist_name         0
track_name          0
popularity          0
acousticness        0
danceability        0
duration_ms         0
energy              0
instrumentalness    0
key                 0
liveness            0
loudness            0
mode                0
speechiness         0
tempo               0
obtained_date       0
valence             0
music_genre         0
dtype: int64
```

Popularity

- Convert dtype from float to int
- Set popular song to the value 1 and nonpopular song to 0

In [14]:

```
# get popularity frequency
most_popular = df.sort_values('popularity', ascending = False)
most_popular.head(10)
```

Out[14]:

	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness
26239	84744.0	Post Malone	Wow.	99.0	0.16300	0.833	149520.0	0.539	0.000002	B	0.1010
25194	59859.0	Post Malone	Sunflower - Spider-Man: Into the Spider-Verse	97.0	0.55600	0.760	158040.0	0.479	0.000000	D	0.0703
47024	89355.0	J. Cole	MIDDLE CHILD	96.0	0.14900	0.837	213594.0	0.364	0.000000	G#	0.2710
105	49721.0	DJ Snake	Taki Taki (with Selena Gomez, Ozuna & Cardi B)	96.0	0.15300	0.841	212500.0	0.798	0.000003	C#	0.0618
47596	86123.0	Paulo Londra	Adan y Eva	95.0	0.32300	0.767	258639.0	0.709	0.000000	C#	0.0676
48249	27221.0	Meek Mill	Going Bad (feat. Drake)	95.0	0.25900	0.889	180522.0	0.496	0.000000	E	0.2520
28537	59982.0	Travis Scott	SICKO MODE	94.0	0.00513	0.834	312820.0	0.730	0.000000	G#	0.1240
28055	25783.0	Post Malone	Better Now	93.0	0.35400	0.680	231267.0	0.563	0.000000	A#	0.1360
29974	35484.0	21 Savage	a lot	93.0	0.03950	0.837	288624.0	0.636	0.001250	C#	0.3420
48850	28227.0	XXXTENTACION	SAD!	92.0	0.25800	0.740	166606.0	0.613	0.003720	G#	0.1230

The above shows the dataset's top ten most popular songs.

In [15]:

```
# convert to integer
df['popularity'] = convert_dtype(df['popularity'],'int64')
```

In [16]:

```
# set all the rows that have a popularity > 50 : 1, popularity < 50 : 0

df['popular_song'] = df['popularity'].map(lambda x: 1 if x >= 50 else 0)
```

Tempos

- Exploring the missing tempos
- Converting dtype to float

In [17]:

```
# Find all the tempos that have a question mark
df[df['tempo'] == '?']
```

Out[17]:

	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loud
5	89064.0	Axel Boman	Hello	47	0.00523	0.755	519468.0	0.731	0.854000	D	0.2160	-10
32	25836.0	PEEKABOO	Arrival	45	0.02330	0.729	274286.0	0.869	0.585000	F	0.0944	-7
35	27048.0	Fabian Mazur	If U Wanted To	33	0.10800	0.493	-1.0	0.682	0.000000	A	0.1960	-5
36	55617.0	Wax Tailor	The Games You Play	45	0.04780	0.646	253333.0	0.649	0.002520	G	0.3530	-5
39	69685.0	Dahu	Vessel	37	0.20300	0.769	429941.0	0.551	0.882000	A#	0.1090	-12
...	...	...	...	...	...	...	...	...	...	...	...	
49918	63058.0	Big Sean	Bigger Than Me	58	0.29600	0.379	292520.0	0.644	0.000000	A#	0.3130	-7
49964	53387.0	Millonario	Rayas de Patrón	59	0.08470	0.929	215200.0	0.737	0.000000	G#	0.8610	-6
49967	76585.0	MadeinTYO	I Want (feat. 2 Chainz)	62	0.17900	0.860	233293.0	0.625	0.000136	D	0.3000	-6
49976	79654.0	Big Sean	Sunday Morning Jetpack	52	0.70000	0.462	225067.0	0.741	0.000000	A#	0.3400	-8
49977	63945.0	Nate Dogg	Music & Me	58	0.10500	0.905	240627.0	0.414	0.000366	G#	0.0914	-8

4980 rows × 19 columns

In [18]:

```
# 4980 entries that have missing tempo info, that's a lot since it is an important feature
missing_tempo = df[df['tempo'] == '?']
missing_tempo
```

Out[18]:

	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loud
5	89064.0	Axel Boman	Hello	47	0.00523	0.755	519468.0	0.731	0.854000	D	0.2160	-10
32	25836.0	PEEKABOO	Arrival	45	0.02330	0.729	274286.0	0.869	0.585000	F	0.0944	-7
35	27048.0	Fabian Mazur	If U Wanted To	33	0.10800	0.493	-1.0	0.682	0.000000	A	0.1960	-5
36	55617.0	Wax Tailor	The Games You Play	45	0.04780	0.646	253333.0	0.649	0.002520	G	0.3530	-5
39	69685.0	Dahu	Vessel	37	0.20300	0.769	429941.0	0.551	0.882000	A#	0.1090	-12
...	...	...	...	...	...	...	...	...	...	...	...	
49918	63058.0	Big Sean	Bigger Than Me	58	0.29600	0.379	292520.0	0.644	0.000000	A#	0.3130	-7
49964	53387.0	Millonario	Rayas de Patrón	59	0.08470	0.929	215200.0	0.737	0.000000	G#	0.8610	-6
49967	76585.0	MadeinTYO	I Want (feat. 2 Chainz)	62	0.17900	0.860	233293.0	0.625	0.000136	D	0.3000	-6
49976	79654.0	Big Sean	Sunday Morning Jetpack	52	0.70000	0.462	225067.0	0.741	0.000000	A#	0.3400	-8
49977	63945.0	Nate Dogg	Music & Me	58	0.10500	0.905	240627.0	0.414	0.000366	G#	0.0914	-8

4980 rows × 19 columns

In [19]:

```
get_value_counts(missing_tempo)
```

```
instance_id
30215.0    1
76066.0    1
74069.0    1
75112.0    1
74052.0    1
          ..
69294.0    1
20092.0    1
88920.0    1
83631.0    1
51200.0    1
Name: instance_id, Length: 4980, dtype: int64

artist_name
empty_field                260
Nobuo Uematsu               42
Wolfgang Amadeus Mozart     37
Ludwig van Beethoven        30
Frédéric Chopin             29
                          ...
GZA                          1
The Driver Era               1
2 LIVE CREW                  1
David Monrad Johansen        1
The Roots                    1
Name: artist_name, Length: 2368, dtype: int64

track_name
Paradise                          3
The Light                         3
Rudolph The Red-Nosed Reindeer    3
Smile                             3
Closer                            3
                                 ..
Soul Survivor                     1
Yellow Calx                       1
Put You Into Words                1
Wya?                              1
Y'all Boys                        1
Name: track_name, Length: 4870, dtype: int64

popularity
50    138
38    137
36    133
52    129
40    124
     ...
1       1
5       1
85      1
6       1
89      1
Name: popularity, Length: 89, dtype: int64

acousticness
0.99500    24
0.99200    23
0.99400    21
0.98900    16
0.99100    16
           ..
0.00310     1
0.02670     1
0.87700     1
0.00703     1
0.53500     1
Name: acousticness, Length: 2196, dtype: int64

danceability
0.6280    22
0.6570    18
0.5260    18
0.5280    17
0.5150    17
          ..
0.0661     1
0.1330     1
0.8730     1
0.2060     1
0.1000     1
Name: danceability, Length: 825, dtype: int64

duration_ms
-1.0         479
 216000.0      4
 192800.0      4
 192000.0      4
 211107.0      3
            ...
 238253.0      1
 247080.0      1
 188373.0      1
 266587.0      1
 188120.0      1
Name: duration_ms, Length: 4125, dtype: int64

energy
0.7600    16
0.6560    16
0.6370    16
0.9780    15
0.7440    15
          ..
0.0346     1
0.0478     1
0.2700     1
0.0687     1
0.0928     1
Name: energy, Length: 1147, dtype: int64

instrumentalness
0.000000    1509
0.891000      11
0.911000      10
0.920000       9
0.917000       9
            ...
0.000072       1
0.000692       1
0.008290       1
0.000540       1
0.828000       1
Name: instrumentalness, Length: 2198, dtype: int64

key
G     597
D     546
C     539
C#    499
F     461
A     441
B     391
E     381
A#    353
F#    321
G#    288
D#    163
Name: key, dtype: int64

liveness
0.1100    60
0.1110    58
0.1060    57
0.1040    56
0.1080    55
          ..
0.0616     1
0.0343     1
0.0417     1
0.4650     1
0.5640     1
Name: liveness, Length: 1091, dtype: int64

loudness
-6.081     5
-5.508     4
-5.553     4
-4.605     4
-5.480     4
          ..
-6.673     1
-12.195    1
-25.351    1
-5.733     1
-6.875     1
Name: loudness, Length: 4167, dtype: int64

mode
Major    3225
Minor    1755
Name: mode, dtype: int64

speechiness
0.0279    20
0.0424    20
0.0342    20
0.0374    20
0.0381    19
          ..
0.0846     1
0.0919     1
0.4710     1
0.0246     1
0.0996     1
Name: speechiness, Length: 1048, dtype: int64

tempo
?    4980
Name: tempo, dtype: int64

obtained_date
4-Apr    4447
3-Apr     410
5-Apr      74
1-Apr      48
0/4         1
Name: obtained_date, dtype: int64

valence
0.4040    16
0.5290    14
0.4840    14
0.3640    14
0.4760    13
          ..
0.0616     1
0.0585     1
0.8760     1
0.0759     1
0.0799     1
Name: valence, Length: 1135, dtype: int64

music_genre
Electronic     534
Blues          530
Country        514
Alternative    505
Anime          503
Classical      500
Rap            496
Hip-Hop        480
Jazz           479
Rock           439
Name: music_genre, dtype: int64

popular_song
0    3030
1    1950
Name: popular_song, dtype: int64
```

Out[19]: 'popular_song'

In [20]:
```python
missing_tempo['track_name'].value_counts().head(100)
```

Out[20]:
```
Paradise                          3
The Light                         3
Rudolph The Red-Nosed Reindeer    3
Smile                             3
Closer                            3
                                 ..
You Lie                           2
Good Times                        2
Runaway                           2
King                              2
Pull Up                           2
Name: track_name, Length: 100, dtype: int64
```

In [21]:
```python
missing_tempo.sort_values('popularity', ascending = False).head(100)
```

Out[21]:

	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loud
47596	86123.0	Paulo Londra	Adan y Eva	95	0.32300	0.767	258639.0	0.709	0.000000	C#	0.0676	-4
35822	88617.0	Imagine Dragons	Believer	89	0.06220	0.776	204347.0	0.780	0.000000	A#	0.0810	-4
26495	28877.0	Logic	Keanu Reeves	87	0.05910	0.710	225987.0	0.888	0.000000	D	0.1340	-6
49259	43309.0	Metro Boomin	Space Cadet (feat. Gunna)	87	0.36800	0.901	203267.0	0.464	0.000017	F	0.2380	-9
49213	58295.0	Future	Fine China	85	0.04840	0.656	141587.0	0.542	0.000000	G	0.1260	-7
...	...	...	...	...	...	...	...	...	...	...	...	
29161	20944.0	Eminem	Stepping Stone	73	0.03050	0.616	309638.0	0.684	0.000000	G	0.3760	-6
46902	78161.0	Drake	Emotionless	73	0.02490	0.413	-1.0	0.677	0.000000	C#	0.0793	-5
45733	42893.0	Offset	On Fleek (feat. Quavo)	73	0.24300	0.872	229587.0	0.472	0.000002	A	0.0902	-8
28227	76704.0	Drake	Elevate	73	0.01500	0.758	184960.0	0.474	0.000000	C#	0.1160	-8
29899	23467.0	Huncho Jack	Saint	73	0.00823	0.857	140793.0	0.642	0.000000	C	0.1060	-3

100 rows × 19 columns

In [133...
```python
missing_tempo['popular_song'] = missing_tempo['popularity'].map(lambda x: 1 if x >= 50 else 0)
```

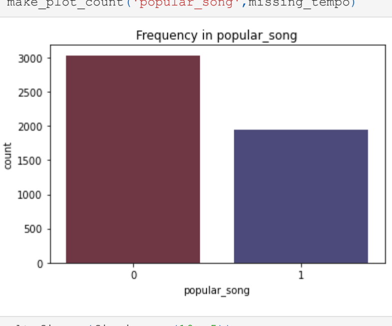
In [23]:
```python
missing_tempo
```

Out[23]:

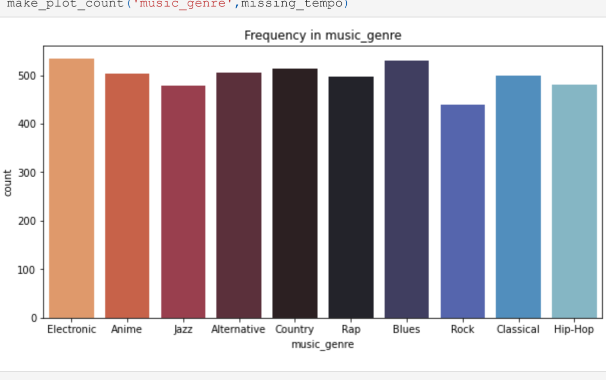
	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loud
5	89064.0	Axel Boman	Hello	47	0.00523	0.755	519468.0	0.731	0.854000	D	0.2160	-10
32	25836.0	PEEKABOO	Arrival	45	0.02330	0.729	274286.0	0.869	0.585000	F	0.0944	-7
35	27048.0	Fabian Mazur	If U Wanted To	33	0.10800	0.493	-1.0	0.682	0.000000	A	0.1960	-5
36	55617.0	Wax Tailor	The Games You Play	45	0.04780	0.646	253333.0	0.649	0.002520	G	0.3530	-5
39	69685.0	Dahu	Vessel	37	0.20300	0.769	429941.0	0.551	0.882000	A#	0.1090	-12
...	...	...	...	...	...	...	...	...	...	...	...	
49918	63058.0	Big Sean	Bigger Than Me	58	0.29600	0.379	292520.0	0.644	0.000000	A#	0.3130	-7
49964	53387.0	Millonario	Rayas de Patrón	59	0.08470	0.929	215200.0	0.737	0.000000	G#	0.8610	-6
49967	76585.0	MadeinTYO	I Want (feat. 2 Chainz)	62	0.17900	0.860	233293.0	0.625	0.000136	D	0.3000	-6
49976	79654.0	Big Sean	Sunday Morning Jetpack	52	0.70000	0.462	225067.0	0.741	0.000000	A#	0.3400	-8
49977	63945.0	Nate Dogg	Music & Me	58	0.10500	0.905	240627.0	0.414	0.000366	G#	0.0914	-8

4980 rows × 19 columns

In [24]:
```python
make_plot_count('popular_song',missing_tempo)
```



In [25]:
```python
plt.figure(figsize = (10, 5))
make_plot_count('music_genre',missing_tempo)
```



In [26]:
```python
df.drop(df[df['tempo'] == '?'].index, inplace = True)
```

In [27]:
```python
df['tempo'] = convert_dtype(df['tempo'],'float')
```

In [28]:
```python
# round the tempo decimal places to 3 decimal places
df['tempo'] = np.round(df['tempo'], decimals = 3)
df['tempo'].value_counts
```

Out[28]:
```
<bound method IndexOpsMixin.value_counts of 0        100.889
1        115.002
2        127.994
3        128.014
4        145.036
          ...
50000     98.028
50001    122.043
50002    131.079
50003     75.886
50004     99.201
Name: tempo, Length: 45020, dtype: float64>
```

Duration_ms

- What does it mean to have a track duration of -1.0 millisecond?
- Explore the songs that have a during of -1.0 millisecond

In [29]:
```python
df.duration_ms.value_counts()
```

Out[29]:
```
-1.0         4460
 240000.0      31
 192000.0      28
 180000.0      26
 185600.0      17
            ...
 193425.0       1
 189597.0       1
 204056.0       1
 187671.0       1
 171363.0       1
Name: duration_ms, Length: 24280, dtype: int64
```

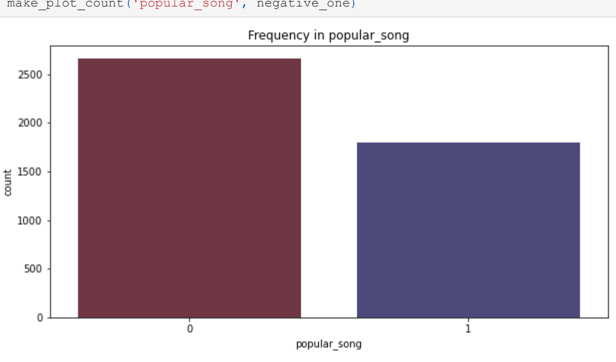
In [30]:
```python
negative_one = df[df['duration_ms'] == -1.0]
negative_one
```

Out[30]:

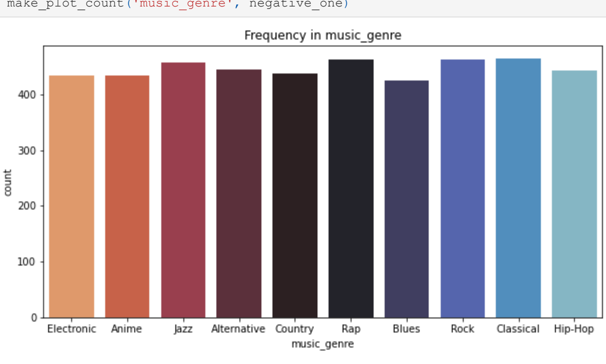
	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loud
0	32894.0	Röyksopp	Röyksopp's Night Out	27	0.00468	0.652	-1.0	0.941	0.792000	A#	0.1150	-5
13	62039.0	DJ Shadow	Broken Levee Blues	31	0.86000	0.737	-1.0	0.405	0.036100	A	0.1730	-10
16	83926.0	San Holo	One Thing	59	0.13600	0.336	-1.0	0.746	0.000000	C#	0.7370	-4
24	40033.0	The Prodigy	Diesel Power	56	0.06800	0.725	-1.0	0.877	0.000036	C	0.0900	-3
40	50080.0	The Presets	Ghosts	36	0.18100	0.611	-1.0	0.676	0.000005	C#	0.1390	-9
...	...	...	...	...	...	...	...	...	...	...	...	
49956	37037.0	empty_field	What You Like (feat. Ty Dolla $ign & Wiz Khalifa)	52	0.13300	0.867	-1.0	0.618	0.000002	B	0.1280	-4
49969	61010.0	Bone Thugs-N-Harmony	No Surrender	47	0.01270	0.706	-1.0	0.787	0.000000	A	0.2650	-5
49979	29598.0	Young Dolph	Thinking Out Loud	47	0.48300	0.789	-1.0	0.452	0.000000	B	0.0892	-7
49981	90232.0	Mac Miller	Party On Fifth Ave.	60	0.06350	0.594	-1.0	0.823	0.000000	A	0.0950	-5
50000	58878.0	BEXEY	GO GETTA	59	0.03340	0.913	-1.0	0.574	0.000000	C#	0.1190	-7

4460 rows × 19 columns

In [31]:
```python
plt.figure(figsize = (10, 5))
make_plot_count('popular_song', negative_one)
```



In [32]:
```python
plt.figure(figsize = (10, 5))
make_plot_count('music_genre', negative_one)
```



For the sake of accuracy in our model we will be dropping the tracks that have a duration of -1.0 since it could negatively impact our model. Based on the Spotify search feature, the correct track duration_ms is provided as well.

In [33]:
```python
df.drop(df[df['duration_ms'] == -1.0].index, inplace = True)
df.shape
```

Out[33]: (40560, 19)

In [34]:
```python
df['duration_ms'] = convert_dtype(df['duration_ms'],'int64')
```

In [35]:
```python
df.info()
```

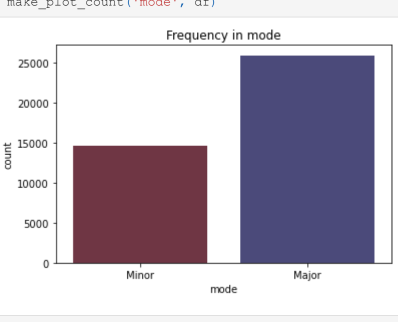
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 40560 entries, 1 to 50004
Data columns (total 19 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   instance_id       40560 non-null  float64
 1   artist_name       40560 non-null  object
 2   track_name        40560 non-null  object
 3   popularity        40560 non-null  int64
 4   acousticness      40560 non-null  float64
 5   danceability      40560 non-null  float64
 6   duration_ms       40560 non-null  int64
 7   energy            40560 non-null  float64
 8   instrumentalness  40560 non-null  float64
 9   key               40560 non-null  object
 10  liveness          40560 non-null  float64
 11  loudness          40560 non-null  float64
 12  mode              40560 non-null  object
 13  speechiness       40560 non-null  float64
 14  tempo             40560 non-null  float64
 15  obtained_date     40560 non-null  object
 16  valence           40560 non-null  float64
 17  music_genre       40560 non-null  object
 18  popular_song      40560 non-null  int64
dtypes: float64(10), int64(3), object(6)
memory usage: 6.2+ MB
```

Mode

Mode is based on whether the key of the track is major or minor. At a music theory stand point, the difference between the two is that a Major scale has a natural third (whole step) when going up the scale and a Minor scale consists of a minor third (half step) when going up the scale. (Knowledge based on being an orchestra dork during my adolescence)

- Change mode key signature values from 'Major': 1 and 'Minor': 0
- Convert dtype to int

In [36]:
```python
make_plot_count('mode', df)
```



In [37]:
```python
df['mode'] = df['mode'].map(lambda x: 1 if x == 'Major' else 0)
df
```

Out[37]:

	instance_id	artist_name	track_name	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loud
1	46652.0	Thievery Corporation	The Shining Path	31	0.01270	0.622	218293	0.890	0.950000	D	0.124	-7
2	30097.0	Dillon Francis	Hurricane	28	0.00306	0.620	215613	0.755	0.011800	G#	0.534	-4
3	62177.0	Dubloadz	Nitro	34	0.02540	0.774	166875	0.700	0.002530	C#	0.157	-4
4	24907.0	What So Not	Divide & Conquer	32	0.00465	0.638	222369	0.587	0.909000	F#	0.157	-6
6	43760.0	Jordan Comolli	Clash	46	0.02890	0.572	214408	0.803	0.000008	B	0.106	-4
...	...	...	...	...	...	...	...	...	...	...	...	
49999	28408.0	Night Lovell	Barbie Doll	56	0.13300	0.849	237667	0.660	0.000008	C	0.296	-7
50001	43557.0	Roy Woods	Drama (feat. Drake)	72	0.15700	0.709	251860	0.362	0.000000	B	0.109	-9
50002	39767.0	Berner	Lovin' Me (feat. Smiggz)	51	0.00597	0.693	189483	0.763	0.000000	D	0.143	-5
50003	57944.0	The-Dream	Shawty Is Da Shit	65	0.08310	0.782	262773	0.472	0.000000	G	0.106	-5
50004	63470.0	Naughty By Nature	Hip Hop Hooray	67	0.10200	0.862	267267	0.642	0.000000	F#	0.272	-13

40560 rows × 19 columns

In [38]:
```python
df.value_counts('mode')
```

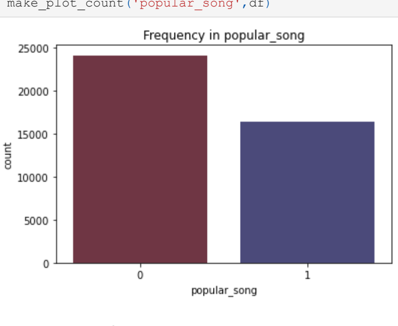
Out[38]:
```
mode
1    25959
0    14601
dtype: int64
```

In [39]:
```python
df['mode'] = convert_dtype(df['mode'],'int64')
```

Data Visualization

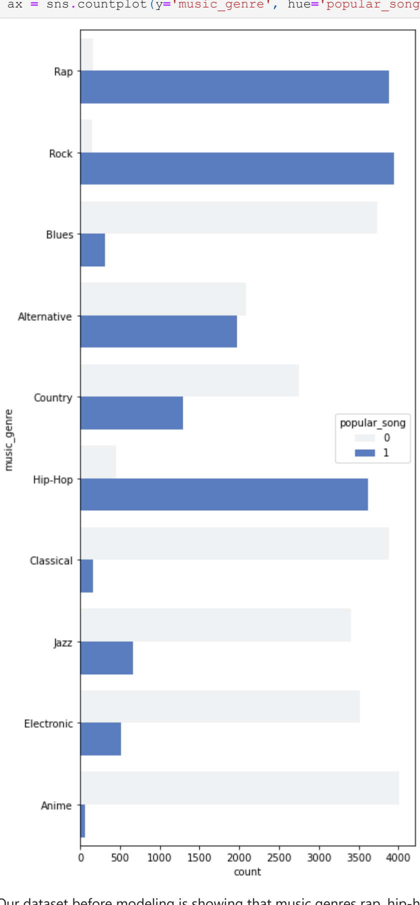
Frequency of Popular Songs

In [42]:
```python
make_plot_count('popular_song',df)
```



Frequency of Popular Songs Among Genres

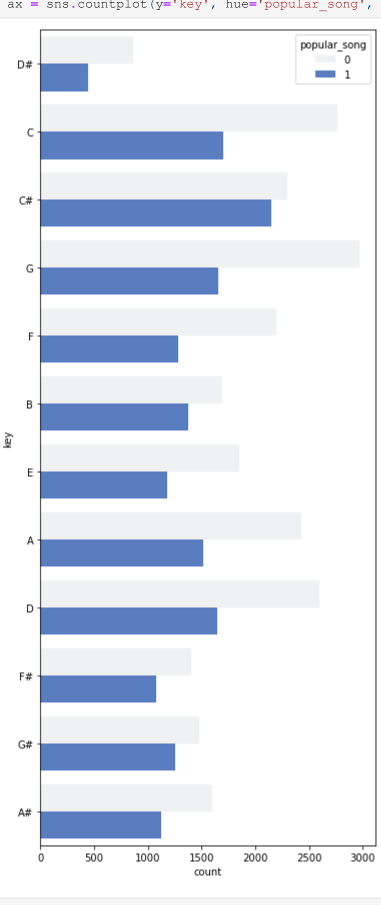
In [43]:
```python
# visualizing the popularity among the music genres

fig, ax = plt.subplots(figsize=(6,15))
# sns.set_color_codes('pastel')
sns.set_color_codes("muted")
ax = sns.countplot(y='music_genre', hue='popular_song', data=df.sort_values('popular_song', ascending=False), c
```



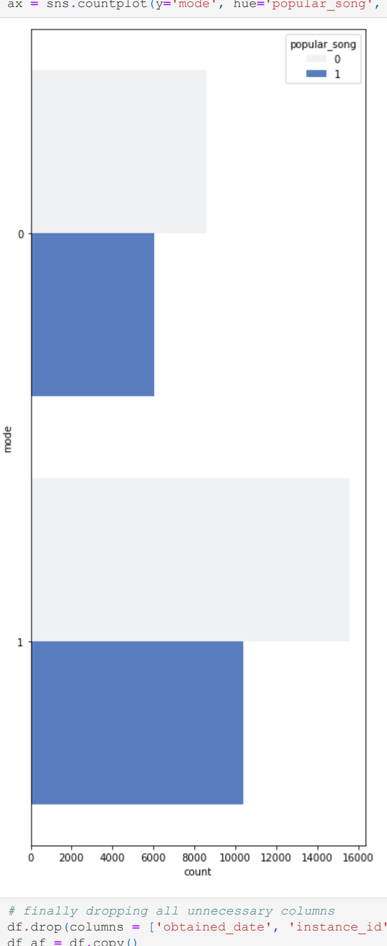
Our dataset before modeling is showing that music genres rap, hip-hop, and rock are the most popular music genres while Anime, Classical, and Blues are the least popular.

Frequency of Popular Songs Among Key Signatures

In [44]:
```python
fig, ax = plt.subplots(figsize=(6,15))
# sns.set_color_codes('pastel')
sns.set_color_codes("muted")
ax = sns.countplot(y='key', hue='popular_song', data=df.sort_values('popular_song', ascending=False), color='b'
```



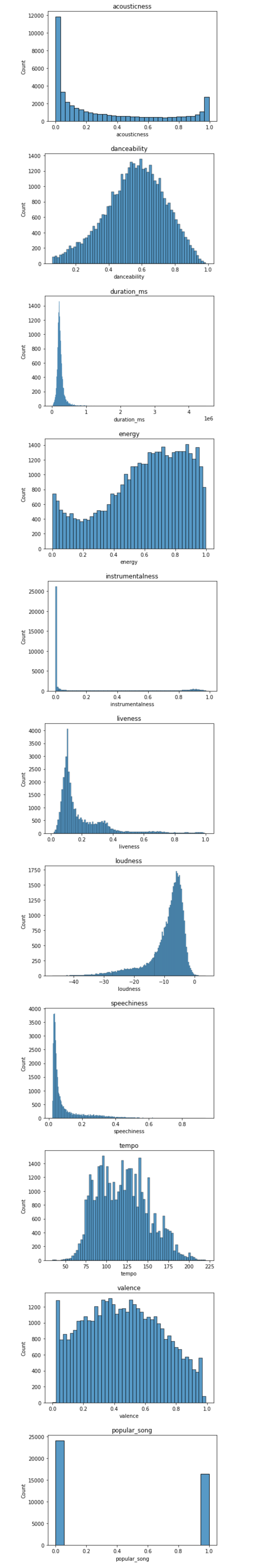
In [45]:
```python
fig, ax = plt.subplots(figsize=(6,15))
# sns.set_color_codes('pastel')
sns.set_color_codes("muted")
ax = sns.countplot(y='mode', hue='popular_song', data=df.sort_values('popular_song', ascending=False), color='b
```



In [47]:
```python
# finally dropping all unnecessary columns
df.drop(columns = ['obtained_date', 'instance_id', 'popularity', 'artist_name','track_name', 'mode'], inplace =
df_af = df.copy()
```

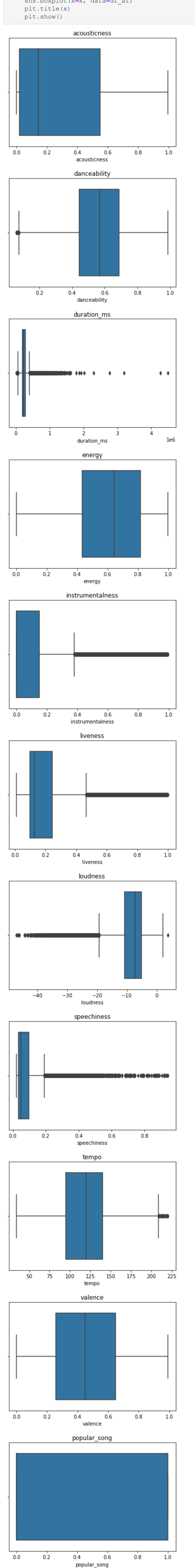
Distribution of Audio Features

In [48]:
```python
# Check for the distribution of each audio feature
numeric_feats = df.select_dtypes(exclude = 'object')

for x in numeric_feats.columns:
    sns.histplot(x=x, data=df_af)
    plt.title(x)
    plt.show()
```

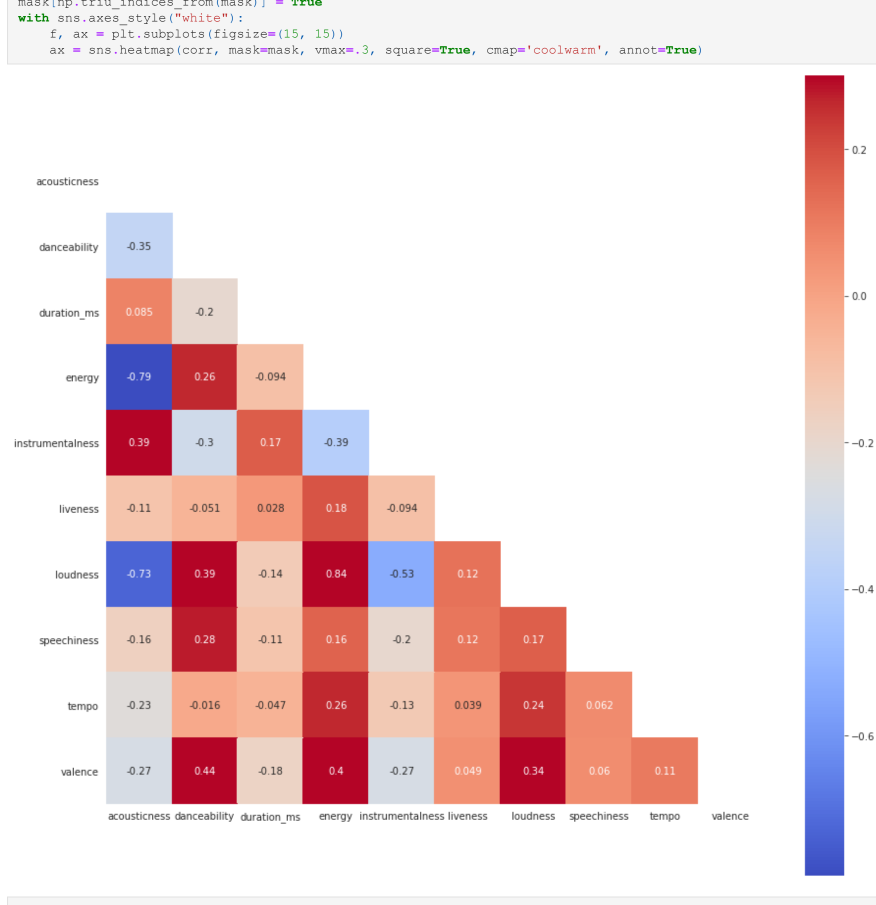


Checking for Outliers

```
In [49]:
for x in numeric_feats.columns:
    sns.boxplot(x=x, data=df_af)
    plt.title(x)
    plt.show()
```



```
In [50]:
# Looking at the correlation among the audio features

TARGET = 'popular_song'
FEATURES = [x_col for x_col in df_af.columns if x_col != TARGET]

corr = df_af[FEATURES].corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
with sns.axes_style("white"):
    f, ax = plt.subplots(figsize=(15, 15))
    ax = sns.heatmap(corr, mask=mask, vmax=.3, square=True, cmap='coolwarm', annot=True)
```



```
In [51]:
df_af.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 40560 entries, 1 to 50004
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   acousticness      40560 non-null  float64
 1   danceability      40560 non-null  float64
 2   duration_ms       40560 non-null  int64  
 3   energy            40560 non-null  float64
 4   instrumentalness  40560 non-null  float64
 5   key               40560 non-null  object 
 6   liveness          40560 non-null  float64
 7   loudness          40560 non-null  float64
 8   speechiness       40560 non-null  float64
 9   tempo             40560 non-null  float64
 10  valence           40560 non-null  float64
 11  music_genre       40560 non-null  object 
 12  popular_song      40560 non-null  int64  
dtypes: float64(9), int64(2), object(2)
memory usage: 5.6+ MB
```

Model Prepping

- Train test split the data

```
In [52]:
# Split the data into popular song and audio features
y = df['popular_song']
X = df.drop(columns=['popular_song'], axis=1)
```

```
In [53]:
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

X_train.reset_index(drop=True, inplace=True)
X_test.reset_index(drop=True, inplace=True)
y_train.reset_index(drop=True, inplace=True)
y_test.reset_index(drop=True, inplace=True)

# Create X_train and X_test variable for categorical & numerical column
train_cat = X_train.select_dtypes('object').columns
train_num = X_train.select_dtypes('number').columns

# OneHotEncode genres & keys
ohe = OneHotEncoder(sparse=False)
X_train_ohe = ohe.fit_transform(X_train[train_cat])
X_test_ohe = ohe.transform(X_test[train_cat])

# Create into a dataframe
X_train_ohe = pd.DataFrame(X_train_ohe, columns = ohe.get_feature_names(train_cat))
X_test_ohe = pd.DataFrame(X_test_ohe, columns = ohe.get_feature_names(train_cat))

# Combine
X_train_processed = pd.concat([X_train[train_num], X_train_ohe], axis=1)
X_test_processed = pd.concat([X_test[train_num], X_test_ohe], axis=1)
```

```
In [54]:
# looking at our train test split data
X_train_processed
```

Out[54]:

	acousticness	danceability	duration_ms	energy	instrumentalness	liveness	loudness	speechiness	tempo	valence	...	music_genre_Al
0	0.012400	0.585	154105	0.6500	0.000000	0.1120	-6.316	0.0657	189.923	0.7330	...	
1	0.054100	0.703	203800	0.5850	0.000000	0.1290	-7.602	0.0443	93.067	0.5620	...	
2	0.117000	0.480	224307	0.8750	0.000000	0.2340	-3.867	0.1490	147.914	0.3350	...	
3	0.918000	0.143	635387	0.0618	0.908000	0.1360	-21.566	0.0412	90.317	0.0332	...	
4	0.015900	0.682	313600	0.9510	0.000993	0.6310	0.118	0.2500	150.064	0.5480	...	
...	...	...	...	...	...	...	...	...	...	...	...	
30415	0.655000	0.785	157038	0.5630	0.009160	0.1080	-7.805	0.1030	86.025	0.4250	...	
30416	0.000126	0.626	188600	0.7910	0.021900	0.4390	-2.734	0.0721	133.204	0.4330	...	
30417	0.142000	0.347	265981	0.9190	0.005420	0.7140	-7.390	0.1390	133.860	0.1300	...	
30418	0.020000	0.378	250627	0.6380	0.000077	0.0849	-5.576	0.0750	184.086	0.7350	...	
30419	0.092100	0.724	211960	0.9060	0.000390	0.1780	-5.914	0.1240	101.739	0.6950	...	

30420 rows × 32 columns

Model

Model Functions

```
In [55]:
def get_model(model):

    #Fit model
    model.fit(X_train_processed, y_train)

    # Get predictions
    y_pred_train = model.predict(X_train_processed)
    y_pred_test = model.predict(X_test_processed)

    # Get classification report
    target_names =  ['not popular', 'popular']
    print('               Classification Report for Training Set')
    print(classification_report(y_train, y_pred_train, target_names = target_names))
    print('               Classification Report for Test Set')
    print(classification_report(y_test, y_pred_test, target_names = target_names))

    # Plot confusion Matrix
    fig, (ax0, ax1) = plt.subplots(1, 2, figsize = (10,6))
    plot_confusion_matrix(model, X_train_processed, y_train,
                      cmap=plt.cm.Blues, ax=ax0,
                       display_labels = target_names, normalize = 'all')
    plot_confusion_matrix(model, X_test_processed, y_test,
                      cmap=plt.cm.Blues, ax=ax1,
                      display_labels = target_names, normalize = 'all')

    ax0.set(title = 'Train Confusion Matrix')
    ax1.set(title = 'Test Confusion Matrix')
    ax0.grid(False)
    ax1.grid(False)
    plt.show()

    return model
```

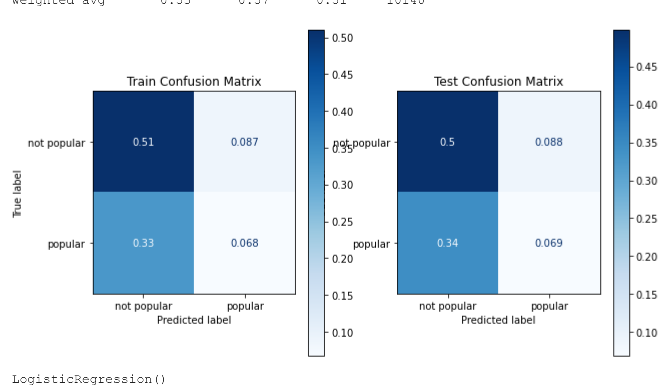
```
In [56]:
def tuned_metrics(model):

    # Get predictions
    y_pred_train = model.predict(X_train_processed)
    y_pred_test = model.predict(X_test_processed)

    # Get classification report
    target_names =  ['not popular', 'popular']
    print(f'               Classification Report for Training Set')
    print(classification_report(y_train, y_pred_train, target_names = target_names))
    print(f'               Classification Report for Test Set ')
    print(classification_report(y_test, y_pred_test, target_names = target_names))

    # Plot confusion Matrix
    fig, (ax0, ax1) = plt.subplots(1, 2, figsize = (10,6))
    plot_confusion_matrix(model, X_train_processed, y_train,
                      cmap=plt.cm.Blues, ax=ax0,
                       display_labels = target_names, normalize = 'all')
    plot_confusion_matrix(model, X_test_processed, y_test,
                      cmap=plt.cm.Blues, ax=ax1,
                      display_labels = target_names, normalize = 'all')

    ax0.set(title = f'Train Confusion Matrix')
    ax1.set(title = f'Test Confusion Matrix')
    ax0.grid(False)
    ax1.grid(False)
    plt.show()

    return model
```

Logistics Regression Model

Fit the baseline model to the training set.

```
In [57]:
logreg = LogisticRegression()
get_model(logreg)
```

```
               Classification Report for Training Set
              precision    recall  f1-score   support

 not popular       0.60      0.85      0.71     18190
     popular       0.44      0.17      0.24     12230

    accuracy                           0.58     30420
   macro avg       0.52      0.51      0.48     30420
weighted avg       0.54      0.58      0.52     30420

               Classification Report for Test Set
              precision    recall  f1-score   support

 not popular       0.59      0.85      0.70      5956
     popular       0.44      0.17      0.24      4184

    accuracy                           0.57     10140
   macro avg       0.51      0.51      0.47     10140
weighted avg       0.53      0.57      0.51     10140
```



```
Out[57]: LogisticRegression()
```

Accuracy: Accuracy shows how many of our overall **True Positive and True Negative predictions** were correct. Whether it is a positive or negative prediction. True Positive + False Positive / Total of Observations (TN+FP+TP+FN)

Precision: Out of all the **predictions** how many were right? What percentage of your **predictions** were corect? True Positive / True Positive + False Positive

Recall: Out of all the **true positives** how many were right? What percentage of your **True Positives** were correct? True Positive / True Positive + False Negative

F1-Score: This metric takes into account precision and recall. What percentage of positive predictions were correct?

Confusion Matrix

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Predicted</td></tr>
<tr><td>Negative (N)
-</td><td>Positive (P)
+</td></tr>
<tr><td rowspan="2">Actual</td><td>Negative
-</td><td>True Negative (TN)</td><td>False Positive (FP)
Type I Error</td></tr>
<tr><td>Positive
+</td><td>False Negative (FN)
Type II Error</td><td>True Positive (TP)</td></tr>
</table>

Based on our classification report and confusion matrix, our model seems to predicting the non-popular songs better than popular song. This could be the cause of slight class imbalance since since our confusion matrix seems to favor the non-popular classification.

```
In [58]:
# checking for class imbalance for target
y_train.value_counts(normalize = True)
```

```
Out[58]:
0    0.597962
1    0.402038
Name: popular_song, dtype: float64
```

```
In [59]:
# explain results
```

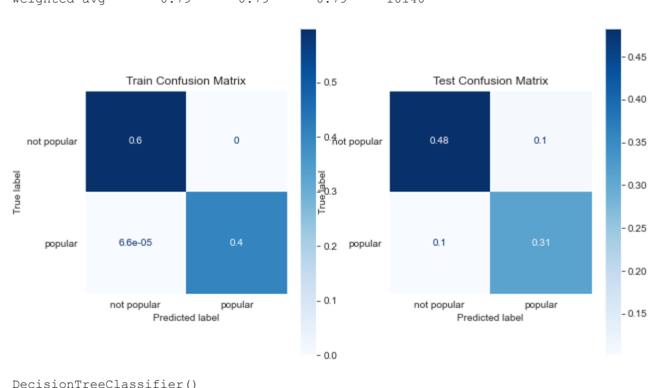
Decision Tree

Decision Tree #1 Vanilla Classifier

Using the default setting without tweaking or tuning the data

```
In [63]:
dtc = DecisionTreeClassifier()
get_model(dtc)
```

```
               Classification Report for Training Set
              precision    recall  f1-score   support

 not popular       1.00      1.00      1.00     18190
     popular       1.00      1.00      1.00     12230

    accuracy                           1.00     30420
   macro avg       1.00      1.00      1.00     30420
weighted avg       1.00      1.00      1.00     30420

               Classification Report for Test Set
              precision    recall  f1-score   support

 not popular       0.83      0.82      0.82      5956
     popular       0.75      0.75      0.75      4184

    accuracy                           0.79     10140
   macro avg       0.79      0.79      0.79     10140
weighted avg       0.79      0.79      0.79     10140
```



```
Out[63]: DecisionTreeClassifier()
```

100% on the training data and a lower test score shows a sign of overfitting. Meaning there is a godo performance on the training data but a poor generalization of the the other data.

```
In [64]:
# check AUC of predictions
get_auc(dtc)
```

```
Out[64]: 0.7878777542642218
```

Hyperparameter Tuning Decision Tree using Grid Search

```
In [66]:
# Set parameters
params = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [10, 50, 100, 150],
    'min_samples_leaf' : [.25, .50, 1,],
    'max_features' : ['sqrt', 'log2', None]
}
```

```
In [67]:
num_decision_trees = 2 * 4 * 3 * 3
print(f"Grid Search will have to search through {num_decision_trees} different permutations.")
```

```
Grid Search will have to search through 72 different permutations.
```

```
In [68]:
# Get parameters
grid = GridSearchCV(dtc, param_grid=params, cv=3)
```

```
In [69]:
grid.fit(X_train_processed, y_train)
```

```
Out[69]: GridSearchCV(cv=3, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [10, 50, 100, 150],
                         'max_features': ['sqrt', 'log2', None],
                         'min_samples_leaf': [0.25, 0.5, 1]})
```

```
In [70]:
# Find best estimator
grid.best_estimator_
```

```
Out[70]: DecisionTreeClassifier(criterion='entropy', max_depth=10)
```

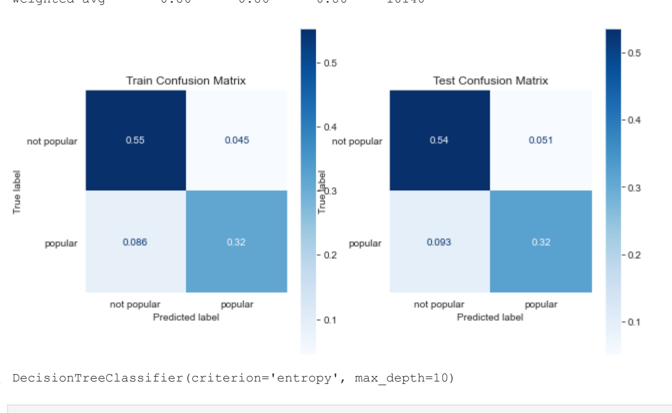
```
In [71]:
# Find best parameters
best_parameters = grid.best_params_
best_parameters
```

```
Out[71]: {'criterion': 'entropy',
 'max_depth': 10,
 'max_features': None,
 'min_samples_leaf': 1}
```

Decision Tree with Tuned Parameters

```
In [106…
dtuned1 = grid.best_estimator_
tuned_metrics(grid.best_estimator_)
```

```
               Classification Report for Training Set
              precision    recall  f1-score   support

 not popular       0.87      0.92      0.89     18190
     popular       0.88      0.79      0.83     12230

    accuracy                           0.87     30420
   macro avg       0.87      0.86      0.86     30420
weighted avg       0.87      0.87      0.87     30420

               Classification Report for Test Set
              precision    recall  f1-score   support

 not popular       0.85      0.91      0.88      5956
     popular       0.86      0.77      0.82      4184

    accuracy                           0.86     10140
   macro avg       0.86      0.84      0.85     10140
weighted avg       0.86      0.86      0.86     10140
```



```
Out[106… DecisionTreeClassifier(criterion='entropy', max_depth=10)
```

```
In [105…
# check AUC of predictions
get_auc(dtuned1)
```

```
Out[105… 0.8443624822952769
```

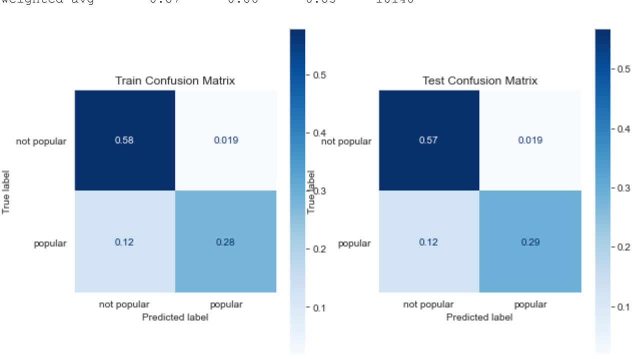
The AUC score improves by 6%. Meaning the our tuned decision tree is able to predict the popular songs better than our vanilla decision tree.

Random Forest Classifier

We're choosing entropy to reduce uncertainty as much as possible.

```
In [79]:
rfc = RandomForestClassifier(criterion='entropy', max_depth = 5)
get_model(rfc)
```

```
              Classification Report for Training Set
              precision    recall  f1-score   support

 not popular       0.83      0.97      0.89     18190
     popular       0.94      0.70      0.80     12230

    accuracy                           0.86     30420
   macro avg       0.88      0.83      0.85     30420
weighted avg       0.87      0.86      0.85     30420

              Classification Report for Test Set
              precision    recall  f1-score   support

 not popular       0.82      0.97      0.89      5956
     popular       0.94      0.70      0.80      4184

    accuracy                           0.86     10140
   macro avg       0.88      0.84      0.85     10140
weighted avg       0.87      0.86      0.85     10140
```



Out[79]: RandomForestClassifier(criterion='entropy', max_depth=5)

In [98]:
```
# check AUC of predictions
get_auc(rfc)
```

Out[98]: 0.8357209562284028

Hyperparameter Tuning Random Forest Classifier

In [80]:
```
# Set parameters
params = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [10, 50, 100, 150],
    'min_samples_leaf' : [.25, .50, 1,],
    'max_features' : ['sqrt', 'log2', None]
}
```

In [81]:
```
num_random_forest = 2 * 4 * 3 * 3
print(f"Grid Search will have to search through {num_decision_trees} different permutations.")
```

```
Grid Search will have to search through 72 different permutations.
```

In [82]:
```
rtc_grid = RandomForestClassifier(random_state=51)
rf_tuned_grid = GridSearchCV(rtc_grid, param_grid = params, cv=3)
```

In [83]:
```
rf_tuned_grid.fit(X_train_processed, y_train)
```

Out[83]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(random_state=51),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [10, 50, 100, 150],
                         'max_features': ['sqrt', 'log2', None],
                         'min_samples_leaf': [0.25, 0.5, 1]})
```

In [84]:
```
# Find the best parameters
rf_tuned_grid.best_params_
```

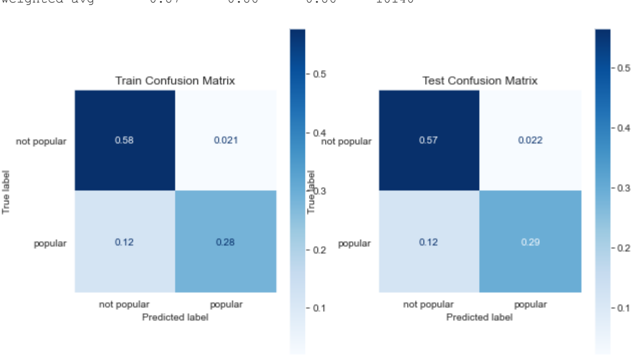
Out[84]:
```
{'criterion': 'entropy',
 'max_depth': 10,
 'max_features': 'sqrt',
 'min_samples_leaf': 1}
```

In [85]:
```
# Find best estimator
rf_tuned_grid.best_estimator_
```

Out[85]:
```
RandomForestClassifier(criterion='entropy', max_depth=10, max_features='sqrt',
                       random_state=51)
```

In [107…
```
rf_tuned = rf_tuned_grid.best_estimator_
tuned_metrics(rf_tuned_grid.best_estimator_)
```

```
              Classification Report for Training Set
              precision    recall  f1-score   support

 not popular       0.83      0.97      0.89     18190
     popular       0.93      0.71      0.80     12230

    accuracy                           0.86     30420
   macro avg       0.88      0.84      0.85     30420
weighted avg       0.87      0.86      0.86     30420

              Classification Report for Test Set
              precision    recall  f1-score   support

 not popular       0.83      0.96      0.89      5956
     popular       0.93      0.71      0.81      4184

    accuracy                           0.86     10140
   macro avg       0.88      0.84      0.85     10140
weighted avg       0.87      0.86      0.86     10140
```



Out[107…
```
RandomForestClassifier(criterion='entropy', max_depth=10, max_features='sqrt',
                       random_state=51)
```

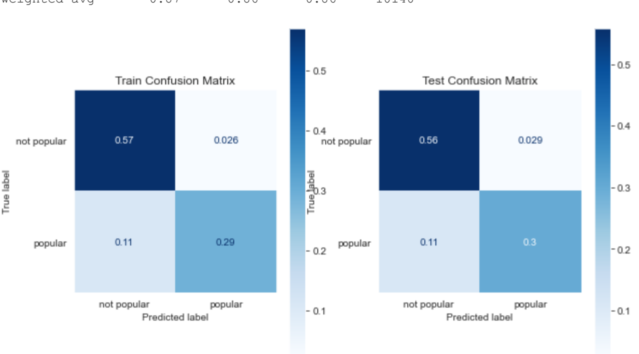
In [108…
```
# check AUC of predictions
get_auc(rf_tuned)
```

Out[108… 0.83723003106272

XGBoost

In [95]:
```
# Instantiate an GradientBoostingClassifier
xgb_clf = GradientBoostingClassifier(random_state=42)
get_model(xgb_clf)
```

```
              Classification Report for Training Set
              precision    recall  f1-score   support

 not popular       0.84      0.96      0.89     18190
     popular       0.92      0.73      0.81     12230

    accuracy                           0.86     30420
   macro avg       0.88      0.84      0.85     30420
weighted avg       0.87      0.86      0.86     30420

              Classification Report for Test Set
              precision    recall  f1-score   support

 not popular       0.83      0.95      0.89      5956
     popular       0.91      0.73      0.81      4184

    accuracy                           0.86     10140
   macro avg       0.87      0.84      0.85     10140
weighted avg       0.87      0.86      0.86     10140
```



Out[95]: GradientBoostingClassifier(random_state=42)

In [97]:
```
# check AUC of predictions
get_auc(xgb_clf)
```

Out[97]: 0.8409138333759232

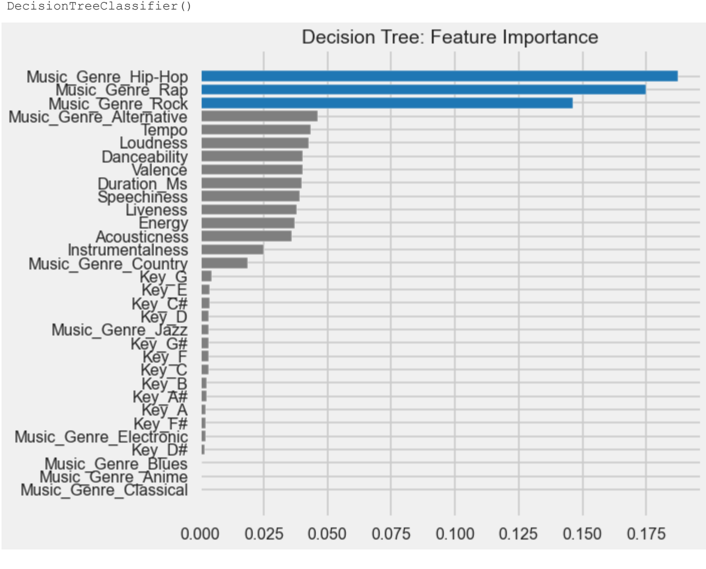
Feature Importance

In [110…
```
def plot_feature_importances(model, data, title):
    with plt.style.context(['fivethirtyeight', 'seaborn-poster']):
    # Sorting and coloring.
        formatted_data = list(
            zip(model.feature_importances_,
                [x.title() for x in data.columns])
        )
        formatted_data.sort(key=lambda x: x[0])
        colors=['#7f7f7f' if x[0]<=0.1 else '#1f77b4' for x in formatted_data]

        # Plotting.
        fig, ax = plt.subplots(figsize=(8,8))
        ax.barh(
            width=[d[0] for d in formatted_data],
            y=[d[1] for d in formatted_data],
            color=colors)
        ax.set(title=f'{title}: Feature Importance')

    return model
```

Decision Tree

In [115…
```
plot_feature_importances(dtc, X_train_processed, 'Decision Tree')
```

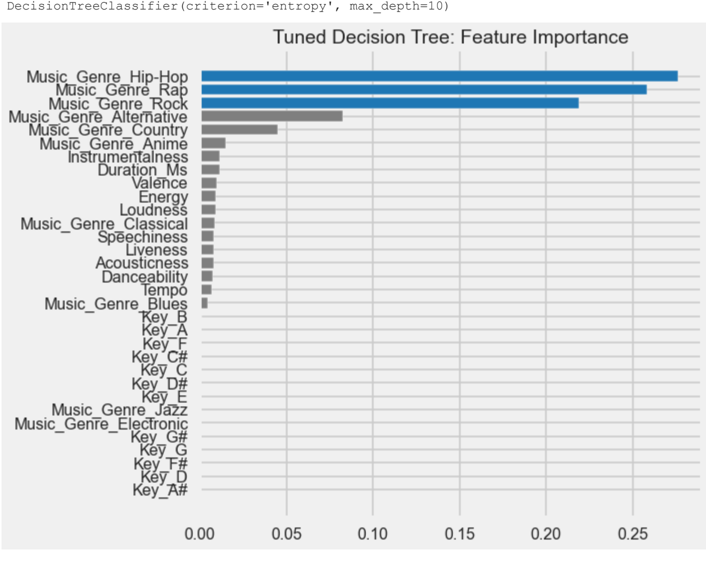
Out[115… DecisionTreeClassifier()



Tuned Decision Tree

In [134…
```
plot_feature_importances(dtuned1, X_train_processed, 'Tuned Decision Tree')
```

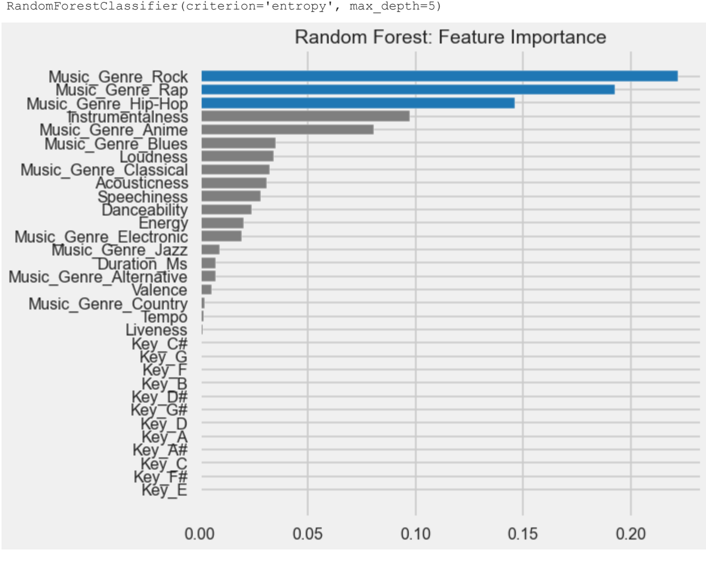
Out[134… DecisionTreeClassifier(criterion='entropy', max_depth=10)



Random Forest

In [121…
```
plot_feature_importances(rfc, X_train_processed, 'Random Forest')
```

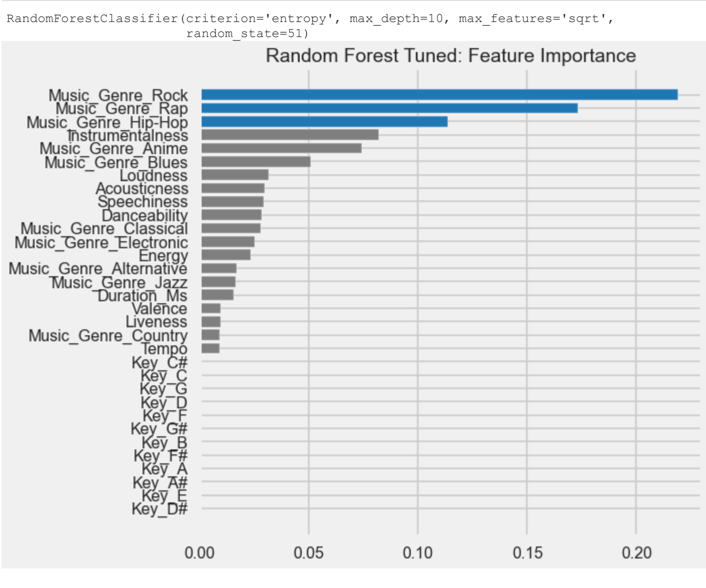
Out[121… RandomForestClassifier(criterion='entropy', max_depth=5)



Random Forest Tuned

In [122…
```
plot_feature_importances(rf_tuned, X_train_processed, 'Random Forest Tuned')
```

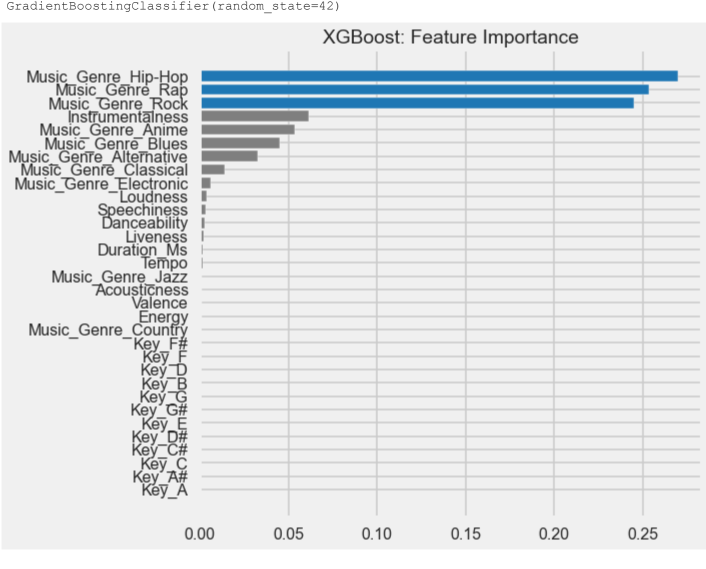
Out[122…
```
RandomForestClassifier(criterion='entropy', max_depth=10, max_features='sqrt',
                       random_state=51)
```



XGBoost

In [123…
```
plot_feature_importances(xgb_clf, X_train_processed, 'XGBoost')
```

Out[123… GradientBoostingClassifier(random_state=42)



ROC & AUC Model Performance

The **Receiver Operating Characteristic (ROC)** is known for giving us a visual of the trade off between the **false positive** and **true positive rates**. While the Area Under Curve is the metric to compare the classes which is the summary to compare the ROC curve.

AUC = 1 means that the classifier is able to perfectly distinguish all the Positive and Negative class points correctly. So our goal is the achieve a AUC closest to 1.

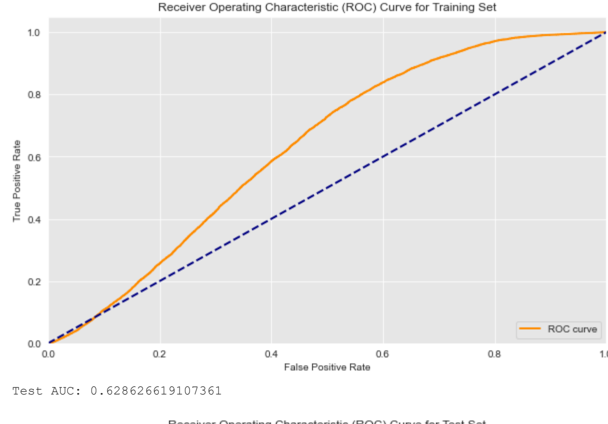
In [126…
```
def get_roc(model):
    # Calculate the probability scores of each point in the training set
    y_train_score = model.decision_function(X_train_processed)

    # Calculate the fpr, tpr, and thresholds for the training set
    train_fpr, train_tpr, thresholds = roc_curve(y_train, y_train_score)

    # Calculate the probability scores of each point in the test set
    y_test_score = model.decision_function(X_test_processed)

    # Calculate the fpr, tpr, and thresholds for the test set
    test_fpr, test_tpr, test_thresholds = roc_curve(y_test, y_test_score)

    # plotting ROC curve
    plt.subplots(figsize = (10,6))

    sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

    # training set
    lw = 2
    plt.plot(train_fpr, train_tpr, color='darkorange',
             lw=lw, label='ROC curve')
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve for Training Set')
    plt.legend(loc='lower right')
    print('Training AUC: {}'.format(auc(train_fpr, train_tpr)))
    plt.show()

    # ROC curve for test set
    plt.figure(figsize=(10, 8))
    lw = 2
    plt.plot(test_fpr, test_tpr, color='darkorange',
             lw=lw, label='ROC curve')
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve for Test Set')
    plt.legend(loc='lower right')
    print('Test AUC: {}'.format(auc(test_fpr, test_tpr)))
    print('')
    plt.show()
```

In [127…
```
def get_auc(model):
    y_pred = model.predict(X_test_processed)

    # Check the AUC of predictions
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    roc_auc
    return roc_auc
```

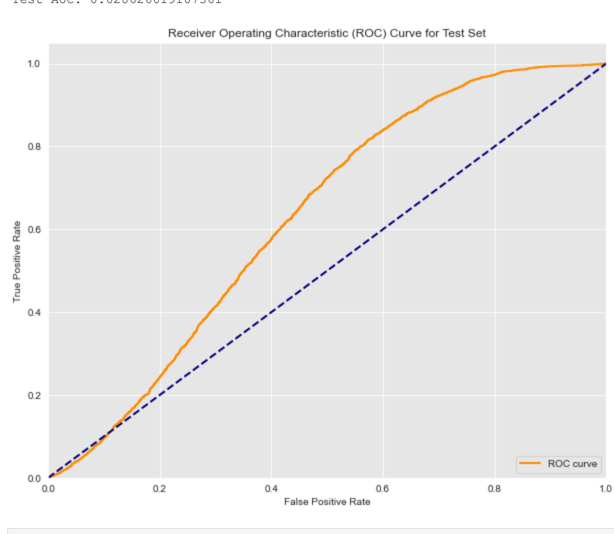
Logistic Regression

In [128…
```
get_roc(logreg)
```

```
Training AUC: 0.6315859126679993
```




```
Test AUC: 0.628626619107361
```



In [129…
```
print(f' The AUC score for our Decision Tree Model is {get_auc(dtc)}')
print(f' The AUC score for our Tuned Decision Tree Model is {get_auc(dtuned1)}')
print(f' The AUC score for our Random Forest Tree Model is {get_auc(rfc)}')
print(f' The AUC score for our Tuned Random Forest Tree Model is {get_auc(rf_tuned)}')
print(f' The AUC score for our XGBoost Model is {get_auc(xgb_clf)}')
```

```
 The AUC score for our Decision Tree Model is 0.7878777542642218
 The AUC score for our Tuned Decision Tree Model is 0.8443624822952769
 The AUC score for our Random Forest Tree Model is 0.8357209562284028
 The AUC score for our Tuned Random Forest Tree Model is 0.83723003106272
 The AUC score for our XGBoost Model is 0.8409138333759232
```

Conclusion

Out of all the models that were trained, the final model that performed the best is our **Tuned Decision Tree Classifier**. As we optimized the Decision tree the test accuracy score improved by 7 points. For AUC, the Decision Tree Classifier after optimizing the percentage increases by ~7% on detecting how well it was able to predict the popular songs from the false positive popular songs.

The reason we choose our Tuned Decision Tree's accuracy score of .87 as our metric because we want to know how well the model predicted the popular (true positive) and not popular (true negative) tracks overall. As for our Area Under the Curve it proved to have the highest percentage out of all the models.

Reccomendations:

Based on the Decision Tree's feature importance, record labels should focus on artists who specialize in genres like **Rock, Hip-Hop and Rap** while prioritizing audio features such as **instrumentals, track duration, valence and loudness**. On the other hand, the key signature and the genre Jazz and EDM music does not play into a huge factor on a song's popularity.

Future Work

- Iterate the missing feature information and scaping more audio features from Spotify's API to see if other audio features changes our predictions
- Scape data from other platforms such as BillBoard, SoundCloud, Apple Music and use classification models to compare their popular audio features
- Look into various Rock, Hip-Hop, and Rap artists to see who is the most popular based on scarping data from Spotify's API based on their popularity or follow count

In [ ]: