Spotify Songs Exploratory Data Analysis Project

Project Overview:

This project focuses on performing an in-depth **Exploratory Data Analysis (EDA)** of the **Spotify Songs Dataset** downloaded from Kaggle. The goal is to analyze various audio features of songs to understand the objectives mentioned below which is based on the downloaded datatset.

OBJECTIVE

-Top 5 most popular artists
-Top 5 loudest tracks
-To 10 instrumentalness tracks
-Top 10 energetic tracks
-Top 10 tracks with the most valence
-Most common durations
-Most popular artist
-Artist with the most danceability song
-Multiple feature plots

(To understand the above terms refers to the Spotify Audio Features doc)

[Link for Spotify Audio Features Docs]
(https://developer.spotify.com/documentation/web-api/reference/get-audio-features)

[Link for Spotify Songs Dataset Download]
(https://www.kaggle.com/datasets/geomack/spotifyclassification)

Loading Libraries and Dataset

```
#Loading all the necessary python libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
C:\Users\salon\anaconda3\lib\site-packages\pandas\core\computation\
expressions.py:20: UserWarning: Pandas requires version '2.7.3' or
newer of 'numexpr' (version '2.7.1' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
```

```
#To set the style for Seaborn plots
sns.set_style("darkgrid")
```

```python
#Loading the Spotify Songs dataset
df=pd.read_csv("C:/Users/salon/Desktop/projects/Python/spotify_data.cs
v")
df.drop("Unnamed: 0", axis=1, inplace=True) #axis=1 because it is a
column and inplace is True because removing it permanentaly
df.head() #for the first five rows
```

```
   acousticness  danceability  duration_ms  energy  instrumentalness
key  \
0        0.0102         0.833       204600   0.434          0.021900
2
1        0.1990         0.743       326933   0.359          0.006110
1
2        0.0344         0.838       185707   0.412          0.000234
2
3        0.6040         0.494       199413   0.338          0.510000
5
4        0.1800         0.678       392893   0.561          0.512000
5

   liveness  loudness  mode  speechiness    tempo  time_signature
valence  \
0    0.1650    -8.795     1       0.4310  150.062             4.0
0.286
1    0.1370   -10.401     1       0.0794  160.083             4.0
0.588
2    0.1590    -7.148     1       0.2890   75.044             4.0
0.173
3    0.0922   -15.236     1       0.0261   86.468             4.0
0.230
4    0.4390   -11.648     0       0.0694  174.004             4.0
0.904

   target      song_title            artist
0       1        Mask Off            Future
1       1         Redbone  Childish Gambino
2       1    Xanny Family            Future
3       1  Master Of None       Beach House
4       1  Parallel Lines       Junior Boys
```

DATA CLEANING

```python
df.isna().sum()
#Returns the added True(missing values) values for each column,
effectively counting the number of missing values in each column.
```

```
acousticness        0
danceability        0
```

```
duration_ms         0
energy              0
instrumentalness    0
key                 0
liveness            0
loudness            0
mode                0
speechiness         0
tempo               0
time_signature      0
valence             0
target              0
song_title          0
artist              0
dtype: int64
```

```
df.info() #Returns the summary of the Data Frame
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2017 entries, 0 to 2016
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   acousticness      2017 non-null   float64
 1   danceability      2017 non-null   float64
 2   duration_ms       2017 non-null   int64
 3   energy            2017 non-null   float64
 4   instrumentalness  2017 non-null   float64
 5   key               2017 non-null   int64
 6   liveness          2017 non-null   float64
 7   loudness          2017 non-null   float64
 8   mode              2017 non-null   int64
 9   speechiness       2017 non-null   float64
 10  tempo             2017 non-null   float64
 11  time_signature    2017 non-null   float64
 12  valence           2017 non-null   float64
 13  target            2017 non-null   int64
 14  song_title        2017 non-null   object
 15  artist            2017 non-null   object
dtypes: float64(10), int64(4), object(2)
memory usage: 252.2+ KB
```

```
df.shape #Returns the total number of rows and columns
```

```
(2017, 16)
```

```
df.columns #Returns the names of columns
len(df.columns) #len function is used to get the length
```

```
16
```

```
df.describe() #Rreturns the summary of statistics for the numerical
columns
```

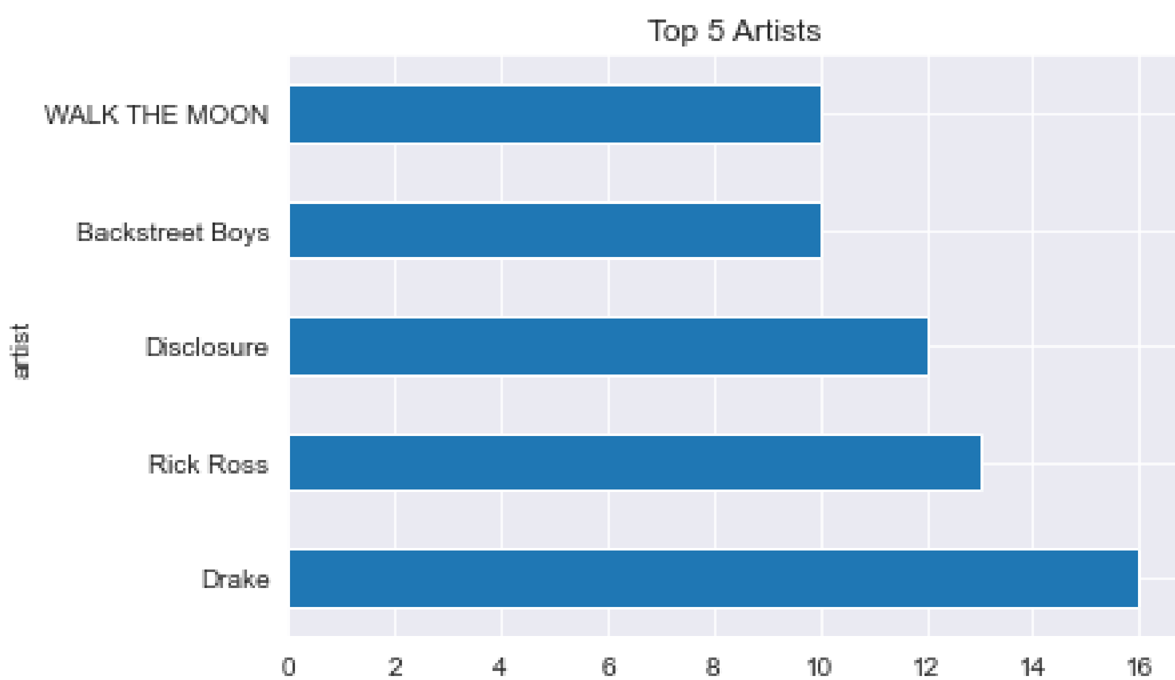
```
       acousticness  danceability   duration_ms       energy  \
count   2017.000000   2017.000000  2.017000e+03  2017.000000
mean       0.187590      0.618422  2.463062e+05     0.681577
std        0.259989      0.161029  8.198181e+04     0.210273
min        0.000003      0.122000  1.604200e+04     0.014800
25%        0.009630      0.514000  2.000150e+05     0.563000
50%        0.063300      0.631000  2.292610e+05     0.715000
75%        0.265000      0.738000  2.703330e+05     0.846000
max        0.995000      0.984000  1.004627e+06     0.998000

       instrumentalness          key     liveness     loudness
mode  \
count       2017.000000  2017.000000  2017.000000  2017.000000
2017.000000
mean           0.133286     5.342588     0.190844    -7.085624
0.612295
std            0.273162     3.648240     0.155453     3.761684
0.487347
min            0.000000     0.000000     0.018800   -33.097000
0.000000
25%            0.000000     2.000000     0.092300    -8.394000
0.000000
50%            0.000076     6.000000     0.127000    -6.248000
1.000000
75%            0.054000     9.000000     0.247000    -4.746000
1.000000
max            0.976000    11.000000     0.969000    -0.307000
1.000000

       speechiness        tempo  time_signature      valence
target
count  2017.000000  2017.000000     2017.000000  2017.000000
2017.000000
mean      0.092664   121.603272        3.968270     0.496815
0.505702
std       0.089931    26.685604        0.255853     0.247195
0.500091
min       0.023100    47.859000        1.000000     0.034800
0.000000
25%       0.037500   100.189000        4.000000     0.295000
0.000000
50%       0.054900   121.427000        4.000000     0.492000
1.000000
75%       0.108000   137.849000        4.000000     0.691000
1.000000
max       0.816000   219.331000        5.000000     0.992000
1.000000
```

Data Analysis

```
#Top 5 Most Popular Artists
top_five_artists=df.groupby("artist").count().sort_values(by='song_tit
le',ascending=False)["song_title"][:5]
print("Top 5 Artists are:\n")
top_five_artists

#This groups the dataframe by the "artist" column and counts the no.
of songs for each artist.
#It then sorts the counts in descending order based on the
"song_title" column and selects the top five artists.)
```

```
Top 5 Artists are:


artist
Drake              16
Rick Ross          13
Disclosure         12
Backstreet Boys    10
WALK THE MOON      10
Name: song_title, dtype: int64
```

```
top_five_artists.plot.barh()
plt.title("Top 5 Artists")
plt.show()
```



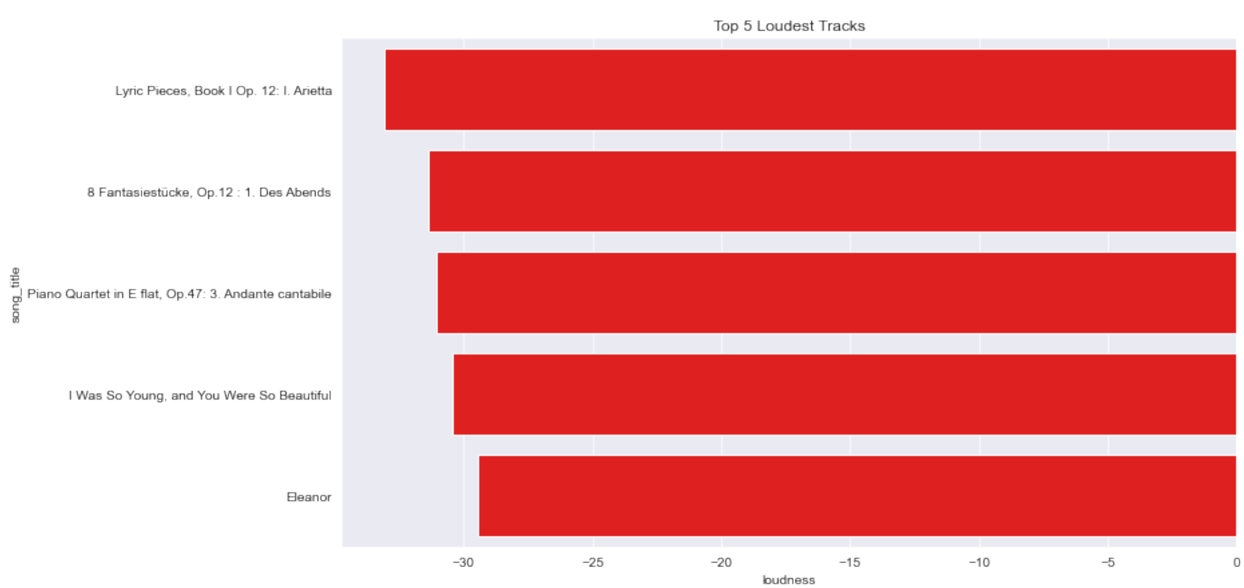
This chart highlights Drake as the dominant artist in terms of song count within this selection. The others are also prominent but with fewer contributions.

```
#Top 5 Loudest Tracks
top_five_loudest_tracks=df[["loudness","song_title"]].sort_values(by="
loudness",ascending=True)[:5]
print("Top 5 Loudest Tracks are:\n")
top_five_loudest_tracks

#This selects the 'loudness' and 'song_title' columns, sorts the
DataFrame by 'loudness' in ascending order, and takes the top five
rows.
#"loudest" would be represented by the most negative values
```

```
Top 5 Loudest Tracks are:
```

	loudness	song_title
1594	-33.097	Lyric Pieces, Book I Op. 12: I. Arietta
1596	-31.367	8 Fantasiestücke, Op.12 : 1. Des Abends
1598	-31.082	Piano Quartet in E flat, Op.47: 3. Andante can...
1531	-30.447	I Was So Young, and You Were So Beautiful
1549	-29.460	Eleanor

```
plt.figure(figsize=(12,7))
sns.barplot(x="loudness",y="song_title",data=top_five_loudest_tracks,c
olor="red")
plt.title("Top 5 Loudest Tracks")
plt.show()
```



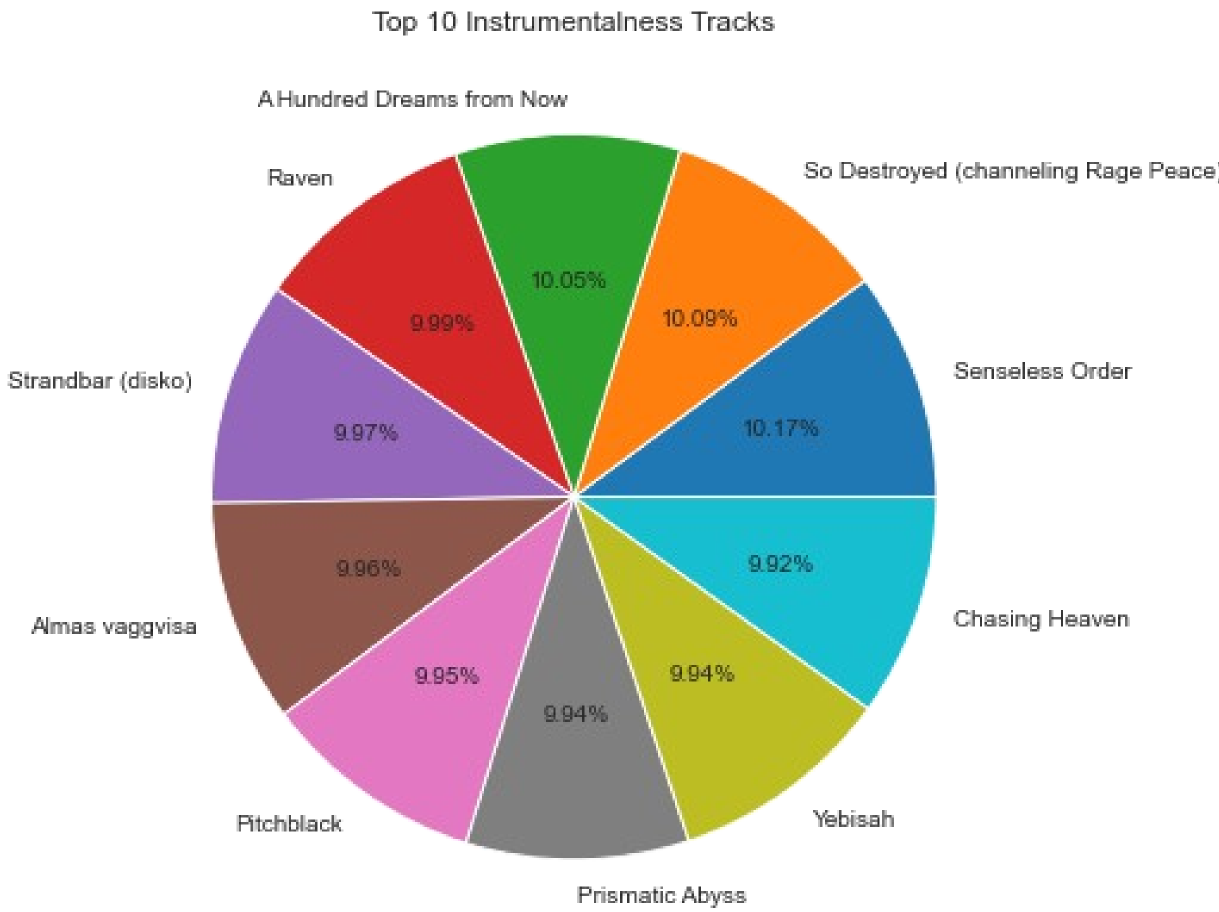
This chart highlights the Top 5 Loudest Tracks, where "Lyric Pieces, Book I Op. 12: I. Arietta" is the Loudest song followed by "8 Fantasiestücke, Op.12 : 1. Des Abends","Piano Quartet in E flat, Op.47: 3. Andante cantabile","I Was So Young, and You Were So Beautiful" and "Eleanor" respectively.

```
#Top 10 Instrumentalness Tracks
top_ten_instrumental_tracks=df[["instrumentalness","song_title"]].sort
_values(by="instrumentalness",ascending=False)[:10]
print("Top 10 Instrumentalness Tracks are:\n")
top_ten_instrumental_tracks

#This selects the 'instrumentalness', 'song_title', and 'artist'
columns, sorts the df by 'instrumentalness' in descending order, and
takes the top ten rows.
```

```
Top 10 Instrumentalness Tracks are:
```

	instrumentalness	song_title
1313	0.976	Senseless Order
271	0.968	So Destroyed (channeling Rage Peace)
1575	0.964	A Hundred Dreams from Now
1619	0.958	Raven
725	0.957	Strandbar (disko)
1546	0.956	Almas vaggvisa
1322	0.955	Pitchblack
1349	0.954	Prismatic Abyss
1661	0.954	Yebisah
121	0.952	Chasing Heaven

```
plt.figure(figsize=(12,7))
plt.pie(x="instrumentalness",data=top_ten_instrumental_tracks,autopct=
"%1.2f%%",labels=top_ten_instrumental_tracks.song_title)
plt.title("Top 10 Instrumentalness Tracks")
plt.show()

#autopct is used to show percentange of each slice
```



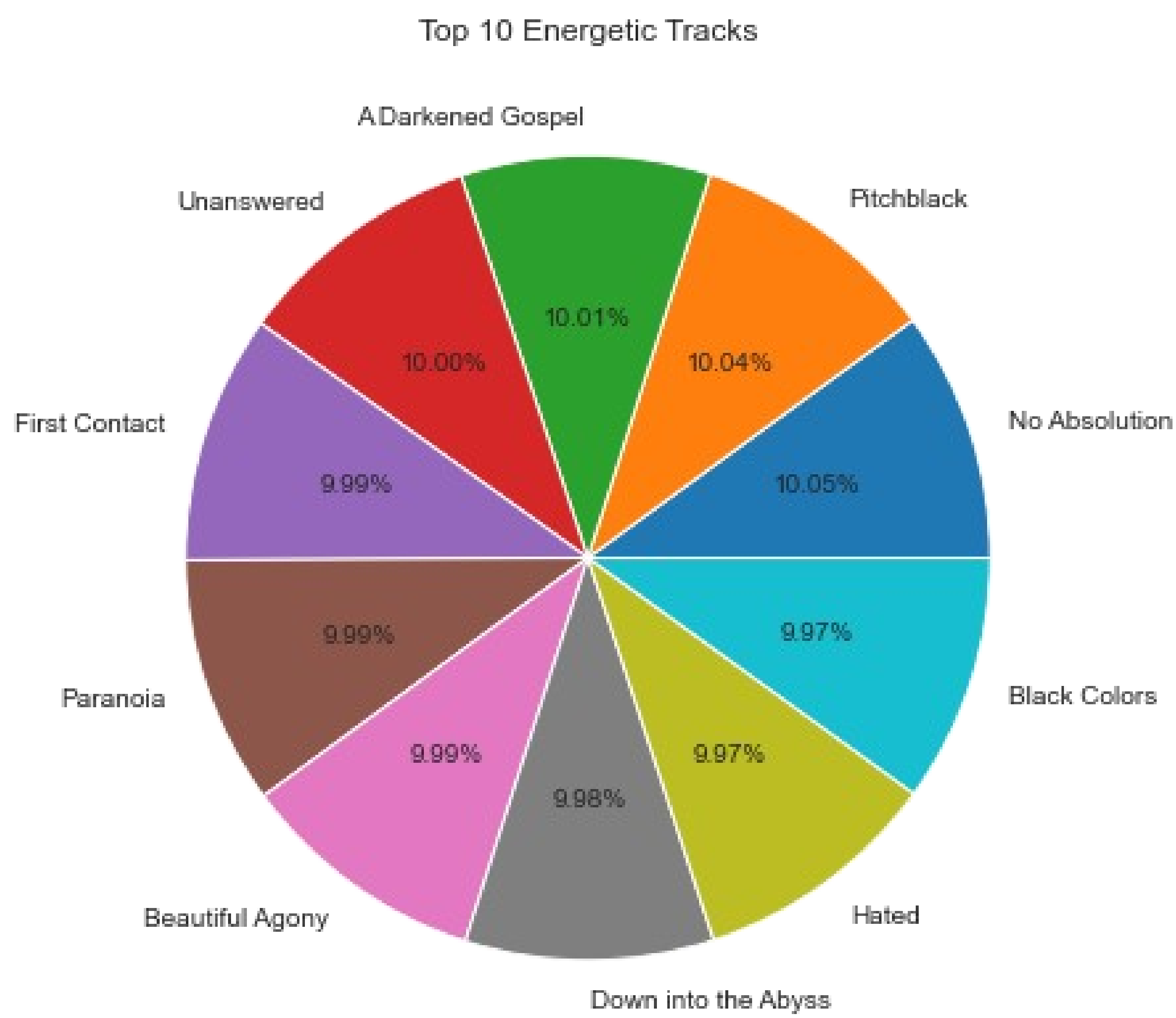
This Pie Chart highlights the Top 10 Instrumentalness Tracks, where "Senseless Order" is one of the Instrumental Track followed by "So Destroyed","A Hundered Dreams" and others.

```
#Top 10 Energetic Tracks
top_ten_energetic_tracks=df[["energy","song_title"]].sort_values(by="e
nergy",ascending=False)[:10]
print("Top 10 Energetic Tracks are:\n")
top_ten_energetic_tracks

#This selects the 'energy' and 'song_title' columns, sorts the df by
'energy' in descending order, and takes the top ten rows.
```

```
Top 10 Energetic Tracks are:
```

	energy	song_title
1299	0.998	No Absolution
1322	0.997	Pitchblack
1297	0.994	A Darkened Gospel
1347	0.993	Unanswered
2015	0.992	First Contact

```
1680   0.992             Paranoia
1332   0.992      Beautiful Agony
1328   0.991  Down into the Abyss
1681   0.990                Hated
1296   0.990         Black Colors

plt.figure(figsize=(12,7))
plt.pie(x="energy",data=top_ten_energetic_tracks,autopct="%1.2f%
%",labels=top_ten_energetic_tracks.song_title)
plt.title("Top 10 Energetic Tracks")
plt.show()
```



This Pie Chart highlights the Top 10 Energetic Tracks, where "No Absolution" is one of the Energetic Track followed by others.

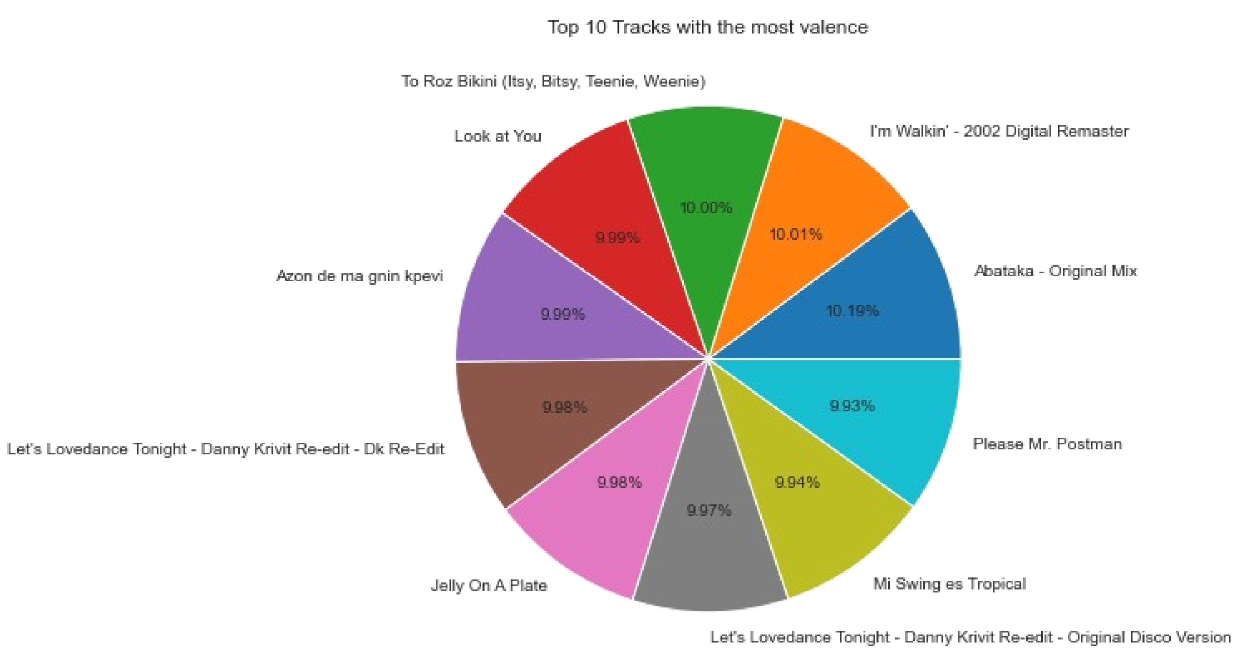
```
#Top 10 tracks with the most valence
top_ten_tracks_with_valence=df[["valence","song_title"]].sort_values(b
```

```
y="valence",ascending=False)[:10]
print("Top 10 Tracks with most valence are:\n")
top_ten_tracks_with_valence

#This selects the 'valence' and 'song_title' columns, sorts the df by
'valence' in descending order, and takes the top ten rows.
```

```
Top 10 Tracks with most valence are:
```

	valence	song_title
460	0.992	Abataka - Original Mix
912	0.975	I'm Walkin' - 2002 Digital Remaster
1966	0.974	To Roz Bikini (Itsy, Bitsy, Teenie, Weenie)
207	0.973	Look at You
48	0.973	Azon de ma gnin kpevi
337	0.972	Let's Lovedance Tonight - Danny Krivit Re-edit...
1590	0.972	Jelly On A Plate
838	0.971	Let's Lovedance Tonight - Danny Krivit Re-edit...
497	0.968	Mi Swing es Tropical
112	0.967	Please Mr. Postman

```
plt.figure(figsize=(12,7))
plt.pie(x="valence",data=top_ten_tracks_with_valence,autopct="%1.2f%
%",labels=top_ten_tracks_with_valence.song_title)
plt.title("Top 10 Tracks with the most valence")
plt.show()
```



This Pie Chart highlights the Top 10 Tracks with the most Valeance, where "Abataka-Original Mix" has the most Valeance followed by others.

```
#Most Common Duration
most_common_duration=df[['duration_ms']].mode().values[0]
most_common_duration_count=df[['duration_ms']].value_counts().max()
print("The most common duration is",most_common_duration,"
milliseconds with the occurrences of",most_common_duration_count)
```

```
The most common duration is [192000]  milliseconds with the
occurrences of 5
```

```
#Most Popular Artist
most_popular_artist=df['artist'].value_counts().idxmax()
most_popular_artist
most_popular_artist_count=df['artist'].value_counts().max()
most_popular_artist_count
print("The most popular artist
is",most_popular_artist,"with",most_popular_artist_count,"occurrences.
")
```

```
The most popular artist is Drake with 16 occurrences.
```

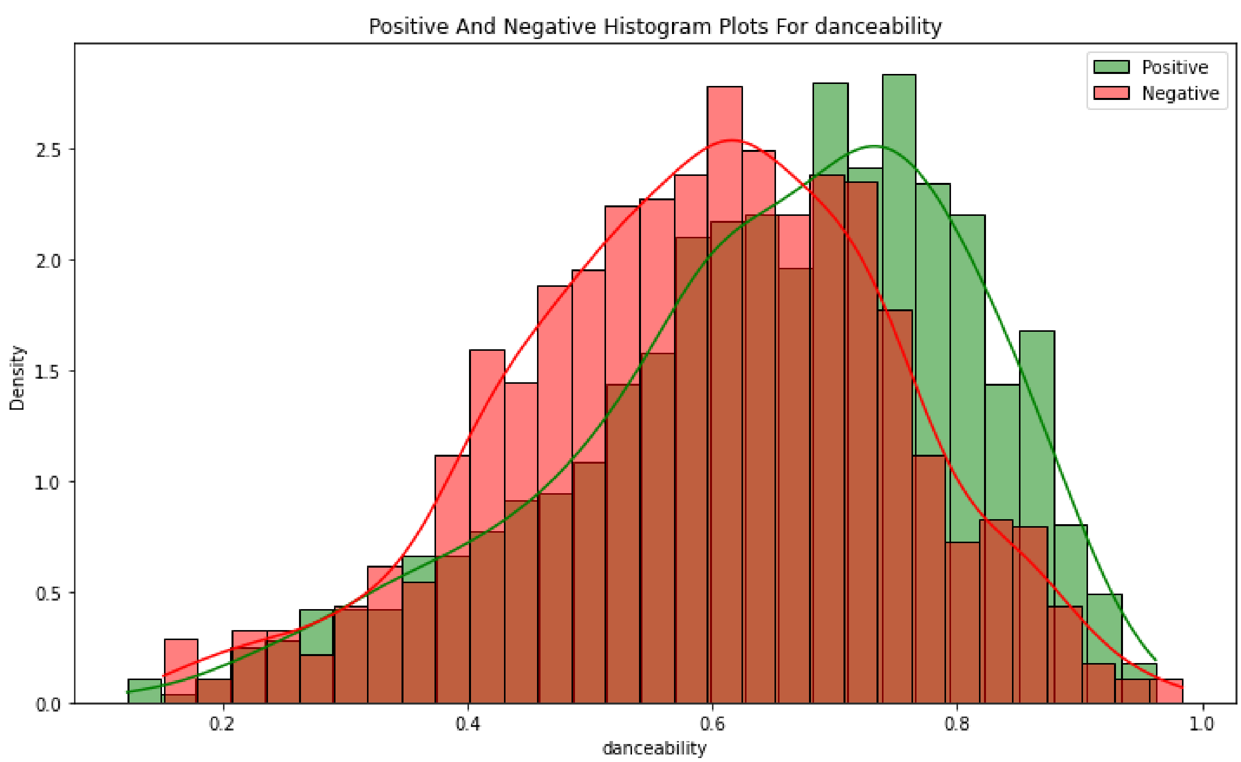
```
#Artist with the most danceability song
artist_with_danceable_songs=df[['danceability',"song_title","artist"]]
.sort_values(by="danceability",ascending=False)[:1]
print("Artist's name with the song title and it's danceability:\n")
artist_with_danceable_songs

#This selects the 'danceability', 'song_title', and 'artist' columns,
sorts the df by 'danceability' in descending order, and takes the top
five rows.
```

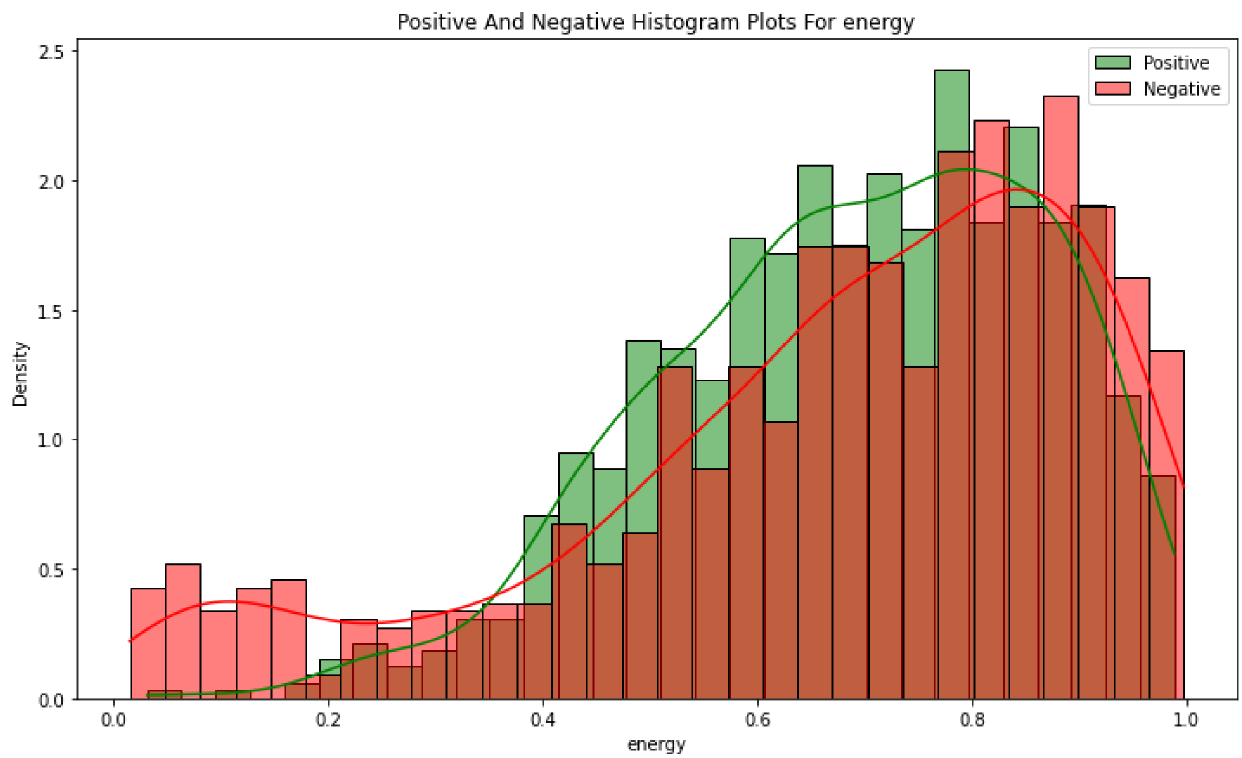
```
Artist's name with the song title and it's danceability:


      danceability                song_title        artist
1433         0.984  Flashwind - Radio Edit  Ben Remember
```

Multiple Feature Plot

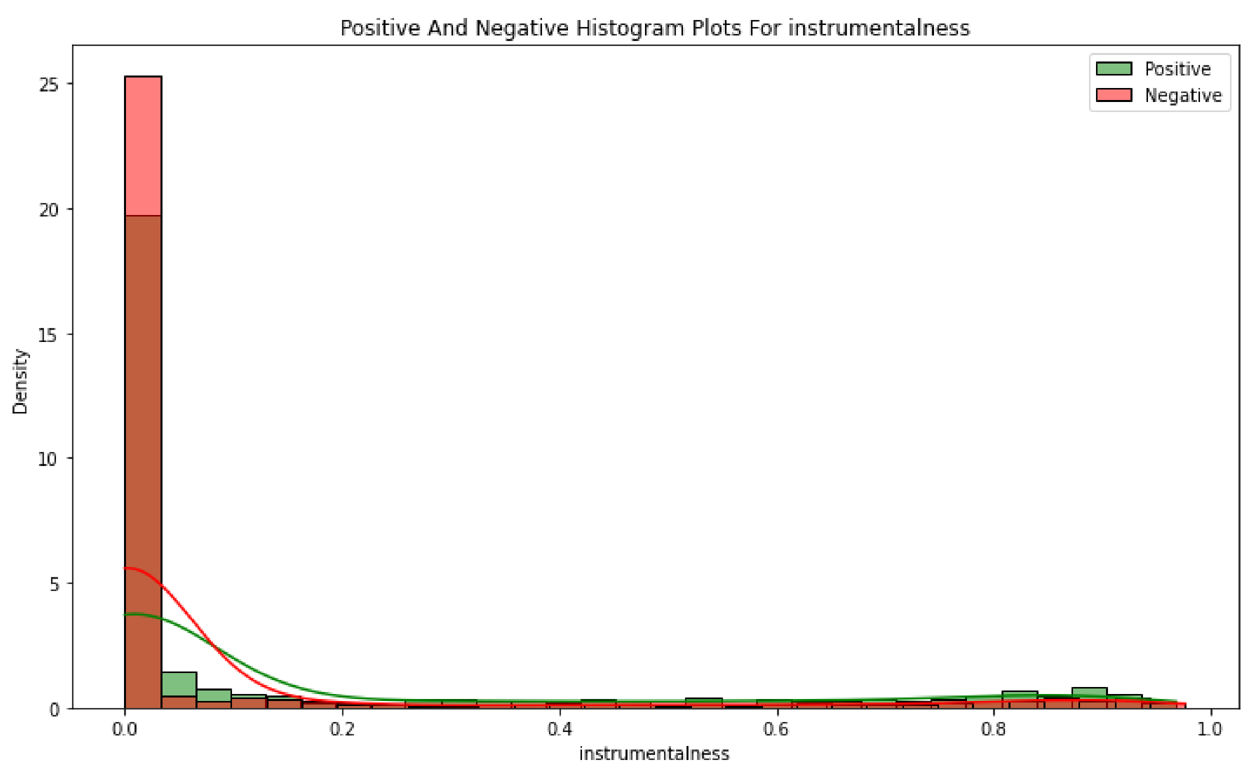
```
interest_feature_cols=['danceability', 'energy','instrumentalness',
'loudness', 'tempo', 'valence']

for feature_col in interest_feature_cols:
  pos_data=df[df["target"]==1][feature_col]
  #This line filters the DataFrame to include only rows where the
target column equals 1 (indicating the positive class/Liked).
  #It then selects the data from the column specified by feature_col
and stores it in pos_data.

  neg_data=df[df["target"]==0][feature_col]
```

```
  #This line filters the DataFrame df to include only rows where the
target column equals 0 (indicating the negative class/disliked).
  #It then selects the data from the column specified by feature_col
and stores it in neg_data.

  plt.figure(figsize=(12,7))


sns.histplot(pos_data,bins=30,label="Positive",color="green",kde=True,
stat="density",common_norm=False)

sns.histplot(neg_data,bins=30,label="Negative",color="red",kde=True,st
at="density",common_norm=False)
  #kde=True adds a Kernel Density Estimate (KDE) curve to the
histogram, showing the smoothed distribution of the data.
  #stat="density" scales the histogram to display the density rather
than the count.
  #common_norm=False ensures that the histograms for positive and
negative data are not normalized together, allowing them to be scaled
independently.

  plt.legend(loc="upper right")
  plt.title(f"Positive And Negative Histogram Plots For
{feature_col}")
  plt.show()
```

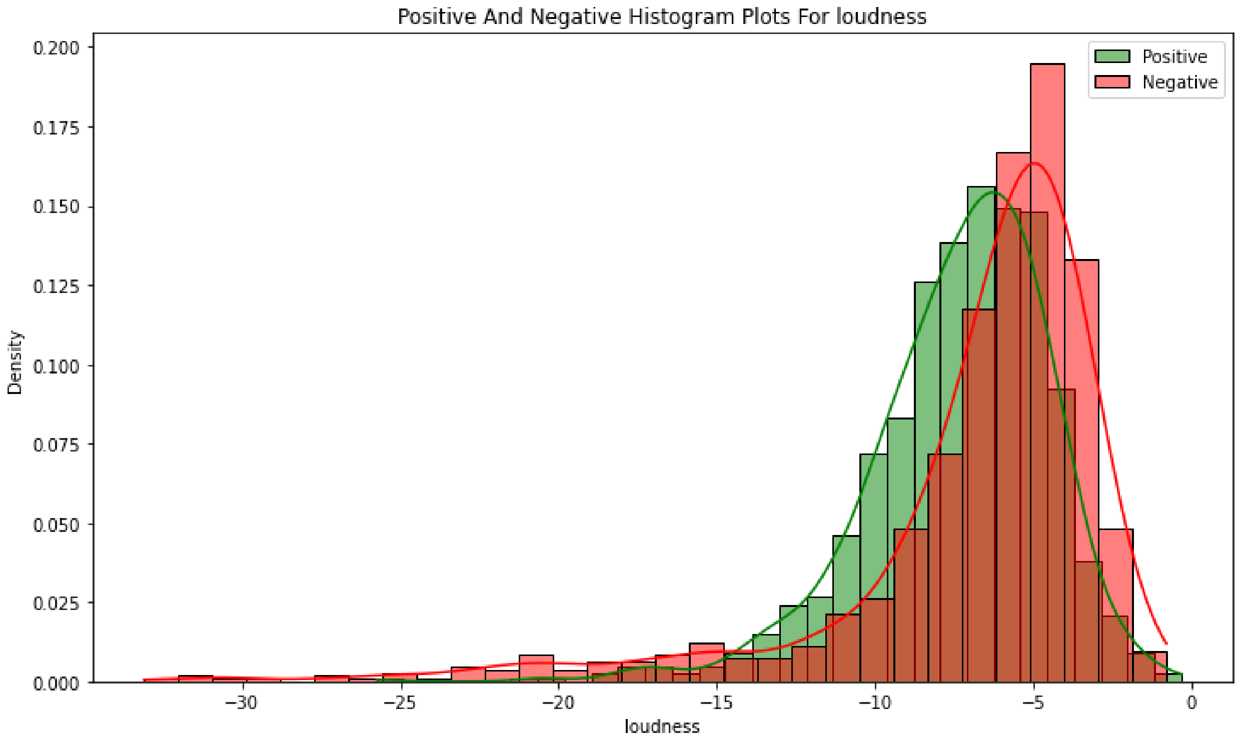


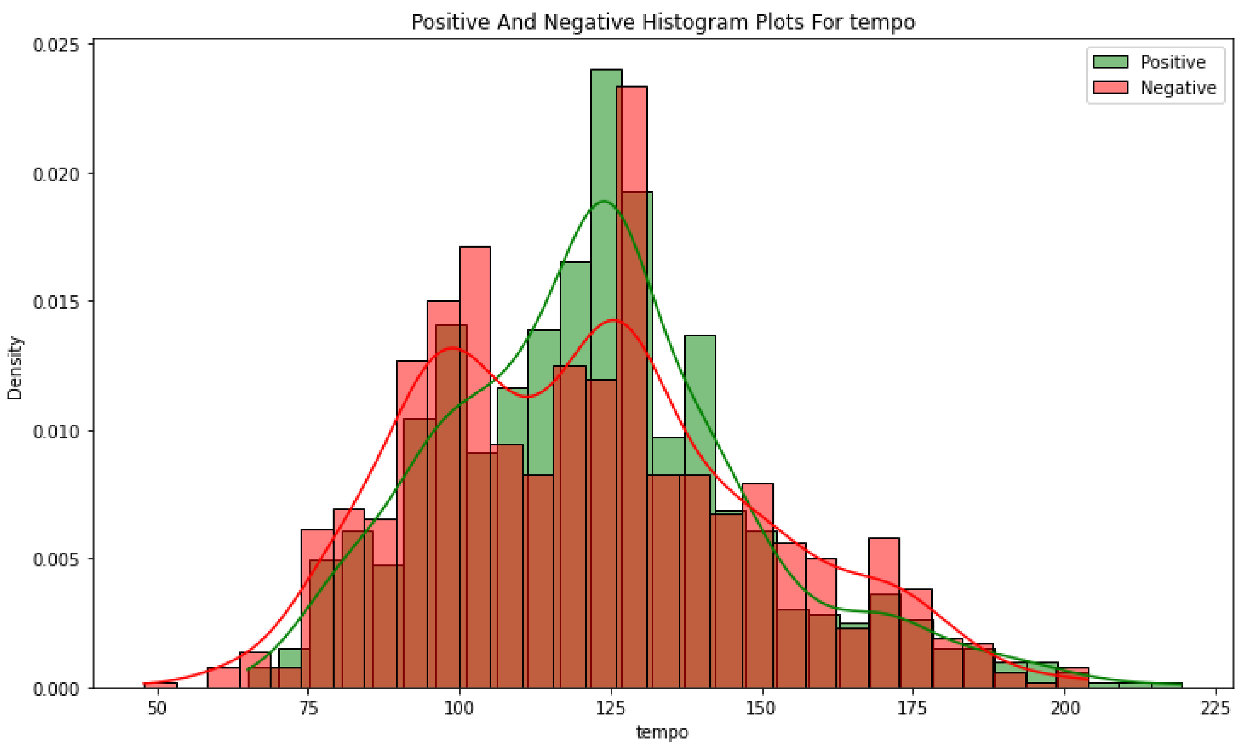


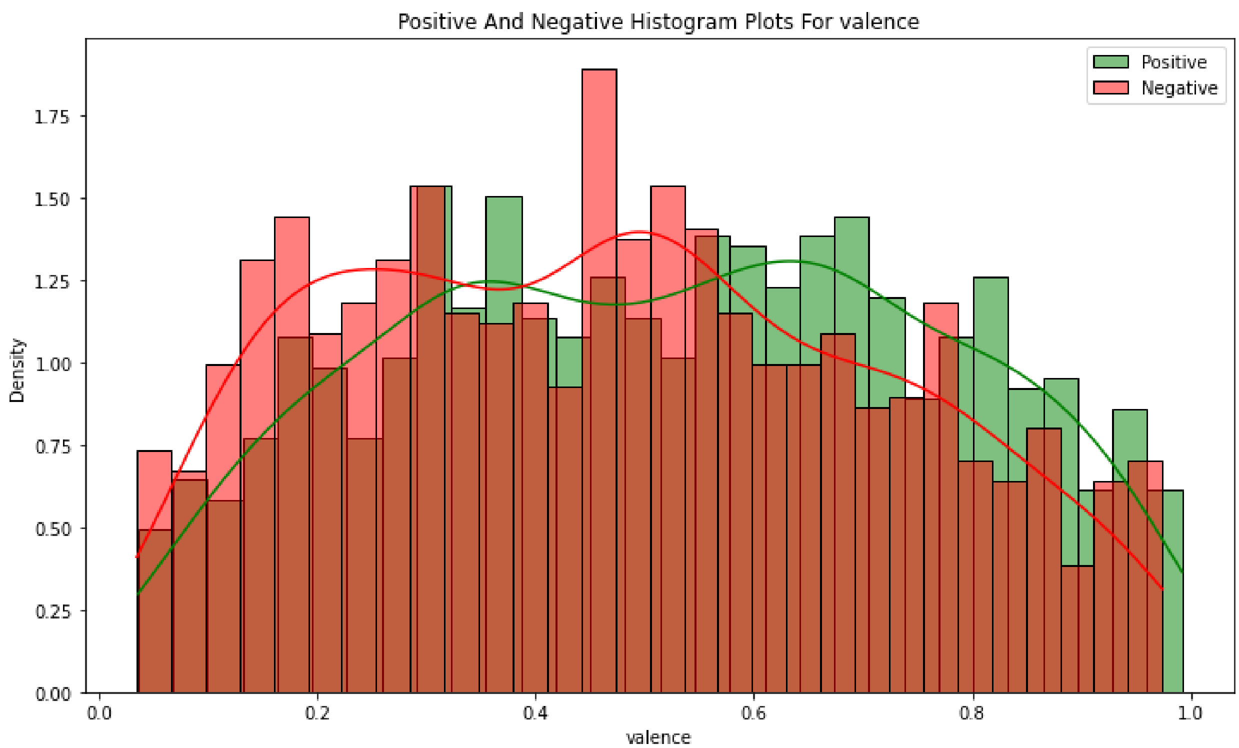
Positive And Negative Histogram Plots For energy
Positive
Negative
Density
energy
0.0
0.5
1.0
1.5
2.0
2.5
0.0
0.2
0.4
0.6
0.8
1.0



Positive And Negative Histogram Plots For instrumentalness
Positive
Negative
Density
instrumentalness
0
5
10
15
20
25
0.0
0.2
0.4
0.6
0.8
1.0


Positive And Negative Histogram Plots For loudness
Positive
Negative
Density
loudness
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
−30
−25
−20
−15
−10
−5
0


Positive And Negative Histogram Plots For tempo
Positive
Negative
Density
tempo
0.000
0.005
0.010
0.015
0.020
0.025
50
75
100
125
150
175
200
225



Positive and Negative Histogram PLots

danceability From this histogram we can conclude that, people like(Positive) songs when the danceability is more than **0.7** where as people tends to dislike(Negative) songs when it's danceability is less.

energy From this histogram we can conclude that, people like(Positive)songs when the energy is between **0.4 to 0.8** where as people tends to dislike(Negative) songs when it is less than 0.4 and more than 0.8.

instrumentalness From this histogram we can conclude that, people like(Positive)songs when the instrumentalness is around **0.1 and more** where as people tends to dislike(Negative) songs when it is around 0.

Loudness From this histogram we can conclude that, people like(Positive) songs when the loudness is between **-15 to -7** where as people tends to dislike(Negative) songs when it is too loud or too quiet.

Tempo From this histogram we can conclude that, people like(Positive)songs when the Tempo around **125 - 130** where as people tends to dislike(Negative)songs when the Tempo is to fast or to slow.