

Introduction:

Spotify is an audio streaming platform that provides DRM-restricted music, videos, and podcasts from record labels and media companies. It has more than 50 million tracks which user can browse using various parameters like artists, album, genre, or via playlists.

Here we have taken the data of top 50 songs of 2019 from spotify database and we have performed various data analytics and visualisation operations on the dataset. Hereby using these mathematical models we can analyise the genre, beats per minute, loudness, valence, length, acousticeness, speechiness and hence finding out the popularity and the common thread between them.

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load in
import numpy as np \# used for working with arrays \& linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from scipy import stats # used for scientific computing and technical computing.
!pip install squarify
import squarify as sq # Bar charts can't be effective to handle and visualize large data
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
import seaborn as sns # provides a high-level interface for drawing attractive and informative statistical graphics
import sklearn #including classification, regression, clustering and dimensionality reduction
import warnings
warnings.filterwarnings("ignore")
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import MinMaxScaler,LabelEncoder
from sklearn.model_selection import train_test_split,cross_val_score, KFold
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive bayes import GaussianNB, MultinomialNB, BernoulliNB
from sklearn.svm import LinearSVC, SVC
from sklearn import metrics
from sklearn.metrics import confusion_matrix, classification_report
%matplotlib inline
# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
# Any results you write to the current directory are saved as output.
     Looking in indexes: <a href="https://pypi.org/simple">https://us-python.pkg.dev/colab-wheels/public/simple/</a>
     Collecting squarify
       Downloading squarify-0.4.3-py3-none-any.whl (4.3 kB)
     Installing collected packages: squarify
     Successfully installed squarify-0.4.3 \,
```

• Question 1: Print the first 5 rows that are present in the data?

```
filename='top50.csv'
df=pd.read_csv(filename,encoding='ISO-8859-1')
df.head()
```

	Unnamed: 0	Track.Name	Artist.Name	Genre	Beats.Per.Minute	Energy	Danceability	LoudnessdB	Liveness	Valence.
0	1	Señorita	Shawn Mendes	canadian pop	117	55	76	-6	8	75
1	2	China	Anuel AA	reggaeton flow	105	81	79	-4	8	61
2	3	boyfriend (with Social House)	Ariana Grande	dance pop	190	80	40	-4	16	70
3	4	Beautiful People (feat. Khalid)	Ed Sheeran	рор	93	65	64	-8	8	55
4	5	Goodbyes (Feat. Young	Post Malone	dfw rap	150	65	58	-4	11	18
his is formatted as code										

• Question 2: How many rows and columns are present in the data?

#Calculates the number of rows and columns
print(df.shape)

(50, 14)

▼ Question 3: Rename the columns as given below?

Track.Name:'track_name'

- Artist.Name:'artist_name'
- · Track.Name:'track_name'
- Genre: 'genre'
- Energy: 'energy'
- · Liveness: 'liveness'
- List item
- Popularity: 'popularity"
- Loudness..dB..:'Loudness(dB)'
- Valence.:'Valence'
- Speechiness-:Speechiness
- · Acousticness..:'Acousticness'
- Beats.Per.Minute:'beats_per_minute'
- · Length.:'Length'

#Renaming the columns
df.rename(columns={'Track.Name':'track_name','Artist.Name':'artist_name','Beats.Per.Minute':'beats_per_minute','Loudness..dB..':'Loudness
df.head()

	Unnamed: 0	track_name	artist_name	Genre	beats_per_minute	Energy	Danceability	Loudness(dB)	Liveness	Valence	Len
0	1	Señorita	Shawn Mendes	canadian pop	117	55	76	-6	8	75	
1	2	China	Anuel AA	reggaeton flow	105	81	79	-4	8	61	
2	3	boyfriend (with Social House)	Ariana Grande	dance pop	190	80	40	-4	16	70	
3	4	Beautiful People (feat. Khalid)	Ed Sheeran	рор	93	65	64	-8	8	55	
4	5	Goodbyes (Feat. Young Thug)	Post Malone	dfw rap	150	65	58	-4	11	18	

▼ Question 4: Replace all the null values and missing values by '0'?

```
#counts the null values and replace it by 0 df.isnull().sum() #show the missing values in the data set df.fillna(0)
```

```
from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

• Question 5: What are the datatypes of the different columns in the dataset?

artist_name object
Genre object
beats_per_minute int64
Energy int64
Danceability int64

```
Loudness(dB) int64
Liveness int64
Valence int64
Length int64
Acousticness int64
Speechiness int64
Popularity int64
dtype: object
```

Question 6: How many genre are there? List the number of songs in each genre.

```
(feat Khalid)
#Calculating the number of songs of each genre
print(type(df['Genre']))
popular_genre=df.groupby('Genre').size().unique
print(popular_genre)
genre_list=df['Genre'].values.tolist()
     <class 'pandas.core.series.Series'>
     atl hip hop
     australian pop
                       1
    big room
                       1
    boy band
                       1
     brostep
     canadian hip hop
                       3
    canadian pop
    country rap
    dance pop
    dfw rap
                       2
    edm
                        3
    electropop
                        2
     escape room
    latin
    panamanian pop
    pop
    pop house
    r&b en espanol
    reggaeton
    reggaeton flow
     trap music
    dtype: int64>
                        Ι Λ ΟΛΝΙΟΙΌΝ
     16
                                          I Ralvin
```

▼ Question 7: How many artist are there? list the number of songs each artist has created.

```
Snider-Verse
#Calculating the number of songs by each of the artists
print(df.groupby('artist_name').size())
popular_artist=df.groupby('artist_name').size()
print(popular_artist)
artist list=df['artist name'].values.tolist()
     artist_name
     Ali Gatie
     Anuel AA
     Ariana Grande
     Bad Bunny
     Billie Eilish
     Chris Brown
     DJ Snake
     Daddy Yankee
     Drake
                         1
     Ed Sheeran
     J Balvin
     Jhay Cortez
     Jonas Brothers
                         1
     Katy Perry
     Khalid
     Kygo
     Lady Gaga
     Lauv
     Lewis Capaldi
     Lil Nas X
     Lil Tecca
     1 i z z o
                         1
     Lunay
     MEDUZA
     Maluma
     Marshmello
     Martin Garrix
     Nicky Jam
     Post Malone
                          2
     ROSALÍA
                         1
     Sam Smith
                         1
     Sech
```

```
Shawn Mendes
Taylor Swift
The Chainsmokers
Tones and I
Y2K
                    1
Young Thug
                    1
dtype: int64
artist_name
Ali Gatie
                    1
Anuel AA
Ariana Grande
Bad Bunny
Billie Eilish
Chris Brown
DJ Snake
Daddy Yankee
Drake
Ed Sheeran
J Balvin
Jhay Cortez
Jonas Brothers
Katy Perry
Khalid
Kygo
Lady Gaga
                                        Khalid
                                                                         136
                                                                                               90
```

Question 8 : Set the precision for the data values in the table 3.

```
pd.set_option('precision', 3)
df.describe()
```

	Unnamed:	beats_per_minute	Energy	Danceability	Loudness(dB)	Liveness	Valence	Length	Acousticness	Speechiness
count	50.000	50.000	50.000	50.00	50.000	50.000	50.000	50.000	50.000	50.000
mean	25.500	120.060	64.060	71.38	-5.660	14.660	54.600	200.960	22.160	12.480
std	14.577	30.898	14.232	11.93	2.056	11.118	22.336	39.144	18.996	11.162
min	1.000	85.000	32.000	29.00	-11.000	5.000	10.000	115.000	1.000	3.000
25%	13.250	96.000	55.250	67.00	-6.750	8.000	38.250	176.750	8.250	5.000
50%	25.500	104.500	66.500	73.50	-6.000	11.000	55.500	198.000	15.000	7.000
75%	37.750	137.500	74.750	79.75	-4.000	15.750	69.500	217.500	33.750	15.000
max	50.000	190.000	88.000	90.00	-2.000	58.000	95.000	309.000	75.000	46.000

Question 9 : Plot a histogram for the dataset keeping liveness as the base measure with normalization bin size -

```
#Finding out the skew for each attribute
skew=df.skew()
print(skew)
# Removing the skew by using the boxcox transformations
#transform=np.asarray(df[['Liveness']].values)
#df_transform = stats.boxcox(transform)[0]
# Plotting a histogram to show the difference
plt.hist(df['Liveness'],bins=10) #original data
plt.show()
```

```
Unnamed: 0 0.000000
Beats.Per.Minute 0.854504
Energy -0.453199
Danceability -1.37989
Loudness..dB. -0.831915
Liveness 2.203937
```

Question 10 : Calculate the correlation among the attributes. Set the precision at 3 use the spearman method to plot.

```
dtype: float64
pd.set_option('display.width', 100)
pd.set_option('precision', 3)
correlation=df.corr(method='spearman')
print(correlation)
                      Unnamed: 0 beats_per_minute Energy Danceability Loudness(dB) Liveness
    Unnamed: 0
                          1.000
                                                                                          0.102
                                            -0.263
                                                    0.132
                                                                  0.053
                                                                               -0.014
    beats_per_minute
                                                                 -0.092
                          -0.263
                                             1.000
                                                    0.012
                                                                                0.014
                                                                                         -0.033
                                            0.012
                                                                 -0.049
                                                                                         0.013
    Energy
                          0.132
                                                    1.000
                                                                                0.635
    Danceability
                                                                  1,000
                          0.053
                                            -0.092 -0.049
                                                                                0.009
                                                                                         -0.261
    Loudness(dB)
                          -0.014
                                            0.014
                                                    0.635
                                                                  0.009
                                                                                1,000
                                                                                          0.114
     Liveness
                          0.102
                                            -0.033
                                                    0.013
                                                                 -0.261
                                                                                0.114
                                                                                          1.000
    Valence
                          0.113
                                            -0.048
                                                    0.467
                                                                  0.155
                                                                                0.317
                                                                                         -0.187
                          0.045
                                            -0.198
                                                    0.189
                                                                 -0.079
                                                                                0.165
                                                                                          0.202
     Length
    Acousticness
                          0.058
                                            -0.010 -0.211
                                                                 -0.128
                                                                               -0.040
                                                                                          0.204
     Speechiness
                          -0.232
                                             0.392 -0.035
                                                                  0.104
                                                                               -0.063
                                                                                         -0.137
     Popularity
                          -0.221
                                             0.217 -0.044
                                                                 -0.141
                                                                                0.072
                                                                                          0.012
                      Valence Length Acousticness Speechiness Popularity
    Unnamed: 0
                       0.113
                              0.045
                                             0.058
                                                         -0.232
                                                                     -0.221
    beats_per_minute
                       -0.048 -0.198
                                             -0.010
                                                          0.392
                                                                      0.217
    Energy
                       0.467
                              0.189
                                             -0.211
                                                         -0.035
                                                                     -0.044
    Danceability
                        0.155 -0.079
                                             -0.128
                                                          0.104
                                                                     -0.141
     Loudness(dB)
                        0.317
                                0.165
                                             -0.040
                                                         -0.063
                                                                      0.072
     Liveness
                       -0.187 0.202
                                             0.204
                                                         -0.137
                                                                      0.012
     Valence
                        1.000 -0.081
                                             -0.053
                                                          -0.095
                                                                     -0.265
    Length
                       -0.081 1.000
                                             -0.005
                                                          0.020
                                                                     -0.122
     Acousticness
                       -0.053
                              -0.005
                                             1.000
                                                          0.017
                                                                      0.036
                                                          1.000
                       -0.095
                              0.020
                                              0.017
                                                                      0.165
     Speechiness
                       -0.265 -0.122
                                              0.036
                                                          0.165
                                                                      1.000
    Popularity
```

▼ Question 11: Plot a bar graph with count of tracks on the Y axis and Genre on the X axis

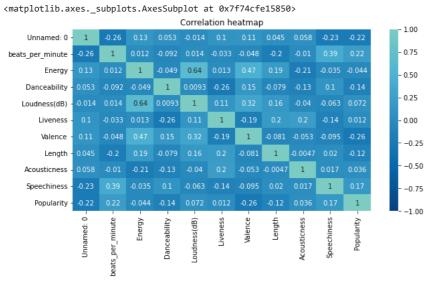
```
xtick = ['dance pop', 'pop', 'latin', 'edm', 'canadian hip hop',
    'panamanian pop', 'electropop', 'reggaeton flow', 'canadian pop',
    'reggaeton', 'dfw rap', 'brostep', 'country rap', 'escape room',
    'trap music', 'big room', 'boy band', 'pop house', 'australian pop',
    'r&b en espanol', 'atl hip hop']
    length = np.arange(len(xtick))
    genre_groupby = df.groupby('Genre')['track_name'].agg(len)
    plt.figure(figsize = (15,7))
    plt.bar(length, genre_groupby)
    plt.xticks(length, xtick)
    plt.xticks(rotation = 90)
    plt.xlabel('Genre', fontsize = 20)
    plt.ylabel('Count of the tracks', fontsize = 20)
    plt.title('Genre vs Count of the tracks', fontsize = 25)
```

Text(0.5, 1.0, 'Genre vs Count of the tracks')

Genre vs Count of the tracks

• Question 12 : Plot a heatmap showing correlation between different attributes?

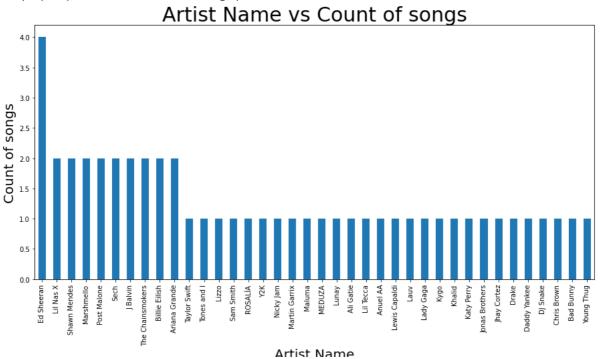
```
# heatmap of the correlation
plt.figure(figsize=(10,5))
plt.title('Correlation heatmap')
sns.heatmap(correlation,annot=True,vmin=-1,vmax=1,cmap="GnBu_r",center=1)
```



Question 13: Plot a bar graph with count of songs on the Y axis and Artist Name on the X axis

```
fig = plt.figure(figsize = (15,7))
df.groupby('artist_name')['track_name'].agg(len).sort_values(ascending = False).plot(kind = 'bar')
plt.xlabel('Artist Name', fontsize = 20)
plt.ylabel('Count of songs', fontsize = 20)
plt.title('Artist Name vs Count of songs', fontsize = 30)
```

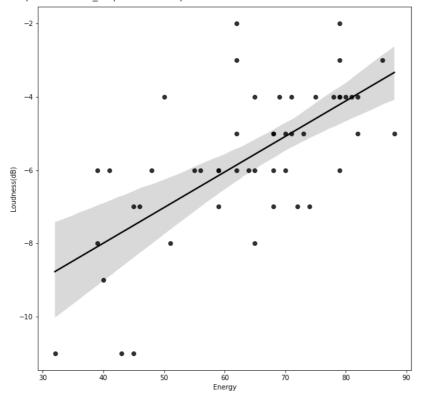
Text(0.5, 1.0, 'Artist Name vs Count of songs')



▼ Question 14: Plot data and a linear regression model corresponding to loudness and energy attributes.

```
# Analysing the relationship between energy and loudness
fig=plt.subplots(figsize=(10,10))
sns.regplot(x='Energy',y='Loudness(dB)',data=df,color='black')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fa586fb15e0>

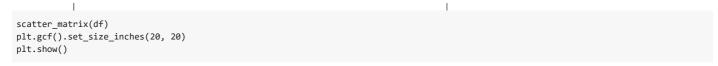


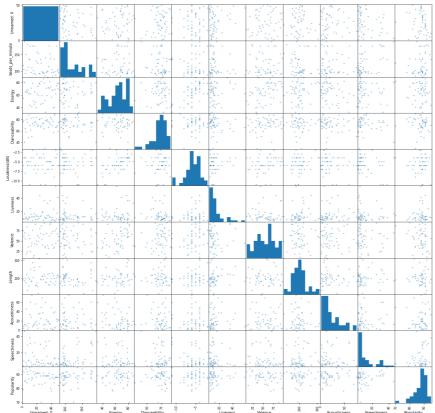
▼ Question 15 : Plot regression model on energy and popularity also plot its kernel density estimate

```
fig=plt.subplots(figsize=(10,10))
plt.title('Dependence between energy and popularity')
sns.regplot(x='Energy', y='Popularity',ci=None, data=df) #regression plot
sns.kdeplot(df.Energy,df.Popularity) #kernel density estimation
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f74d16e88b0>

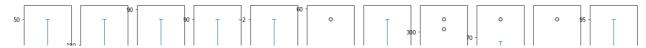
Question 16: Plot a scatter matrix to show the interdependency between the attributes of the dataset.





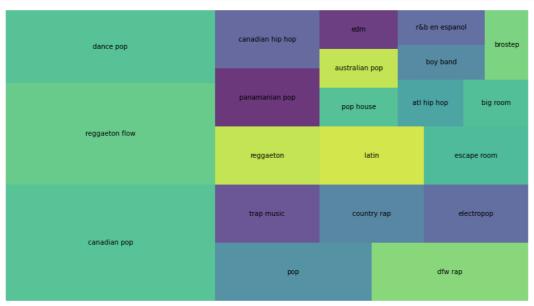
▼ Question 17: Plot a box plot of each attributes scaling from 0 to 50.

```
df.plot(kind='box', subplots=True)
plt.gcf().set_size_inches(20,10)
plt.show()
```



Question 18: Plot a square chart on the basis of number of song.

```
plt.figure(figsize=(14,8))
sq.plot(sizes=df.Genre.value_counts(), label=df["Genre"].unique(), alpha=.8 )
plt.axis('off')
plt.show()
```



▼ Question 19: Plot a pie chart on the number of songs created by each artist.

```
#Pie charts
labels = df.artist_name.value_counts().index
sizes = df.artist_name.value_counts().values
colors = ['red', 'yellowgreen', 'lightcoral', 'lightskyblue','cyan', 'green', 'black','yellow']
plt.figure(figsize = (10,10))
plt.pie(sizes, labels=labels, colors=colors)
autopct=('%1.1f%')
plt.axis('equal')
plt.show()
```

```
#Linear regression, first create test and train dataset
x=df.loc[:,['Energy','Danceability','Length','Loudness(dB)','Acousticness']].values
y=df.loc[:,'Popularity'].values
# Creating a test and training dataset
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.30)
# Linear regression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
print(regressor.intercept_)
print(regressor.coef_)
    92.64763022338748
    [-0.01605118 -0.04818298 0.00354461 0.00463808 0.00351609]
                                                                                  Lil Tecca
#Displaying the difference between the actual and the predicted
y_pred = regressor.predict(X_test)
df_output = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(df_output)
        Actual Predicted
                   86.199
    1
            88
                   86.133
    2
                   87.541
            86
    3
            87
                  87.730
                  86,681
    4
            90
    5
            84
                   90.481
    6
            92
                  89.236
    7
            91
                  85.948
    8
            89
                  86.691
    9
            91
                  86.060
    10
            91
                   87.499
                   87.918
    11
                   88.050
    13
            79
                   89.001
            88
                   88.264
    14
#Checking the accuracy of Linear Regression
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
\verb|print('Root Mean Squared Error:', np.sqrt(metrics.mean\_squared\_error(y\_test, y\_pred)))| \\
    Mean Absolute Error: 3.580070796867278
    Mean Squared Error: 18.562267625004147
    Root Mean Squared Error: 4.308395017289402
plt.figure(figsize=(10,10))
plt.title('Error analysis')
plt.xlabel('Predicted values')
plt.ylabel('Test values')
```

```
Text(0, 0.5, 'Test values')
                                          Error analysis
# Cross validation score
x=df.loc[:,['Energy','Danceability']].values
y=df.loc[:,'Popularity'].values
regressor=LinearRegression()
\verb|mse=cross_val_score| (regressor, X_train, y_train, scoring='neg_mean_squared_error', cv=5)|
mse_mean=np.mean(mse)
print(mse_mean)
diff=metrics.mean_squared_error(y_test, y_pred)-abs(mse_mean)
print(diff)
     -30.780336724856106
     -12.21806909985196
x=df.loc[:,['artist_name']].values
y=df.loc[:,'Genre'].values
       82 1
# Label encoding of features
x.shape
encoder=LabelEncoder()
x = encoder.fit_transform(x)
x=pd.DataFrame(x)
     ValueError
                                                Traceback (most recent call last)
     <ipython-input-58-df6d978d87f4> in <module>
           2 x.shape
           3 encoder=LabelEncoder()
     ----> 4 x = encoder.fit_transform(x)
           5 x=pd.DataFrame(x)
           6 x
                                       1 frames
     /usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py in column_or_1d(y, warn)
        1036
                     return np.ravel(y)
        1037
     -> 1038
                 raise ValueError(
        1039
                     "y should be a 1d array, got an array of shape {} instead.".format(shape)
     ValueError: y should be a 1d array, got an array of shape (50, 2) instead.
      SEARCH STACK OVERFLOW
# Label Encoding of target
Encoder_y=LabelEncoder()
Y = Encoder_y.fit_transform(y)
Y=pd.DataFrame(Y)
```

```
0
   2
1 14
2
3
  8
4 16
```

8 9

9 17

10 15

11 8

12 10 **13** 9

14 14

15 4

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state = 1)
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
sc.fit(x_train)
x_train=sc.transform(x_train)
x_test=sc.transform(x_test)
# KNN Classification
# sorted(sklearn.neighbors.VALID_METRICS['brute'])
knn = KNeighborsClassifier(n_neighbors = 17)
knn.fit(x_train,y_train)
y_pred=knn.predict(x_test)
error=[]
for i in range(1,30):
    knn=KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train,y_train)
    pred_i=knn.predict(X_test)
    error.append(np.mean(pred_i!=y_test))
plt.figure(figsize=(10,10))
plt.plot(range(1,30),error,color='black',marker='o',markerfacecolor='cyan',markersize=10)
plt.title('Error Rate K value')
plt.xlabel('K Value')
plt.ylabel('Mean error')
```

```
Text(0, 0.5, 'Mean error')
                                          Error Rate K value
        1.000
        0.975
x=df.loc[:,['Energy','Length','Danceability','beats_per_minute', 'Acousticness']].values
y=df.loc[:,'Popularity'].values
     KeyError
                                                Traceback (most recent call last)
     <ipython-input-64-da327dffed40> in <module>
     ----> 1 x=df.loc[:,['Energy','Length','Danceability','beats_per_minute', 'Acousticness']].values
           2 y=df.loc[:,'Popularity'].values
                                      – 💲 6 frames 🗕
     /usr/local/lib/python3.8/dist-packages/pandas/core/indexing.py in _validate_read_indexer(self, key, indexer, axis)
        1376
                         not_found = list(ensure_index(key)[missing_mask.nonzero()[0]].unique())
     -> 1377
                         raise KeyError(f"{not_found} not in index")
        1378
        1379
     KeyError: "['Length', 'beats_per_minute', 'Acousticness'] not in index"
      SEARCH STACK OVERFLOW
# Creating a test and training dataset
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.30)
gnb = GaussianNB()
gnb.fit(X_train, y_train)
y_pred=gnb.predict(X_test)
df_output = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(df_output)
         Actual Predicted
     0
             87
                        88
             88
                        88
     1
     2
                        89
             89
     3
                        91
             70
     4
             90
                        91
     5
             89
                        88
     6
             91
                        91
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             82
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             86
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     12
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                        91
     14
             89
# Testing the accuracy of Naive Bayes
scores=cross_val_score(gnb,X_train,y_train,scoring='accuracy',cv=3).mean()*100
print(scores)
     11.616161616161618
sns.jointplot(x=y_test, y=y_pred, kind="kde", color="r")
x=df.loc[:,['Energy','Length','Danceability','beats_per_minute', 'Acousticness']].values
y=df.loc[:,'Popularity'].values
```

```
Traceback (most recent call last)
     KeyError
     <ipython-input-68-da327dffed40> in <module>
     ----> 1 x=df.loc[:,['Energy','Length','Danceability','beats_per_minute', 'Acousticness']].values 2 y=df.loc[:,'Popularity'].values
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.30)
     /usi/jucat/itu/pythons.o/utst-packages/panuas/core/indexing.py in _varidate_read_indexer(seif, key, indexer, axis)
# Linear SVM model
LinSVC = LinearSVC(penalty='12', loss='squared_hinge', dual=True)
LinSVC.fit(X_train, y_train)
y_pred=gnb.predict(X_test)
df_output = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(df_output)
     _____
     NameError
                                              Traceback (most recent call last)
     <ipython-input-46-b77ecb340b7f> in <module>
           2 LinSVC = LinearSVC(penalty='12', loss='squared_hinge', dual=True)
           3 LinSVC.fit(X_train, y_train)
     ----> 4 y_pred=gnb.predict(X_test)
           5 df_output = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
           6 print(df_output)
     NameError: name 'gnb' is not defined
      SEARCH STACK OVERFLOW
# Testing the accuracy
scores=cross_val_score(LinSVC,X_train,y_train,scoring='accuracy',cv=3).mean()*100
print(scores)
     -----
                                              Traceback (most recent call last)
     <ipython-input-45-0ca458fa1a16> in <module>
          1 # Testing the accuracy
     ----> 2 scores=cross_val_score(LinSVC,X_train,y_train,scoring='accuracy',cv=3).mean()*100
          3 print(scores)
     NameError: name 'LinSVC' is not defined
      SEARCH STACK OVERFLOW
sns.jointplot(x=y_test, y=y_pred, kind="reg", color="b");
```

• >