ITI105 Machine Learning Project

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Project Problem: 4 (a) as in suggested project:

- The success of the song can often been measured by whether the song is on the Hit Chart such as Billboard Hot 100. It is important for music labels to know what makes a song successful so that they can focus their budget on making songs that has the highest chance of being successful.

We want to solve the problem statement by using the follow steps:

1. Load dataset
2. Discover & visualize data to gain insights
3. Split data into train and test datasets
4. Scale training data for Feature Selection
5. Feature scaling
6. Train, fine tune and evaluate models
7. Compare performance of models
8. Deployment

(1) Load dataset

```
# Suppress warnings about too few trees from the early models
import warnings
warnings.filterwarnings("ignore", category=UserWarning)
warnings.filterwarnings("ignore", category=RuntimeWarning)

import math
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.svm import SVR
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.ensemble import StackingRegressor
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import ElasticNet
from sklearn.datasets import make_regression
from sklearn.ensemble import GradientBoostingRegressor

df = pd.read_csv('https://raw.githubusercontent.com/dy018/project105/main/song_data.csv')
```

(2) Discover & visualize data to gain insights

```
df.head()
```

	song_name	song_popularity	song_duration_ms	acousticness	danceability	energy	instrumentalness	key	liveness	loudness	a
0	Boulevard of Broken Dreams	73	262333	0.005520	0.496	0.682	0.000029	8	0.0589	-4.095	
1	In The End	66	216933	0.010300	0.542	0.853	0.000000	3	0.1080	-6.407	
2	Seven Nation Army	76	231733	0.008170	0.737	0.463	0.447000	0	0.2550	-7.828	
3	By The Way	74	216933	0.026400	0.451	0.970	0.003550	0	0.1020	-4.938	
4	How You Remind Me	56	223826	0.000954	0.447	0.766	0.000000	10	0.1130	-5.065	

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18835 entries, 0 to 18834
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   song_name         18835 non-null  object
 1   song_popularity   18835 non-null  int64
 2   song_duration_ms  18835 non-null  int64
 3   acousticness      18835 non-null  float64
 4   danceability      18835 non-null  float64
 5   energy            18835 non-null  float64
 6   instrumentalness  18835 non-null  float64
 7   key               18835 non-null  int64
 8   liveness          18835 non-null  float64
 9   loudness          18835 non-null  float64
 10  audio_mode        18835 non-null  int64
 11  speechiness       18835 non-null  float64
 12  tempo             18835 non-null  float64
 13  time_signature    18835 non-null  int64
 14  audio_valence     18835 non-null  float64
dtypes: float64(9), int64(5), object(1)
memory usage: 2.2+ MB
```

```
# Drop song_name since it's not feature to determine song popularity
df.drop(['song_name'], axis=1, inplace=True)

print(">>> Display first 5 records:\n")
df.head()
```

```
>>> Display first 5 records:
```

	song_popularity	song_duration_ms	acousticness	danceability	energy	instrumentalness	key	liveness	loudness	audio_mode
0	73	262333	0.005520	0.496	0.682	0.000029	8	0.0589	-4.095	1
1	66	216933	0.010300	0.542	0.853	0.000000	3	0.1080	-6.407	0
2	76	231733	0.008170	0.737	0.463	0.447000	0	0.2550	-7.828	1
3	74	216933	0.026400	0.451	0.970	0.003550	0	0.1020	-4.938	1
4	56	223826	0.000954	0.447	0.766	0.000000	10	0.1130	-5.065	1

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
#Checking number of unique rows in each feature

df.nunique().sort_values()
```

	0
audio_mode	2
time_signature	5
key	12
song_popularity	101
danceability	849
energy	1132
speechiness	1224
audio_valence	1246
liveness	1425
acousticness	3209
instrumentalness	3925
loudness	8416
song_duration_ms	11771
tempo	12112

dtype: int64

- audio_mode, time_signature and key most likely are categorical features. The rest are numeric features

```
# Study each columns in df
df.describe()
```

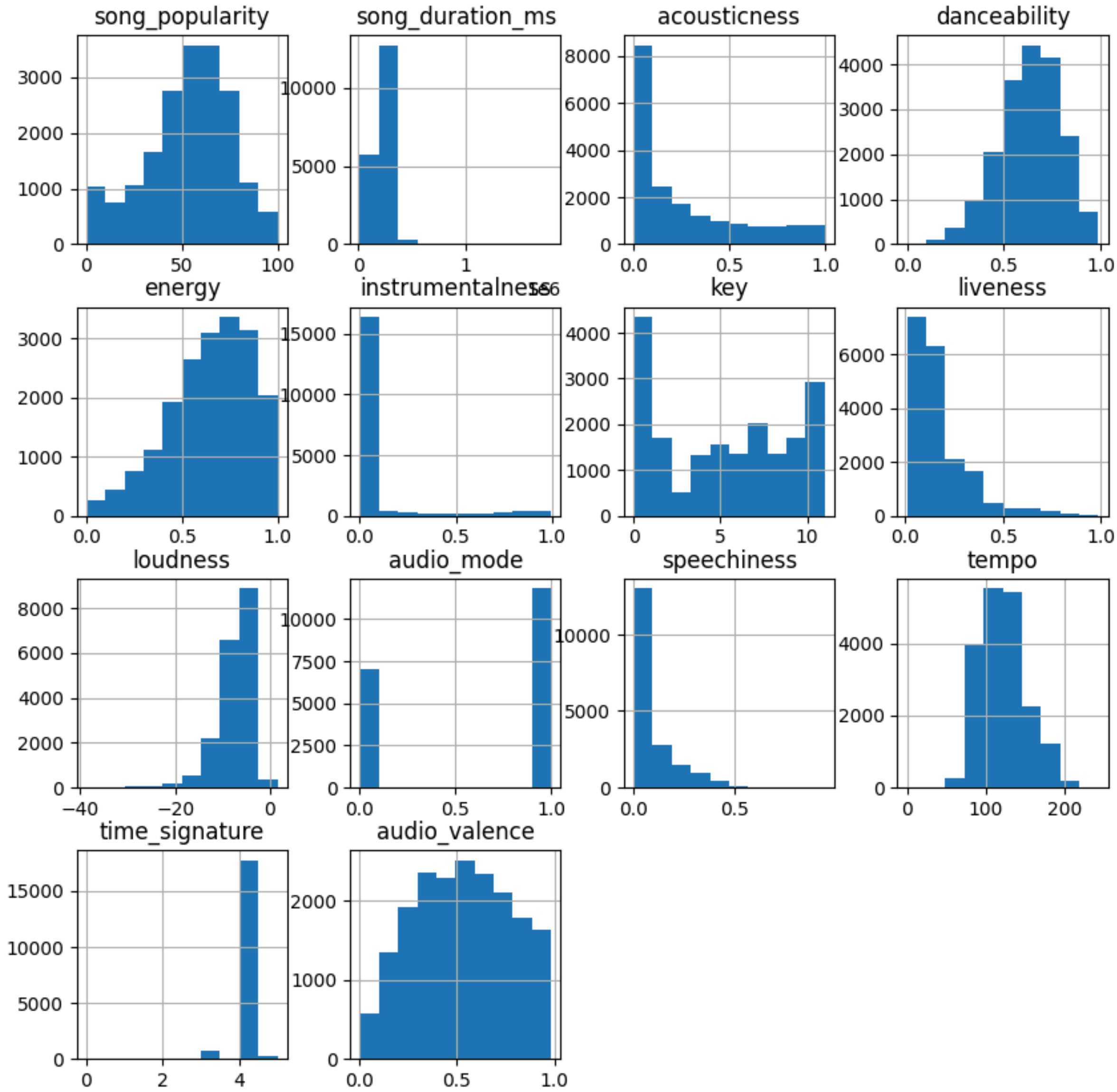
	song_popularity	song_duration_ms	acousticness	danceability	energy	instrumentalness	key	liveness	
count	18835.000000	1.883500e+04	18835.000000	18835.000000	18835.000000	18835.000000	18835.000000	18835.000000	188
mean	52.991877	2.182116e+05	0.258539	0.633348	0.644995	0.078008	5.289196	0.179650	
std	21.905654	5.988754e+04	0.288719	0.156723	0.214101	0.221591	3.614595	0.143984	
min	0.000000	1.200000e+04	0.000001	0.000000	0.001070	0.000000	0.000000	0.010900	-
25%	40.000000	1.843395e+05	0.024100	0.533000	0.510000	0.000000	2.000000	0.092900	
50%	56.000000	2.113060e+05	0.132000	0.645000	0.674000	0.000011	5.000000	0.122000	
75%	69.000000	2.428440e+05	0.424000	0.748000	0.815000	0.002570	8.000000	0.221000	
max	100.000000	1.799346e+06	0.996000	0.987000	0.999000	0.997000	11.000000	0.986000	

```
df['time_signature'].unique()
```

```
array([4, 3, 1, 5, 0])
```

2.2) Data visulisation using histogram

```
# Plot histograms for df to see data distribution

import matplotlib.pyplot as plt
df.hist(figsize=(10,10))
plt.show()
```



Observations:

- Target = Song_popularity (Popularity score from 0 to 100 with 100 as the most popular song).
- Instrumentalness has small data variance and may not be good feature to determine song_popularity

```
df['song_popularity'].skew()
```

```
-0.501487468097605
```

- Skewness is negative, the tail of the distribution is longer towards the left hand side of the curve.

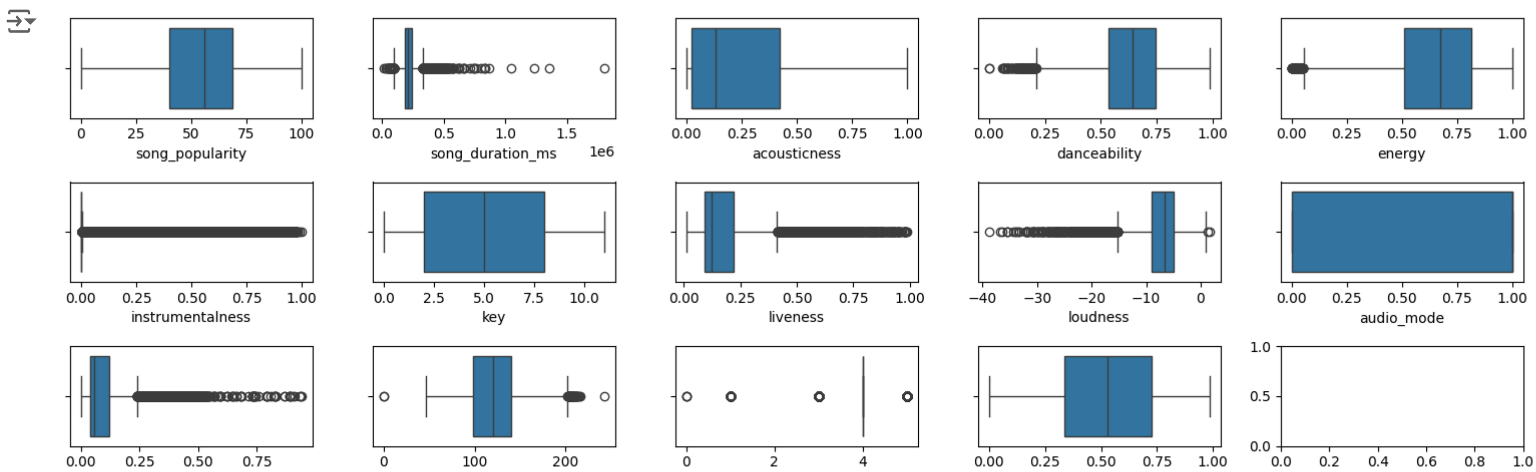
```
df['song_popularity'].kurt()
```

```
-0.16910371120787238
```

- Kurtosis is <3. This is call platykurtic. Compared to a normal distribution, its tails are shorter and thinner, and often its central peak is lower and broader.

2.3) Data visualisation using boxplot

```
# Plot boxplot for numeric features
fig, axs = plt.subplots(3, 5, figsize=(15, 5))

for i, feature in enumerate(df.columns):
    sns.boxplot(x=df[feature], ax=axs[i // 5, i % 5])

# Adjust the layout so that the plots do not overlap
plt.tight_layout()

# Show the plot
plt.show()
```



Observation from boxplots:

- song_duration_ms, danceability, energy, liveness, loudness and speechiness and tempo seem to have outliers.
- instrumentalness can't be plot using boxplot, highly suspect that it's not a feature that is useful to determine song_popularity.

2.4) Data visulisation using correlation matrix

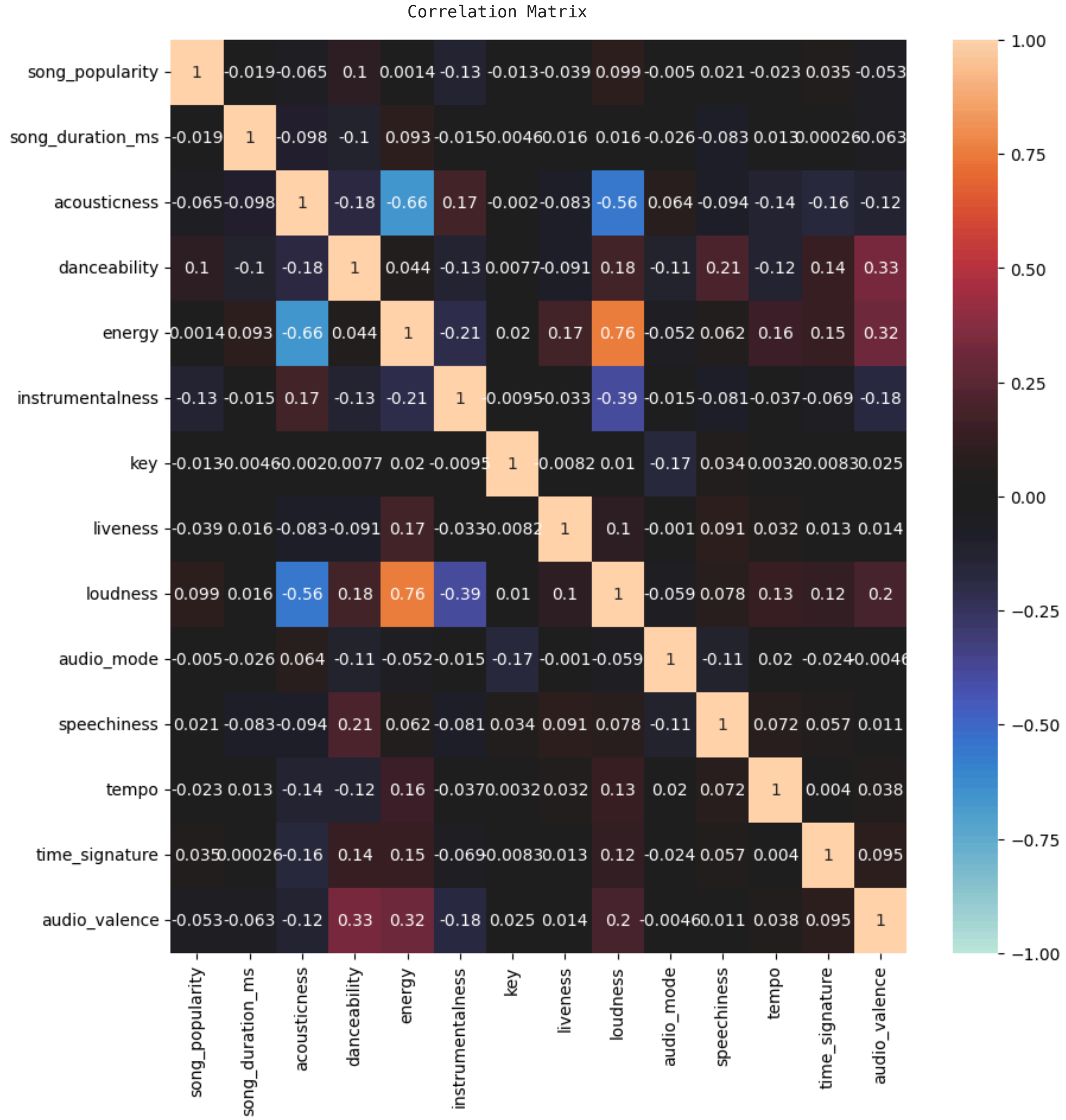
```
corr_matrix = df.corr()
target_correlation = corr_matrix['song_popularity'].sort_values(ascending=False)
print(target_correlation)
```

```
song_popularity     1.000000
danceability        0.104290
loudness            0.099442
time_signature      0.034983
speechiness         0.021479
energy              0.001365
audio_mode         -0.004969
key                -0.013160
song_duration_ms   -0.018899
tempo              -0.022672
liveness           -0.038937
audio_valence      -0.052895
acousticness       -0.065181
instrumentalness   -0.130907
Name: song_popularity, dtype: float64
```

Observation:

- features that has weak & positive correlation to song_popularity are (0.1 to 0.3): danceablity. loudness
- features that has weak negative correlation to song_popularity are: (-0.1 to -0.3) are: instrumentalness
- The rest of the features has negliglbe correlation (0.0 to 0.1 and 0.0 to -0.1)
- Top 3 numeric features that have higher correlation (either positive or negative) to song_popularity are: danceability, loudness and intrumentalness

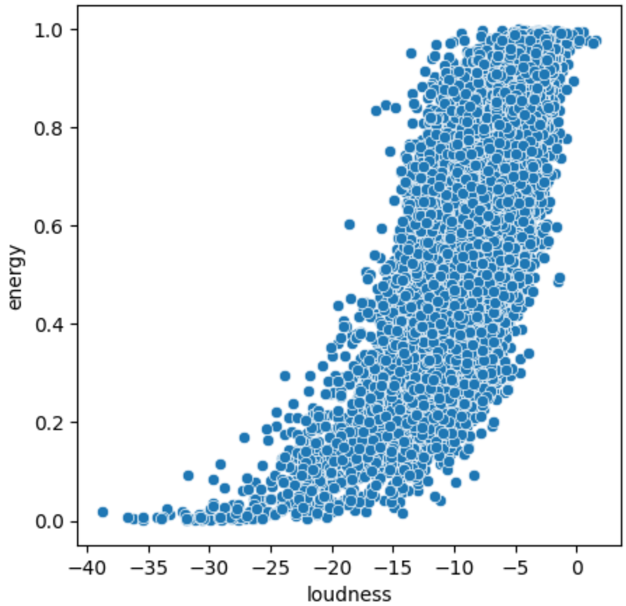
```
print('Correlation Matrix'.center(100))
plt.figure(figsize=[10,10])
sns.heatmap(corr_matrix, annot=True, vmin=-1, vmax=1, center=0) #cmap='BuGn'
plt.show()
```



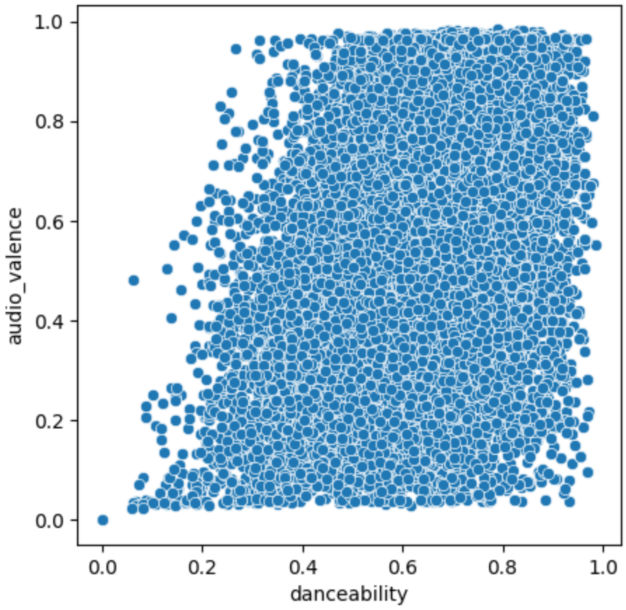
Obeservations:

- there are multi-colinearity between the following features:
-
  - danceability and audio_valence (0.33)
-
  - loudness and energy (0.76)

```
# plot scatterplot for loundnes vs energy to visualize their colinearlity.
plt.figure(figsize=[5,5])
sns.scatterplot(x=df['loudness'],y=df['energy'])

# Show the plot
plt.show()
```




```
# plot scatterplot for danceability and audio_valence  to visualize their colinearlity.
plt.figure(figsize=[5,5])
sns.scatterplot(x=df['danceability'],y=df['audio_valence'])

# Show the plot
plt.show()
```



3) Split dataset to training and test data

```
# Y is target, X is features
Y = df['song_popularity']
X = df.drop(['song_popularity'], axis=1)
```

```
X_train0, X_test, y_train0, y_test = train_test_split(X, Y, train_size=0.8, test_size=0.2, random_state=40)

print(">>> Size of trainig set: ", X_train0.shape)
print(">>> Size of testing set: ", X_test.shape)
```

```
>>> Size of trainig set:  (15068, 13)
>>> Size of testing set:  (3767, 13)
```

```
X_train0.head()
```

	song_duration_ms	acousticness	danceability	energy	instrumentalness	key	liveness	loudness	audio_mode	speechiness
12508	193816	0.001880	0.602	0.433	0.336000	4	0.1800	-13.092	0	0.0308
6546	235773	0.062200	0.839	0.832	0.000005	0	0.2820	-2.492	1	0.0531
6790	228613	0.002390	0.728	0.735	0.000280	0	0.0982	-6.247	1	0.0325
3628	230546	0.187000	0.801	0.410	0.025800	7	0.0993	-12.359	1	0.0322
18219	212438	0.000458	0.804	0.657	0.011900	0	0.1890	-6.021	1	0.0385

Next steps: Generate code with X_train0 | View recommended plots | New interactive sheet

```
y_train0.head()
```

	song_popularity
12508	37
6546	83
6790	41
3628	60
18219	48

dtype: int64

(4) Feature engineerings

```
# conbine X_train0 and y_train0
train_df = pd.concat([y_train0, X_train0], axis=1)
train_df.head()
```

	song_popularity	song_duration_ms	acousticness	danceability	energy	instrumentalness	key	liveness	loudness	audio_mo
12508	37	193816	0.001880	0.602	0.433	0.336000	4	0.1800	-13.092	
6546	83	235773	0.062200	0.839	0.832	0.000005	0	0.2820	-2.492	
6790	41	228613	0.002390	0.728	0.735	0.000280	0	0.0982	-6.247	
3628	60	230546	0.187000	0.801	0.410	0.025800	7	0.0993	-12.359	
18219	48	212438	0.000458	0.804	0.657	0.011900	0	0.1890	-6.021	

Next steps: Generate code with train_df | View recommended plots | New interactive sheet

```
train_df.shape
```

```
(15068, 14)
```

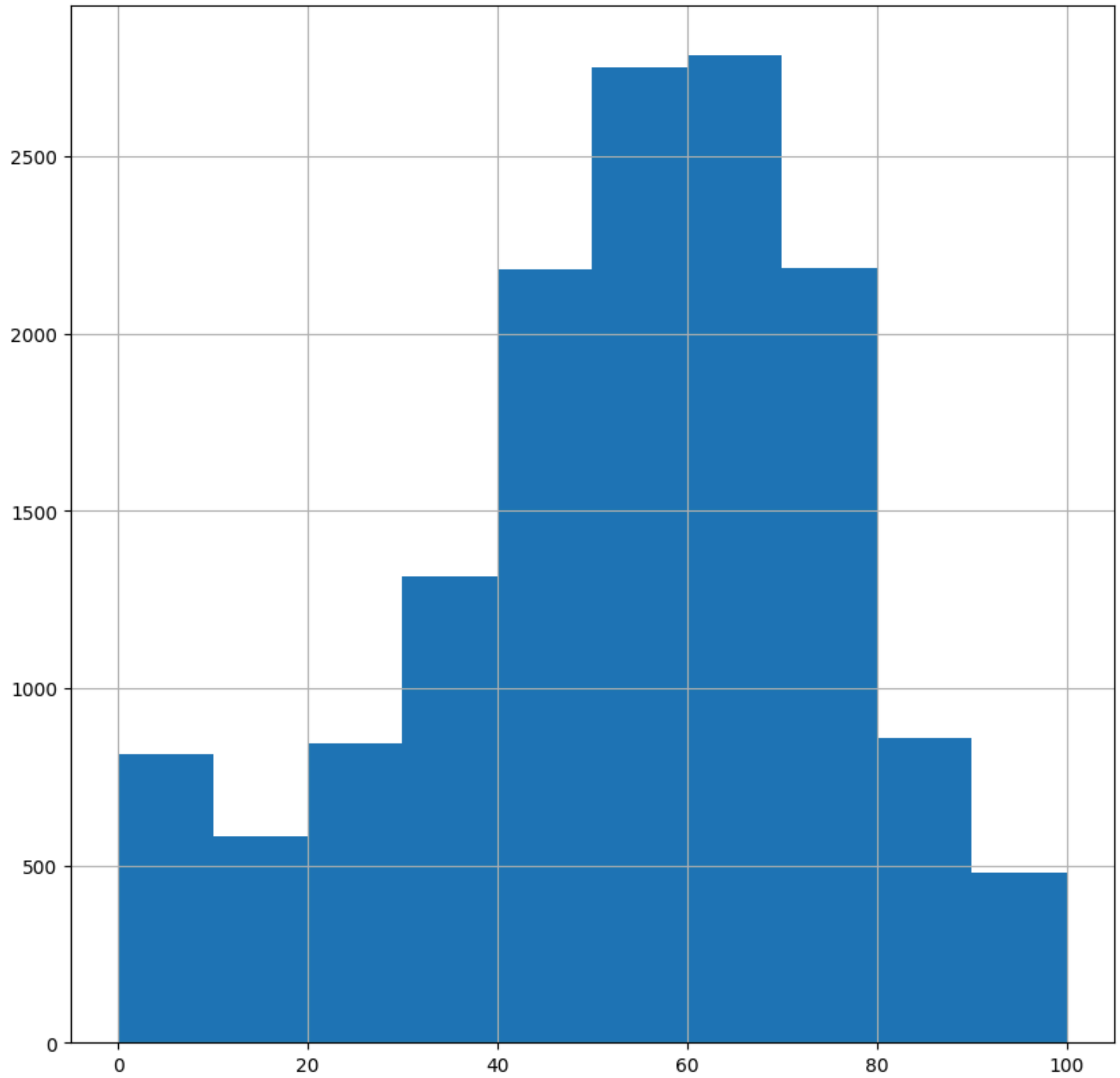
4.1) Remove outliners

- The IQR method is used to remove outliners. This method identifies outliers by measuring the spread of the middle 50% of the data. Data points outside 1.5 times the IQR above the third quartile or below the first quartile are considered outliers.

```
#df1 is df without outliners
df1 = train_df.copy()

# remove outliners in Tempo, danceability, energy featuers that are outside 40% of IQR for both Q1 and Q3 ends respectively
features_w_outliners = ['tempo', 'danceability', 'energy']

for i in features_w_outliners:
  Q1 = df1[i].quantile(0.25)
  Q3 = df1[i].quantile(0.75)
  IQR = Q3 - Q1
  df1 = df1[df1[i] <= (Q3+(1.5*IQR))]
  df1 = df1[df1[i] >= (Q1-(1.5*IQR))]
  df1 = df1.reset_index(drop=True)

print(">>> df's shape after removing outliers:\n", df1.shape)
print(">>> Number of outliers that was removed\n", train_df.shape[0] - df1.shape[0])
```

```
>>> df's shape after removing outliers:
 (14789, 14)
>>> Number of outliers that was removed
 279
```

```
import matplotlib.pyplot as plt
df1['song_popularity'].hist(figsize=(10,10))
plt.show()
```



Double-click (or enter) to edit

```
# Backup training df
df2_imbalanced = df1.copy()
```

4.2) Handle imbalanced datasets

```
Q1_df = df2_imbalanced[df2_imbalanced['song_popularity'] <= 25]
Q2_df = df2_imbalanced[(df2_imbalanced['song_popularity'] > 25) & (df2_imbalanced['song_popularity'] <= 50)]
Q3_df = df2_imbalanced[(df2_imbalanced['song_popularity'] > 51) & (df2_imbalanced['song_popularity'] <= 75)]
Q4_df = df2_imbalanced[(df2_imbalanced['song_popularity'] > 75) & (df2_imbalanced['song_popularity'] <= 100)]

Q1_length = len(Q1_df)
Q2_length = len(Q2_df)
Q3_length = len(Q3_df)
Q4_length = len(Q4_df)
print(">>> Number of records in Q1:", Q1_length)
print(">>> Number of records in Q2:", Q2_length)
print(">>> Number of records in Q3:", Q3_length)
print(">>> Number of records in Q4:", Q4_length)
```

```
>>> Number of records in Q1: 1897
>>> Number of records in Q2: 4091
>>> Number of records in Q3: 6509
>>> Number of records in Q4: 2036
```

```
# determine which df has highest number of data
df_lengths = {
    'Q1_df': Q1_df,
    'Q2_df': Q2_df,
    'Q3_df': Q3_df,
    'Q4_df': Q4_df
}

max_df_name = max(df_lengths, key=lambda k: len(df_lengths[k]))
max_df = df_lengths[max_df_name]
print(f">>> The DataFrame with the maximum number of records is: {max_df_name} with {len(max_df)} records")
```

```
>>> The DataFrame with the maximum number of records is: Q3_df with 6509 records
```

```
from sklearn.model_selection import cross_val_score, KFold
from sklearn.metrics import mean_squared_error
from sklearn.utils import resample

# Upsample 3 df to be the same length with max_df
def upsample_df(tmp_df, max_length):
  df_upsampled = resample(tmp_df,
                          replace=True,     # sample with replacement
                          n_samples=max_length,    # to match majority class
                          random_state=40)  # reproducible results
  return df_upsampled

Q1_df_upsampled = upsample_df(Q1_df, len(max_df))
Q2_df_upsampled = upsample_df(Q2_df, len(max_df))
Q4_df_upsampled = upsample_df(Q4_df, len(max_df))


print(">>> Number of records in Q1_df_upsampled:", len(Q1_df_upsampled))
print(">>> Number of records in Q2_df_upsampled:", len(Q2_df_upsampled))
print(">>> Number of records in Q4_df_upsampled:", len(Q4_df_upsampled))
```

```
>>> Number of records in Q1_df_upsampled: 6509
>>> Number of records in Q2_df_upsampled: 6509
>>> Number of records in Q4_df_upsampled: 6509
```

```
# Combine majority class with upsampled minority class
df_upsampled = pd.concat([Q1_df_upsampled, Q2_df_upsampled, Q3_df, Q4_df_upsampled])
```

```
print(">>> New DF's shape after upsizing minority Quarters is:", df_upsampled.shape)
```

```
>>> New DF's shape after upsizing minority Quarters is: (26036, 14)
```

```
df_upsampled.head(10)
```

	song_popularity	song_duration_ms	acousticness	danceability	energy	instrumentalness	key	liveness	loudness	audio_mo
10560	0	187727	0.745000	0.714	0.447	0.02940	1	0.2200	-15.467	
1592	14	238653	0.000018	0.550	0.917	0.21400	7	0.0333	-4.575	
53	21	161174	0.833000	0.411	0.176	0.87900	2	0.1330	-22.848	
1202	0	186026	0.001420	0.549	0.935	0.00000	2	0.2950	-3.350	
7943	6	202933	0.006490	0.753	0.719	0.00115	1	0.0947	-5.125	
11515	23	221049	0.977000	0.389	0.294	0.00393	8	0.1070	-5.429	
10354	14	210900	0.001200	0.380	0.873	0.43900	7	0.3390	-7.368	
13578	2	224754	0.062900	0.739	0.921	0.00010	7	0.4480	-3.882	
10136	22	301400	0.077100	0.573	0.645	0.01480	8	0.1050	-7.248	
14512	5	253793	0.006340	0.458	0.947	0.63000	3	0.4310	-2.650	

Next steps: Generate code with df_upsampled | View recommended plots | New interactive sheet

4.3) Split features into numeric and categorical features

```
y_train_upsample = df_upsampled['song_popularity']
X_train_upsample = df_upsampled.drop(['song_popularity'], axis=1)
```

```
# song_popularity is target. The rest of columns are features
# Get list of features from df
features = X_train_upsample.columns.tolist()

# put features into 2 types: categorical features and numeric features
category_features = ['audio_mode', 'time_signature', 'key']
numeric_features = [feature for feature in features if feature not in category_features]
print(">>> Categorical features are:", category_features)
print(">>> Numeric features are:", numeric_features)
```

```
>>> Categorical features are: ['audio_mode', 'time_signature', 'key']
>>> Numeric features are: ['song_duration_ms', 'acousticness', 'danceability', 'energy', 'instrumentalness', 'liveness', 'loud
```

```
# split target, numeric and categorical features
X_train_numeric = X_train_upsample[numeric_features]
X_train_category = X_train_upsample[category_features]


print(y_train_upsample.shape)
print(X_train_numeric.shape)
print(X_train_category.shape)
```

```
(26036,)
(26036, 10)
(26036, 3)
```

```
for feature in category_features:
    dummies = pd.get_dummies(X_train_category[feature], prefix=feature)
    X_train_category = pd.concat([X_train_category, dummies], axis=1)
    X_train_category.drop(feature, axis=1, inplace=True)

print(">>> X_train_category's shape using dummy encoding:", X_train_category.shape)
print(">>> Columns in new df_cotegory:\n", X_train_category.columns)
print(">>> First 5 records in X_train_category:\n")
X_train_category.head()
```

```
>>> X_train_category's shape using dummy encoding: (26036, 19)
>>> Columns in new df_cotegory:
 Index(['audio_mode_0', 'audio_mode_1', 'time_signature_0', 'time_signature_1',
       'time_signature_3', 'time_signature_4', 'time_signature_5', 'key_0',
       'key_1', 'key_2', 'key_3', 'key_4', 'key_5', 'key_6', 'key_7', 'key_8',
       'key_9', 'key_10', 'key_11'],
      dtype='object')
>>> First 5 records in X_train_category:
```

	audio_mode_0	audio_mode_1	time_signature_0	time_signature_1	time_signature_3	time_signature_4	time_signature_5	key_
10560	False	True	False	False	False	True	False	Fal
1592	False	True	False	False	True	False	False	Fal
53	False	True	False	False	False	True	False	Fal
1202	False	True	False	False	False	True	False	Fal
7943	True	False	False	False	False	True	False	Fal

Next steps: Generate code with X_train_category | View recommended plots | New interactive sheet

```
print(">>> X_train_numeric's shape is:", X_train_numeric.shape)
print(">>> Columns in new df:\n", X_train_numeric.columns)
print(">>> First 5 records in new X_train_numeric:\n")
X_train_numeric.head()
```

```
>>> X_train_numeric's shape is: (26036, 10)
>>> Columns in new df:
 Index(['song_duration_ms', 'acousticness', 'danceability', 'energy',
       'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo',
       'audio_valence'],
      dtype='object')
>>> First 5 records in new X_train_numeric:
```

	song_duration_ms	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	audio_val
10560	187727	0.745000	0.714	0.447	0.02940	0.2200	-15.467	0.0357	132.986	
1592	238653	0.000018	0.550	0.917	0.21400	0.0333	-4.575	0.0378	109.552	
53	161174	0.833000	0.411	0.176	0.87900	0.1330	-22.848	0.0559	170.450	
1202	186026	0.001420	0.549	0.935	0.00000	0.2950	-3.350	0.0545	150.053	
7943	202933	0.006490	0.753	0.719	0.00115	0.0947	-5.125	0.0347	99.948	

Next steps: Generate code with X_train_numeric | View recommended plots | New interactive sheet

```
# Combine numeric and categorical features before scaling
# X_train_29 = X_train upsampled with 29 features
X_train_29 = pd.concat([X_train_numeric, X_train_category], axis=1)


print(len(X_train_29.columns))
print(X_train_29.columns)
```

```
29
Index(['song_duration_ms', 'acousticness', 'danceability', 'energy',
       'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo',
       'audio_valence', 'audio_mode_0', 'audio_mode_1', 'time_signature_0',
       'time_signature_1', 'time_signature_3', 'time_signature_4',
       'time_signature_5', 'key_0', 'key_1', 'key_2', 'key_3', 'key_4',
       'key_5', 'key_6', 'key_7', 'key_8', 'key_9', 'key_10', 'key_11'],
      dtype='object')
```

```
X_train_29.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 26036 entries, 10560 to 6482
Data columns (total 29 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   song_duration_ms  26036 non-null  int64  
 1   acousticness      26036 non-null  float64
 2   danceability      26036 non-null  float64
 3   energy            26036 non-null  float64
 4   instrumentalness  26036 non-null  float64
 5   liveness          26036 non-null  float64
 6   loudness          26036 non-null  float64
 7   speechiness       26036 non-null  float64
 8   tempo             26036 non-null  float64
 9   audio_valence     26036 non-null  float64
 10  audio_mode_0      26036 non-null  bool   
 11  audio_mode_1      26036 non-null  bool   
 12  time_signature_0  26036 non-null  bool   
 13  time_signature_1  26036 non-null  bool   
 14  time_signature_3  26036 non-null  bool   
 15  time_signature_4  26036 non-null  bool   
 16  time_signature_5  26036 non-null  bool   
 17  key_0             26036 non-null  bool   
 18  key_1             26036 non-null  bool   
 19  key_2             26036 non-null  bool   
 20  key_3             26036 non-null  bool   
 21  key_4             26036 non-null  bool   
 22  key_5             26036 non-null  bool   
 23  key_6             26036 non-null  bool   
 24  key_7             26036 non-null  bool   
 25  key_8             26036 non-null  bool   
 26  key_9             26036 non-null  bool   
 27  key_10            26036 non-null  bool   
 28  key_11            26036 non-null  bool   
dtypes: bool(19), float64(9), int64(1)
memory usage: 2.7 MB
```

4.4) Scale Train data before feature selection

```
# Scale training data
min_max_scaler = MinMaxScaler()

# Fit the scaler to the training data
min_max_scaler.fit(X_train_29)
```

```
▾ MinMaxScaler
MinMaxScaler()
```

```
#Transform training datasets
Xd = min_max_scaler.transform(X_train_29)
```

```
print(Xd)
```

```
[[1.33783582e-01 7.47991710e-01 6.52343750e-01 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [1.75959022e-01 1.75502188e-05 4.38802083e-01 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [1.11793156e-01 8.36345214e-01 2.57812500e-01 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 ...
 [1.56495346e-01 2.67067522e-01 7.86458333e-01 ... 0.00000000e+00
  0.00000000e+00 1.00000000e+00]
 [1.62034982e-01 5.29106767e-02 6.06770833e-01 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [2.25737900e-01 1.65661796e-01 2.21354167e-01 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]]
```

4) Scale training data for Feature Selection

4.1) Feature selection using Lasso Regression

```
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV

# Step 1: Use Lasso Regression for Feature Selection
lasso = Lasso()

# Define the hyperparameter grid
param_grid = {'alpha': [0.008, 0.01, 0.08, 0.1, 0.12]}

# Perform GridSearchCV to find the best alpha
grid_search = GridSearchCV(estimator=lasso, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search.fit(Xd, y_train_upsample)

# Get the best Lasso model
best_lasso = grid_search.best_estimator_

print(f">>> Best Hyperparameters: {grid_search.best_params_}")
print(f">>> Best Score: {grid_search.best_score_}")
print(">>> Lasso's coef are:", best_lasso.coef_)

# Get the indices of the selected features
selected_features = np.where(best_lasso.coef_ != 0)[0]
print(">>> Selected features:", selected_features)
print(f">>> Number of selected features:", len(selected_features))
```

```
>>> Best Hyperparameters: {'alpha': 0.008}
>>> Best Score: -1050.2452507435682
>>> Lasso's coef are: [ -9.63887346  -3.81406329  21.06824113 -17.10395387 -18.24287583
  -2.27468689  48.36081415  -0.77661328   0.3541166  -13.74790312
  -0.87290435   0.           0.          -7.82727082  -2.94718044
   0.           1.63105266   1.38715232   2.62651869  -1.0903901
  -1.32482249  -0.32175736   0.51844664   1.9945622   -2.07383154
  -1.05465958  -1.59575939   1.49607765   1.45545948]
>>> Selected features: [ 0  1  2  3  4  5  6  7  8  9 10 13 14 16 17 18 19 20 21 22 23 24 25 26
 27 28]
>>> Number of selected features: 26
```

```
features_list = selected_features.tolist()

selected_columns = X_train_29.columns[features_list]
selected_columns
```

```
Index(['song_duration_ms', 'acousticness', 'danceability', 'energy',
       'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo',
       'audio_valence', 'audio_mode_0', 'time_signature_1', 'time_signature_3',
       'time_signature_5', 'key_0', 'key_1', 'key_2', 'key_3', 'key_4',
```

```
 'key_5', 'key_6', 'key_7', 'key_8', 'key_9', 'key_10', 'key_11'],
dtype='object')
```

```
out_of_selected_columns = [col for col in X_train_29.columns if col not in selected_columns]
out_of_selected_columns
```

```
['audio_mode_1', 'time_signature_0', 'time_signature_4']
```

Observation:

- 'audio_mode_1', 'time_signature_0', 'time_signature_4' should be removed

Double-click (or enter) to edit

4.2) Feature selection using variance_inflation_factor

```
# Convert the result back to a DataFrame for better visualization
all_features = X_train_29.columns
df_encoded = pd.DataFrame(Xd, columns=all_features)
```

Double-click (or enter) to edit

```
!pip install statsmodels
```

```
Requirement already satisfied: statsmodels in /usr/local/lib/python3.10/dist-packages (0.14.2)
Requirement already satisfied: numpy>=1.22.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (1.26.4)
Requirement already satisfied: scipy!=1.9.2,>=1.8 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (1.13.1)
Requirement already satisfied: pandas!=2.1.0,>=1.4 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (2.1.4)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (0.5.6)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (24.1)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas!=2.1.0,>=1.4->st
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas!=2.1.0,>=1.4->statsmodels)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas!=2.1.0,>=1.4->statsmodel
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.6->statsmodels) (1.16.0)
```

```
from statsmodels.stats.outliers_influence import variance_inflation_factor

DROP=[];

for i in range(len(df_encoded.columns)):
    vif = pd.DataFrame()
    vif['Features'] = df_encoded.columns
    vif['VIF'] = [variance_inflation_factor(df_encoded.values, i) for i in range(df_encoded.shape[1])]
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False)
    vif.reset_index(drop=True, inplace=True)

vif
```

	Features	VIF
0	time_signature_3	inf
1	time_signature_4	inf
2	key_10	inf
3	key_9	inf
4	key_8	inf
5	key_7	inf
6	key_6	inf
7	key_5	inf
8	key_4	inf
9	key_3	inf
10	key_2	inf
11	key_1	inf
12	key_0	inf
13	time_signature_5	inf
14	key_11	inf
15	time_signature_1	inf
16	time_signature_0	inf
17	audio_mode_1	inf
18	audio_mode_0	inf
19	energy	3.44
20	loudness	2.53
21	acousticness	1.86
22	danceability	1.45
23	audio_valence	1.36
24	instrumentalness	1.15
25	speechiness	1.14
26	tempo	1.06
27	liveness	1.05
28	song_duration_ms	1.05

```
# VIF ≥ 5: Indicates high correlation. Use threshold of 5
tobe_drop = vif[(vif['VIF'] > 5)]['Features'].tolist()
print(tobe_drop)
```

```
['time_signature_3', 'time_signature_4', 'key_10', 'key_9', 'key_8', 'key_7', 'key_6', 'key_5', 'key_4', 'key_3', 'key_2', 'ke
```

Observations:

- Base on VIF, audio_mode, key and time_signature shall be removed.

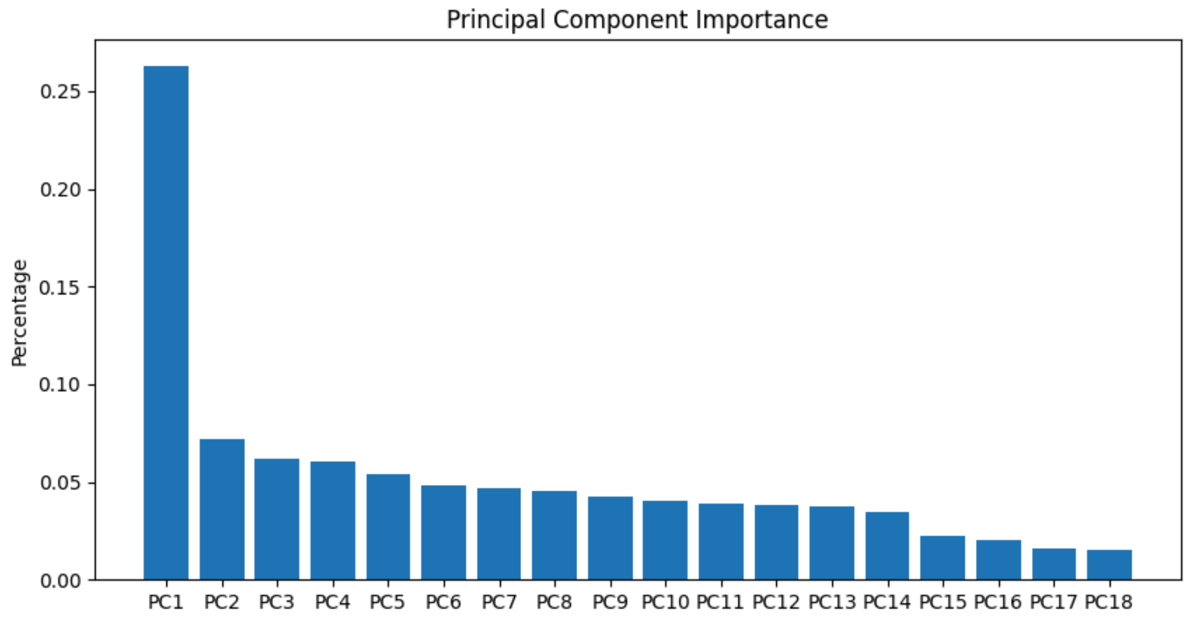
4.3) Feature selection using PCA

- use n_components = 95%

```
from sklearn.decomposition import PCA
pca = PCA(n_components =0.95)
X_pca = pca.fit_transform(Xd)
X_pca.shape
```

```
(26036, 18)
```

```
Cols = ['PC1','PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10','PC11','PC12','PC13','PC14','PC15','PC16','PC17', 'PC18']
rData = pca.explained_variance_ratio_

plt.figure(figsize=(10,5))
plt.bar(Cols, rData)
plt.title('Principal Component Importance')
plt.ylabel('Percentage')
plt.show()
```



Observations from PCA"

- PCA is not a good way to be used to reduce features in this case. We need 18 features if use PCA.

4.4) Final Feature selection

```
# drop 'audio_mode', 'key', 'time_signature' from both training and test data
X_train3 = X_train_upsample.drop(['audio_mode', 'key', 'time_signature'], axis=1)
print(X_train3.shape)
X_train3.head()
y_train3 = y_train_upsample.copy()
```

```
(26036, 10)
```

```
y_train3.head()
```

	song_popularity
10560	0
1592	14
53	21
1202	0
7943	6

dtype: int64

```
y_train3.shape
```

```
(26036,)
```

```
X_test= X_test.drop(['audio_mode', 'key', 'time_signature'], axis=1)
print(X_test.shape)
X_test.head()
```

```
(3767, 10)
```

	song_duration_ms	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	audio_val
16990	223413	0.530000	0.440	0.591	0.000010	0.1710	-7.859	0.0369	121.398	
4028	200400	0.000156	0.591	0.939	0.011100	0.0882	-4.911	0.0533	150.249	
6897	168440	0.628000	0.697	0.656	0.000024	0.4220	-5.380	0.0424	125.624	
9817	215453	0.823000	0.609	0.622	0.000000	0.0999	-4.933	0.1030	135.119	
17869	205933	0.021600	0.554	0.878	0.000006	0.3620	-4.271	0.1340	126.045	

Next steps: Generate code with X_test | View recommended plots | New interactive sheet

5) Scale test and training data before training models

```
# scale train data
mm_scaler = MinMaxScaler()
mm_scaler.fit(X_train3)
```

```
▾ MinMaxScaler
MinMaxScaler()
```

```
import pickle

# Save the pipeline to a pickle file
with open('mm_scaler1.pkl', 'wb') as file:
    pickle.dump(mm_scaler, file)
```

```
# transform train data & test data
X_train = mm_scaler.transform(X_train3)
X_test = mm_scaler.transform(X_test)
```

```
#rename y_train3 to y_train
y_train = y_train3.copy()
```

6. Train, fine tune, and evaluate model's performance

Model Evaluation Functions

```
# calculates r2_score
def cal_r2(y_true, y_pred):
  r2 = r2_score(y_true, y_pred)
  return r2

# Calculates adjusted_r2
def cal_adj_r2(x_df, r2):
  number_variables = x_df[1] - 1
  adjusted_r2 = 1 - ((1-r2) * (x_df[0]-1)) / (x_df[0] - number_variables -1)
  return adjusted_r2

def cal_mse(y_true, y_pred):
  mse = mean_squared_error(y_true, y_pred)
  return mse

def cal_performance(x_train_shape, x_test_shape, y_train, y_train_pred, y_test, y_test_pred):
  r2_train = cal_r2(y_train, y_train_pred)
  r2_test = cal_r2(y_test, y_test_pred)
  adj_r2_train = cal_adj_r2(x_train_shape, r2_train)
  adj_r2_test = cal_adj_r2(x_test_shape, r2_test)
  mse_train = cal_mse(y_train, y_train_pred)
  mse_test = cal_mse(y_test, y_test_pred)

  performance_dict = {
    'r2_train': r2_train,
    'r2_test': r2_test,
    'adj_r2_train': adj_r2_train,
    'adj_r2_test': adj_r2_test,
    'mse_train': mse_train,
    'mse_test': mse_test
    }
  return performance_dict
```

6a) Polynomial Regression (PR)

```
# specify degree of 3 for polynomial regression model
# include bias=False means don't force y-intercept to equal zero
poly = PolynomialFeatures(degree=3, include_bias=False)
poly_train_features = poly.fit_transform(X_train)
poly_test_features = poly.fit_transform(X_test)

# Create LinearRegression
pr = LinearRegression()

# train the model
pr.fit(poly_train_features, y_train)

pr_pred_train = pr.predict(poly_train_features)
pr_pred_test = pr.predict(poly_test_features)


pr_performance = cal_performance(X_train.shape, X_test.shape, y_train, pr_pred_train, y_test, pr_pred_test)
print(pr_performance)
```

```
{'r2_train': 0.18369459084098538, 'r2_test': -0.1880345863613584, 'adj_r2_train': 0.18341230586894086, 'adj_r2_test': -0.19088
```

6b) Multiple Linear Regression (mlr)

```
mlr = LinearRegression()
mlr_param = {'copy_X': [True, False], 'fit_intercept': [True, False], 'n_jobs': [1,5,10,15,None], 'positive': [Tr

random_search = RandomizedSearchCV(mlr, mlr_param, n_iter=100, cv=5)
random_search.fit(X_train, y_train)

# Parameter which gives the best results
print(f"Best Hyperparameters: {random_search.best_params_}")

# Accuracy of the model after using best parameters
print(f"Best Score: {random_search.best_score_}")

# Train the Elastic Net model with the best parameters
best_mlr = random_search.best_estimator_
best_mlr.fit(X_train, y_train)

# Predict on the test set
mlr_pred_train = best_mlr.predict(X_train)
mlr_pred_test = best_mlr.predict(X_test)
```

```
Best Hyperparameters: {'positive': False, 'n_jobs': 1, 'fit_intercept': False, 'copy_X': True}
Best Score: -14.10004061454984
```

```
# Evalute performance
mlr_performance = cal_performance(X_train.shape, X_test.shape, y_train, mlr_pred_train, y_test, mlr_pred_test)
print(mlr_performance)
```

```
{'r2_train': 0.0862277387164525, 'r2_test': -0.07982652966803117, 'adj_r2_train': 0.0859117489234934, 'adj_r2_test': -0.082413
```

6c) Elastic Net Regression (enr)

```
# Create an ElasticNet regression model instance
# l1_ratio corresponds to the mix of L1 and L2 regularization
# alpha corresponds to the strength of the regularization
enr = ElasticNet()

# Define the hyperparameters grid to search
param_grid = {
    'alpha': [0.0005, 0.001, 0.005, 0.1],
    'l1_ratio': [0.1, 0.5, 0.7, 0.9, 1.0],
    'fit_intercept': [True, False],
    'max_iter': [200, 300]
}

# Perform GridSearchCV to find the best hyperparameters
grid_search = GridSearchCV(enr, param_grid, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Print the best parameters and the best score
print("Best parameters found: ", grid_search.best_params_)
print("Best cross-validation score (negative MSE): ", grid_search.best_score_)

# Train the Elastic Net model with the best parameters
best_elastic_net = grid_search.best_estimator_
best_elastic_net.fit(X_train, y_train)

# Predict on the test set
enr_pred_train = best_elastic_net.predict(X_train)
enr_pred_test = best_elastic_net.predict(X_test)
```

```
Best parameters found:  {'alpha': 0.005, 'fit_intercept': False, 'l1_ratio': 0.9, 'max_iter': 300}
Best cross-validation score (negative MSE):  -1048.1163181669212
```

```
# Evaluate the model
enr_performance = cal_performance(X_train.shape, X_test.shape, y_train, enr_pred_train, y_test, enr_pred_test)
print(enr_performance)
```

```
{'r2_train': 0.08598942449800084, 'r2_test': -0.07823928039864714, 'adj_r2_train': 0.08567335229406947, 'adj_r2_test': -0.0808
```

6d) Adaboost (ada)

```
# Define the AdaBoost Regressor model
adaboost = AdaBoostRegressor() # base estimator is DecisionTreeRegressor

# Define the hyperparameters grid to search
param_grid = {
```

```
# Evaluate the model
ada_performance = cal_performance(X_train.shape, X_test.shape, y_train, ada_pred_train, y_test, ada_pred_test)
print(ada_performance)
```

```
{'r2_train': 0.0730457929210826, 'r2_test': -0.06768204977519687, 'adj_r2_train': 0.0727252447053095, 'adj_r2_test': -0.070239
```

```
grid_search.fit(X_train, y_train)
```

6e) Gradient Boosting Regressor (gbr)

```
print("Best cross-validation score (negative MSE): ", grid_search.best_score_)
```

```
from sklearn.ensemble import GradientBoostingRegressor

# Create a Gradient Boosting Regressor model
gbr = GradientBoostingRegressor()

# Define the hyperparameters grid to search
param_grid = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.001, 0.005, 0.01, 0.05, 1],
    'max_depth': [3,5,7,9,11,13,15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Perform GridSearchCV to find the best hyperparameters
random_search = RandomizedSearchCV(gbr, param_distributions=param_grid, n_iter=100, cv=5, scoring='neg_mean_squared_error', n_jobs
random_search.fit(X_train, y_train)


# Print the best parameters and the best score
print("Best parameters found: ", random_search.best_params_)
print("Best cross-validation score (negative MSE): ", random_search.best_score_)

# Train the AdaBoost Regressor model with the best parameters
best_gbr = random_search.best_estimator_
best_gbr.fit(X_train, y_train)

# Predict on the test data
gbr_pred_train = best_gbr.predict(X_train)
gbr_pred_test = best_gbr.predict(X_test)
```

```
Best parameters found:  {'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_depth': 13, 'learning_rate':
Best cross-validation score (negative MSE):  -348.39125056614023
```

```
# Evaluate the model
gbr_performance = cal_performance(X_train.shape, X_test.shape, y_train, gbr_pred_train, y_test, gbr_pred_test)
print(gbr_performance)
```

```
{'r2_train': 0.9761310835580804, 'r2_test': 0.31936756311143355, 'adj_r2_train': 0.9761228294949137, 'adj_r2_test': 0.31773708
```

6f) RBF SVC (RBF)

```
# Define the SVR model with RBF kernel
svr = SVR(kernel='rbf')

# Define the hyperparameters grid to search
param_grid = {
    'C': [0.1, 1, 10, 100, 200],
    'gamma': [1e-1, 1, 2, 3, 4, 5],
    'epsilon': [0.01, 0.1, 1, 10]
}
```