EDA

March 28, 2024

1 EDA - Spotify Top Songs and Audio Features

The goals of this analysis are: * Loading the data into a code environment and in a dataframe that can be manipulated * Getting familiar with the data * Basic preprocessing, checking for anomalous data or wrongly formatted data or NANs etc. * First visualizations of the data and its distributions. * Creating a new dataset that is indexed by artists and not by tracks and finding suitable ways to "average" the values across all the tracks from an artist.

Imports

[18]:
```
#Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import mode
```

[19]:
```
# Load the dataset into a DataFrame
df = pd.read_csv('data.csv')

# Display the first few rows of the DataFrame
df.head(10)
```

[19]:
```
                       id                                        artist_names  \
0  000xQL6tZNLJzIrtIgxqSl                                 ZAYN, PARTYNEXTDOOR
1  003eoIwxETJujVWmNFMoZy                                        Alessia Cara
2  003vvx7Niy0yvhvHt4a68B                                         The Killers
3  00B7TZ0Xawar6NZ00JFomN                          Cardi B, Chance the Rapper
4  00Blm7zeNqgYLPtW6zg8cj                             Post Malone, The Weeknd
5  00EPIEnX1JFjff8sC6bccd                              Thalia, NATTI NATASHA
6  00ETaeHUQ6lops3oWU1Wrt                                 Kygo, Donna Summer
7  00ZKeP47bZtswtANkvxz2j  Tropa do Bruxo, DJ Ws da Igrejinha, SMU, Triz,…
8  00gpGR84M27moP7AFuqHIx                                         YBN Nahmir
9  00imgaPlYRrMGn9o83hfmk                                        Brent Faiyaz

                             track_name  \
0  Still Got Time (feat. PARTYNEXTDOOR)
1                          Growing Pains
```

```
2                     Mr. Brightside
3  Best Life (feat. Chance The Rapper)
4      One Right Now (with The Weeknd)
5                      No Me Acuerdo
6                          Hot Stuff
7                     Baile do Bruxo
8               Bounce Out With That
9                       LOOSE CHANGE

                                      source     key   mode time_signature  \
0                          RCA Records Label       G  Major        4 beats
1                        Def Jam Recordings  C#/Db  Minor        4 beats
2                            Island Records  C#/Db  Major        4 beats
3                              Atlantic/KSR       A  Major        4 beats
4                          Republic Records  C#/Db  Major        4 beats
5                          Sony Music Latin       G  Minor        4 beats
6                         RCA Records Label       F  Major        4 beats
7                            Tropa Do Bruxo       G  Minor        5 beats
8                                      2018  G#/Ab  Major        4 beats
9  Lost Kids LLC., Marketed by Venice / Stem  C#/Db  Minor        4 beats

   danceability  energy  speechiness  acousticness  instrumentalness  \
0         0.748   0.627       0.0639       0.13100          0.000000
1         0.353   0.755       0.7330       0.08220          0.000000
2         0.352   0.911       0.0747       0.00121          0.000000
3         0.620   0.625       0.5530       0.28700          0.000000
4         0.687   0.781       0.0530       0.03610          0.000000
5         0.836   0.799       0.0873       0.18700          0.000000
6         0.681   0.773       0.1480       0.01900          0.000001
7         0.734   0.228       0.5300       0.88900          0.006420
8         0.857   0.560       0.1730       0.04260          0.000000
9         0.574   0.369       0.0814       0.75300          0.000000

   liveness  valence  loudness    tempo  duration_ms  weeks_on_chart  \
0    0.0852    0.524    -6.029  120.963       188491              17
1    0.3900    0.437    -6.276  191.153       193680               2
2    0.0995    0.236    -5.230  148.033       222973             125
3    0.3140    0.665    -7.438  167.911       284856               2
4    0.0755    0.688    -4.806   97.014       193507              30
5    0.0920    0.772    -4.247   94.033       217653              16
6    0.1100    0.429    -5.749  119.961       199008               1
7    0.1020    0.522    -4.731  162.524       221538               3
8    0.1530    0.482    -8.278   94.949        91011               6
9    0.1470    0.440    -8.931   84.975       226011               1

     streams
0  107527761
```

```
1      9944865
2    512388123
3     11985346
4    301860377
5     98123727
6      4569978
7     27916960
8      4913180
9      5854629
```

1.0.1 Inspecting the data

We notice that we have some basic information about each songs, like for example the artist name, the track name, the record label, these identify a song and is information that is searched by the user. We also have other metrics like the mode (Major or Minor) and the key, time signature, duration of the song and tempo. These are the musical "stats" of a track. In addition we have some spotify platform specific data, the number of streams for each track, and the number of weeks that the data was on charts. What makes the dataset very interesting to us however, is the addition of these tasteful features about each track such as "danceability", "energy" and "valence" etc. These features are calculated by the author of the dataset, the code for the creation of the dataset can be viewed here: github link to the dataset creation code. We will be making full use of these highly unusual and fun features in our visualizations, but let us first define what is meant by each feature as they are not all self-evident.

- Danceability: How suitable a track is for dancing. (0.0 -> 1.0).
- Energy: A perceptual measure of intensity and activity (0.0 -> 1.0).
- Speechiness: The presence of spoken words in a track. (0.0 -> 1.0).
- Acousticness: A confidence measure of whether a track is acoustic (0.0 -> 1.0).
- Instrumentalness: Predicts whether a track contains no vocals (0.0 -> 1.0).
- Liveness: Detects the presence of an audience in the recording (0.0 -> 1.0).
- Valence: Describes how positive the track is conveyed to be (0.0 -> 1.0).
- Loudness: The overall loudness of the track in decibels (-34.5 -> 1.51).

Let's inspect the shape of this data

[20]:
```
np.shape(df)
```

[20]:
```
(6513, 19)
```

Indeed, there are 6513 different rows, indicating 6513 tracks, and 19 different columns, uniquely inded by the ID column. We would like to first check that there are actually 6513 distinct tracks,

[21]:
```
unique_tracks = df['track_name'].nunique()
print(f"Number of unique tracks: {unique_tracks}")
```

```
Number of unique tracks: 5351
```

As we might expect, there are fewer unique tracks than there are rows, suggesting the possibility for duplicate tracks. In practice this makes sense as some tracks share the same name but are different songs (for example "Afterglow" - by Ed Sheeran, and "Afterglow" - by Taylor Swift). We might similarly expect the same, or a vastly similar song to be "remixed" and published by multiple artists. Lastly, some artists will even re-release some of their older songs, an example of this is taylor swift's album "Fearless" - Taylor's version.

Let's see if there are any null values in the dataset.

[22]:
```
df.isnull().sum()
```

[22]:
```
id                  0
artist_names        0
track_name          0
source              0
key                 0
mode                0
time_signature      0
danceability        0
energy              0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
loudness            0
tempo               0
duration_ms         0
weeks_on_chart      0
streams             0
dtype: int64
```

We observe that there are no null values in the dataset which is nice to see!

Next we would like to start creating new dataframes from this raw dataframe so that it is more fit to be used for our purpose. To this end, we will need two separate dataframes, one that is indexed by artists, and one that is indexed by the tracks, as the one we have above already is what we are looking for, we will proceed by creating a dataframe that is indexed by the artists.

Our approach for doing this will be as follows: * We will split artist_names into artists, so that we have at most one artist per row. This will lead to some tracks being repeated, but that is fine. * We will split the features into categorical features and continuous numerical columns (excluding weeks_on_chart and streams), and we will take the mean for the numerical features such as energy, on an artist to artist basis, and we will take the mode of the categorical features on an artist to artist basis. instead of averaging streams and weeks_on_charts, we think it is more suitable to aggregate and sum the streams. * Finally we sort by the number of streams for each artist.

[28]:
```
# Splitting artists and expanding the DataFrame to have one artist per row
df['artist'] = df['artist_names'].str.split(', ')
df_expanded = df.explode('artist')

# Drop the 'id' column and the original 'artist_names' column
df_expanded.drop(['id', 'artist_names'], axis=1, inplace=True)
```

```python
# Update numerical columns list, excluding 'weeks_on_chart' and 'streams' for␣
↪special treatment
numerical_cols = ['danceability', 'energy', 'speechiness', 'acousticness',
                  'instrumentalness', 'liveness', 'valence', 'loudness',
                  'tempo', 'duration_ms']

# Define categorical columns
categorical_cols = ['key', 'mode', 'time_signature']

# Update aggregation functions
aggregations = {**{col: 'mean' for col in numerical_cols},
                **{col: lambda x: pd.Series.mode(x)[0] if not pd.Series.mode(x).
↪empty else np.nan for col in categorical_cols},
                'weeks_on_chart': 'sum',  # Summing weeks_on_chart
                'streams': 'sum'}  # Summing streams

# Performing the aggregation
artist_df = df_expanded.groupby('artist', as_index=False).agg(aggregations)

# Rename columns 'weeks_on_chart' and 'streams' for clarity
artist_df.rename(columns={'weeks_on_chart': 'weeks_on_chart_total', 'streams':␣
↪'total_streams'}, inplace=True)

# Sort the DataFrame by 'total_streams' in descending order
artist_df_sorted = artist_df.sort_values(by='total_streams', ascending=False)

artist_df_sorted.head(10)
```

[28]:

```
               artist  danceability    energy  speechiness  acousticness  \
172         Bad Bunny      0.749264  0.675874     0.123582      0.240423
1810       The Weeknd      0.612779  0.639500     0.097388      0.192148
509             Drake      0.706118  0.544405     0.194416      0.201880
1462      Post Malone      0.633874  0.637225     0.081846      0.261542
1757     Taylor Swift      0.596606  0.577000     0.062285      0.307204
535        Ed Sheeran      0.672726  0.610749     0.092308      0.323409
892     Justin Bieber      0.668372  0.587333     0.083179      0.276969
772          J Balvin      0.750067  0.729067     0.128871      0.126857
515          Dua Lipa      0.728800  0.722178     0.085451      0.064339
128     Ariana Grande      0.657109  0.614119     0.101528      0.233330

      instrumentalness  liveness   valence  loudness       tempo  \
172           0.012356  0.172444  0.497427 -5.591346  122.768327
1810          0.007456  0.198514  0.389238 -6.732298  121.133731
509           0.013069  0.200462  0.366806 -7.848524  118.929795
1462          0.005981  0.159996  0.393936 -5.367523  122.025838
1757          0.004629  0.139067  0.401780 -7.631493  123.227473
```

```
535           0.000282  0.172138  0.534940 -6.035131  110.235393
892           0.004377  0.148803  0.550290 -6.618321  122.068397
772           0.008111  0.187484  0.647556 -4.684467  123.145311
515           0.000172  0.143736  0.647844 -5.124644  116.704222
128           0.000670  0.177766  0.472035 -6.133743  117.480604

        duration_ms    key   mode time_signature  weeks_on_chart_total  \
172   214440.276730  C#/Db  Major        4 beats                  2912
1810  220141.932692      C  Minor        4 beats                  2243
509   226178.131004  C#/Db  Major        4 beats                  2436
1462  194904.702703      C  Major        4 beats                  2213
1757  237324.142857      C  Major        4 beats                  1545
535   217245.000000  G#/Ab  Major        4 beats                  2080
892   189779.294872  F#/Gb  Major        4 beats                  1602
772   215137.966667      A  Minor        4 beats                  1891
515   202467.600000      B  Minor        4 beats                  1447
128   191435.039604      C  Major        4 beats                  1308

      total_streams
172     31355337608
1810    21530493586
509     20961364679
1462    17775430798
1757    17106209239
535     16646366081
892     15666378558
772     14396444218
515     13890564424
128     12850455403
```

Unsurprisingly, the more popular artists have the most number of streams. It would now be interesting to take the top 50 most popular artists and find the top 5 artitsts for each "interesting" feature. Let us proceed.

[31]:
```python
# Isolating the top 50 most popular artists
top_50_artists = artist_df_sorted.head(50)

# Define "interesting" features
interesting_features = ['danceability', 'energy', 'speechiness', 'acousticness',
                        'instrumentalness', 'liveness', 'valence', 'loudness',␣
 ↪'tempo']

# Initialize a dictionary to hold the top 5 artists for each feature
top_5_artists_per_feature = {}

# For each feature, find the top 5 artists
for feature in interesting_features:
```

```
    top_5_artists = top_50_artists.nlargest(5, feature)[['artist', feature]]
    top_5_artists_per_feature[feature] = top_5_artists

# Now, top_5_artists_per_feature contains the top 5 artists for each␣
 ↪interesting feature
# Let's display the results
for feature, top_5_df in top_5_artists_per_feature.items():
    print(f"Top 5 artists for {feature}:")
    print(top_5_df)
    print("\n---\n")
```

```
Top 5 artists for danceability:
          artist  danceability
305       Cardi B      0.837542
414        DaBaby      0.817590
1340  Nicki Minaj      0.795565
1977   Young Thug      0.793333
904       KAROL G      0.781964

---

Top 5 artists for energy:
            artist    energy
415   Daddy Yankee  0.802250
1439    Peso Pluma  0.743395
118       Anuel AA  0.734823
1403         Ozuna  0.733974
1180    Marshmello  0.730393

---

Top 5 artists for speechiness:
              artist  speechiness
563           Eminem     0.267535
414           DaBaby     0.251990
944   Kendrick Lamar     0.236410
8          21 Savage     0.227059
1340     Nicki Minaj     0.210558

---

Top 5 artists for acousticness:
              artist  acousticness
213    Billie Eilish      0.674056
1027   Lewis Capaldi      0.632300
1596       Sam Smith      0.467740
1383  Olivia Rodrigo      0.455837
1947    XXXTENTACION      0.402349
```

```
Top 5 artists for instrumentalness:
             artist  instrumentalness
213   Billie Eilish          0.161094
954          Khalid          0.073047
363        Coldplay          0.042076
1947   XXXTENTACION          0.036406
8         21 Savage          0.021267
```

```
Top 5 artists for liveness:
            artist  liveness
563         Eminem  0.288039
415   Daddy Yankee  0.215920
363       Coldplay  0.214458
1853  Travis Scott  0.207632
509          Drake  0.200462
```

```
Top 5 artists for valence:
            artist   valence
1439    Peso Pluma  0.750070
1158        Maluma  0.700223
415   Daddy Yankee  0.698659
414         DaBaby  0.676256
515       Dua Lipa  0.647844
```

```
Top 5 artists for loudness:
              artist  loudness
415     Daddy Yankee -3.861568
1506  Rauw Alejandro -3.974327
118         Anuel AA -4.389758
1158          Maluma -4.452564
1403           Ozuna -4.461092
```

```
Top 5 artists for tempo:
              artist       tempo
1042       Lil Nas X  140.948441
1383  Olivia Rodrigo  136.295677
643           Future  132.135346
```

```
881       Juice WRLD  131.735691
1439      Peso Pluma  131.702070
```

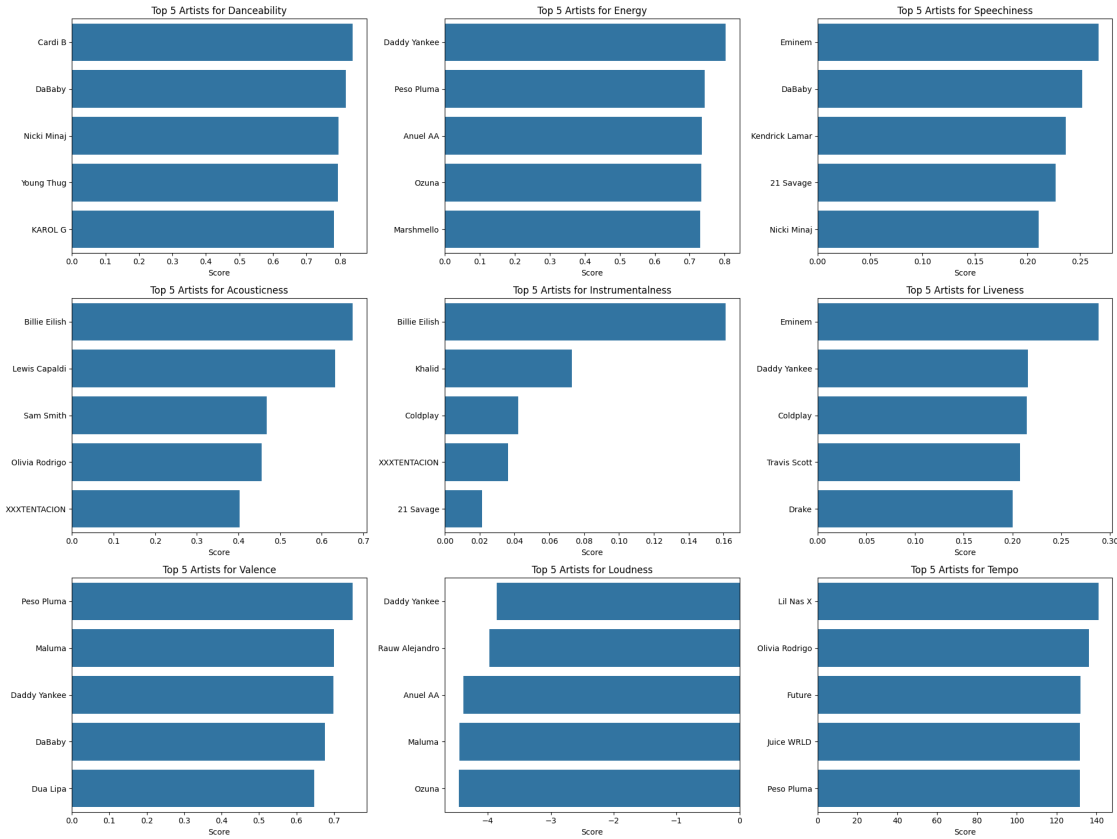
Let's visualize this data!

[32]:
```python
# Set up the matplotlib figure
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(20, 15),␣
 ↪constrained_layout=True)
axes = axes.flatten()

# Iterate over each interesting feature and its corresponding top 5 DataFrame
for i, (feature, top_5_df) in enumerate(top_5_artists_per_feature.items()):
    sns.barplot(x=feature, y='artist', data=top_5_df, ax=axes[i])
    axes[i].set_title(f'Top 5 Artists for {feature.capitalize()}')
    axes[i].set_xlabel('Score')
    axes[i].set_ylabel('')

#plot
plt.tight_layout()
plt.show()
```

```
C:\Users\Christopher\AppData\Local\Temp\ipykernel_302612\1380144436.py:13:
UserWarning: The figure layout has changed to tight
  plt.tight_layout()
```



Observing this data, we can kind of make sense of it, we would expect rappers like eminem to have the most"speechiness" in their songs on average. We would also expect the popular songs in the night club scene to appear on the "danceability" top 5.