main

April 24, 2024

[ ]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import datetime as dt
```

[ ]:

```python
# load data from data/tracks.csv
tracks = pd.read_csv('data/tracks.csv')
tracks.head()
```

```
C:\Users\sevcn\AppData\Local\Temp\ipykernel_6124\363931543.py:2: DtypeWarning:
Columns (4) have mixed types. Specify dtype option on import or set
low_memory=False.
  tracks = pd.read_csv('data/tracks.csv')
```

[ ]:

```
                       id                                 name  popularity  \
0  35iwgR4jXetI318WEWsa1Q                                Carve           6
1  021ht4sdgPcrDgSk7JTbKY  Capítulo 2.16 - Banquero Anarquista           0
2  07A5yehtSnoedViJAZkNnc   Vivo para Quererte - Remasterizado           0
3  08FmqUhxtyLTn6pAh6bk45        El Prisionero - Remasterizado           0
4  08y9GfoqCWfOGsKdwojr5e                  Lady of the Evening           0

   duration_ms explicit              artists                  id_artists  \
0       126903        0              ['Uli']  ['45tIt06XoI0Iio4LBEVpls']
1        98200        0  ['Fernando Pessoa']  ['14jtPCOoNZwquk5wd9DxrY']
2       181640        0  ['Ignacio Corsini']  ['5LiOoJbxVSAMkBS2fUm3X2']
3       176907        0  ['Ignacio Corsini']  ['5LiOoJbxVSAMkBS2fUm3X2']
4       163080        0      ['Dick Haymes']  ['3BiJGZsyX9sJchTqcSA7Su']

  release_date  danceability  energy  key  loudness  mode  speechiness  \
0   1922-02-22         0.645  0.4450  0.0   -13.338   1.0       0.4510
1   1922-06-01         0.695  0.2630  0.0   -22.136   1.0       0.9570
2   1922-03-21         0.434  0.1770  1.0   -21.180   1.0       0.0512
3   1922-03-21         0.321  0.0946  7.0   -27.961   1.0       0.0504
4         1922         0.402  0.1580  3.0   -16.900   0.0       0.0390

   acousticness  instrumentalness  liveness  valence    tempo  time_signature
```

```
0       0.674        0.7440    0.151    0.127  104.851            3.0
1       0.797        0.0000    0.148    0.655  102.009            1.0
2       0.994        0.0218    0.212    0.457  130.418            5.0
3       0.995        0.9180    0.104    0.397  169.980            3.0
4       0.989        0.1300    0.311    0.196  103.220            4.0
```

[ ]:
```
tracks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 586672 entries, 0 to 586671
Data columns (total 20 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   id                586672 non-null  object
 1   name              586601 non-null  object
 2   popularity        586672 non-null  int64
 3   duration_ms       586672 non-null  int64
 4   explicit          586672 non-null  object
 5   artists           586672 non-null  object
 6   id_artists        586672 non-null  object
 7   release_date      586672 non-null  object
 8   danceability      586672 non-null  float64
 9   energy            586672 non-null  float64
 10  key               586672 non-null  float64
 11  loudness          586672 non-null  float64
 12  mode              586672 non-null  float64
 13  speechiness       586672 non-null  float64
 14  acousticness      586672 non-null  float64
 15  instrumentalness  586672 non-null  float64
 16  liveness          586672 non-null  float64
 17  valence           586672 non-null  float64
 18  tempo             586672 non-null  float64
 19  time_signature    586671 non-null  float64
dtypes: float64(12), int64(2), object(6)
memory usage: 89.5+ MB
```

[ ]:
```
tracks.shape
```

[ ]:
```
(586672, 20)
```

[ ]:
```
tracks.isnull().sum()
```

[ ]:
```
id                   0
name                71
popularity           0
duration_ms          0
explicit             0
artists              0
```

```
id_artists          0
release_date        0
danceability        0
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
tempo               0
time_signature      1
dtype: int64
```

```
[ ]: # show the distribution of length of string in release_date
     tracks['release_date'].apply(len).value_counts()
```

```
[ ]: release_date
     10    448080
     4     136489
     7       2102
     5          1
     Name: count, dtype: int64
```

```
[ ]: tracks.dropna(inplace=True)
```

```
[ ]: tracks.describe()
```

```
[ ]:          popularity   duration_ms   danceability         energy  \
     count  586600.000000  5.866000e+05  586600.000000  586600.000000
     mean       27.573173  2.300548e+05       0.563612       0.542071
     std        18.369407  1.265329e+05       0.166102       0.251911
     min         0.000000  3.344000e+03       0.000000       0.000000
     25%        13.000000  1.750830e+05       0.453000       0.343000
     50%        27.000000  2.149070e+05       0.577000       0.549000
     75%        41.000000  2.638670e+05       0.686000       0.748000
     max       100.000000  5.621218e+06       0.991000       1.000000

                      key       loudness           mode    speechiness  \
     count  586600.000000  586600.000000  586600.000000  586600.000000
     mean        5.221596     -10.205784       0.658798       0.104870
     std         3.519422       5.089425       0.474113       0.179903
     min         0.000000     -60.000000       0.000000       0.000000
     25%         2.000000     -12.891000       0.000000       0.034000
     50%         5.000000      -9.242000       1.000000       0.044300
```

```
75%         8.000000      -6.481000       1.000000       0.076300
max        11.000000       5.376000       1.000000       0.971000

        acousticness  instrumentalness       liveness        valence  \
count  586600.000000     586600.000000  586600.000000  586600.000000
mean        0.449803          0.113425       0.213933       0.552306
std         0.348813          0.266843       0.184328       0.257673
min         0.000000          0.000000       0.000000       0.000000
25%         0.096900          0.000000       0.098300       0.346000
50%         0.422000          0.000024       0.139000       0.564000
75%         0.784000          0.009550       0.278000       0.769000
max         0.996000          1.000000       1.000000       1.000000

               tempo  time_signature
count  586600.000000   586600.000000
mean      118.467907        3.873409
std        29.762962        0.473112
min         0.000000        0.000000
25%        95.606000        4.000000
50%       117.387000        4.000000
75%       136.324000        4.000000
max       246.381000        5.000000
```

[ ]:

```python
tracks['release_year'] = tracks['release_date'].apply(lambda x: int(x[:4]))
print(tracks['release_year'].min())
print(tracks['release_year'].max())
tracks.head()
```

```
1900
2021
```

[ ]:

```
                       id                                  name  popularity  \
0  35iwgR4jXetI318WEWsa1Q                                 Carve           6
1  021ht4sdgPcrDgSk7JTbKY  Capítulo 2.16 - Banquero Anarquista           0
2  07A5yehtSnoedViJAZkNnc   Vivo para Quererte - Remasterizado           0
3  08FmqUhxtyLTn6pAh6bk45        El Prisionero - Remasterizado           0
4  08y9GfoqCWfOGsKdwojr5e                  Lady of the Evening           0

   duration_ms explicit              artists                  id_artists  \
0       126903        0              ['Uli']  ['45tIt06XoI0Iio4LBEVpls']
1        98200        0  ['Fernando Pessoa']  ['14jtPCOoNZwquk5wd9DxrY']
2       181640        0  ['Ignacio Corsini']  ['5LiOoJbxVSAMkBS2fUm3X2']
3       176907        0  ['Ignacio Corsini']  ['5LiOoJbxVSAMkBS2fUm3X2']
4       163080        0      ['Dick Haymes']  ['3BiJGZsyX9sJchTqcSA7Su']

  release_date  danceability  energy  …  loudness  mode  speechiness  \
0   1922-02-22         0.645  0.4450  …   -13.338   1.0       0.4510
1   1922-06-01         0.695  0.2630  …   -22.136   1.0       0.9570
```

```
2   1922-03-21         0.434  0.1770  …   -21.180   1.0       0.0512
3   1922-03-21         0.321  0.0946  …   -27.961   1.0       0.0504
4         1922         0.402  0.1580  …   -16.900   0.0       0.0390

   acousticness  instrumentalness  liveness  valence    tempo  time_signature  \
0         0.674            0.7440     0.151    0.127  104.851             3.0
1         0.797            0.0000     0.148    0.655  102.009             1.0
2         0.994            0.0218     0.212    0.457  130.418             5.0
3         0.995            0.9180     0.104    0.397  169.980             3.0
4         0.989            0.1300     0.311    0.196  103.220             4.0

   release_year
0          1922
1          1922
2          1922
3          1922
4          1922

[5 rows x 21 columns]
```

```
[ ]: #  remove songs that were not released between 1930 and 2019
     tracks = tracks[tracks['release_year'] >= 1930]
     tracks = tracks[tracks['release_year'] < 2020]

     # remove songs that lasted less than 10 seconds or more than 600 seconds
     tracks['duration_ms'] = tracks['duration_ms'] / 1000
     tracks = tracks[tracks['duration_ms'] >= 10]
     tracks = tracks[tracks['duration_ms'] <= 1000]
     # tracks.rename(columns={'duration_ms': 'duration'}, inplace=True)

     # the data has explicit values two types of 0 and two types of 1, so count␣
      ↪gives me 4 values instead of 2. Fix it
     print(tracks['explicit'].value_counts())
     tracks['explicit'] = tracks['explicit'].apply(lambda x: 1 if (x == 1 or x ==␣
      ↪'1' or x == 1.0) else 0)
     print(tracks['explicit'].value_counts())
     # this does not work but is good enough as I just incorectly label 270 samples␣
      ↪into the majority catagory


     print(tracks.shape)

     tracks.describe()
```

```
explicit
0    503649
0     32387
```

```
1     20868
1       272
Name: count, dtype: int64
explicit
0    536036
1     21140
Name: count, dtype: int64
(557176, 21)
```

[ ]:

```
          popularity    duration_ms       explicit   danceability  \
count  557176.000000  557176.000000  557176.000000  557176.000000
mean       27.455553     227.587536       0.037941       0.559922
std        17.711150      92.236910       0.191055       0.165117
min         0.000000      10.371000       0.000000       0.000000
25%        13.000000     176.067000       0.000000       0.450000
50%        27.000000     216.600000       0.000000       0.573000
75%        40.000000     265.160000       0.000000       0.681000
max        94.000000     999.827000       1.000000       0.991000

              energy            key       loudness           mode  \
count  557176.000000  557176.000000  557176.000000  557176.000000
mean        0.542784       5.222646     -10.222948       0.661531
std         0.251932       3.515898       5.045423       0.473189
min         0.000000       0.000000     -60.000000       0.000000
25%         0.345000       2.000000     -12.899000       0.000000
50%         0.549000       5.000000      -9.306000       1.000000
75%         0.750000       8.000000      -6.530000       1.000000
max         1.000000      11.000000       5.376000       1.000000

         speechiness   acousticness  instrumentalness       liveness  \
count  557176.000000  557176.000000     557176.000000  557176.000000
mean        0.101438       0.449533          0.109939       0.214752
std         0.175508       0.347307          0.262525       0.185173
min         0.000000       0.000000          0.000000       0.000000
25%         0.033700       0.097600          0.000000       0.098200
50%         0.043600       0.425000          0.000025       0.139000
75%         0.073300       0.781000          0.008750       0.279000
max         0.971000       0.996000          1.000000       1.000000

             valence          tempo  time_signature   release_year
count  557176.000000  557176.000000   557176.000000  557176.000000
mean        0.554099     118.453761        3.872283    1988.304783
std         0.258203      29.732064        0.472374      21.376568
min         0.000000       0.000000        0.000000    1930.000000
25%         0.347000      95.598750        4.000000    1974.000000
50%         0.566000     117.359500        4.000000    1992.000000
75%         0.772000     136.277000        4.000000    2006.000000
```

```
max         1.000000     246.381000        5.000000    2019.000000
```

[ ]:

```
tracks['musical_era'] = pd.cut(tracks['release_year'],
    bins=[1929, 1939, 1949, 1959, 1969, 1979, 1989, 1999, 2009, 2019],
    labels=['30s', '40s', '50s', '60s', '70s', '80s', '90s', '00s', '10s'])

print(tracks['musical_era'].value_counts())
print(tracks['musical_era'].isnull().sum())
tracks.head()
```

```
musical_era
90s    108665
10s    105042
00s     86741
80s     82164
70s     61557
60s     47055
50s     35127
40s     17879
30s     12946
Name: count, dtype: int64
0
```

[ ]:

```
                          id  \
5505  7CIoJE0JfVFcmmUY3fFojH
5506  1URyyv3KRVnqlVkQQi3O1Q
5507  66QFC1l8Oe1bKSLdZYwr9B
5508  5RXchQNEfOrsAtfklgYNnR
5509  1EwvP4mPzurPA5axgvUoM6

                                                   name  popularity  \
5505  Hungarian Rhapsody No. 2 in C-Sharp Minor, S. …          48
5506                                             Chorra          38
5507        Consolation No. 3 in D-Flat Major, S. 172/3          37
5508                                       Fita Amarela          31
5509             Consolation No. 2 in E Major, S. 172/2          30

      duration_ms  explicit                               artists  \
5505      541.600         0  ['Franz Liszt', 'Vladimir Horowitz']
5506      124.147         0                     ['Carlos Gardel']
5507      264.560         0  ['Franz Liszt', 'Vladimir Horowitz']
5508      148.219         0     ['Francisco Alves', 'Mario Reis']
5509      210.827         0  ['Franz Liszt', 'Vladimir Horowitz']

                                             id_artists release_date  \
5505  ['1385hLNbrnbCJGokfH2ac2', '4Ws5hSoABAwvGJ4LhH…         1930
5506                         ['05Q9xndTxhXhD5trpmTtfU']   1930-08-18
5507  ['1385hLNbrnbCJGokfH2ac2', '4Ws5hSoABAwvGJ4LhH…         1930
```

```
5508  ['7pjGFyFFzIThPQNEfLRdiP', '0zh59roqkP8QYcrXGP…   1930-06-14
5509  ['1385hLNbrnbCJGokfH2ac2', '4Ws5hSoABAwvGJ4LhH…         1930

      danceability   energy  …  mode  speechiness  acousticness  \
5505         0.349  0.32600  …   1.0       0.0551         0.987
5506         0.699  0.44700  …   1.0       0.1600         0.971
5507         0.269  0.00856  …   1.0       0.0367         0.991
5508         0.700  0.59300  …   1.0       0.1810         0.983
5509         0.294  0.00684  …   1.0       0.0470         0.993

      instrumentalness  liveness  valence    tempo  time_signature  \
5505          0.886000    0.7840   0.1680   80.233             4.0
5506          0.000236    0.1900   0.6030  124.463             3.0
5507          0.913000    0.1320   0.0808   70.131             4.0
5508          0.000083    0.3790   0.7500  107.391             4.0
5509          0.939000    0.0616   0.0550   49.792             4.0

      release_year  musical_era
5505          1930          30s
5506          1930          30s
5507          1930          30s
5508          1930          30s
5509          1930          30s

[5 rows x 22 columns]
```

[ ]:
```
tracks.value_counts('explicit')
```

[ ]:
```
explicit
0    536036
1     21140
Name: count, dtype: int64
```

[ ]:
```
data_columns = [
    'popularity',
    'duration',
    'explicit',
    'danceability',
    'energy',
    'key',
    'loudness',
    'mode',
    'speechiness',
    'acousticness',
    'instrumentalness',
    'liveness',
    'valence',
    'tempo',
    'time_signature'
    'musical_era'
]

# make a 4x4 plot
plt.figure(figsize=(20, 20))

# make a plot for popularity
plt.subplot(4, 4, 1)
plt.hist(tracks['popularity'], bins=120, color='red', alpha=0.7)
plt.xlabel('Popularity')
plt.ylabel('Count')
plt.title('Distribution of Popularity')

# make a plot for duration_ms
plt.subplot(4, 4, 2)
plt.hist(tracks['duration_ms'], bins=120, color='blue', alpha=0.7)
plt.xlabel('Duration (s)')
plt.ylabel('Count')
plt.title('Distribution of Duration')

# make a pir chart for explicit
plt.subplot(4, 4, 3)
tracks['explicit'].value_counts().plot.pie(autopct='%1.1f%%',␣
 ↪colors=['skyblue', 'orange'])
plt.title('Distribution of Explicit')

# make a plot for danceability
plt.subplot(4, 4, 4)
plt.hist(tracks['danceability'], bins=120, color='green', alpha=0.7)
plt.xlabel('Danceability')
plt.ylabel('Count')
plt.title('Distribution of Danceability')

# make a plot for energy
plt.subplot(4, 4, 5)
plt.hist(tracks['energy'], bins=60, color='red', alpha=0.7)
plt.xlabel('Energy')
plt.ylabel('Count')
plt.title('Distribution of Energy')

# make a plot for key
plt.subplot(4, 4, 6)
plt.hist(tracks['key'], color='blue', alpha=0.7)
plt.xlabel('Key')
plt.ylabel('Count')
plt.title('Distribution of Key')

# make a plot for loudness
plt.subplot(4, 4, 7)
plt.hist(tracks['loudness'], bins=120, color='green', alpha=0.7)
plt.xlabel('Loudness')
plt.ylabel('Count')
plt.title('Distribution of Loudness')

# make a plot for mode
plt.subplot(4, 4, 8)
tracks['mode'].value_counts().plot.pie(autopct='%1.1f%%', colors=['skyblue',␣
 ↪'orange'])
plt.title('Distribution of Mode')

# make a plot for speechiness (y axis should be log scale)
plt.subplot(4, 4, 9)
plt.hist(tracks['speechiness'], bins=120, color='red', alpha=0.7)
plt.xlabel('Speechiness')
plt.ylabel('Count')
plt.title('Distribution of Speechiness')
plt.yscale('log')

# make a plot for acousticness
plt.subplot(4, 4, 10)
plt.hist(tracks['acousticness'], bins=120, color='blue', alpha=0.7)
plt.xlabel('Acousticness')
plt.ylabel('Count')
plt.title('Distribution of Acousticness')
plt.yscale('log')

# make a plot for instrumentalness
plt.subplot(4, 4, 11)
plt.hist(tracks['instrumentalness'], bins=120, color='green', alpha=0.7)
plt.xlabel('Instrumentalness')
plt.ylabel('Count')
plt.title('Distribution of Instrumentalness')
plt.yscale('log')

# make a plot for liveness
plt.subplot(4, 4, 12)
plt.hist(tracks['liveness'], bins=120, color='red', alpha=0.7)
plt.xlabel('Liveness')
plt.ylabel('Count')
plt.title('Distribution of Liveness')

# make a plot for valence
```

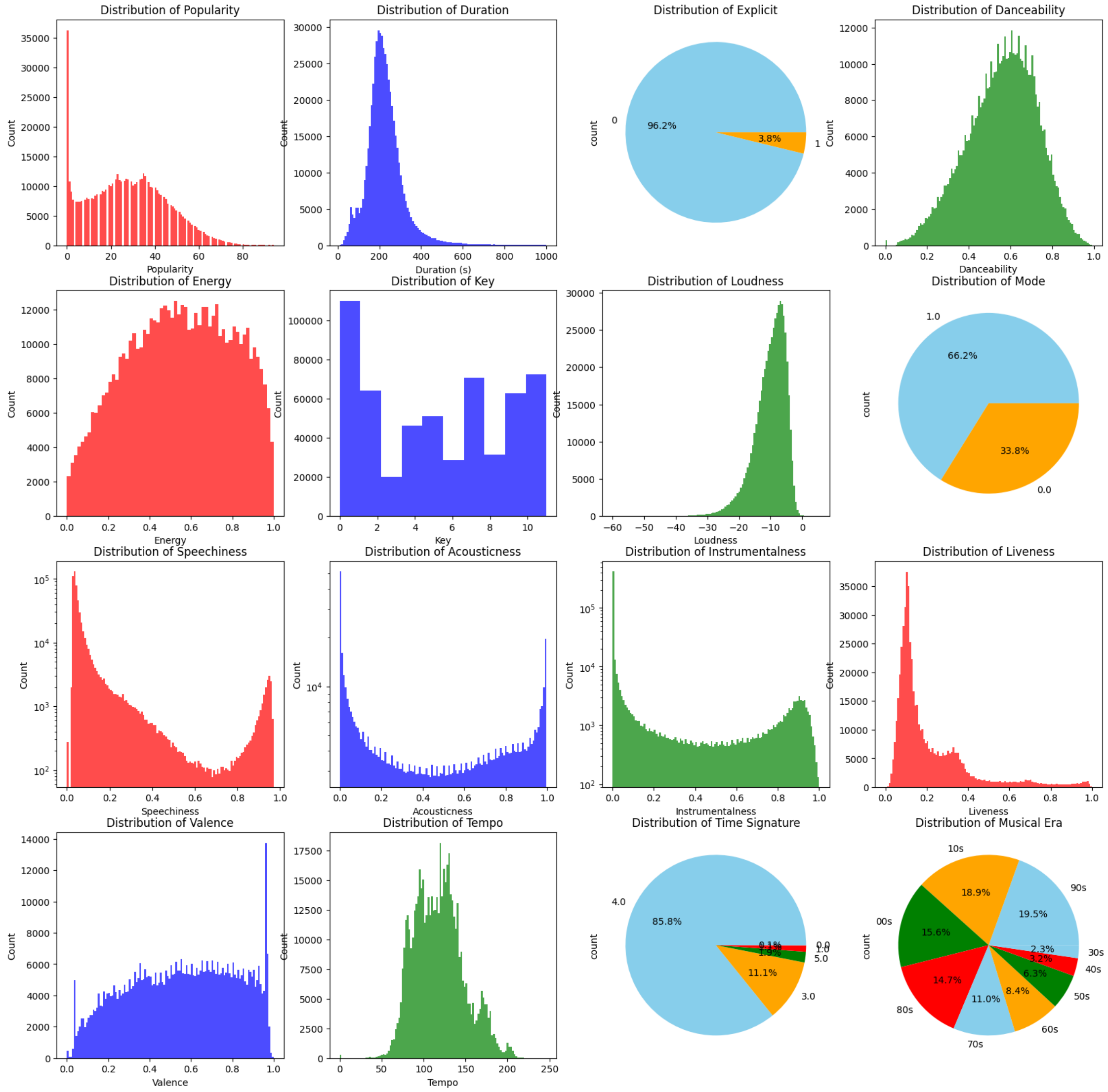
```
plt.subplot(4, 4, 13)
plt.hist(tracks['valence'], bins=120, color='blue', alpha=0.7)
plt.xlabel('Valence')
plt.ylabel('Count')
plt.title('Distribution of Valence')

# make a plot for tempo
plt.subplot(4, 4, 14)
plt.hist(tracks['tempo'], bins=120, color='green', alpha=0.7)
plt.xlabel('Tempo')
plt.ylabel('Count')
plt.title('Distribution of Tempo')

# make a plot for time_signature
plt.subplot(4, 4, 15)
tracks['time_signature'].value_counts().plot.pie(autopct='%1.1f%%',␣
 ↪colors=['skyblue', 'orange', 'green', 'red'])
plt.title('Distribution of Time Signature')

# make a plot for musical_era
plt.subplot(4, 4, 16)
tracks['musical_era'].value_counts().plot.pie(autopct='%1.1f%%',␣
 ↪colors=['skyblue', 'orange', 'green', 'red'])
plt.title('Distribution of Musical Era')


plt.show()
```



```
[ ]: # Acousticness: A score from 0.0 to 1.0 indicating the likelihood of the track being acoustic.
     # Danceability: A value between 0.0 and 1.0 that reflects a track's suitability for dancing.
     # Instrumentalness: A value up to 1.0 predicting if a track lacks vocals.
     # Duration: The length of the track in seconds.
     # Energy: A 0.0 to 1.0 measure of a track's intensity and activity level.
     # Key: The pitch of the track, represented by integers where 0 = C.
     # Liveness: Indicates the probability of the track being recorded live.
     # Loudness: The average loudness of the track in decibels (dB).
     # Mode: The modality of the track, with 1 for major and 0 for minor.
     # Speechiness: Measures the presence of spoken words, with 1.0 being all speech.
     # Tempo: The track's speed in beats per minute (BPM).
     # Time Signature: The notational convention indicating the number of beats per␣
      ↪bar.
     # Valence: A 0.0 to 1.0 measure of a track’s musical positiveness.
```

[ ]:

```
percent_data = [
    'popularity',
    'duration_ms',
    'danceability',
    'energy',
    'loudness',
    'speechiness',
    'acousticness',
    'instrumentalness',
    'liveness',
    'valence',
    'tempo'
]

def find_percentiles(data, percentiles):
    return data.quantile(percentiles)
percentiles = find_percentiles(tracks[percent_data], [i/100 for i in range(0,␣
 ↪101, 1)])


def track_normalised_signiture(track):
    track_values = {
        'popularity': track['popularity'],
        'duration': track['duration_ms'],
        'explicit': track['explicit'],
        'danceability': track['danceability'],
        'energy': track['energy'],
        'key': track['key'],
        'loudness': track['loudness'],
        'mode': track['mode'],
        'speechiness': track['speechiness'],
        'acousticness': track['acousticness'],
        'instrumentalness': track['instrumentalness'],
        'liveness': track['liveness'],
        'valence': track['valence'],
        'tempo': track['tempo'],
        'time_signature': track['time_signature'],
        'musical_era': track['musical_era'],

        'track_id': track['id'],
        'track_name': track['name'].lower(),
        'artist_name': track['artists'],
    }
    for key in track_values:
        if key in percent_data:
            track_values[key] = (track_values[key] - percentiles[key][0]) /␣
↪(percentiles[key][1] - percentiles[key][0])

    track_values['key'] = track_values['key'] / 11
    track_values['time_signature'] = track_values['time_signature'] / 5

    musical_era_dict = {
        '30s': 0.0,
        '40s': 0.1,
        '50s': 0.2,
        '60s': 0.3,
        '70s': 0.4,
        '80s': 0.5,
        '90s': 0.6,
        '00s': 0.7,
        '10s': 0.8,
        '20s': 0.9
    }

    track_values['musical_era'] = musical_era_dict[track_values['musical_era']]

    return track_values

normalized_track_example = track_normalised_signiture(tracks.iloc[0])
norm_table_columns = list(normalized_track_example.keys())

print(norm_table_columns)
print(normalized_track_example)
```

```
['popularity', 'duration', 'explicit', 'danceability', 'energy', 'key',
'loudness', 'mode', 'speechiness', 'acousticness', 'instrumentalness',
'liveness', 'valence', 'tempo', 'time_signature', 'musical_era', 'track_id',
'track_name', 'artist_name']
{'popularity': 0.5106382978723404, 'duration': 541.6, 'explicit': 0,
'danceability': 0.3521695257315842, 'energy': 0.326, 'key': 0.09090909090909091,
'loudness': 0.6830182329906999, 'mode': 1.0, 'speechiness':
0.056745623069001036, 'acousticness': 0.9909638554216867, 'instrumentalness':
0.886, 'liveness': 0.784, 'valence': 0.168, 'tempo': 0.32564605225240584,
'time_signature': 0.8, 'musical_era': 0.0, 'track_id': '7CIoJE0JfVFcmmUY3fFojH',
'track_name': 'Hungarian Rhapsody No. 2 in C-Sharp Minor, S. 244/2',
'artist_name': "['Franz Liszt', 'Vladimir Horowitz']"}
```

```
[ ]: norm_data = []
     for i in range(tracks.shape[0]):
```

```
    norm_data.append(track_normalised_signiture(tracks.iloc[i]))

norm_df = pd.DataFrame(norm_data)
norm_df.head()
```

[ ]:

```
   popularity  duration  explicit  danceability   energy       key  loudness  \
0    0.510638   541.600         0      0.352170  0.32600  0.090909  0.683018
1    0.404255   124.147         0      0.705348  0.44700  0.272727  0.755797
2    0.393617   264.560         0      0.271443  0.00856  0.090909  0.463687
3    0.329787   148.219         0      0.706357  0.59300  0.545455  0.828484
4    0.319149   210.827         0      0.296670  0.00684  0.363636  0.469591

   mode  speechiness  acousticness  instrumentalness  liveness  valence  \
0   1.0     0.056746      0.990964          0.886000    0.7840   0.1680
1   1.0     0.164779      0.974900          0.000236    0.1900   0.6030
2   1.0     0.037796      0.994980          0.913000    0.1320   0.0808
3   1.0     0.186406      0.986948          0.000083    0.3790   0.7500
4   1.0     0.048404      0.996988          0.939000    0.0616   0.0550

      tempo  time_signature  musical_era                track_id  \
0  0.325646             0.8          0.0  7CIoJE0JfVFcmmUY3fFojH
1  0.505165             0.6          0.0  1URyyv3KRVnqlVkQQi3OlQ
2  0.284645             0.8          0.0  66QFC1l8Oe1bKSLdZYwr9B
3  0.435874             0.8          0.0  5RXchQNEf0rsAtfklgYNnR
4  0.202094             0.8          0.0  1EwvP4mPzurPA5axgvUoM6

                                          track_name  \
0  Hungarian Rhapsody No. 2 in C-Sharp Minor, S. …
1                                             Chorra
2        Consolation No. 3 in D-Flat Major, S. 172/3
3                                       Fita Amarela
4             Consolation No. 2 in E Major, S. 172/2

                            artist_name
0  ['Franz Liszt', 'Vladimir Horowitz']
1                     ['Carlos Gardel']
2  ['Franz Liszt', 'Vladimir Horowitz']
3     ['Francisco Alves', 'Mario Reis']
4  ['Franz Liszt', 'Vladimir Horowitz']
```

[ ]:

```
# save the norm_data to data/normalized_tracks.csv
norm_df.to_csv('data/normalized_tracks.csv', index=False)
```

[ ]:

```
def cosine_similarity(track1, track2):
    norm_table_columns = track1.keys()
    norm_table_columns = [key for key in norm_table_columns if key not in␣
 ↪['track_id', 'track_name', 'artist_name']]
```

```
    track1_values = [track1[key] for key in norm_table_columns]
    track2_values = [track2[key] for key in norm_table_columns]

    dot_product = np.dot(track1_values, track2_values)
    norm_track1 = np.linalg.norm(track1_values)
    norm_track2 = np.linalg.norm(track2_values)

    return dot_product / (norm_track1 * norm_track2)
```

[ ]:

```
songs_to_find  = [
    'A String of Pearls'.lower(),
    'Can\'t Help Falling in Love'.lower(),
    'I want to hold your hand'.lower(),
    'respect'.lower(),
    'like a prayer'.lower(),
    'rapper\'s delight'.lower(),
    'fight the power'.lower(),
    'ice ice baby'.lower(),
    'california love'.lower(),
    'johnny b. goode'.lower(),
    'like a rolling stone'.lower(),
    'whole lot of rosie'.lower(),
    'november rain'.lower(),
    'over the rainbow'.lower(),
    'bohemian rhapsody'.lower(),
]

# find the track_id and artist_name of the songs in songs_to_find
songs = {}
for song in songs_to_find:
    for i in range(tracks.shape[0]):
        if song in tracks.iloc[i]['name'].lower():
            songs[song] = {
                'track_id': tracks.iloc[i]['id'],
                'artist_name': tracks.iloc[i]['artists'],
                'title': tracks.iloc[i]['name']
            }
            break

songs
```

[ ]:

```
{'a string of pearls': {'track_id': '4Q5cK2GOoSTO8Col01lB54',
  'artist_name': "['Glenn Miller']",
  'title': 'A String of Pearls'},
 "can't help falling in love": {'track_id': '44AyOl4qVkzS48vBsbNXaC',
  'artist_name': "['Elvis Presley']",
  'title': "Can't Help Falling in Love"},
 'i want to hold your hand': {'track_id': '5Qe7NHxeLAn8KoLTNLSdwe',
  'artist_name': "['The Beatles']",
  'title': 'I Want To Hold Your Hand - Remastered 2009'},
 'respect': {'track_id': '5e3isD5st7PGYzSJuoRSIV',
  'artist_name': "['The Kinks']",
  'title': 'A Well Respected Man'},
 'like a prayer': {'track_id': '2v7ywbUzCgcVohHaKUcacV',
  'artist_name': "['Madonna']",
  'title': 'Like a Prayer'},
 "rapper's delight": {'track_id': '7hqpYgtDckN5wX0jxaaAPx',
  'artist_name': "['The Sugarhill Gang']",
  'title': "Rapper's Delight - Long Version"},
 'fight the power': {'track_id': '5idtcCtrCgNywqssGXGXTU',
  'artist_name': "['The Isley Brothers']",
  'title': 'Fight the Power, Pts. 1 & 2'},
 'ice ice baby': {'track_id': '11d9oUiwHuYt216EFA2tiz',
  'artist_name': "['Vanilla Ice']",
  'title': 'Ice Ice Baby'},
 'california love': {'track_id': '2Low9dwyJeUtqlpgVbFFMn',
  'artist_name': "['2Pac', 'Roger', 'Dr. Dre']",
  'title': 'California Love (remix) (ft. Dr. Dre, Roger Troutman)'},
 'johnny b. goode': {'track_id': '2QfiRTz5Yc8DdShCxG1tB2',
  'artist_name': "['Chuck Berry']",
  'title': 'Johnny B. Goode'},
 'like a rolling stone': {'track_id': '3AhXZa8sUQht0UEdBJgpGc',
  'artist_name': "['Bob Dylan']",
  'title': 'Like a Rolling Stone'},
 'november rain': {'track_id': '3YRCq0hFifThpSRFJ1VWFM',
  'artist_name': '["Guns N\' Roses"]',
  'title': 'November Rain'},
 'over the rainbow': {'track_id': '1aqjIHADlHdZIwSQorUqjo',
  'artist_name': "['Sierra Nelson', 'Ricardo Alvarez']",
  'title': 'Somewhere Over the Rainbow'},
 'bohemian rhapsody': {'track_id': '4u7EnebtmKWzUH433cf5Qv',
  'artist_name': "['Queen']",
  'title': 'Bohemian Rhapsody - Remastered 2011'}}
```

{‘a string of pearls’: {‘track_id’: ‘4Q5cK2G0oSTO8Col01lB54’, ‘artist_name’: “[‘Glenn Miller’]”, ‘title’: ‘A String of Pearls’}, “can’t help falling in love”: {‘track_id’: ‘44AyOl4qVkzS48vBsbNXaC’, ‘artist_name’: “[‘Elvis Presley’]”, ‘title’: “Can’t Help Falling in Love”}, ‘i want to hold your hand’: {‘track_id’: ‘5Qe7NHxeLAn8KoLTNLSdwe’, ‘artist_name’: “[‘The Beatles’]”, ‘title’: ‘I Want To Hold Your Hand - Remastered 2009’}, ‘respect’: {‘track_id’: ‘5e3isD5st7PGYzSJuoRSIV’, ‘artist_name’: “[‘The Kinks’]”, ‘title’: ‘A Well Respected Man’}, ‘like a prayer’: {‘track_id’: ‘2v7ywbUzCgcVohHaKUcacV’, ‘artist_name’: “[‘Madonna’]”, ‘title’: ‘Like a Prayer’}, “rapper’s delight”: {‘track_id’: ‘7hqpYgtDckN5wX0jxaaAPx’, ‘artist_name’: “[‘The Sugarhill Gang’]”, ‘title’: “Rapper’s Delight - Long Version”}, ‘fight the power’: {‘track_id’: ‘5idtcCtrCgNywqssGXGXTU’, ‘artist_name’: “[‘The Isley Brothers’]”, ‘title’: ‘Fight the Power, Pts. 1 & 2’}, ‘ice ice baby’: {‘track_id’: ‘11d9oUiwHuYt216EFA2tiz’, ‘artist_name’: “[‘Vanilla Ice’]”, ‘title’: ‘Ice Ice Baby’}, ‘california love’: {‘track_id’: ‘2Low9dwyJeUtqlpgVbFFMn’, ‘artist_name’: “[‘2Pac’, ‘Roger’, ‘Dr. Dre’]”, ‘title’: ‘California Love (remix) (ft. Dr. Dre, Roger Troutman)’}, ‘johnny b. goode’: {‘track_id’: ‘2QfiRTz5Yc8DdShCxG1tB2’, ‘artist_name’: “[‘Chuck Berry’]”, ‘title’: ‘Johnny B. Goode’}, ‘like a rolling stone’: {‘track_id’: ‘3AhXZa8sUQht0UEdBJgpGc’, ‘artist_name’: “[‘Bob Dylan’]”, ‘title’: ‘Like a Rolling Stone’}, ‘november rain’: {‘track_id’: ‘3YRCqOhFifThpSRFJ1VWFM’, ‘artist_name’: ‘[“Guns N' Roses”]’, ‘title’: ‘November Rain’}, ‘over the rainbow’: {‘track_id’: ‘1aqjIHADlHdZIwSQorUqjo’, ‘artist_name’: “[‘Sierra Nelson’, ‘Ricardo Alvarez’]”, ‘title’: ‘Somewhere Over the Rainbow’}, ‘bohemian rhapsody’: {‘track_id’: ‘4u7EnebtmKWzUH433cf5Qv’, ‘artist_name’: “[‘Queen’]”, ‘title’: ‘Bohemian Rhapsody - Remastered 2011’}}

[ ]:

```python
# for each song in songs, find the top 5 soungs that are most similar to it
for key in songs:
    song = songs[key]
    song_title = song['title']
    song_id = song['track_id']
    song_artist = song['artist_name']

    song_index = tracks[tracks['id'] == song_id].index[0]
    song_values = track_normalised_signiture(tracks.iloc[song_index])

    similarities = []
    for i in range(tracks.shape[0]):
        track_values = track_normalised_signiture(tracks.iloc[i])
        similarity = cosine_similarity(song_values, track_values)
        similarities.append((similarity, i))

    similarities.sort(reverse=True)
    top_5 = similarities[0:6]

    print(f"Top 5 songs similar to {song_title} by {song_artist}")
    for i in range(1, 6):
        track = tracks.iloc[top_5[i][1]]
        print(f"{i}. {track['name']} by {track['artists']} with similarity␣
 ↪{top_5[i][0]}")
    print("\n\n")

# Path: data/normalized_tracks.csv
```

```
Top 5 songs similar to A String of Pearls by ['Glenn Miller']
1. Little Italy by ['Stephen Bishop'] with similarity 0.9999993542087608
2. Nunca Más by ['Camilo Sesto'] with similarity 0.9999988245128374
3. Expecting by ['Minnie Riperton'] with similarity 0.9999988193492092
4. La Mentira by ['Luis Miguel'] with similarity 0.9999987195174853
5. Fallin' Rain by ['Link Wray'] with similarity 0.999998698697377
```

```
Top 5 songs similar to Can't Help Falling in Love by ['Elvis Presley']
1. All Those Years of Learning by ['INXS'] with similarity 0.9999987861534229
2. Okaeri (2019 New Mix) by ['Keiichi Sokabe'] with similarity
0.9999985878008475
3.    (2019 New Mix) by ['Keiichi Sokabe'] with similarity 0.9999984733777026
4. The Cold Hard Facts of Life by ['Bill Anderson'] with similarity
0.99999816898047
5. Termesa by ['Camboy Estevez'] with similarity 0.9999981073821653



Top 5 songs similar to I Want To Hold Your Hand - Remastered 2009 by ['The
Beatles']
1. Dixie Lullaby by ['Leon Russell'] with similarity 0.9999992619273665
2. (I Know) I'm Losing You by ['Gladys Knight & The Pips'] with similarity
0.9999991947088172
3. Roses in the Snow - 2002 Remaster by ['Emmylou Harris'] with similarity
0.9999990073136449
4. Parker's Band by ['Steely Dan'] with similarity 0.9999988573700108
5. Eg e så forelska by ['Mods'] with similarity 0.9999987712132872



Top 5 songs similar to A Well Respected Man by ['The Kinks']
1. Attics of My Life - 2013 Remaster by ['Grateful Dead'] with similarity
0.9999999428095113
2. Happier Than The Morning Sun by ['Stevie Wonder'] with similarity
0.9999997448498996
3. I LOVE YOU by ['Off Course'] with similarity 0.9999997392132842
4. Happier Than The Morning Sun by ['Stevie Wonder'] with similarity
0.9999997308159728
5. God Is the Strength of My Life by ['J. Daniel Smith', "Integrity's Hosanna!
Music"] with similarity 0.9999997004829319



Top 5 songs similar to Like a Prayer by ['Madonna']
1. Mi Primer Amor by ['Liberación'] with similarity 0.999999513972387
2. Dig for Fire by ['Pixies'] with similarity 0.999999470057059
3. I Been to Georgia on a Fast Train by ['Billy Joe Shaver'] with similarity
0.9999994374156901
4. You Set My Heart On Fire - Part 1 by ['Tina Charles'] with similarity
0.9999993638213929
5. The Mighty Quinn - Mono Version by ['Manfred Mann'] with similarity
0.9999993494547104
```

```
Top 5 songs similar to Rapper's Delight - Long Version by ['The Sugarhill Gang']
1. El Satánico Dr. Cadillac - Remasterizado 2008 by ['Los Fabulosos Cadillacs']
with similarity 0.9999997615358431
2. Promises, Promises - US Single Version / 2018 Remaster by ['Naked Eyes'] with
similarity 0.9999997612788318
3. Manuel by ['Ed Motta'] with similarity 0.999999657353789
4. Candy by ['Mandy Moore'] with similarity 0.99999962790514
5. Fiesta En América by ['Chayanne'] with similarity 0.9999996090018276



Top 5 songs similar to Fight the Power, Pts. 1 & 2 by ['The Isley Brothers']
1. Too Hot To Stop (Pt. 1) by ['The Bar-Kays'] with similarity
0.9999998283629911
2. Reggaemylitis by ['Peter Tosh'] with similarity 0.99999981434676
3. Take Me to the Top by ['Advance', 'A. Pignagnoli', 'D. Raimondi', 'I.
Spagna', 'L.WESLEY', 'V. Patterson'] with similarity 0.9999997953545916
4. Fantastic Voyage by ['Lakeside'] with similarity 0.999999792693392
5. Andrea - Live by ['Fabrizio De André'] with similarity 0.9999997837561687



Top 5 songs similar to Ice Ice Baby by ['Vanilla Ice']
1. Adiós papá by ['Los Ronaldos'] with similarity 0.9999997634905368
2. People Are People - 2006 Remaster by ['Depeche Mode'] with similarity
0.9999997608331364
3. Senza giacca e cravatta by ["Nino D'Angelo"] with similarity
0.9999997474165311
4. A Hegyekbe Fönn by ['Hip Hop Boyz'] with similarity 0.9999997226117208
5. If I Only Knew by ['Tom Jones'] with similarity 0.9999997174503373
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[53], line 14
     12 for i in range(tracks.shape[0]):
     13     track_values = track_normalised_signiture(tracks.iloc[i])
---> 14     similarity = cosine_similarity(song_values, track_values)
     15     similarities.append((similarity, i))
     17 similarities.sort(reverse=True)

Cell In[48], line 9, in cosine_similarity(track1, track2)
      6 track2_values = [track2[key] for key in norm_table_columns]
      8 dot_product = np.dot(track1_values, track2_values)
```

```
----> 9 norm_track1 = np.linalg.norm(track1_values)
     10 norm_track2 = np.linalg.norm(track2_values)
     12 return dot_product / (norm_track1 * norm_track2)

File c:\Python311\Lib\site-packages\numpy\linalg\linalg.py:2552, in norm(x, ord ␣
  ↪axis, keepdims)
   2550     sqnorm = x_real.dot(x_real) + x_imag.dot(x_imag)
   2551 else:
-> 2552     sqnorm = x.dot(x)
   2553 ret = sqrt(sqnorm)
   2554 if keepdims:

KeyboardInterrupt:
```

```
[ ]: '''
Top 5 songs similar to A String of Pearls by ['Glenn Miller']
1. Little Italy by ['Stephen Bishop'] with similarity 0.9999993542087608
2. Nunca Más by ['Camilo Sesto'] with similarity 0.9999988245128374
3. Expecting by ['Minnie Riperton'] with similarity 0.9999988193492092
4. La Mentira by ['Luis Miguel'] with similarity 0.9999987195174853
5. Fallin' Rain by ['Link Wray'] with similarity 0.999998698697377




Top 5 songs similar to Can't Help Falling in Love by ['Elvis Presley']
1. All Those Years of Learning by ['INXS'] with similarity 0.9999987861534229
2. Okaeri (2019 New Mix) by ['Keiichi Sokabe'] with similarity 0.
 ↪9999985878008475
3.    (2019 New Mix) by ['Keiichi Sokabe'] with similarity 0.9999984733777026
4. The Cold Hard Facts of Life by ['Bill Anderson'] with similarity 0.
 ↪99999816898047
5. Termesa by ['Camboy Estevez'] with similarity 0.9999981073821653




Top 5 songs similar to I Want To Hold Your Hand - Remastered 2009 by ['The␣
 ↪Beatles']
1. Dixie Lullaby by ['Leon Russell'] with similarity 0.9999992619273665
2. (I Know) I'm Losing You by ['Gladys Knight & The Pips'] with similarity 0.
 ↪9999991947088172
3. Roses in the Snow - 2002 Remaster by ['Emmylou Harris'] with similarity 0.
 ↪9999990073136449
4. Parker's Band by ['Steely Dan'] with similarity 0.9999988573700108
5. Eg e så forelska by ['Mods'] with similarity 0.9999987712132872
```

```
Top 5 songs similar to A Well Respected Man by ['The Kinks']
1. Attics of My Life - 2013 Remaster by ['Grateful Dead'] with similarity 0.
 ↪9999999428095113
2. Happier Than The Morning Sun by ['Stevie Wonder'] with similarity 0.
 ↪9999997448498996
3. I LOVE YOU by ['Off Course'] with similarity 0.9999997392132842
4. Happier Than The Morning Sun by ['Stevie Wonder'] with similarity 0.
 ↪9999997308159728
5. God Is the Strength of My Life by ['J. Daniel Smith', "Integrity's Hosanna!␣
 ↪Music"] with similarity 0.9999997004829319



Top 5 songs similar to Like a Prayer by ['Madonna']
1. Mi Primer Amor by ['Liberación'] with similarity 0.999999513972387
2. Dig for Fire by ['Pixies'] with similarity 0.999999470057059
3. I Been to Georgia on a Fast Train by ['Billy Joe Shaver'] with similarity 0.
 ↪9999994374156901
4. You Set My Heart On Fire - Part 1 by ['Tina Charles'] with similarity 0.
 ↪9999993638213929
5. The Mighty Quinn - Mono Version by ['Manfred Mann'] with similarity 0.
 ↪9999993494547104



Top 5 songs similar to Rapper's Delight - Long Version by ['The Sugarhill Gang']
1. El Satánico Dr. Cadillac - Remasterizado 2008 by ['Los Fabulosos Cadillacs']␣
 ↪with similarity 0.9999997615358431
2. Promises, Promises - US Single Version / 2018 Remaster by ['Naked Eyes']␣
 ↪with similarity 0.9999997612788318
3. Manuel by ['Ed Motta'] with similarity 0.999999657353789
4. Candy by ['Mandy Moore'] with similarity 0.99999962790514
5. Fiesta En América by ['Chayanne'] with similarity 0.9999996090018276



Top 5 songs similar to Fight the Power, Pts. 1 & 2 by ['The Isley Brothers']
1. Too Hot To Stop (Pt. 1) by ['The Bar-Kays'] with similarity 0.
 ↪9999998283629911
2. Reggaemylitis by ['Peter Tosh'] with similarity 0.99999981434676
3. Take Me to the Top by ['Advance', 'A. Pignagnoli', 'D. Raimondi', 'I.␣
 ↪Spagna', 'L.WESLEY', 'V. Patterson'] with similarity 0.9999997953545916
4. Fantastic Voyage by ['Lakeside'] with similarity 0.999999792693392
5. Andrea - Live by ['Fabrizio De André'] with similarity 0.9999997837561687
```

```


Top 5 songs similar to Ice Ice Baby by ['Vanilla Ice']
1. Adiós papá by ['Los Ronaldos'] with similarity 0.9999997634905368
2. People Are People - 2006 Remaster by ['Depeche Mode'] with similarity 0.
 ↪9999997608331364
3. Senza giacca e cravatta by ["Nino D'Angelo"] with similarity 0.
 ↪9999997474165311
4. A Hegyekbe Fönn by ['Hip Hop Boyz'] with similarity 0.9999997226117208
5. If I Only Knew by ['Tom Jones'] with similarity 0.9999997174503373
'''
```

[ ]:
```
songs_to_find = [
    'yesterday',
    'hey jude',
    'let it be',
    'i want to hold your hand',
]

# find the track_id and artist_name of the songs in songs_to_find
songs = {}
beatles_songs = tracks[tracks['artists'] == "['The Beatles']"]
for song in songs_to_find:
    for i in range(beatles_songs.shape[0]):
        if song in beatles_songs.iloc[i]['name'].lower():
            songs[song] = {
                'track_id': beatles_songs.iloc[i]['id'],
                'artist_name': beatles_songs.iloc[i]['artists'],
                'title': beatles_songs.iloc[i]['name']
            }
            break

songs
```

[ ]:
```
{'yesterday': {'track_id': '3BQHpFgAp4l80e1XslIjNI',
  'artist_name': "['The Beatles']",
  'title': 'Yesterday - Remastered 2009'},
 'hey jude': {'track_id': '3m7V717IKZqZLW5qUIOxdD',
  'artist_name': "['The Beatles']",
  'title': 'Hey Jude - Remastered 2009'},
 'let it be': {'track_id': '7iN1s7xHE4ifF5povM6A48',
  'artist_name': "['The Beatles']",
  'title': 'Let It Be - Remastered 2009'},
 'i want to hold your hand': {'track_id': '5Qe7NHxeLAn8KoLTNLSdwe',
  'artist_name': "['The Beatles']",
  'title': 'I Want To Hold Your Hand - Remastered 2009'}}
```

[ ]:

```
sims = []

for index in range(norm_df.shape[0]):
    track = norm_df.iloc[index]
    sim = [track['track_id'], track['track_name'], track['artist_name']]
    for song in songs:
        song_values = track_normalised_signiture(tracks.iloc[track.name])
        sim.append((cosine_similarity(song_values, track), song))

    sims.append(sim)

sims_df = pd.DataFrame(sims, columns=['track_id', 'track_name', 'artist_name', 'sim to yesterday', 'sim to hey jude', 'sim to let it be', 'sim to i want to hold your hand'])
sims_df.head()
```