capstone

September 13, 2020

Introduction

Spotify is one of the most popular music streaming service in the world. Songs of various styles and genres are published on the platform by both indie and professional artists from all over the world. As an asprirant artist who is intending to publish his/her song on the platform, one might be interested to predict how much popluarity the song is going to get based on its characteristics such tempo, key or loudness. In this analysis, we're going to look into a Spotify song dataset of 160,000 songs to explore the relationship between features of a song and its popularity. A predictive model will then be built to predict how well a song would do on Spotify based on the song's characteristics.

On Spotify, beside song tracks, there are also a great amount of audiobooks, podcast or noise tracks. In this dataset, there is a good mix of different types of tracks so we're going to filter out tracks which are not songs. Only songs data entries will be used to build the predictive model.

Lastly, we're going to make a distinction between studio recorded track and live track. Our focus in this analysis is on studio recoded tracks only. Therefore, live session recording shall not be considered.

Dataset

The dataset is named 'Spotify Dataset 1921-2020, 160k+ Tracks' and was published by user Yamac Eren Ay on Kaggle. Homepage of the dataset where details can be found is accessible here.

It contains more than records of more than 160,000 tracks and was collect using Spotify Web API. There are 19 columns in the dataset, description of each column is as follow:

Primary:

id: string value Unique Spotify identifier for each track

Numerical:

acousticness: float value ranges from 0 to 1

Confidence measure of whether the track is acousitc.

danceability: float value ranges from 0 to 1

Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.

energy: float value ranges from 0 to 1

Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy.

duration_ms: integer value, ~250,000 The duration of the track in milliseconds

instrumentalness: (Ranges from 0 to 1)

Predicts whether a track contains no vocals. “Ooh” and “aah” sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly “vocal”. The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.

valence: (Ranges from 0 to 1)

A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

popularity: (Ranges from 0 to 100)

The popularity of a track is a value between 0 and 100, with 100 being the most popular. The popularity is calculated by algorithm and is based, in the most part, on the total number of plays the track has had and how recent those plays are.

tempo: (Float typically ranging from 50 to 150)

The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.

liveness: (Ranges from 0 to 1)

Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.

loudness: (Float typically ranging from -60 to 0)

The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks

speechiness: (Ranges from 0 to 1)

Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.

year: (Ranges from 1921 to 2020)

The year a track was published Dummy:

mode: (0 = Minor, 1 = Major)

explicit: (0 = No explicit content, 1 = Explicit content)

Categorical:

key: (All keys on octave encoded as values ranging from 0 to 11, starting on C as 0, C# as 1 and so on…)

artists: (List of artists mentioned)

release_date: (Date of release mostly in yyyy-mm-dd format, however precision of date may vary)

name: (Name of the track)

Let's take a look at an example record of the song "Radio Ga Ga" by "Queen". Value of 'key' field being 5 indicates that the song is in key F Major. One interesting feature of this track is 'valence' which the song has a score of 0.632. This tells us that the song is musically positive or, in another word, sounds cheerful and upbeat, which is really the case for the song "Radio Ga Ga". Another interesting metric of this song is the 'danceability' score, which it scores an impressive 0.752. This is again understandable since the song, with a simple and catchy beat, is easy to dance to.

It is important to note that these numerical metrics are given to each song using Spotify own machine learning model and aren't assigned human so we can assume that scores for different attributes of each song are given fairly consistently. In order to create an actual test case for a new track, it is important to get values for features of interest through Spotify API rather than having someone artist to assign scores to the track based on his/her feeling. More information on Spotify Web API can be found here

The key data which describe the attributes of a track such as danceability, acousticness, loudness, … are already in numerical format and are already normalized so that will help a lot in the data wrangling process. Data field such as 'artists' or 'name', though might very well have an impact on the popularity of a song, will not be used in this model since in the scope of this analysis, we only want to focus on the muscial virtues of a song.

The dataset was last updated on 19 June, 2020 so it is still highly relevant at the point of writing of this notebook. However, if this model is to be used at some point in the future, it is recommended to update dataset. Data is valid for the US region only.

[1]:
```
# Import relevant libraries and read data from .csv file
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score


spot = pd.read_csv('data.csv')
spot.head()
```

[1]:
```
   acousticness                                      artists  danceability  \
0         0.995                          ['Carl Woitschach']         0.708
1         0.994  ['Robert Schumann', 'Vladimir Horowitz']         0.379
2         0.604                      ['Seweryn Goszczyński']         0.749
3         0.995                          ['Francisco Canaro']         0.781
```

```
4         0.990  ['Frédéric Chopin', 'Vladimir Horowitz']         0.210

   duration_ms  energy  explicit                      id  instrumentalness  \
0       158648  0.1950         0  6KbQ3uYMLKb5jDxLF7wYDD             0.563
1       282133  0.0135         0  6KuQTIu1KoTTkLXKrwlLPV             0.901
2       104300  0.2200         0  6L63VW0PibdM1HDSBoqnoM             0.000
3       180760  0.1300         0  6M94FkXd15sOAOQYRnWPN8             0.887
4       687733  0.2040         0  6N6tiFZ9vLTSOIxkj8qKrd             0.908

   key  liveness  loudness  mode  \
0   10    0.1510   -12.428     1
1    8    0.0763   -28.454     1
2    5    0.1190   -19.924     0
3    1    0.1110   -14.734     0
4   11    0.0980   -16.829     1

                                          name  popularity release_date  \
0                       Singende Bataillone 1. Teil           0         1928
1         Fantasiestücke, Op. 111: Più tosto lento           0         1928
2                      Chapter 1.18 - Zamek kaniowski          0         1928
3  Bebamos Juntos - Instrumental (Remasterizado)           0   1928-09-25
4    Polonaise-Fantaisie in A-Flat Major, Op. 61           1         1928

   speechiness    tempo  valence  year
0       0.0506  118.469   0.7790  1928
1       0.0462   83.972   0.0767  1928
2       0.9290  107.177   0.8800  1928
3       0.0926  108.003   0.7200  1928
4       0.0424   62.149   0.0693  1928
```

[2]:

```python
# For the example in 'Dataset' section
spot[spot['name']=='Radio Ga Ga']
```

[2]:

```
       acousticness    artists  danceability  duration_ms  energy  explicit  \
84438         0.151  ['Queen']         0.752       348173   0.375         0

                           id  instrumentalness  key  liveness  loudness  \
84438  2jAc9KIQ9XoZxkydXh3MVh          0.000481    5     0.143   -12.966

       mode         name  popularity release_date  speechiness    tempo  \
84438     1  Radio Ga Ga          52   1984-02-27       0.0358  112.415

       valence  year
84438    0.632  1984
```

Methodology

First we're going to do some exploratory analysis to have a preliminary understanding of the dataset.

Next, we're going to clean up the dataset by filtering out data entries which are not valid, followed by data normalization. Lastly, we're going to select which attributes to use as independent variables in building the predictive model. Since the variable we're trying to predict is a countinuous value, we're going to use a Regression model, more details below.

[3]:
```
print(spot.shape)
print(spot.dtypes)
```

```
(169909, 19)
acousticness        float64
artists              object
danceability        float64
duration_ms           int64
energy              float64
explicit              int64
id                   object
instrumentalness    float64
key                   int64
liveness            float64
loudness            float64
mode                  int64
name                 object
popularity            int64
release_date         object
speechiness         float64
tempo               float64
valence             float64
year                  int64
dtype: object
```

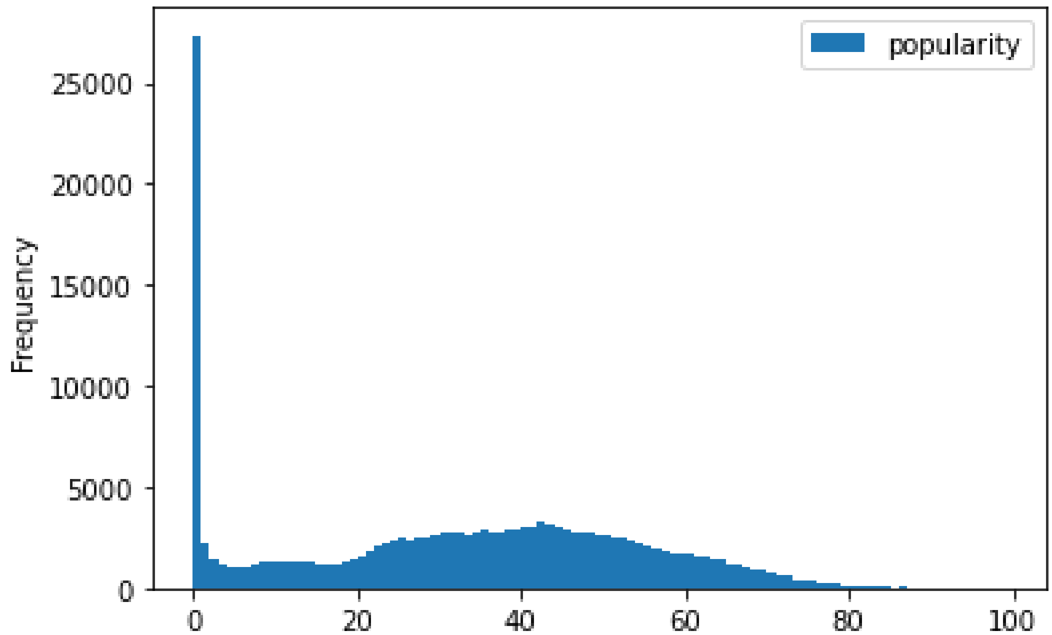
[4]:
```
spot.describe()
```

[4]:
```
        acousticness   danceability   duration_ms          energy  \
count  169909.000000  169909.000000  1.699090e+05  169909.000000
mean        0.493214       0.538150  2.314062e+05       0.488593
std         0.376627       0.175346  1.213219e+05       0.267390
min         0.000000       0.000000  5.108000e+03       0.000000
25%         0.094500       0.417000  1.710400e+05       0.263000
50%         0.492000       0.548000  2.086000e+05       0.481000
75%         0.888000       0.667000  2.629600e+05       0.710000
max         0.996000       0.988000  5.403500e+06       1.000000

            explicit  instrumentalness            key       liveness  \
count  169909.000000     169909.000000  169909.000000  169909.000000
mean        0.084863          0.161937       5.200519       0.206690
std         0.278679          0.309329       3.515257       0.176796
min         0.000000          0.000000       0.000000       0.000000
25%         0.000000          0.000000       2.000000       0.098400
```

```
50%         0.000000          0.000204       5.000000       0.135000
75%         0.000000          0.086800       8.000000       0.263000
max         1.000000          1.000000      11.000000       1.000000

            loudness           mode     popularity    speechiness  \
count  169909.000000  169909.000000  169909.000000  169909.000000
mean      -11.370289       0.708556      31.556610       0.094058
std         5.666765       0.454429      21.582614       0.149937
min       -60.000000       0.000000       0.000000       0.000000
25%       -14.470000       0.000000      12.000000       0.034900
50%       -10.474000       1.000000      33.000000       0.045000
75%        -7.118000       1.000000      48.000000       0.075400
max         3.855000       1.000000     100.000000       0.969000

               tempo        valence           year
count  169909.000000  169909.000000  169909.000000
mean      116.948017       0.532095    1977.223231
std        30.726937       0.262408      25.593168
min         0.000000       0.000000    1921.000000
25%        93.516000       0.322000    1957.000000
50%       114.778000       0.544000    1978.000000
75%       135.712000       0.749000    1999.000000
max       244.091000       1.000000    2020.000000
```

We can see there is no missing data across the fields

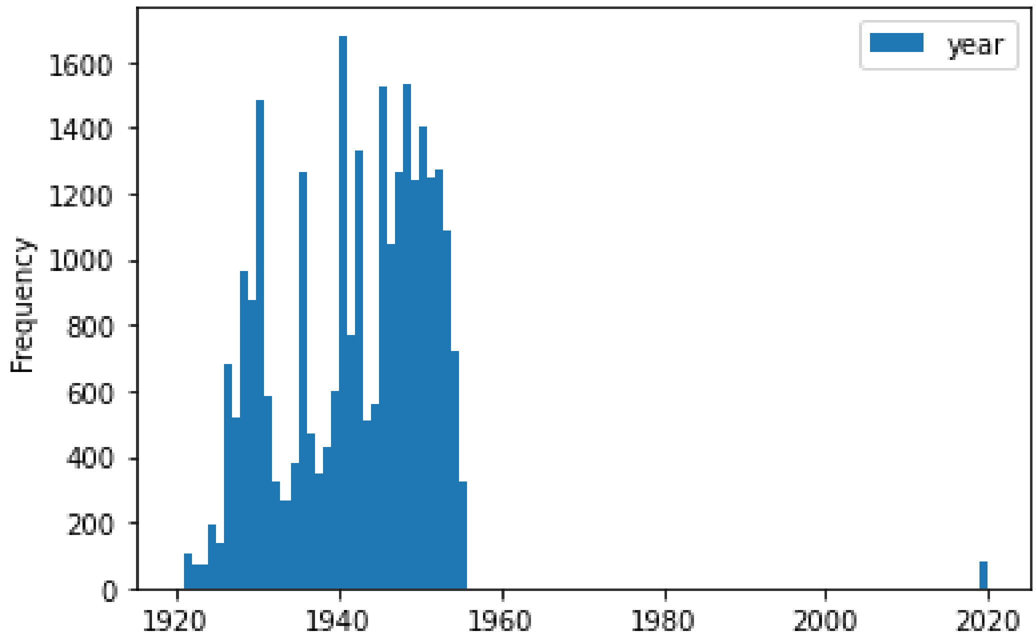
[5]:
```python
bins = np.arange(0, 100, 1)
spot.plot(kind='hist', y='popularity', bins=bins)
plt.show()
print(spot.popularity.value_counts())
```




```
0      27357
42      3280
43      3120
40      3061
44      3054
       …
93         3
97         1
96         1
99         1
100        1
Name: popularity, Length: 100, dtype: int64
```

there are 27357 tracks with 0 popularity score, which is a disproportinate amount as show in the distribution graph below Let's investigate the reasons for this 0 rating, keepi in mind that popularity is calculated mostly using counts of listen and how recent those listens are

[6]:
```
spot_zero = spot[spot.popularity == 0]
bins = np.arange(1920, 2021, 1)
spot_zero.plot(kind='hist', y='year', bins=bins)
plt.show()
```



It's clear that the majority of the 0-popularity tracks are tracks published before 1960 these songs are probably too old for the current user base (largely millenials) to know about Therefore, these songs don't receive enough plays to get a popularity score. Some of these songs might become more popular if somehow the user base decide to give all these old tracks a try, however there's no way to know for sure. Due to this uncertainty, it's best to drop these records because there is no relationship between popularity score and a track's attributes

[7]:
```
print(spot[spot.popularity==0][spot.year==2020][['artists']].squeeze().unique())
```

```
["['Tame Impala']" "['Morat']" "['Morat', 'Juanes']" "['Summer Walker']"
 "['Usher', 'Tyga']" "['Wisin & Yandel', 'Anthony Santos']"
 "['Wisin & Yandel', 'Chris Brown', 'T-Pain']" "['Wisin & Yandel']"
 "['Wisin & Yandel', 'Jennifer Lopez']" "['Arijit Singh']"
 "['Arijit Singh', 'Shadab Faridi']" "['Arijit Singh', 'Shreya Ghoshal']"
 "['Flo Rida']" "['Jack Johnson']" "['Ne-Yo']" "['Becky Hill']"
 "['Alejandro Fernández', 'Christina Aguilera']"
 "['Alejandro Fernández', 'Morat']" "['Luis Fonsi']"
 "['Luis Fonsi', 'Aleks Syntek', 'Noel Schajris', 'David Bisbal']"
 "['Luis Fonsi', 'Demi Lovato']" "['Stevie Wonder']" "['Dean Lewis']"
 "['Johann Sebastian Bach', 'Lucas Jussen', 'Arthur Jussen']"
 "['Marc Anthony']" "['Juanes']" "['Juanes', 'Nelly Furtado']"
 "['Alejandro Sanz']" "['Jax Jones', 'Ina Wroldsen']"
 "['Cali Y El Dandee', 'Sebastian Yatra']" "['Bryan Adams']"
 "['Dire Straits']"
 "['J Balvin', 'Yandel', 'Farruko', 'Nicky Jam', 'De La Ghetto', 'Daddy Yankee',
'Zion', 'Arcangel']"
```

```
 "['J Balvin']" "['J Balvin', 'Pharrell Williams', 'BIA', 'Sky']"
 "['J Balvin', 'Jowell & Randy']" "['Lady Gaga']" "['Future']"
 "['A Boogie Wit da Hoodie']" "['Maroon 5']"
 "['KAROL G', 'Bad Bunny', 'Quavo']" "['KAROL G', 'Ozuna']"
 "['Sebastian Yatra']" "['Sebastian Yatra', 'Wisin', 'Nacho']"
 "['Sebastian Yatra', 'Cosculluela', 'Cali Y El Dandee']"
 "['Black Eyed Peas']" "['G-Eazy']" "['6ix9ine', 'Nicki Minaj']"
 "['Swae Lee']" "['Don Omar']" "['ROSALÍA']" "['Ellie Goulding']"]

<ipython-input-7-76ff31b8f52d>:1: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
print(spot[spot.popularity==0][spot.year==2020][['artists']].squeeze().unique())
```

There's a small group of tracks published recently but also have a 0 popularity score A quick querry shows that these tracks are by relatively popular artists so the reason for 0 popularity score might be because these tracks were released too recently that they haven't got enough time to gather enough plays to get a score Same as above, we're going to drop these records.

[8]:
```python
spot[spot.popularity == 0].index
spot.drop(index=spot[spot.popularity == 0].index, inplace=True)
# drop rows where popularity score = 0
```

According to Spotify API documentation, 'liveness' is defined as detection level of the presence of audience Higher 'liveness' values indicate a higher probability that a certain track is a record of a live session. A 'liveness' score of above 0.8 presents a strong likelihood that a track is live. Since our model is meant to provide prediction for a studio recorded track, we're going to filter and discard tracks which are highly likely to be live records.

[9]:
```python
print((spot.liveness > 0.8).value_counts())
# There are about 3000 tracks in this dataset which are highly likely to be␣
 ↪live records
spot.drop(index=spot[spot.liveness > 0.8].index, inplace=True)
```

```
False    139366
True       3186
Name: liveness, dtype: int64
```

We're also not going to use 'liveness' as one of the predicting variables since it's not an attribute which an artist consciously control when creating a track. As far as we're concerned, 'liveness' helps to classify whether a track is live or not and we're not concerned with how whether a track is live or not affects its popularity on Spotify.

'speechiness' above 0.66 is considered non-musical so therefore we're going to filter out those tracks as well unlike 'liveness', 'speechiness' does characterize a track rather than simply classify whether a track is a podcast/talkshow or a song For example, with 'speechiness' somewhere between 0.33 and 0.66 the song is most likely to be a rap song. We can see this score as a way to quantify how melodic a song is. Therefore, we're going to keep this column to use as a predicting variable

[10]:
```python
spot.drop(index=spot[spot.speechiness > 0.66].index, inplace=True)
spot.shape
```

[10]: (138567, 19)

Now we're going to look into 'tempo' attribute We can notice that there are tracks whose tempo is zero, let's list them out

[11]:
```
spot[spot.tempo == 0]
```

[11]:
```
        acousticness                             artists  danceability  \
2721        0.099500                    ['Frank Sinatra']           0.0
3387        0.756000                  ['Waylon Jennings']           0.0
6930        0.931000                   ['Crain & Taylor']           0.0
7411        0.111000                    ['Sound Dreamer']           0.0
7792        0.145000                       ['Fan Sounds']           0.0
…               …                                     …          …
161443      0.916000  ['Water Sound Natural White Noise']           0.0
164201      0.862000                       ['Bill Cosby']           0.0
169522      0.913000                         ['Granular']           0.0
169743      0.000013                    ['Naturaleza FX']           0.0
169770      0.957000                         ['Granular']           0.0

        duration_ms    energy  explicit                      id  \
2721          60280  0.906000         0  0P7TUyrm6OfIDJJKcidvnu
3387          14708  0.048400         0  2mex2o4uA69pMcLjMtyyGb
6930         598425  0.000075         0  3oKBZhpwrMiOhosXauv3lP
7411        5403500  0.000099         0  7foc25ig7dibxvULPU2kBG
7792         500167  0.000020         0  4xu38KnbRHbRHRwdg4KFul
…               …        …       …                     …
161443        63000  0.032000         0  5pGBDKBaR63vuJ4g8ialcU
164201       215280  0.770000         0  2WOKFIFBFcLBlklD7ugiw6
169522       205161  0.000164         0  2e6fCxto7NzsnujvliBtEk
169743       150879  0.000020         0  4UFlnhDTGyKvlhOQziDHkG
169770       146061  0.148000         0  4rkUd5Juj2icJoNTLq0jmP

        instrumentalness  key  liveness  loudness  mode  \
2721            0.000018    1     0.366    -6.227     1
3387            0.000144    4     0.166   -18.198     1
6930            0.892000    1     0.115   -19.703     0
7411            0.392000    2     0.137   -21.669     1
7792            0.213000    6     0.114   -25.556     1
…                      …   …        …        …     …
161443          0.202000    1     0.103   -30.704     1
164201          0.000002    9     0.694   -15.316     0
169522          0.910000   10     0.155   -31.221     0
169743          0.208000    1     0.311   -16.873     1
169770          0.168000    5     0.112   -22.012     1

                                                name  popularity  \
```

```
2721     My Kind Of Town (Reprise) - Live At The Sands …         22
3387                                        Ride Me Down Easy          29
6930                                              Ocean Waves          47
7411                                  Brown Noise - 90 Minutes          50
7792                               Box Fan Long Loop For Sleep          60
…                                                          …         …
161443                               Deep Sleep Recovery Noise          70
164201                                           Noah: Right!          16
169522                                  White Noise - 700 hz          64
169743                                      Colors of the Rain          68
169770                                     Brown Noise 750 LPF          69

       release_date  speechiness  tempo  valence  year
2721        1966-07          0.0    0.0      0.0  1966
3387     1973-07-01          0.0    0.0      0.0  1973
6930     2008-10-01          0.0    0.0      0.0  2008
7411     2013-06-05          0.0    0.0      0.0  2013
7792     2017-01-01          0.0    0.0      0.0  2017
…               …            …    …        …    …
161443   2020-02-25          0.0    0.0      0.0  2020
164201         1963          0.0    0.0      0.0  1963
169522   2017-10-14          0.0    0.0      0.0  2017
169743   2019-10-10          0.0    0.0      0.0  2019
169770   2019-01-11          0.0    0.0      0.0  2019

[95 rows x 19 columns]
```

Interestingly, by actually search for the track on Spotify and listen to it, we recognize that there are 2 groups of tracks whose tempo is zero The first group are tracks of noises or sounds such as 'white noise' or 'water sound', which people listen to to focus or relax The second group comprises tracks which are actually songs for example with tempo but for some reasons, Spotify engine was unable to detect We assume these data entries are corrupted and going to remove from the dataset

[12]:
```
spot.drop(index=spot[spot.tempo == 0].index, inplace=True)
spot.shape
```

[12]:
```
(138472, 19)
```

[13]:
```
# Rename 'duration_ms' column to 'duration'
spot.rename(columns={'duration_ms':'duration'}, inplace=True)
# We're going to drop colummns not related to the analysis such as 'artists',␣
↪'id', 'release_date' & 'name', ...
spot.drop(columns=['artists', 'id', 'release_date', 'name', 'liveness',␣
↪'year'], inplace=True)
```

[14]:
```
# Normalize 'loudness' column
from sklearn.preprocessing import MinMaxScaler
```

```
mms = MinMaxScaler()
spot.loc[:, 'loudness'] = mms.fit_transform(spot['loudness'].to_frame())
spot.describe()
```

[14]:

```
       acousticness   danceability      duration         energy  \
count 138472.000000  138472.000000  1.384720e+05  138472.000000
mean       0.421318       0.548262  2.329282e+05       0.529960
std        0.355001       0.173255  1.061279e+05       0.260163
min        0.000000       0.055100  2.462700e+04       0.000000
25%        0.062600       0.432000  1.750192e+05       0.323000
50%        0.355000       0.557000  2.154400e+05       0.539000
75%        0.773000       0.673000  2.661070e+05       0.743000
max        0.996000       0.988000  4.270034e+06       1.000000

           explicit  instrumentalness            key       loudness  \
count 138472.000000     138472.000000  138472.000000  138472.000000
mean       0.087122          0.127792       5.200662       0.739011
std        0.282015          0.279001       3.517606       0.097110
min        0.000000          0.000000       0.000000       0.000000
25%        0.000000          0.000000       2.000000       0.688191
50%        0.000000          0.000088       5.000000       0.754971
75%        0.000000          0.025000       8.000000       0.810783
max        1.000000          1.000000      11.000000       1.000000

               mode     popularity    speechiness          tempo  \
count 138472.000000  138472.000000  138472.000000  138472.000000
mean       0.710042      37.827922       0.071856     118.749887
std        0.453744      18.095701       0.077200      30.184993
min        0.000000       1.000000       0.000000      30.946000
25%        0.000000      25.000000       0.033900      95.390750
50%        1.000000      39.000000       0.043000     116.203500
75%        1.000000      51.000000       0.068100     137.478000
max        1.000000     100.000000       0.660000     244.091000

            valence
count 138472.000000
mean       0.537731
std        0.261161
min        0.000000
25%        0.328000
50%        0.548000
75%        0.756000
max        1.000000
```

[15]:
```
spot.shape
```

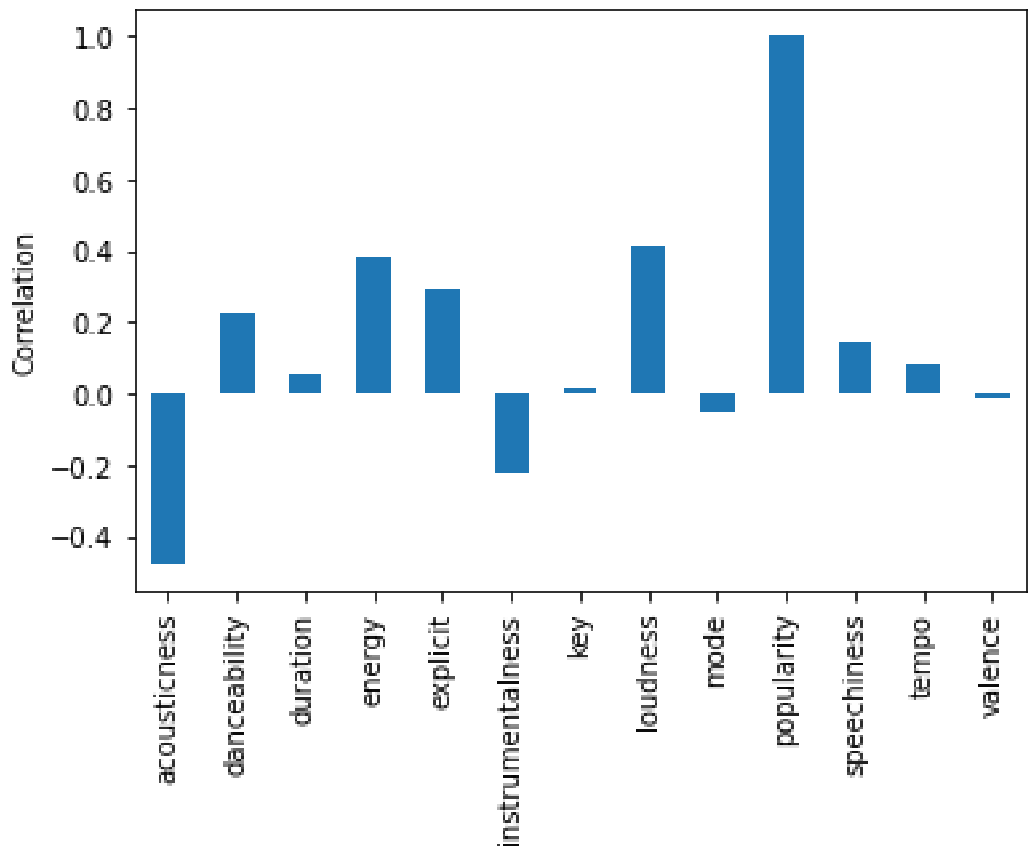
```
[15]: (138472, 13)
```

After cleaning the dataset we've arrived with a dataset having 12 features and 1 label column

```
[16]: # Create dependent and independent variables
X = spot[['acousticness', 'danceability', 'energy', 'explicit',␣
 ↪'instrumentalness', 'loudness', 'speechiness']].to_numpy()
y = spot.popularity.to_numpy()
```

```
[17]: spot.corr().popularity.plot(kind='bar', ylabel='Correlation')
```

```
[17]: <AxesSubplot:ylabel='Correlation'>
```

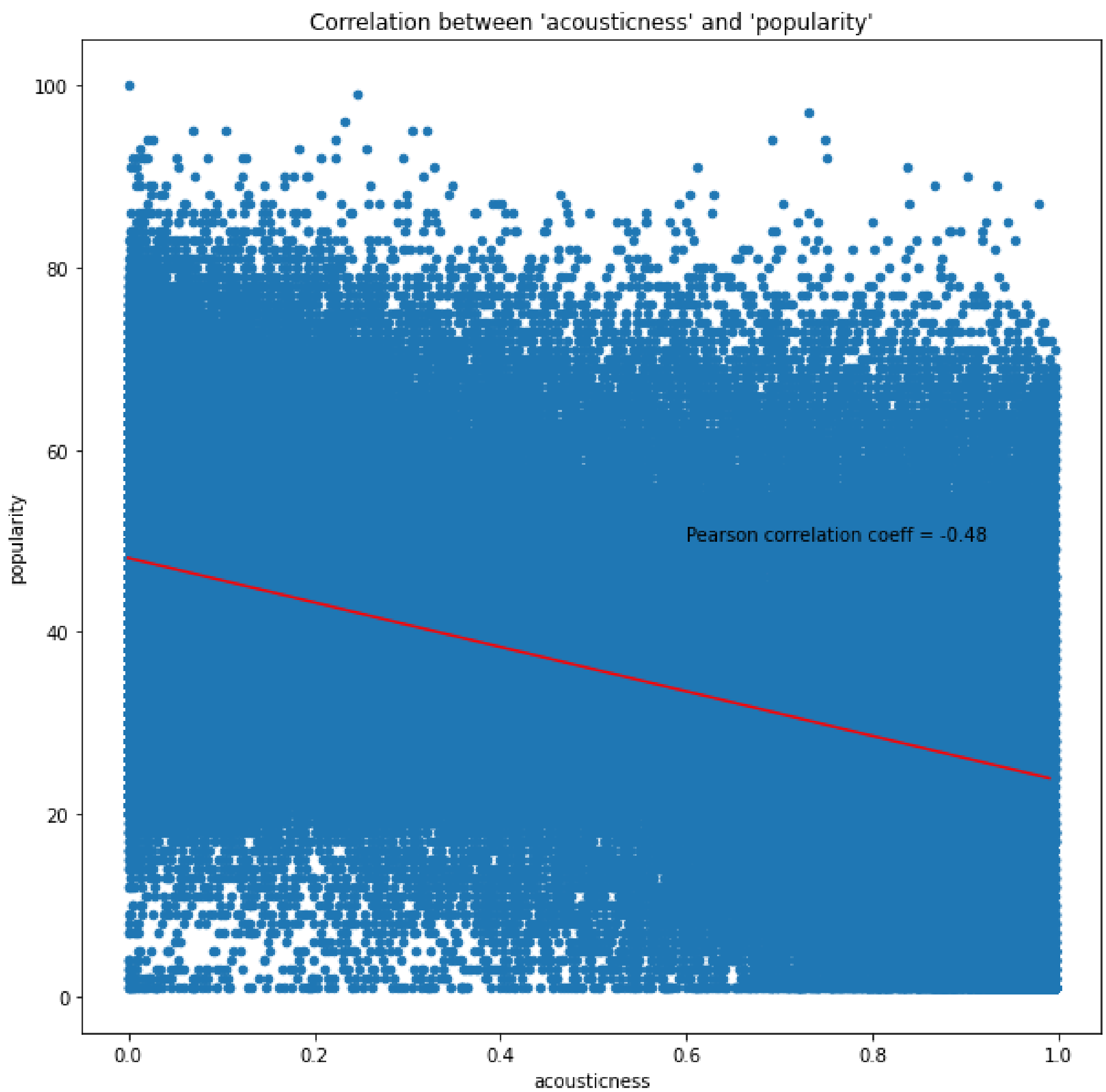


We can see there is a relatively strong correlation in 'acousticness', 'energy', 'loudness' and 'explicit'. Interestingy, 'valence' has close to zero bearing on a track's 'popularity', which means whether the theme of the song is 'happy' or 'sad' has little impact on its popularity. A track's 'duration', 'key' and 'mode' and 'tempo' also have close to no influence over popularity

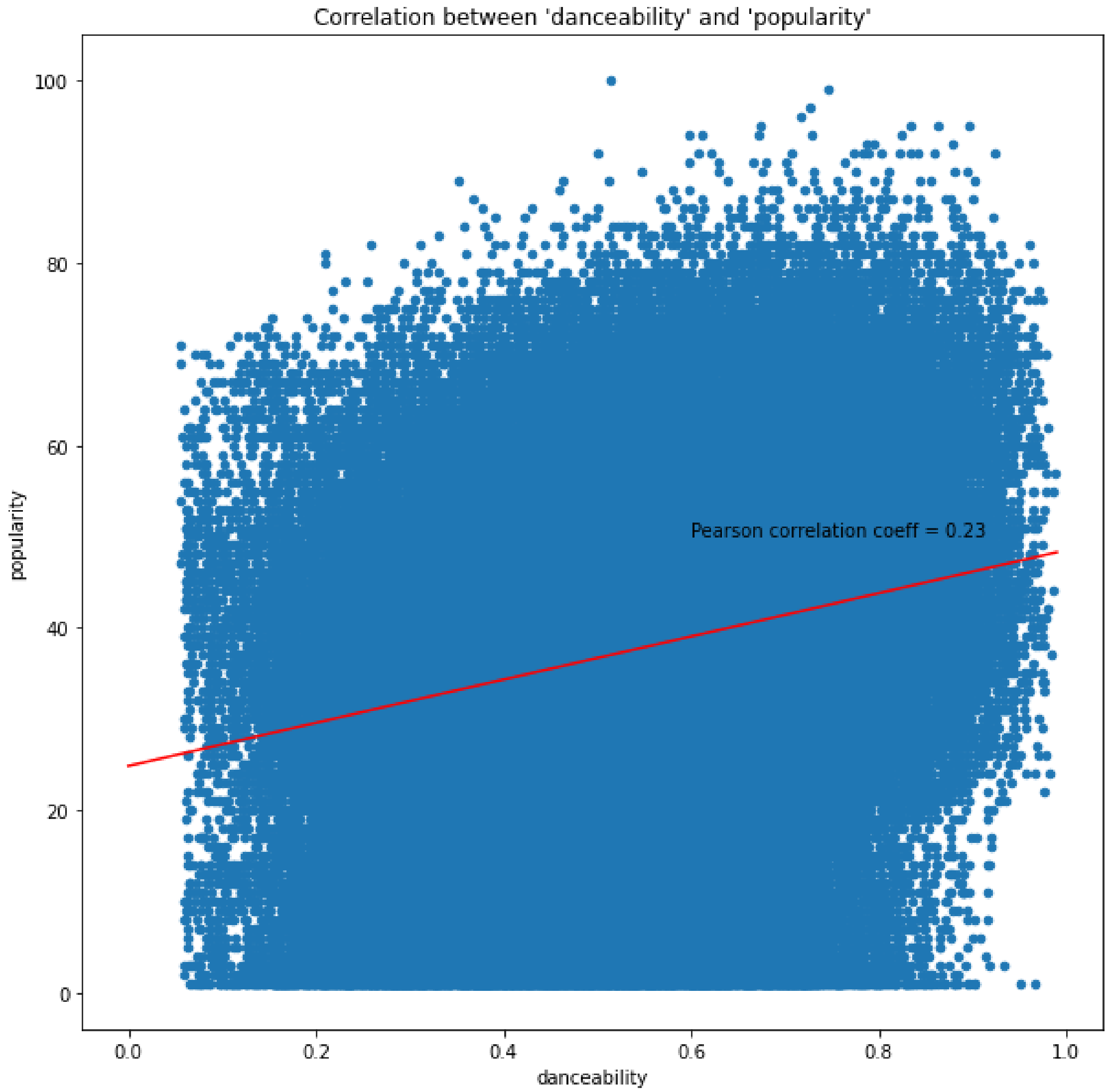
Let's explore the relationship with popularity of each individual attributes of interest

[18]:

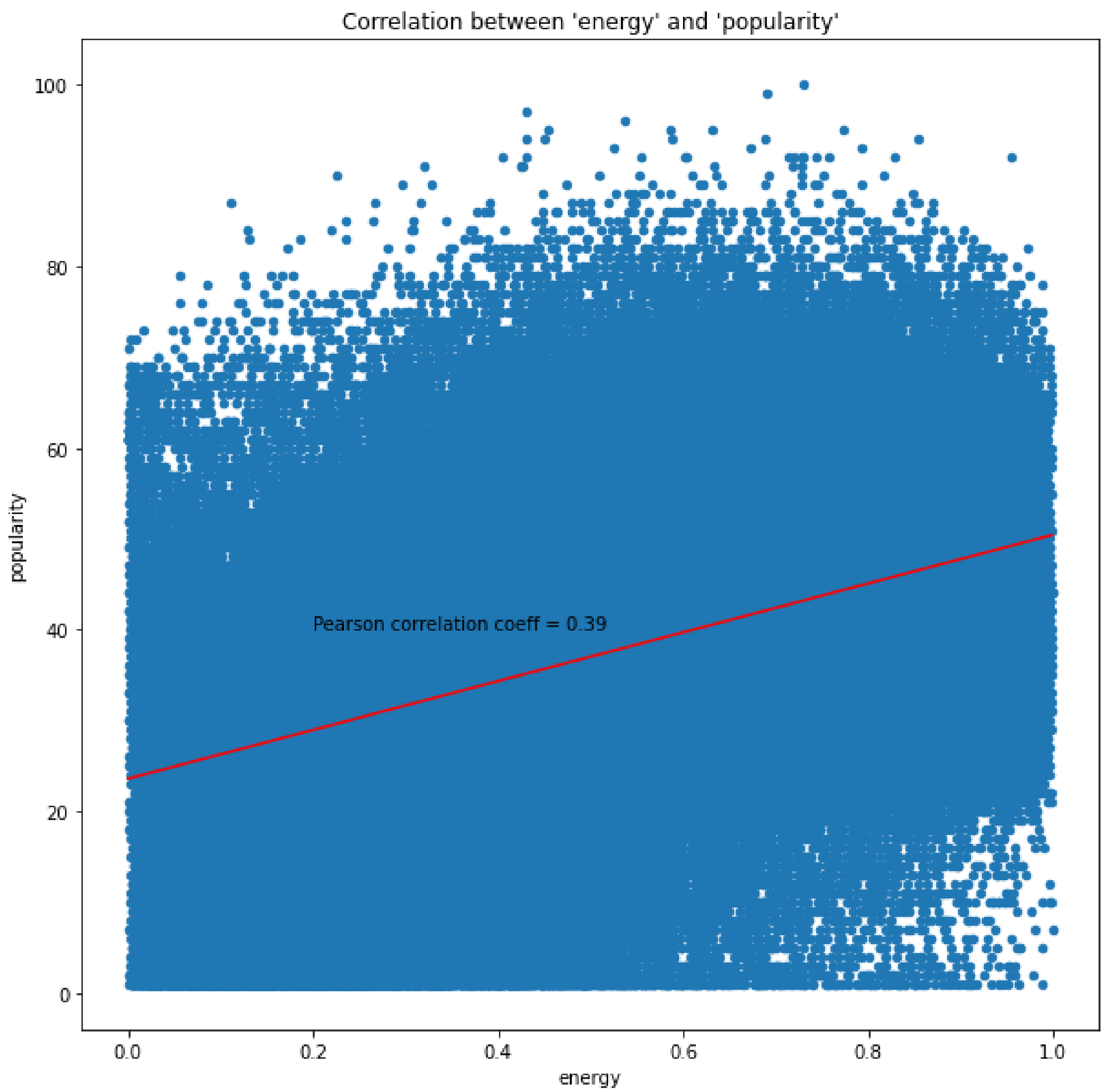
```
s_lr = LinearRegression()
s_lr.fit(X[:, 0].reshape(-1, 1), y)
corr = spot[['acousticness', 'popularity']].corr().to_numpy()

ax = spot.plot(kind='scatter', x='acousticness', y='popularity', figsize=[10,␣
↪10])
x = np.arange(0, 1, 0.01)
y_ = s_lr.intercept_ + s_lr.coef_*x
ax.plot(x, y_, color='red')
ax.set_title('Correlation between \'acousticness\' and \'popularity\'')
ax.text(0.6, 50, 'Pearson correlation coeff = {:.2f}'.format(corr[0, 1]))
plt.show()
```



[19]:
```
s_lr = LinearRegression()
s_lr.fit(X[:, 1].reshape(-1, 1), y)
corr = spot[['danceability', 'popularity']].corr().to_numpy()

ax = spot.plot(kind='scatter', x='danceability', y='popularity', figsize=[10,␣
 ↪10])
x = np.arange(0, 1, 0.01)
y_ = s_lr.intercept_ + s_lr.coef_*x
ax.plot(x, y_, color='red')
ax.set_title('Correlation between \'danceability\' and \'popularity\'')
ax.text(0.6, 50, 'Pearson correlation coeff = {:.2f}'.format(corr[0, 1]))
plt.show()
```

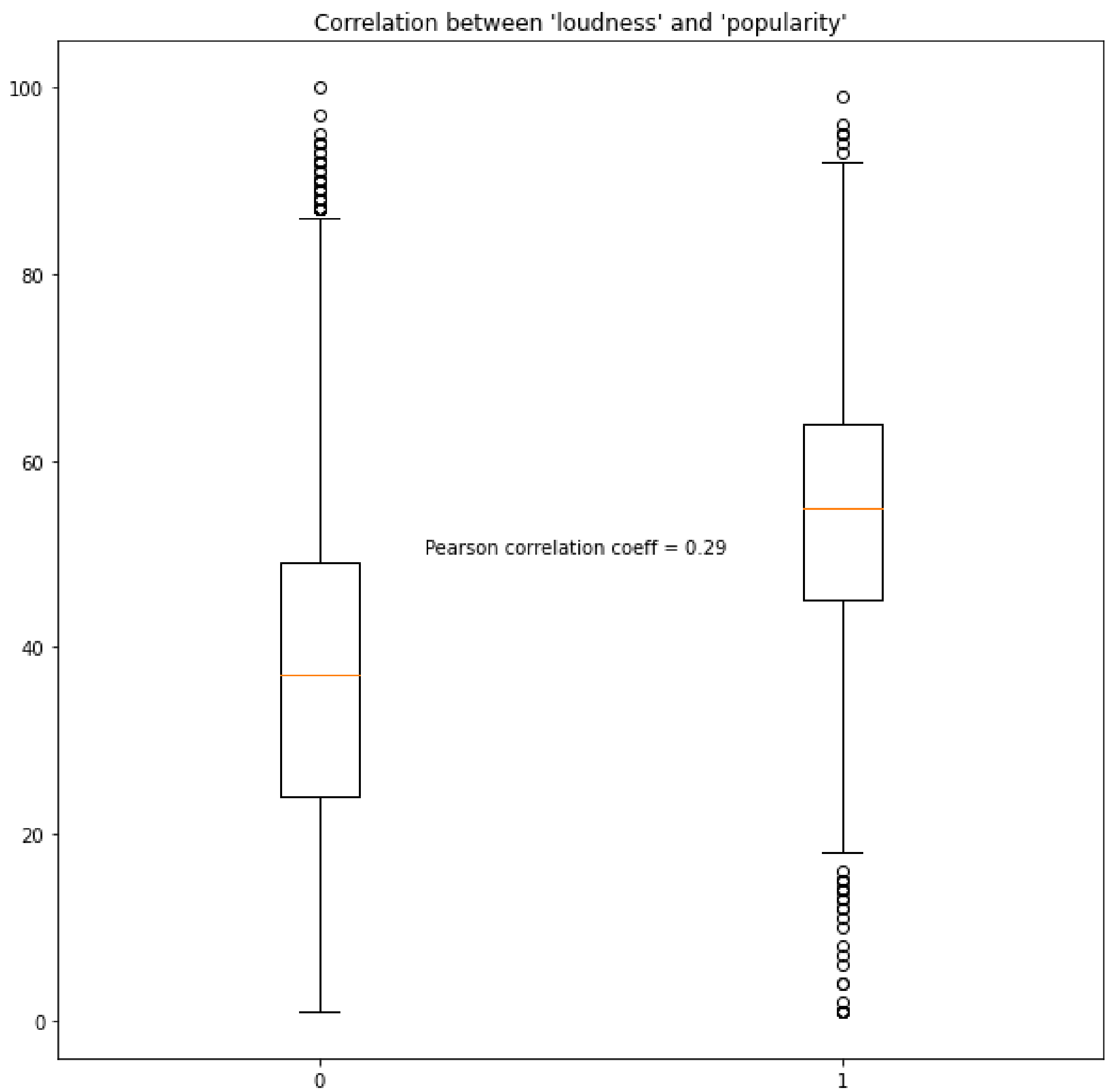


[20]:
```
s_lr = LinearRegression()
s_lr.fit(X[:, 2].reshape(-1, 1), y)
corr = spot[['energy', 'popularity']].corr().to_numpy()

ax = spot.plot(kind='scatter', x='energy', y='popularity', figsize=[10, 10])
x = np.arange(0, 1, 0.001)
y_ = s_lr.intercept_ + s_lr.coef_*x
ax.plot(x, y_, color='red')
ax.set_title('Correlation between \'energy\' and \'popularity\'')
ax.text(0.2, 40, 'Pearson correlation coeff = {:.2f}'.format(corr[0, 1]))
plt.show()
```



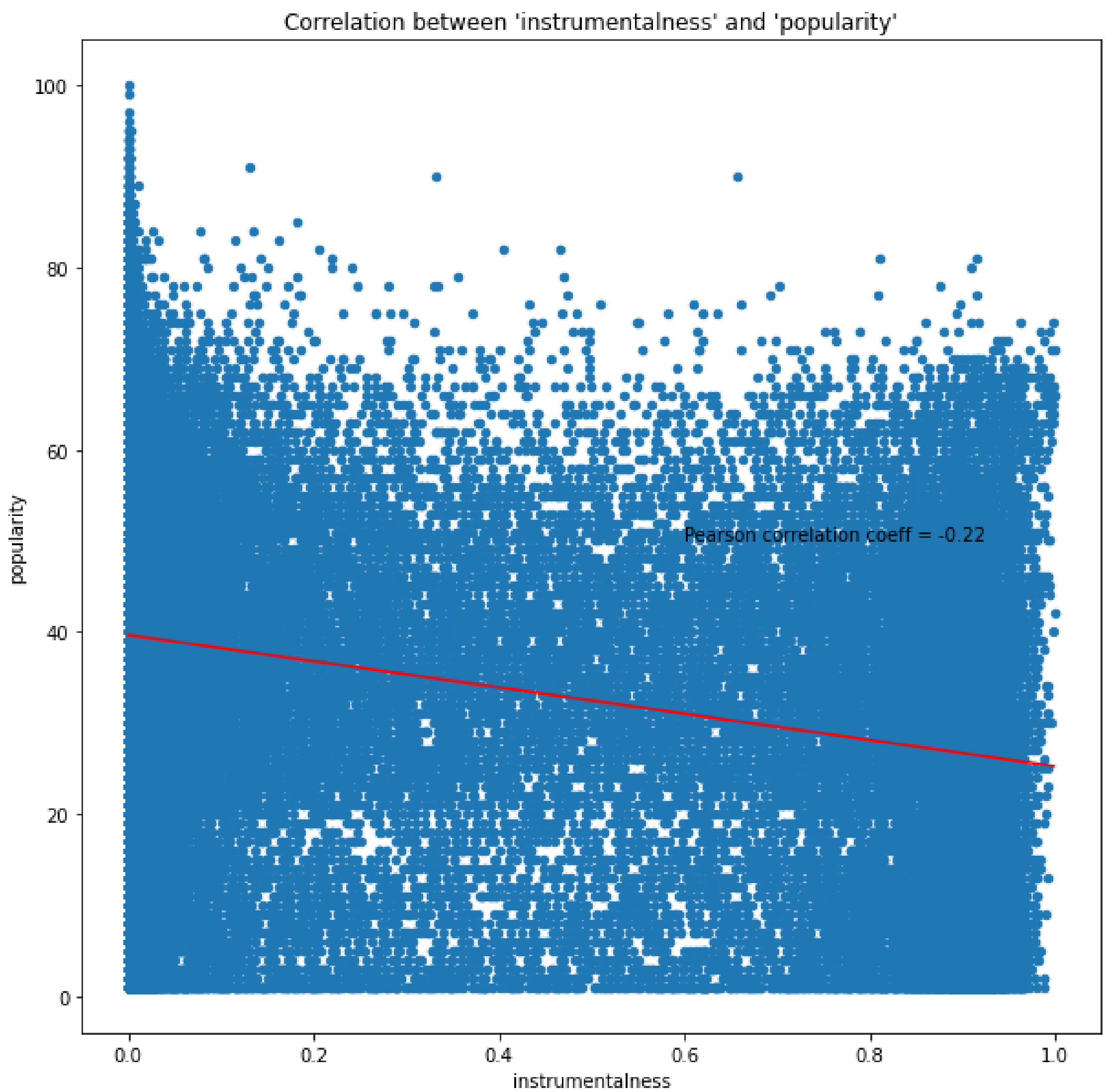
[21]:

```
s_lr = LinearRegression()
s_lr.fit(X[:, 3].reshape(-1, 1), y)
corr = spot[['explicit', 'popularity']].corr().to_numpy()

ex0 = spot.groupby('explicit').get_group(0)['popularity']
ex1 = spot.groupby('explicit').get_group(1)['popularity']

fig, ax = plt.subplots()
fig.set_size_inches(10, 10)
ax.boxplot(x=[ex0, ex1], labels=[0, 1])
ax.set_title('Correlation between \'loudness\' and \'popularity\'')
ax.text(1.2, 50, 'Pearson correlation coeff = {:.2f}'.format(corr[0, 1]))
plt.show()
```



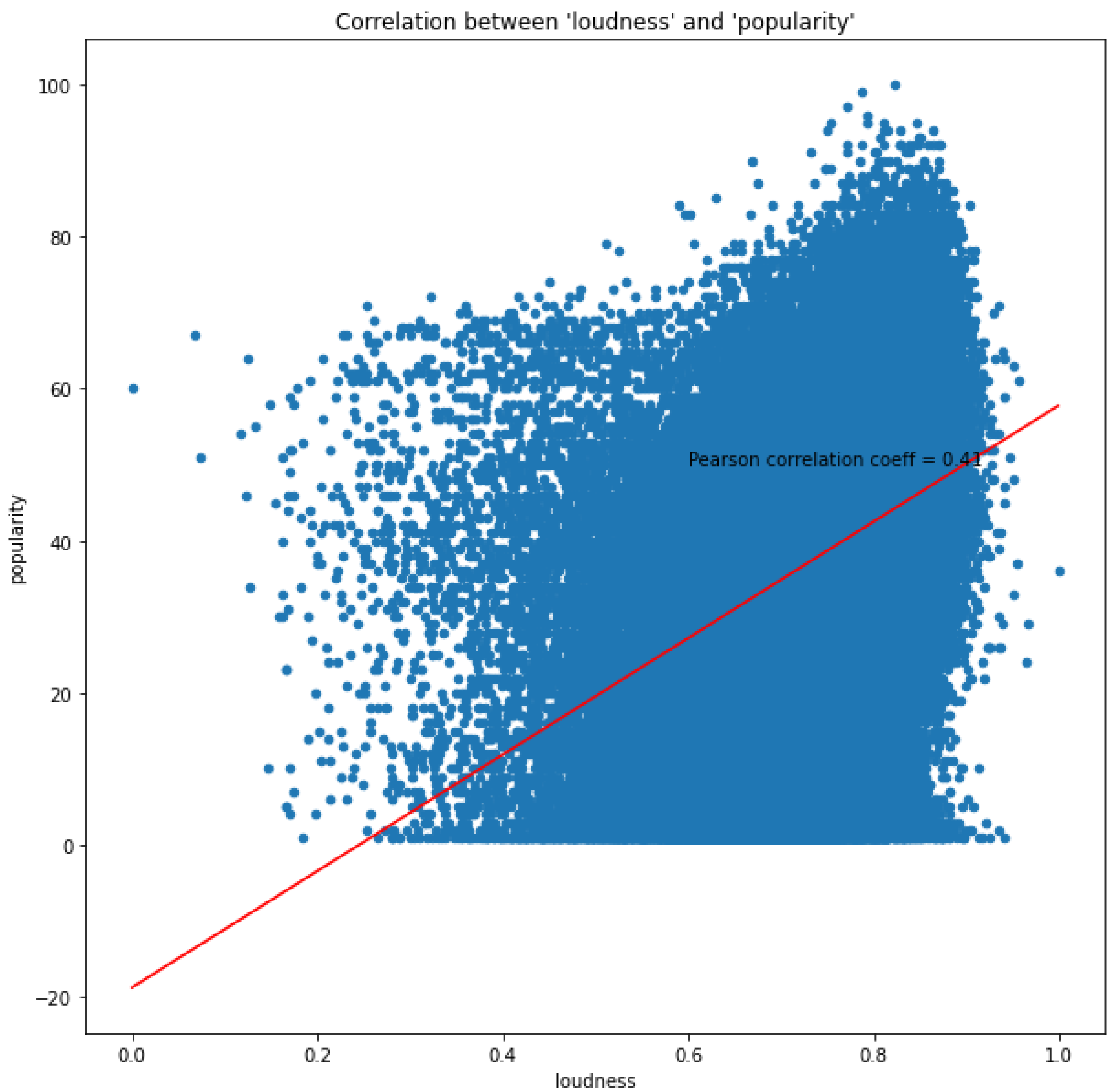
[22]:

```
s_lr = LinearRegression()
s_lr.fit(X[:, 4].reshape(-1, 1), y)
corr = spot[['instrumentalness', 'popularity']].corr().to_numpy()

ax = spot.plot(kind='scatter', x='instrumentalness', y='popularity',␣
 ↪figsize=[10, 10])
x = np.arange(0, 1, 0.001)
y_ = s_lr.intercept_ + s_lr.coef_*x
ax.plot(x, y_, color='red')
ax.set_title('Correlation between \'instrumentalness\' and \'popularity\'')
ax.text(0.6, 50, 'Pearson correlation coeff = {:.2f}'.format(corr[0, 1]))
plt.show()
```

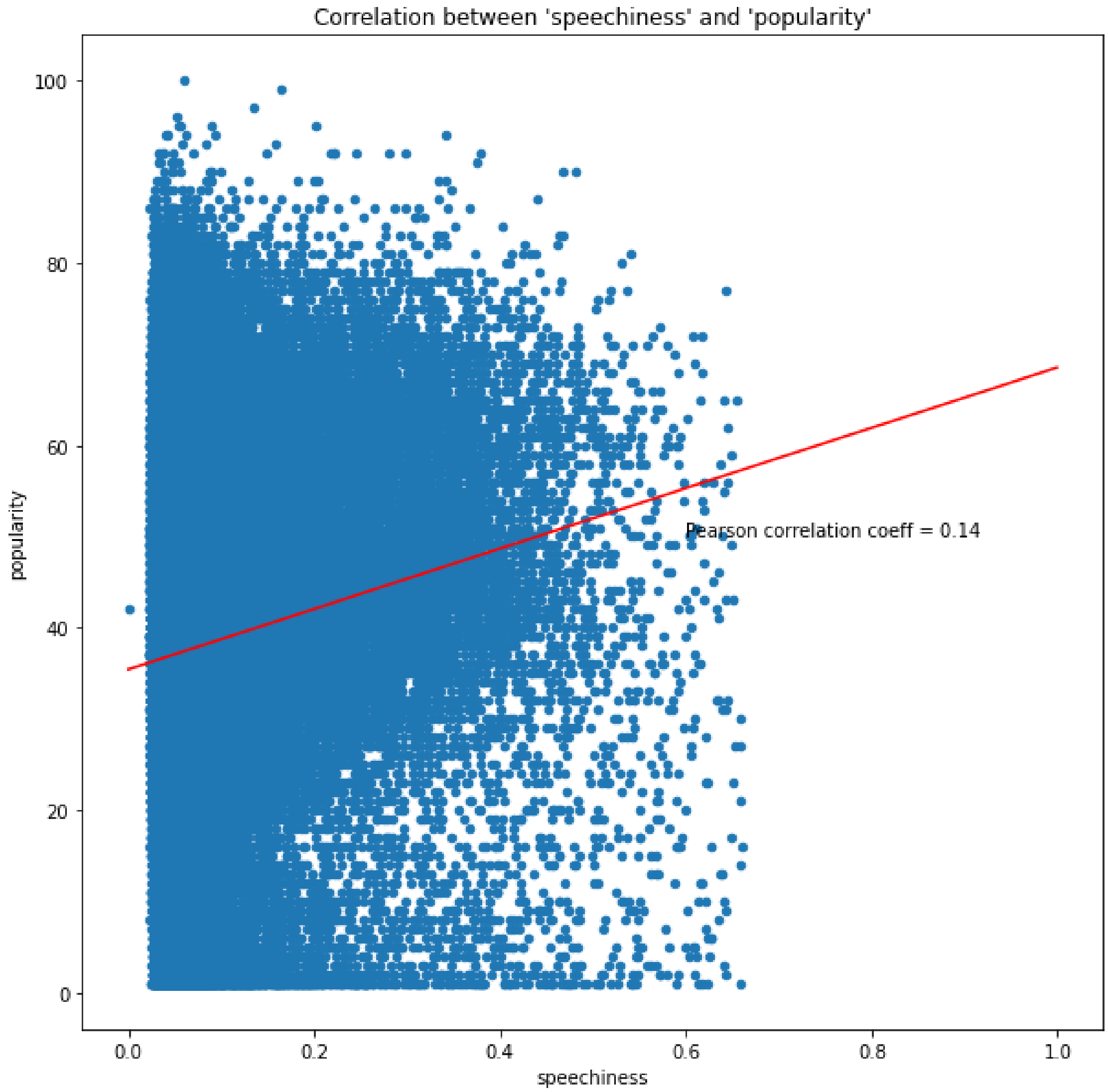


[23]:

```
s_lr = LinearRegression()
s_lr.fit(X[:, 5].reshape(-1, 1), y)
corr = spot[['loudness', 'popularity']].corr().to_numpy()

ax = spot.plot(kind='scatter', x='loudness', y='popularity', figsize=[10, 10])
x = np.arange(0, 1, 0.001)
y_ = s_lr.intercept_ + s_lr.coef_*x
ax.plot(x, y_, color='red')
ax.set_title('Correlation between \'loudness\' and \'popularity\'')
ax.text(0.6, 50, 'Pearson correlation coeff = {:.2f}'.format(corr[0, 1]))
plt.show()
```



[24]:
```
s_lr = LinearRegression()
s_lr.fit(X[:, 6].reshape(-1, 1), y)
corr = spot[['speechiness', 'popularity']].corr().to_numpy()

ax = spot.plot(kind='scatter', x='speechiness', y='popularity', figsize=[10,␣
 ↪10])
x = np.arange(0, 1, 0.001)
y_ = s_lr.intercept_ + s_lr.coef_*x
ax.plot(x, y_, color='red')
ax.set_title('Correlation between \'speechiness\' and \'popularity\'')
ax.text(0.6, 50, 'Pearson correlation coeff = {:.2f}'.format(corr[0, 1]))
plt.show()
```



We can see from the graphs above that the degree of correlation is not very apparent and a great amount of noise is observed for each case. Now we're going to create train and test set using train_test_split() function from sklearn library

[25]:
```
from sklearn.model_selection import train_test_split

# Split into train and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=1)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[25]:
```
((96930, 7), (41542, 7), (96930,), (41542,))
```

Let's now first try to build a prediction model based on a Multiple Linear Regression method and evaluate its accuracy using test set, metrics for accuracy used here are Mean Absolute Error (MAE) score and R2 score

[26]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)
y_hat = lr.predict(X_test)

mean_absolute_error(y_test, y_hat), r2_score(y_test, y_hat)
```

[26]:
```
(12.399115174516796, 0.28638612575513445)
```

Relatively decent score, on average, a prediction for the popularity score of a song is off by +- 12 points. However, we can try to improve evaluation score by trying a Polynomial Regression model

Grid search combined with cross validation method is going to be used to pick out the polynomial degree which yields the highest accuracy score.

[27]:
```
pf = PolynomialFeatures(degree=2)
lr = LinearRegression()
pipe = Pipeline(steps=[('poly', pf), ('reg', lr)])

grid = {'poly__degree': [i for i in range(2, 6, 1)]}

pf.get_params()
search = GridSearchCV(pipe, grid)
search.fit(X_train, y_train)
print(search.best_score_, search.best_params_)
```

```
0.38643776545205477 {'poly__degree': 4}
```

A grid search with cross validation scoring return the best polynominal degree for the Polynomial Regression is 4. We're going to set the model parameter to degree=4 and test using test dataset

Results

[28]:
```
pf = PolynomialFeatures(degree=4)
lr = LinearRegression()
pipe = Pipeline(steps=[('poly', pf), ('reg', lr)])

pipe.fit(X_train, y_train)
y_hat = pipe.predict(X_test)


print('Mean absolute score is: {:.2f}'.format(mean_absolute_error(y_test,␣
↪y_hat)))
print('R2 score is: {:.2f}'.format(r2_score(y_test, y_hat)))
```

```
Mean absolute score is: 11.37
R2 score is: 0.38
```

Fairly consistent with scores obtained from cross validation. Now let's assume we're going to compose an EDM track which is, by Spotify model's definition, very danceable, high in energy and relatively loud with a bit of rap. Let's see how well this song can do

[29]:
```
# X = spot[['acousticness', 'danceability', 'energy', 'explicit',␣
↪'instrumentalness', 'loudness', 'speechiness']].to_numpy()

test = [[0.1, 0.6, 0.8, 1, 0.5, 0.9, 0.2]]

print(pipe.predict(test))
```

```
[52.10633809]
```

Such a song is predicted to receive a score of 51, which is higher than the mean popularity score of the dataset. Not bad!

Discussion

An R2 score of around 0.38 indicates that about 38% of the variance of the values in 'popularity' column is explained by the model. Given that this model involves human behaviours and it is in general difficult to explain why or why not a person like something, a 0.38 R2 score is acceptable as to the model's power to predict.

It is important to note that this model does not take into account the effect of the popularity of the artist, the size of such artist fanbase (and how much of it are Spotify users), or how a track is marketed. These elements could be a deciding factor as to whether a track can gain the intial traction to become more popular.

Another point to note is that this model accuracy depends greatly on how well or how accurately the Spotify machine learning model quantity attributes of a track. For instance, if Spotify model gives a track a 'energy' score of 1 but, in reality, the general perception of the track by the majority of Spotify users who have listened to the song is that it is not very energetic then this data entry will introduce noise into the model.

In order to improve this prediction model, more data about how tracks are recommended to Spotify users or how many times is a track listed under different playlists might prove to be useful.

Conclusion

In this report we have presented an analysis on the Spotify tracks dataset. We found that there's noticeable correlation between a track's 'popularity' and its attributes such as 'loudness', 'energy' and 'acousticness' A predictive model using Polynomial Regression was then built to predict a song's popularity on Spotify based on its intrinsic characteristics The model achieved a reasonable R-2 score of 0.38