eda

November 20, 2021

1 Exploratory Data Analysis of Spotify tracks!

1.0.1 Hope these tracks can be popular ...

[1]:
```
import pandas as pd
from pandas_profiling import ProfileReport
import altair as alt
from sklearn.model_selection import train_test_split
```

1. Formulate our question

We want to predict the popularity of a song, given various features such as genre, duration, energy, tempo and acousticness. Can our raw data do this for us?

2. Read in the data

[2]:
```
audio = pd.read_csv('../data/audio_features.csv')
```

2.1 Split train set and test set

[3]:
```
audio_train, audio_test = train_test_split(audio, test_size=0.2,␣
↪random_state=123)
```

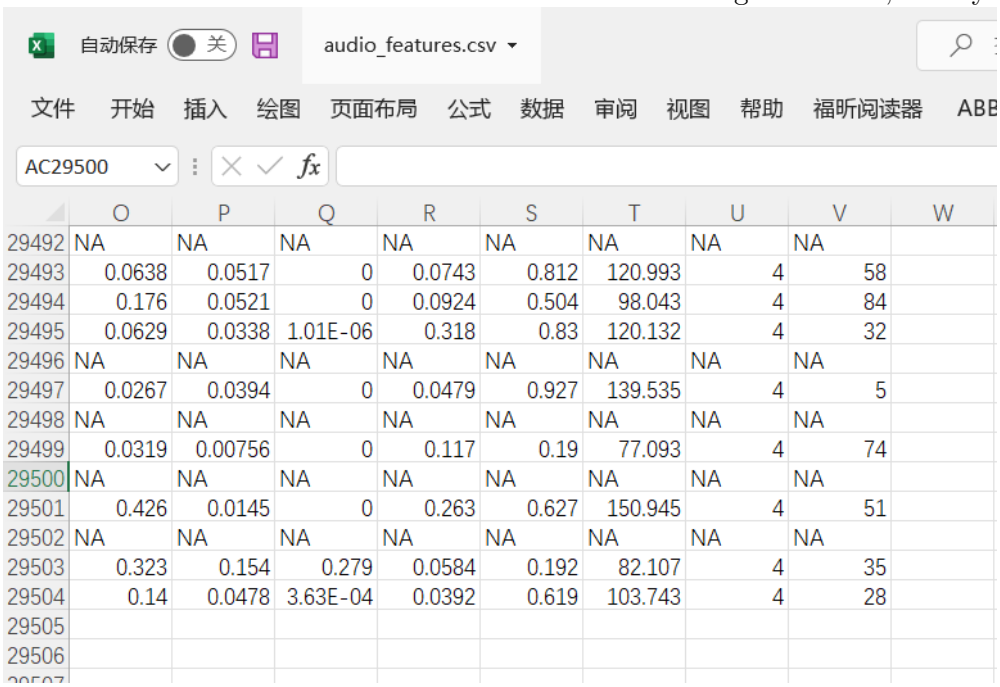
3. Check the packaging

[4]:
```
audio_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 23602 entries, 9624 to 19966
Data columns (total 22 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   song_id                     23602 non-null  object
 1   performer                   23602 non-null  object
 2   song                        23602 non-null  object
 3   spotify_genre               22312 non-null  object
 4   spotify_track_id            19526 non-null  object
 5   spotify_track_preview_url   11591 non-null  object
 6   spotify_track_duration_ms   19526 non-null  float64
 7   spotify_track_explicit      19526 non-null  object
 8   spotify_track_album         19521 non-null  object
```

```
 9   danceability                19473 non-null  float64
 10  energy                      19473 non-null  float64
 11  key                         19473 non-null  float64
 12  loudness                    19473 non-null  float64
 13  mode                        19473 non-null  float64
 14  speechiness                 19473 non-null  float64
 15  acousticness                19473 non-null  float64
 16  instrumentalness            19473 non-null  float64
 17  liveness                    19473 non-null  float64
 18  valence                     19473 non-null  float64
 19  tempo                       19473 non-null  float64
 20  time_signature              19473 non-null  float64
 21  spotify_track_popularity    19526 non-null  float64
dtypes: float64(14), object(8)
memory usage: 4.1+ MB
```

We have 22 columns and 23602 rows in the data. Though there are some missing data, this dataset can support us to build a predictive model. We can check with the original data, they match!



	O	P	Q	R	S	T	U	V	W
29492	NA	NA	NA	NA	NA	NA	NA	NA	
29493	0.0638	0.0517	0	0.0743	0.812	120.993	4	58	
29494	0.176	0.0521	0	0.0924	0.504	98.043	4	84	
29495	0.0629	0.0338	1.01E-06	0.318	0.83	120.132	4	32	
29496	NA	NA	NA	NA	NA	NA	NA	NA	
29497	0.0267	0.0394	0	0.0479	0.927	139.535	4	5	
29498	NA	NA	NA	NA	NA	NA	NA	NA	
29499	0.0319	0.00756	0	0.117	0.19	77.093	4	74	
29500	NA	NA	NA	NA	NA	NA	NA	NA	
29501	0.426	0.0145	0	0.263	0.627	150.945	4	51	
29502	NA	NA	NA	NA	NA	NA	NA	NA	
29503	0.323	0.154	0.279	0.0584	0.192	82.107	4	35	
29504	0.14	0.0478	3.63E-04	0.0392	0.619	103.743	4	28	
29505									
29506									

4. Look at the Top and the Bottom of our Data

[5]:
```
audio_train.head()
```

[5]:
```
                                song_id            performer  \
9624       Here's A HeartThe Diplomats        The Diplomats
5431                          DigIncubus              Incubus
11066       I Like Dreamin'Kenny Nolan          Kenny Nolan
1241   All You Need Is LoveThe Beatles          The Beatles
6453         Eat It"Weird Al" Yankovic  "Weird Al" Yankovic
```

```
                     song  \
9624         Here's A Heart
5431                   Dig
11066       I Like Dreamin'
1241   All You Need Is Love
6453                Eat It

                                          spotify_genre  \
9624   ['gangster rap', 'hardcore hip hop', 'harlem h…
5431   ['alternative metal', 'alternative rock', 'fun…
11066                                  ['bubblegum pop']
1241   ['british invasion', 'merseybeat', 'psychedeli…
6453   ['antiviral pop', 'comedy rock', 'comic', 'par…

            spotify_track_id  \
9624   39xymLsE59O6HtMtqMhb7A
5431   5wvYib82q05wiNjLElD8GJ
11066  4wlRO5dyyO7jYrzs2PltV8
1241   68BTFws92cRztMS1oQ7Ewj
6453   0WuYuWhLws8VahMy2zLLRJ

                               spotify_track_preview_url  \
9624   https://p.scdn.co/mp3-preview/9a96cf7978baef30…
5431   https://p.scdn.co/mp3-preview/869c0cf3f8e04da5…
11066  https://p.scdn.co/mp3-preview/d9006c9b1b11f409…
1241                                                 NaN
6453   https://p.scdn.co/mp3-preview/5b9843b163d62ce6…

       spotify_track_duration_ms spotify_track_explicit  \
9624                    155200.0                  False
5431                    257253.0                  False
11066                   221560.0                  False
1241                    230386.0                  False
6453                    200626.0                  False

                          spotify_track_album  danceability  …  loudness  \
9624   Ace's Golden Age of American Hits Vol 1         0.560  …    -7.113
5431                             Light Grenades         0.450  …    -4.739
11066          All-Time Greatest Performances         0.626  …   -14.203
1241         Magical Mystery Tour (Remastered)         0.400  …    -7.768
6453         The Essential "Weird Al" Yankovic         0.767  …    -8.548

       mode  speechiness  acousticness  instrumentalness  liveness  valence  \
9624    1.0       0.0380        0.5430          0.000000    0.6380    0.555
5431    1.0       0.0386        0.0293          0.000000    0.1160    0.463
11066   0.0       0.0394        0.9530          0.007690    0.1030    0.253
```

```
1241    1.0       0.0295        0.3460          0.000031    0.1550    0.653
6453    1.0       0.0766        0.0866          0.000000    0.0684    0.858

          tempo  time_signature  spotify_track_popularity
9624     81.824             3.0                       0.0
5431     77.577             4.0                      63.0
11066   123.911             4.0                      38.0
1241    103.436             4.0                      69.0
6453    147.423             4.0                      46.0

[5 rows x 22 columns]
```

[6]:
```
audio_train.tail()
```

[6]:
```
                                        song_id  \
28636                                XOJohn Mayer
17730  Nobody But YouKenny Loggins With Jim Messina
28030          Who Do You Think You AreThe Shindogs
15725                               LuanneForeigner
19966        Rich As HellYoungBoy Never Broke Again

                            performer                       song  \
28636                      John Mayer                         XO
17730  Kenny Loggins With Jim Messina             Nobody But You
28030                    The Shindogs  Who Do You Think You Are
15725                       Foreigner                     Luanne
19966      YoungBoy Never Broke Again               Rich As Hell

                                          spotify_genre  \
28636  ['neo mellow', 'pop', 'pop rock', 'singer-song…
17730                                              NaN
28030                                               []
15725  ['album rock', 'classic rock', 'hard rock', 'm…
19966                       ['baton rouge rap', 'trap']

             spotify_track_id  \
28636  7cpCU3Denug5NGZsSpQl8v
17730                     NaN
28030  3DBdTT9nwUOw4ENzumkyWi
15725  0t7szxjCNe2CCnlmIihHwS
19966  5A6tFAdihqILHJrWuR6wD4

                              spotify_track_preview_url  \
28636  https://p.scdn.co/mp3-preview/ae749156ad44a169…
17730                                              NaN
28030  https://p.scdn.co/mp3-preview/9e2488051b846598…
15725  https://p.scdn.co/mp3-preview/5ba2baff8224885c…
```

```
19966  https://p.scdn.co/mp3-preview/5f625ea5748dc9a6…

       spotify_track_duration_ms spotify_track_explicit  \
28636                   213626.0                  False
17730                        NaN                    NaN
28030                   148813.0                  False
15725                   207493.0                  False
19966                   215327.0                   True

                                  spotify_track_album  danceability  …  \
28636                                              XO         0.431  …
17730                                             NaN           NaN  …
28030  Ain't It Hard! Garage & Psych From Viva Records         0.651  …
15725                                   4 (Expanded)         0.600  …
19966                                  AI YoungBoy 2         0.874  …

       loudness  mode  speechiness  acousticness  instrumentalness  liveness  \
28636    -9.753   1.0       0.0288       0.74900               0.0     0.211
17730       NaN   NaN          NaN           NaN               NaN       NaN
28030    -7.693   1.0       0.0306       0.33800               0.0     0.229
15725    -5.362   1.0       0.0411       0.00295               0.0     0.120
19966    -5.256   1.0       0.4410       0.03820               0.0     0.215

       valence    tempo  time_signature  spotify_track_popularity
28636    0.353  173.670             4.0                      73.0
17730      NaN      NaN             NaN                       NaN
28030    0.937  132.727             4.0                       2.0
15725    0.784  141.133             4.0                      38.0
19966    0.228  154.040             4.0                      71.0

[5 rows x 22 columns]
```

5. Check our "n"s

To have a general understanding of our data, we'll use pandas profiling from here. The script that generate the eda report of a `html` version is in `src`. The `html` version eda report is here.

[7]:
```
profile = ProfileReport(audio_train, title="Pandas Profiling Report")  #,␣
 ↪minimal=True)
profile.to_notebook_iframe()
```

```
Summarize dataset:   0%|          | 0/37 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

We can find that most our features are of high cardinality, considering our data is of songs, that seems normal. However, we found `spotify_genre` also have high cardinality, that is because a song may have multiple genres and the combination of the genres may be unique. We may need to transform this column using `explode` or else to unnest it and make it easier to be used in the model.

6. Validate with at least one external data source

The website musicstax provides us all the data from spotify. However, it takes some time to crawl all the data to match ours in the database so let's just try one observation. We pick `bad bad bad` to check. Since the popularity may change time by time, we can validate other features.

[8]:
```
audio_train.loc[audio_train['song']=='Bad Bad Bad', ['song', 'danceability',␣
↪'energy', 'valence','speechiness', 'liveness', 'instrumentalness']].iloc[0, ]
```

[8]:
```
song                Bad Bad Bad
danceability              0.974
energy                    0.596
valence                   0.892
speechiness               0.184
liveness                  0.151
instrumentalness            0.0
Name: 2124, dtype: object
```

Seems not that bad :)

7. Make a plot

The distribution and the correlation of the data are in the eda report. We'll explore the relationship between `spotify_track_popularity` and the features which have at least weak correlation (pearson's r > 0.1).

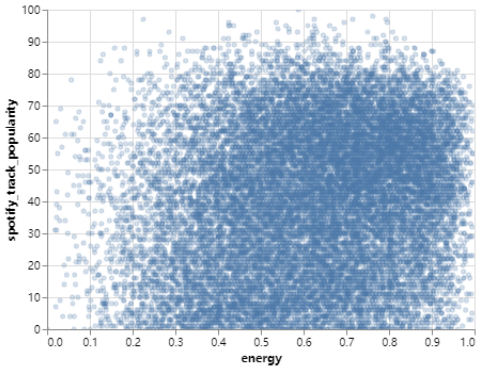
[9]:
```
# List out the correlated features
imp_features = list(audio_train.corr().query('spotify_track_popularity > 0.1').
 ↪sort_values(by=['spotify_track_popularity']).index)
imp_features.remove('spotify_track_popularity')
imp_features.remove('time_signature')
imp_features
```

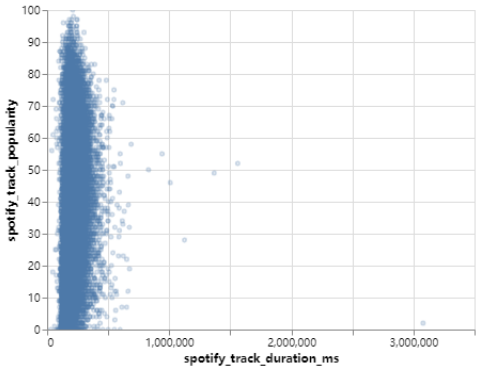
[9]:
```
['energy',
 'spotify_track_duration_ms',
 'danceability',
 'speechiness',
 'loudness']
```

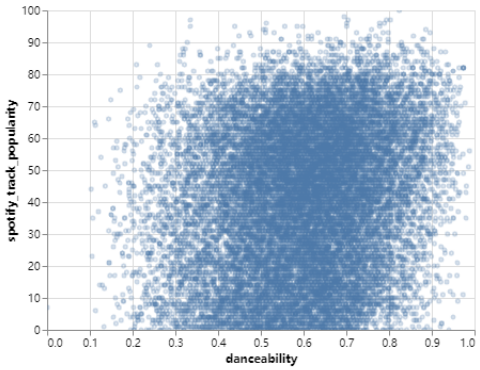
Notice that we remove `time_signature` since it is actually a categorical feature. We may have another plot for this one.

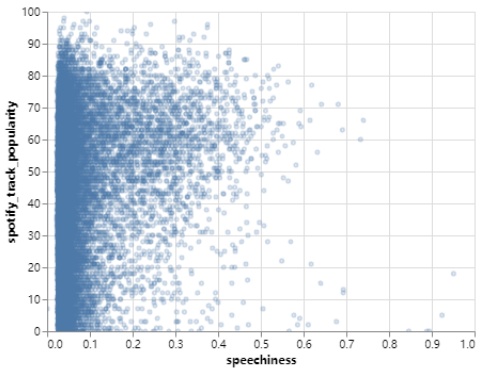
[10]:
```
# Draw them ( ´ )
# The scatter plot for numeric features
alt.renderers.enable('mimetype')
alt.data_transformers.disable_max_rows()

rela = alt.Chart(audio_train).mark_point(opacity=0.3, size=10).encode(
     alt.X(alt.repeat('row'), type='quantitative',
          scale=alt.Scale(zero=False)),
     alt.Y('spotify_track_popularity', type='quantitative',
          scale=alt.Scale(zero=False)),
     tooltip='song'
).repeat(
    row=imp_features
).interactive()

rela
```

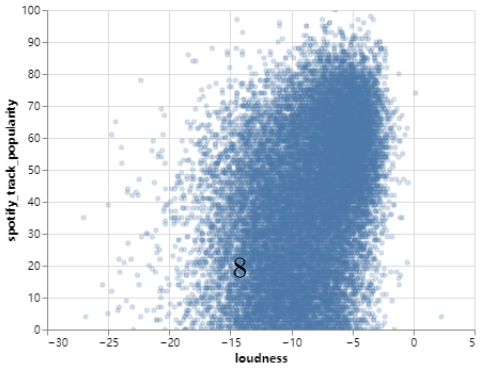
[10]:


spotify_track_popularity
energy


spotify_track_popularity
spotify_track_duration_ms

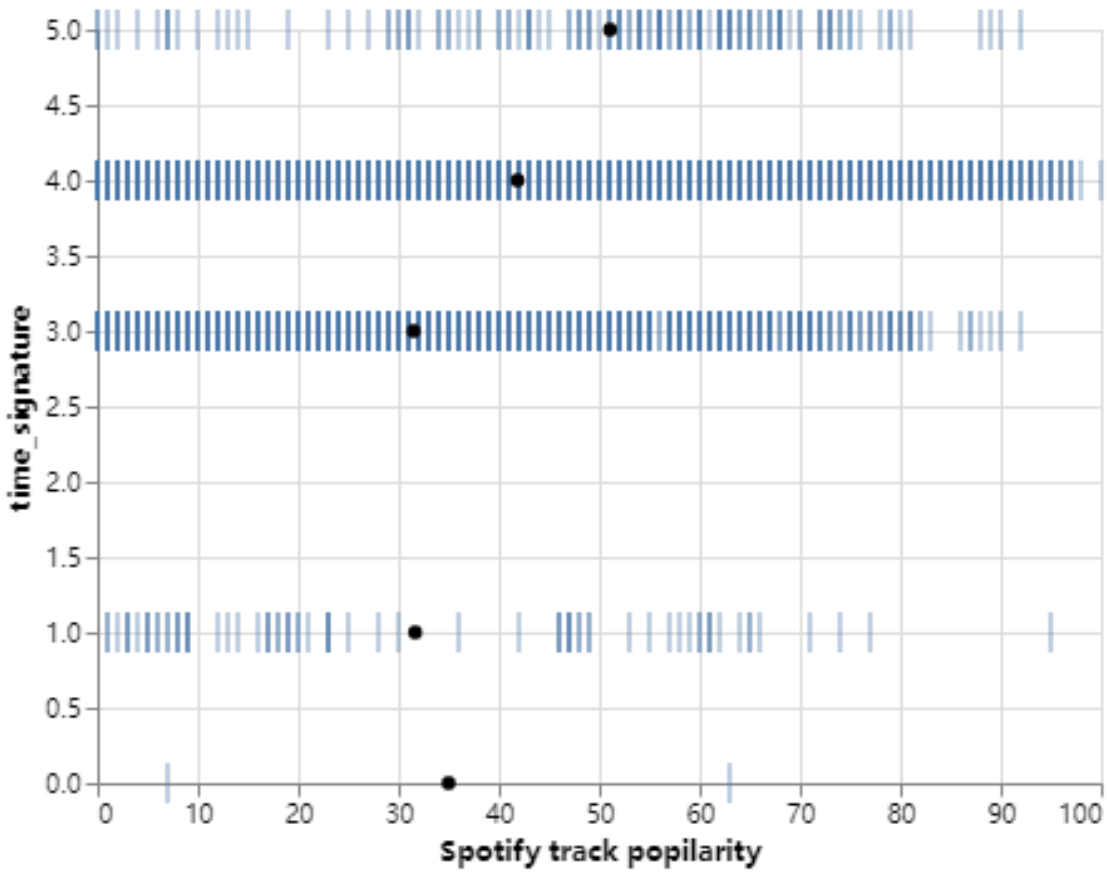

spotify_track_popularity
danceability


spotify_track_popularity
speechiness


spotify_track_popularity
loudness

[11]:
```
# The tick plot for categorical features


tick = alt.Chart(audio_train).mark_tick().encode(
    alt.Y('time_signature'),
    alt.X('spotify_track_popularity', scale = alt.Scale(zero=False), title =␣
 ↪"Spotify track popilarity"),
)

tick_plot = tick + tick.mark_point(filled=True, color='black').encode(x=alt.
 ↪X('spotify_track_popularity', aggregate='mean',

 ↪title = "Spotify track popilarity"),)


# Show the plot
tick_plot
```

[11]:



8. Try the Easy Solution First

Before the machine learning models, let's build up a simple linear model using these features first.

[12]:
```
import numpy as np
from sklearn.linear_model import LinearRegression


reg_col = list(audio_train.corr().query('spotify_track_popularity > 0.1').
 ↪sort_values(by=['spotify_track_popularity']).index)
reg_df = audio_train[reg_col]
reg_df = reg_df.dropna()

reg_X = reg_df[imp_features]
reg_y = reg_df['spotify_track_popularity']
reg = LinearRegression().fit(reg_X, reg_y)
reg.score(reg_X, reg_y)
```

[12]:
```
0.20066395205505516
```

[13]:
```
reg.coef_
```

[13]:
```
array([-2.01133866e+01,  5.79420796e-05,  1.63113602e+01,  3.65997317e+01,
        2.69234949e+00])
```

9.Follow-up Questions

- Do we have the right data? > The data can be matched with external data, and it has enough features and observations for us to answer the question.
- Do we need other data? > This data may be enough.
- Do we have the right question? > We found that linear regression did not perform well on our selected features, that can be caused by distribution of the data as well as the method of the model. We can fix this by transforming the columns and changing the model e.g. ridge.

[ ]: