eda

December 3, 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/raw/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)
```

[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
```

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

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

[5]:

	song_id	performer	song	spotify_genre	spotify_track_id	spotify_track_preview_url
9624	Here's A HeartThe Diplomats	The Diplomats	Here's A Heart	['gangster rap', 'hardcore hip hop', 'harlem h…	39xymLsE59O6HtMtqMhb7A	https://p.scdn.co/mp3-preview/9a96cf7978baef30…
5431	DigIncubus	Incubus	Dig	['alternative metal', 'alternative rock', 'fun…	5wvYib82qO5wiNjLElD8GJ	
11066	I Like Dreamin'Kenny Nolan	Kenny Nolan	I Like Dreamin'	['bubblegum pop']	4wlRO5dyyO7jYrzs2PltV8	
1241	All You Need Is LoveThe Beatles	The Beatles	All You Need Is Love	['british invasion', 'merseybeat', 'psychedeli…	68BTFws92cRztMS1oQ7Ewj	
6453	Eat It"Weird Al" Yankovic	"Weird Al" Yankovic	Eat It	['antiviral pop', 'comedy rock', 'comic', 'par…	0WuYuWhLws8VahMy2zLLRJ	

```
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]
```

[8]:
```
audio_train.tail()
```

[8]:
```
                                      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]
```

4. 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.

[9]:
```
# profile = ProfileReport(audio_train, title="Pandas Profiling Report")  #,␣
 ↪minimal=True)
# profile.to_notebook_iframe()
```

5. 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).

[10]:
```
# 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
```

[10]:
```
['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.

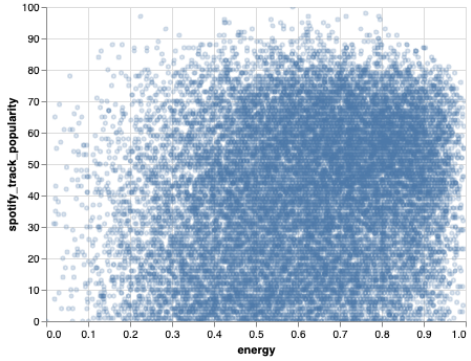
[14]:
```
# The scatter plot for numeric features
alt.renderers.enable('mimetype')
alt.data_transformers.disable_max_rows()

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',
```

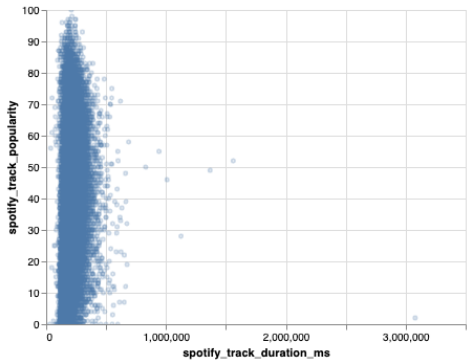
```
          scale=alt.Scale(zero=False)),
     tooltip='song'
).repeat(
    row=imp_features
).properties(
    title={
      "text": ["Relation between popularity of the song and each feature of the␣
 ↪song"],
      "subtitle": ["Single features have least correlation with the song␣
 ↪popularity"],
      "color": "black",
      "subtitleColor": "green"
    }
).interactive()

rela
```

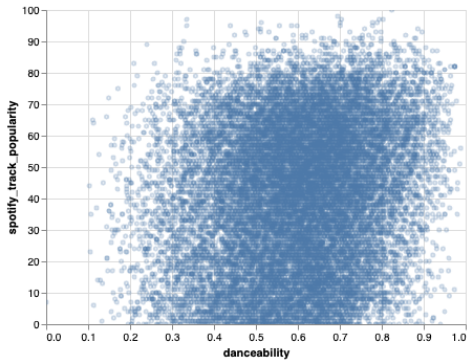
[14]:

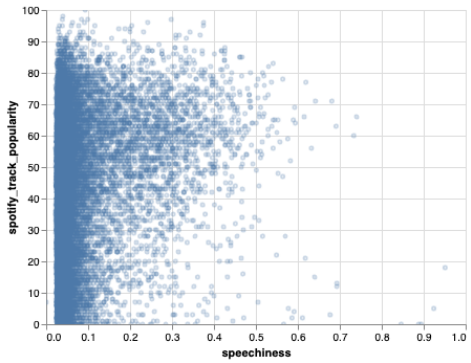
Relation between popularity of the song and each feature of the song

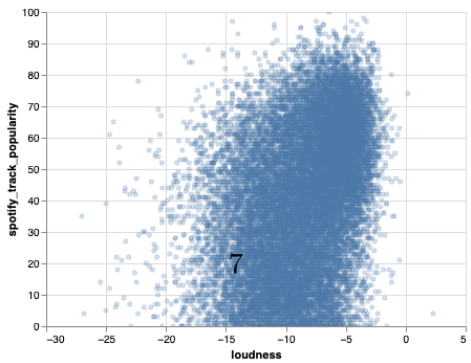
Single features have least correlation with the song popularity





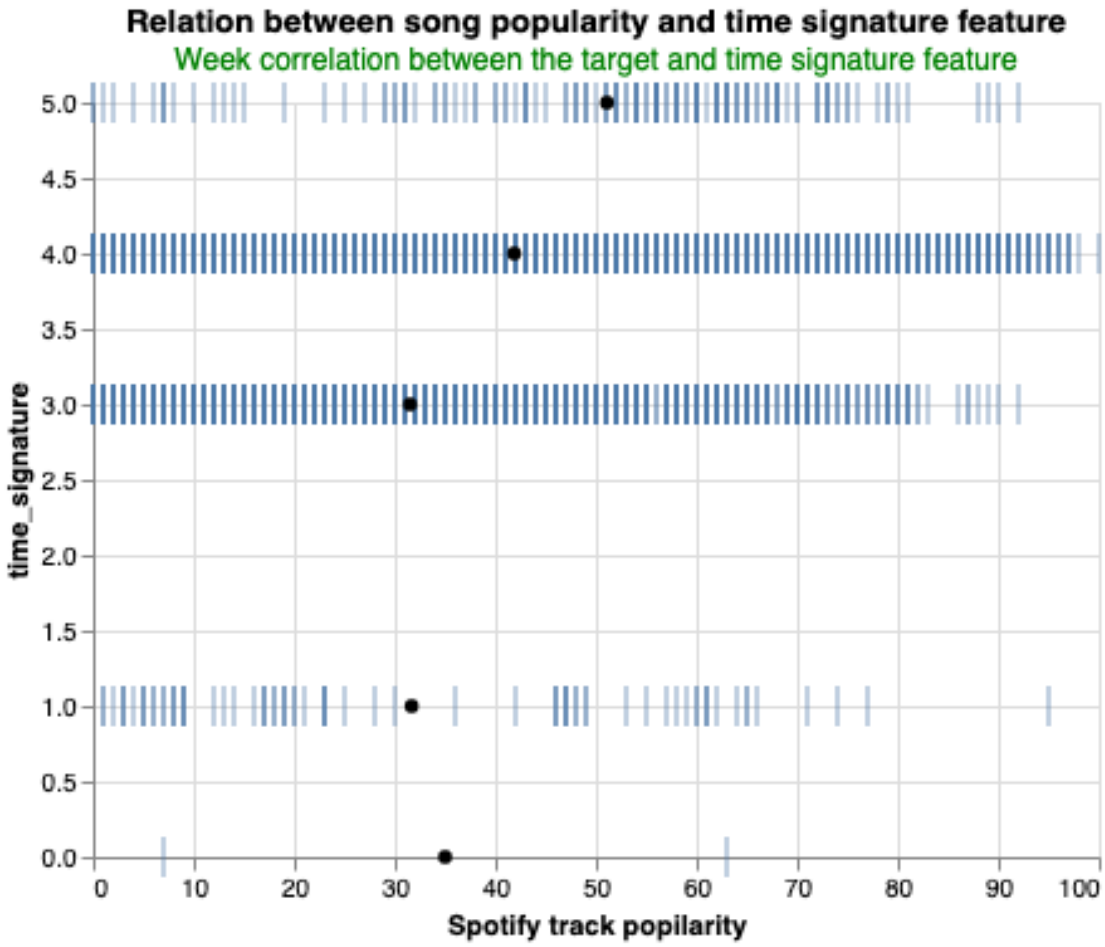






[32]:
```
# The tick plot for categorical features


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"
               )
    )
).properties(
    title={
        "text": ["Relation between song popularity and time signature feature"],
        "subtitle": ["Week correlation between the target and time signature␣
 ↪feature"],
        "subtitleColor": "green"
    }
)


# Show the plot
tick_plot
```

[32]:



[13]:
```
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
```

[26]:
```
obj_features = audio_train.select_dtypes(include='object').columns.to_list()
obj_unique = dict()
for feat in obj_features:
    obj_unique[feat] = len(audio_train[feat].unique())
pd.DataFrame(obj_unique, index = ['unique_class_number']).T
```

[26]:

	unique_class_number
song_id	23526
performer	8710
song	20044
spotify_genre	3131
spotify_track_id	19384
spotify_track_preview_url	11515
spotify_track_explicit	3
spotify_track_album	11398

- We found that `energy`, `spotify_track_duration_ms`, `danceability`, `speechiness`, `loudness` have at least weak correlation to our target. Among them, `danceability` and `loudness` seems have a positive relationship with the target. We may probably pay more attention to these features after in model building.
- The column `spotify_track_preview_url` have more than 10,000 missing values, we may probably drop the column when we build the model.
- For the object features, we found `song_id`, `song`, `spotify_track_id`, `spotify_track_preview_url`, `spotify_track_album` have more than 10,000 unique values. It will difficult for us to use them as categorical features in the model so we may probably drop them or transform them, e.g. for `song`, the tile of the song, we may probably use count vectorizer to grab the information from this column.

6. Try the Easy Solution First

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

[11]:
```
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)
```

[11]:
```
0.20066395205505516
```

[12]:
```
reg.coef_
```

[12]:
```
array([-2.01133866e+01,  5.79420796e-05,  1.63113602e+01,  3.65997317e+01,
        2.69234949e+00])
```

7.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. > But we may need to drop some columns and transform some columns before we build the predictive model.
- 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.