LKH

SPOTIFY ML

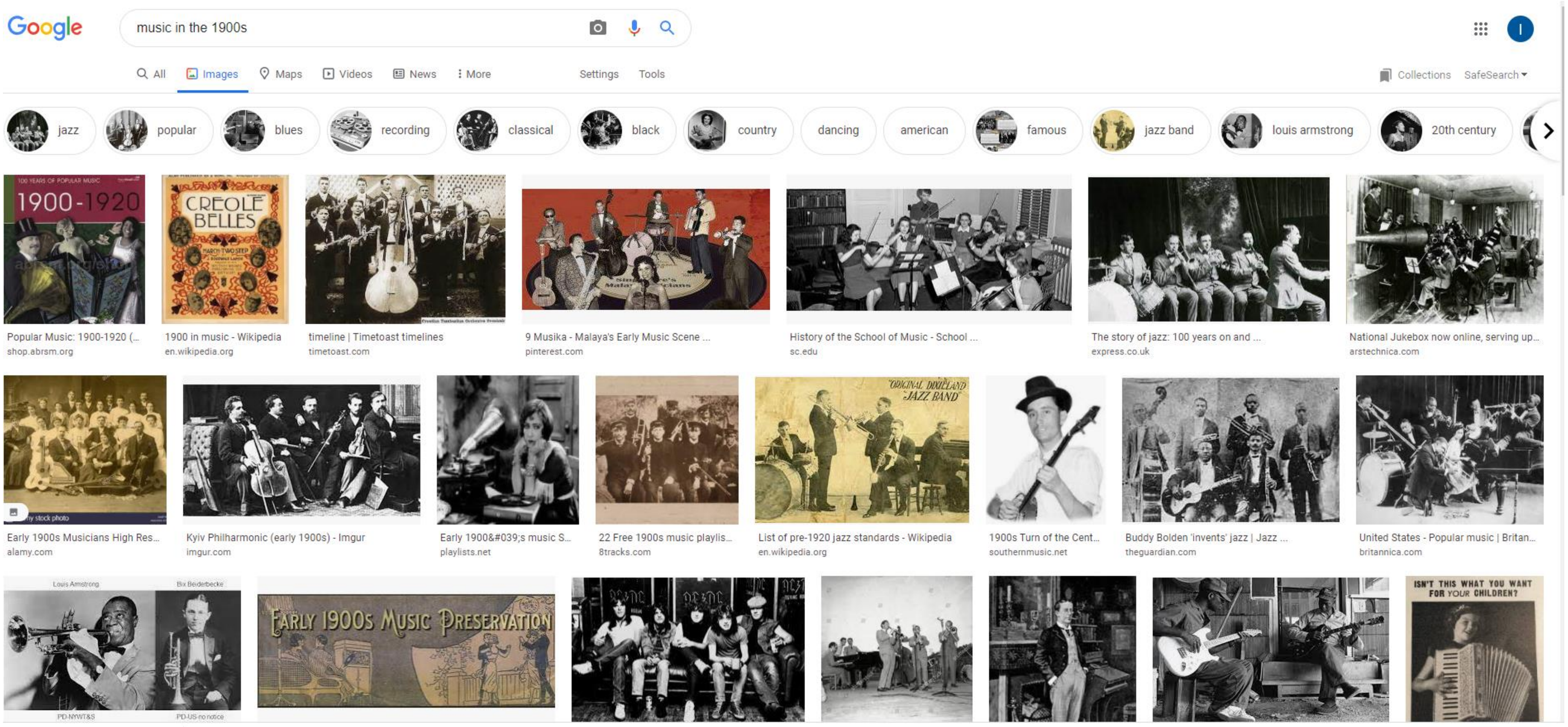
LABEL: TOP 100?

Fun Fact: Spotify launched in 2011

https://github.com/lolasery/khdatasci

https://www.kaggle.com/ektanegi/spotifydata-19212020

A BRIEF OVERVIEW OF MUSIC!
1900S -> JAZZ, CLASSICAL, BLUEGRASS



Popular Music: 1900-1920 (...
shop.abrsm.org

1900 in music - Wikipedia
en.wikipedia.org

timeline | Timetoast timelines
timetoast.com

9 Musika - Malaya's Early Music Scene ...
pinterest.com

History of the School of Music - School ...
sc.edu

The story of jazz: 100 years on and ...
express.co.uk

National Jukebox now online, serving up...
arstechnica.com

Early 1900s Musicians High Res...
alamy.com

Kyiv Philharmonic (early 1900s) - Imgur
imgur.com

Early 1900&#039;s music S...
playlists.net

22 Free 1900s music playlis...
8tracks.com

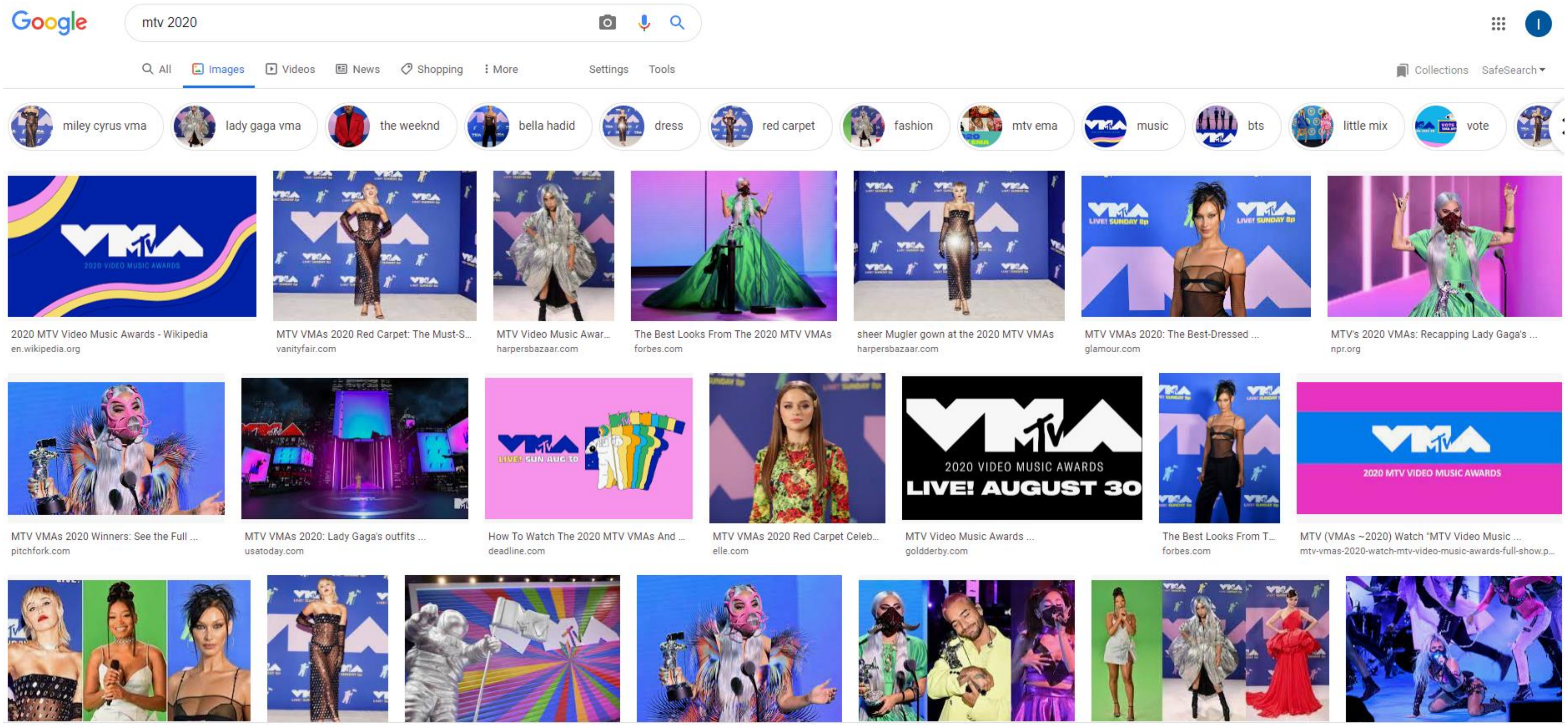
List of pre-1920 jazz standards - Wikipedia
en.wikipedia.org

1900s Turn of the Cent...
southernmusic.net

Buddy Bolden 'invents' jazz | Jazz ...
theguardian.com

United States - Popular music | Britan...
britannica.com

A BRIEF OVERVIEW OF MUSIC!
2020S -> POP, R&B, SOUL, INDIE



mtv 2020

2020 MTV Video Music Awards - Wikipedia
en.wikipedia.org

MTV VMAs 2020 Red Carpet: The Must-S...
vanityfair.com

MTV Video Music Awar...
harpersbazaar.com

The Best Looks From The 2020 MTV VMAs
forbes.com

sheer Mugler gown at the 2020 MTV VMAs
harpersbazaar.com

MTV VMAs 2020: The Best-Dressed ...
glamour.com

MTV's 2020 VMAs: Recapping Lady Gaga's ...
npr.org

MTV VMAs 2020 Winners: See the Full ...
pitchfork.com

MTV VMAs 2020: Lady Gaga's outfits ...
usatoday.com

How To Watch The 2020 MTV VMAs And ...
deadline.com

MTV VMAs 2020 Red Carpet Celeb...
elle.com

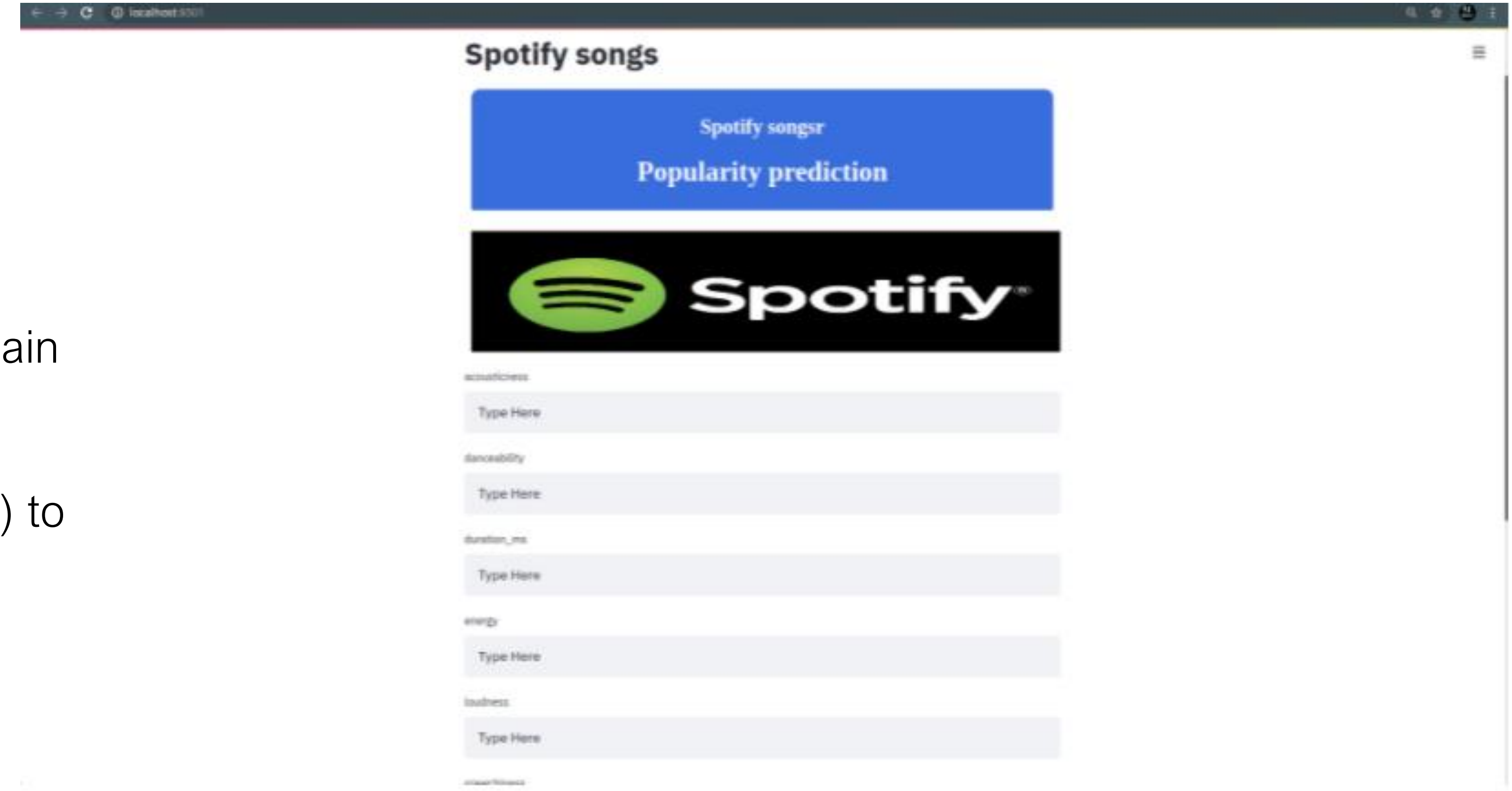
MTV Video Music Awards ...
goldderby.com

The Best Looks From T...
forbes.com

MTV (VMAs ~2020) Watch "MTV Video Music ...
mtv-vmas-2020-watch-mtv-video-music-awards-full-show.p...

- LABEL SIGNIFICANCE

- Very humble and casual
- Can help artistes aim for the top 100s to gain more fame, investors, etc.
- help to shape future trends more easily
- perhaps can create a app (pic on the right) to let spotify users predict a song's popularity based on the features I trained my ML with



Spotify songs

Spotify songsr

Popularity prediction

acousticness

Type Here

danceability

Type Here

duration_ms

Type Here

energy

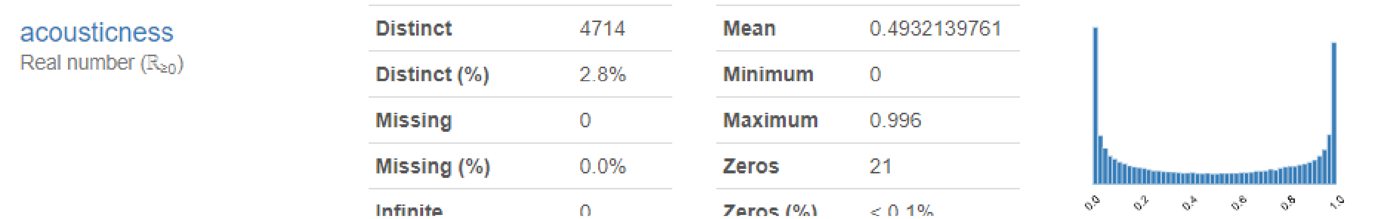
Type Here

loudness

Type Here

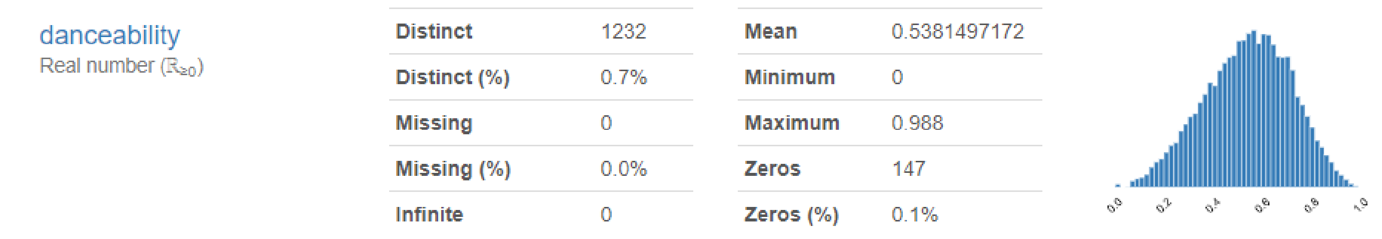
DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

- Using Pandas profile analyze if data is imbalanced



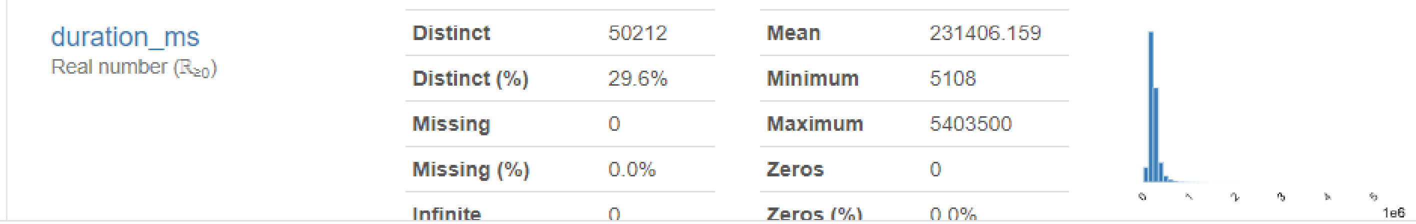
acousticness
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	4714	Mean	0.4932139761
Distinct (%)	2.8%	Minimum	0
Missing	0	Maximum	0.996
Missing (%)	0.0%	Zeros	21
Infinite	0	Zeros (%)	< 0.1%



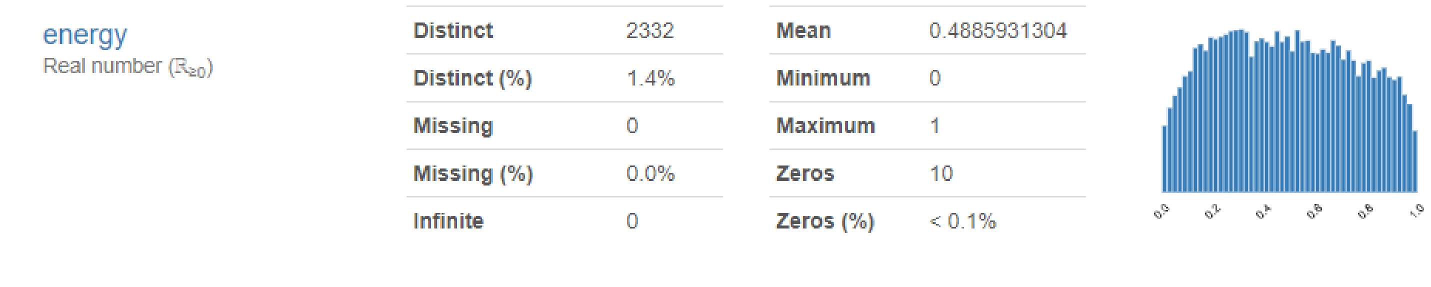
danceability
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	1232	Mean	0.5381497172
Distinct (%)	0.7%	Minimum	0
Missing	0	Maximum	0.988
Missing (%)	0.0%	Zeros	147
Infinite	0	Zeros (%)	0.1%



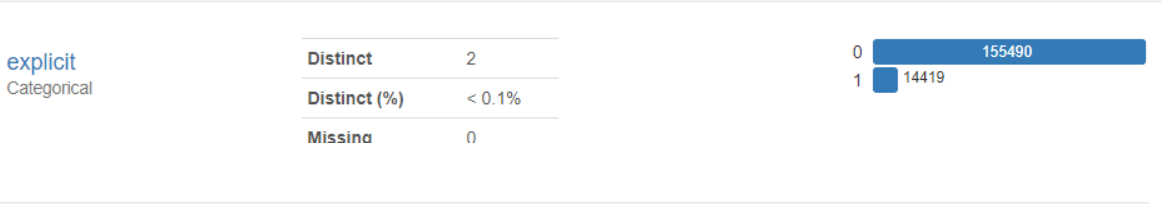
duration_ms
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	50212	Mean	231406.159
Distinct (%)	29.6%	Minimum	5108
Missing	0	Maximum	5403500
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%



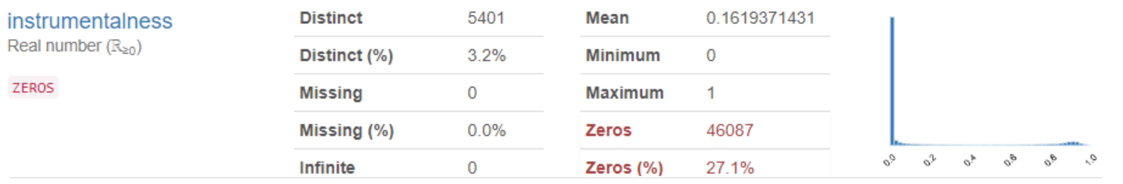
energy
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	2332	Mean	0.4885931304
Distinct (%)	1.4%	Minimum	0
Missing	0	Maximum	1
Missing (%)	0.0%	Zeros	10
Infinite	0	Zeros (%)	< 0.1%



explicit
Categorical

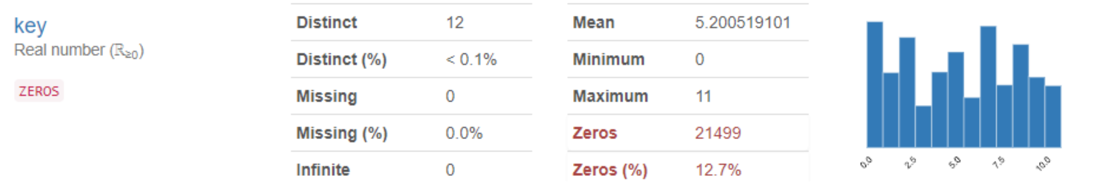
Distinct	2
Distinct (%)	< 0.1%
Missing	0



instrumentalness
Real number ($\mathbb{R}_{\geq 0}$)

ZEROS

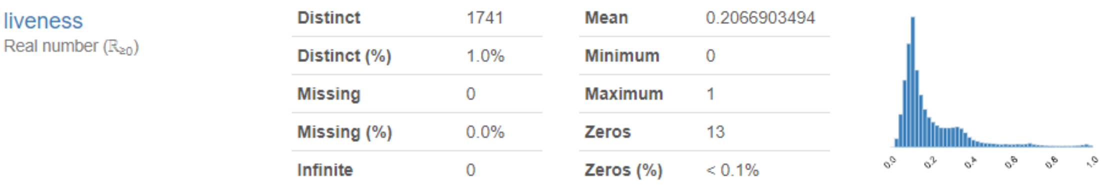
Distinct	5401	Mean	0.1619371431
Distinct (%)	3.2%	Minimum	0
Missing	0	Maximum	1
Missing (%)	0.0%	Zeros	46087
Infinite	0	Zeros (%)	27.1%



key
Real number ($\mathbb{R}_{\geq 0}$)

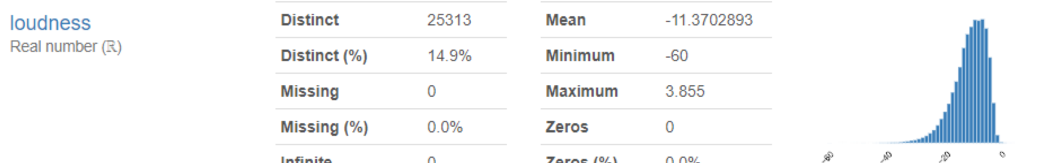
ZEROS

Distinct	12	Mean	5.200519101
Distinct (%)	< 0.1%	Minimum	0
Missing	0	Maximum	11
Missing (%)	0.0%	Zeros	21499
Infinite	0	Zeros (%)	12.7%



liveness
Real number ($\mathbb{R}_{\geq 0}$)

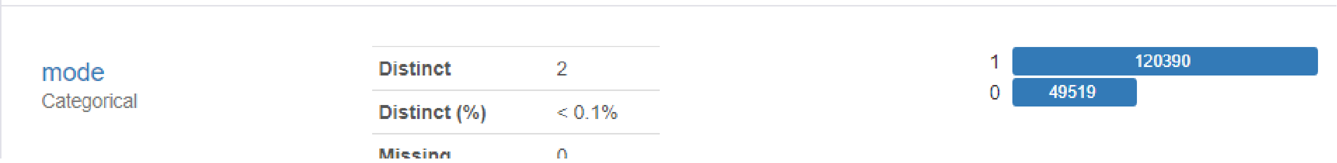
Distinct	1741	Mean	0.2066903494
Distinct (%)	1.0%	Minimum	0
Missing	0	Maximum	1
Missing (%)	0.0%	Zeros	13
Infinite	0	Zeros (%)	< 0.1%



loudness
Real number ($\mathbb{R}$)

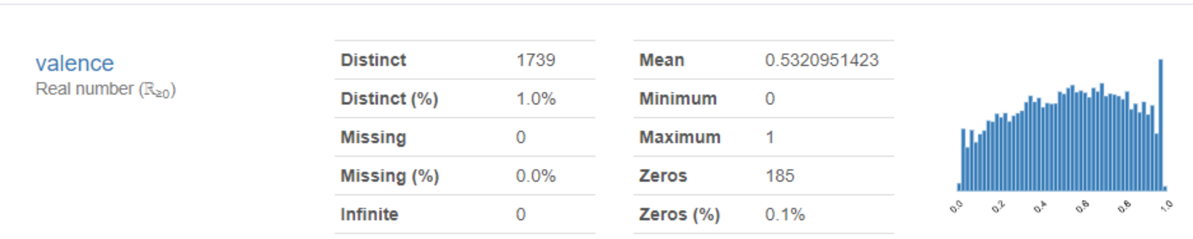
Distinct	25313	Mean	-11.3702893
Distinct (%)	14.9%	Minimum	-60
Missing	0	Maximum	3.855
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING



mode
Categorical

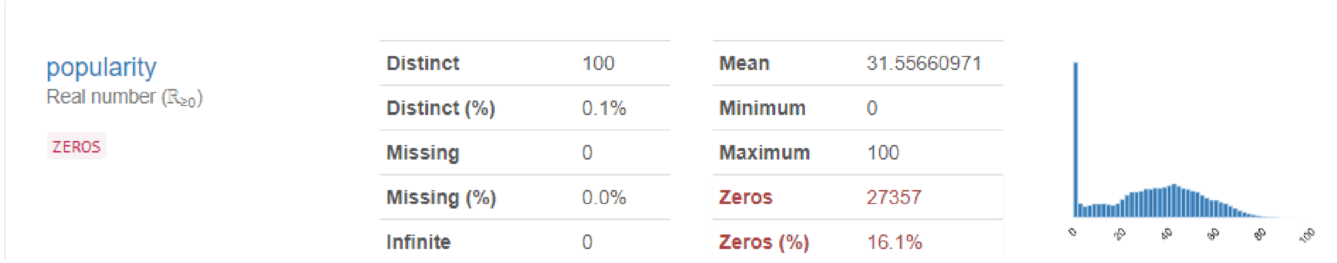
Distinct	2
Distinct (%)	< 0.1%
Missing	0



valence
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	1739
Distinct (%)	1.0%
Missing	0
Missing (%)	0.0%
Infinite	0

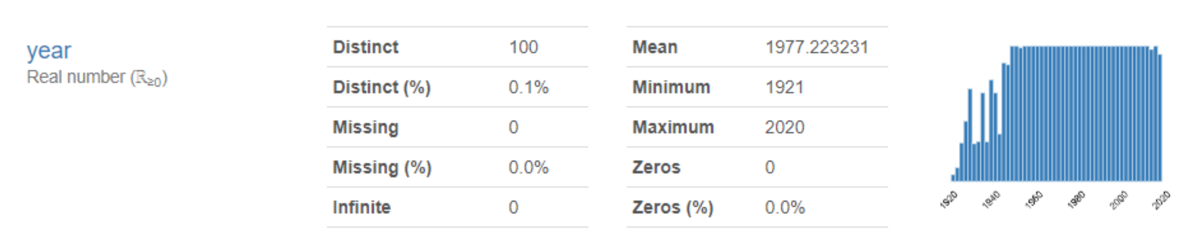
Mean	0.5320951423
Minimum	0
Maximum	1
Zeros	185
Zeros (%)	0.1%



popularity
Real number ($\mathbb{R}_{\geq 0}$)
ZEROS

Distinct	100
Distinct (%)	0.1%
Missing	0
Missing (%)	0.0%
Infinite	0

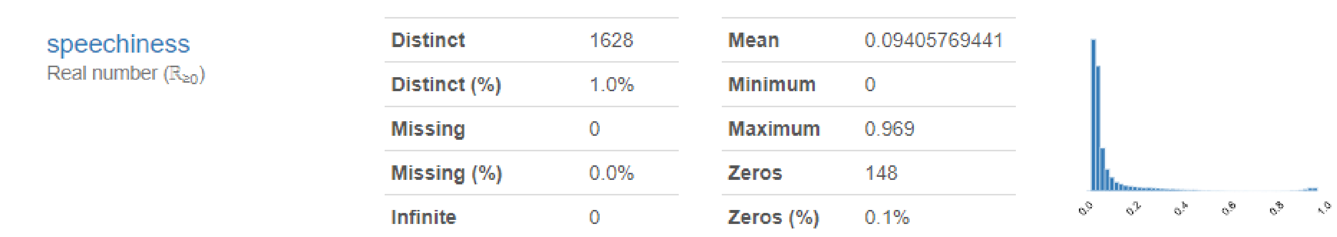
Mean	31.55660971
Minimum	0
Maximum	100
Zeros	27357
Zeros (%)	16.1%



year
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	100
Distinct (%)	0.1%
Missing	0
Missing (%)	0.0%
Infinite	0

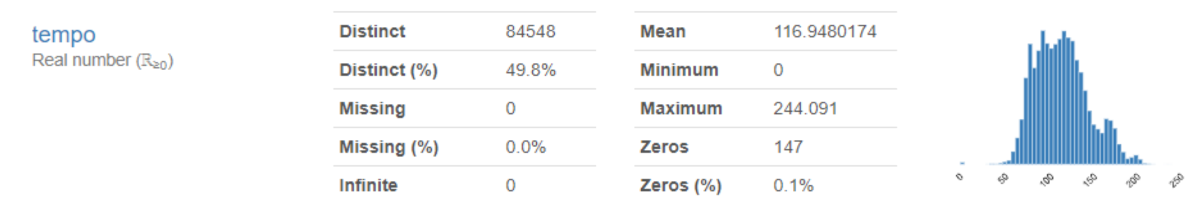
Mean	1977.223231
Minimum	1921
Maximum	2020
Zeros	0
Zeros (%)	0.0%



speechiness
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	1628
Distinct (%)	1.0%
Missing	0
Missing (%)	0.0%
Infinite	0

Mean	0.09405769441
Minimum	0
Maximum	0.969
Zeros	148
Zeros (%)	0.1%



tempo
Real number ($\mathbb{R}_{\geq 0}$)

Distinct	84548
Distinct (%)	49.8%
Missing	0
Missing (%)	0.0%
Infinite	0

Mean	116.9480174
Minimum	0
Maximum	244.091
Zeros	147
Zeros (%)	0.1%

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

- 1. Acousticness (0-1 float, not having electrical amplification eg. guitar over electric guitar, piano over keyboard)
- 2. danceability (0-1 float, How likely one can dance to the song)
- 3. energy (0-1 float, whatever keeps the listener engaged and listening -> abit too subjective, might drop)
- 4. explicit (0 or 1 int, contains explicit language)
- 5. instrumentalness (0-1 float, Predicts whether a track contains no vocals 0 = vocals, 1 = no vocals)
- 6. key (0-11 int, All keys on octave encoded as values ranging from 0 to 11, starting on C as 0, C# as 1 and so on -> needs musical background to determine what it really means eg. C major gives a happy yet melancholic undertone etc.)
- 7. liveness (0-1 float, Detects the presence of an audience in the recording, 0= not live , 1= live)
- 8. loudness (-60 to 3 float, -60 = soft, 3 = loud)
- 9. mode (0-1 float, 0= minor (sad), 1=major(happy))
- 10. release_date (datetime)

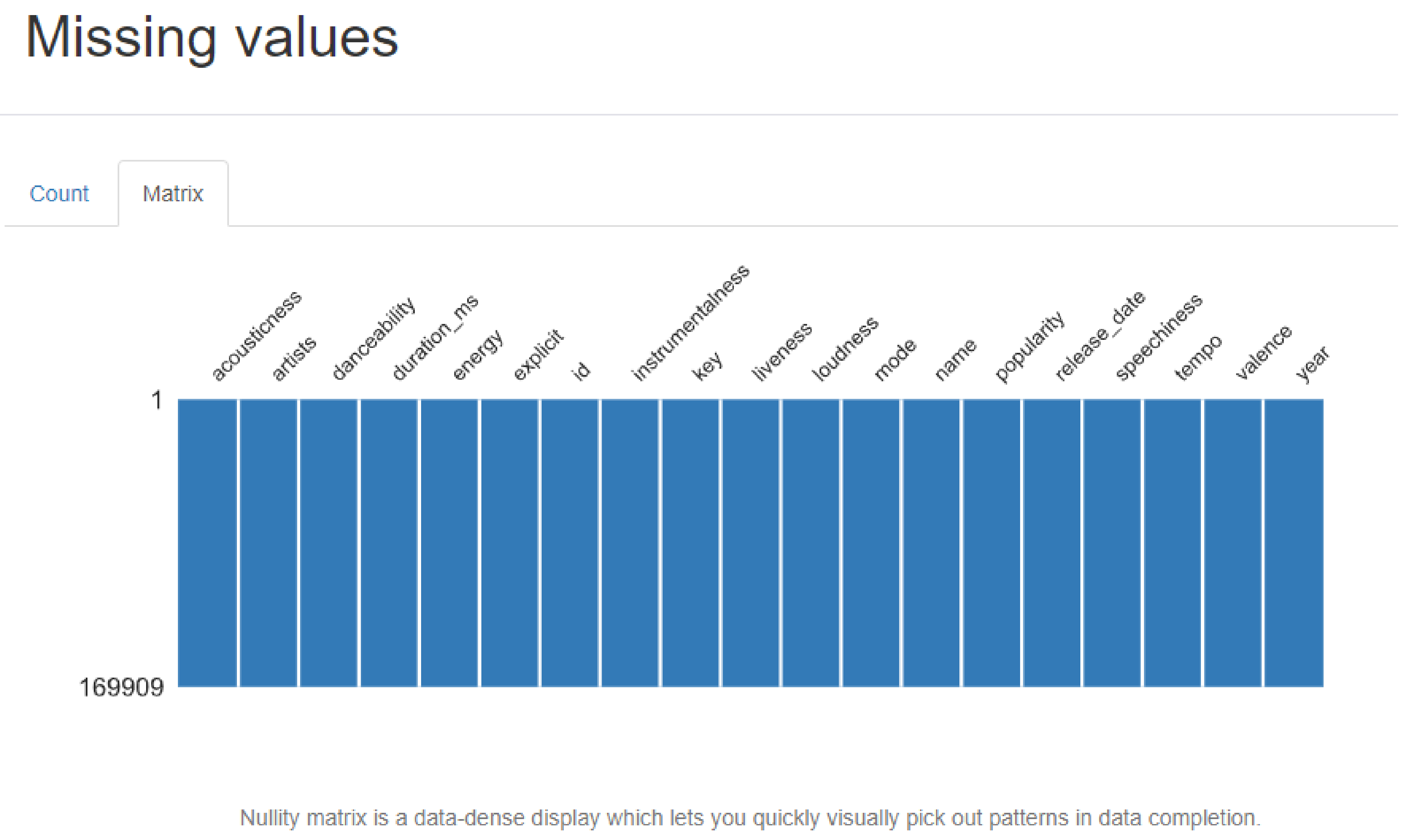
DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

- 11. speechiness (0-1 float, >0.66 = made of spoken words (audio book), 0.33-0.66 = mix of music and speech, <0.33 = no speech)
- - http://open.spotify.com/track/1u9vcc9PQvAv3Nh4qRp3If <-- definitely singing butsomehow is more speechy
- - http://open.spotify.com/track/1UEVy1gNCTTCTjp0Tk01rm <-- there is background talking but also 100% singing
- - There are definitely non-songs (podcasts, readings) in the mix but are too difficult to immediately identify
- 12. tempo (0-244 float, speed of music, higher = faster)
- 13. valence (0-1 float, 0= sad/negative, 1=happy/positive)
- 14. Artist (str, name of artist -> able to feature engineer into length of name)
- 15. duration_ms (float, Duration in miliseconds)
- 16. id (dropping this as it is useless)
- 17. name (str, of song)
- 18. popularity (0-100 int, 0 = no ranking)
- 19. release_date [Song was released] (datetime) ->Considering to remove since not all release dates have same format
- 20. year [Song was released] (1921-2020)

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

- This dataset is special in the sense that Year is not the year in which the popularity was obtained: It is the year song was released.
- Difficulties:
  - Speechiness can be very high despite the person obviously singing.
  - Loudness -> Not too sure which measure they used for this -> Can only assume the higher the value the louder it is

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

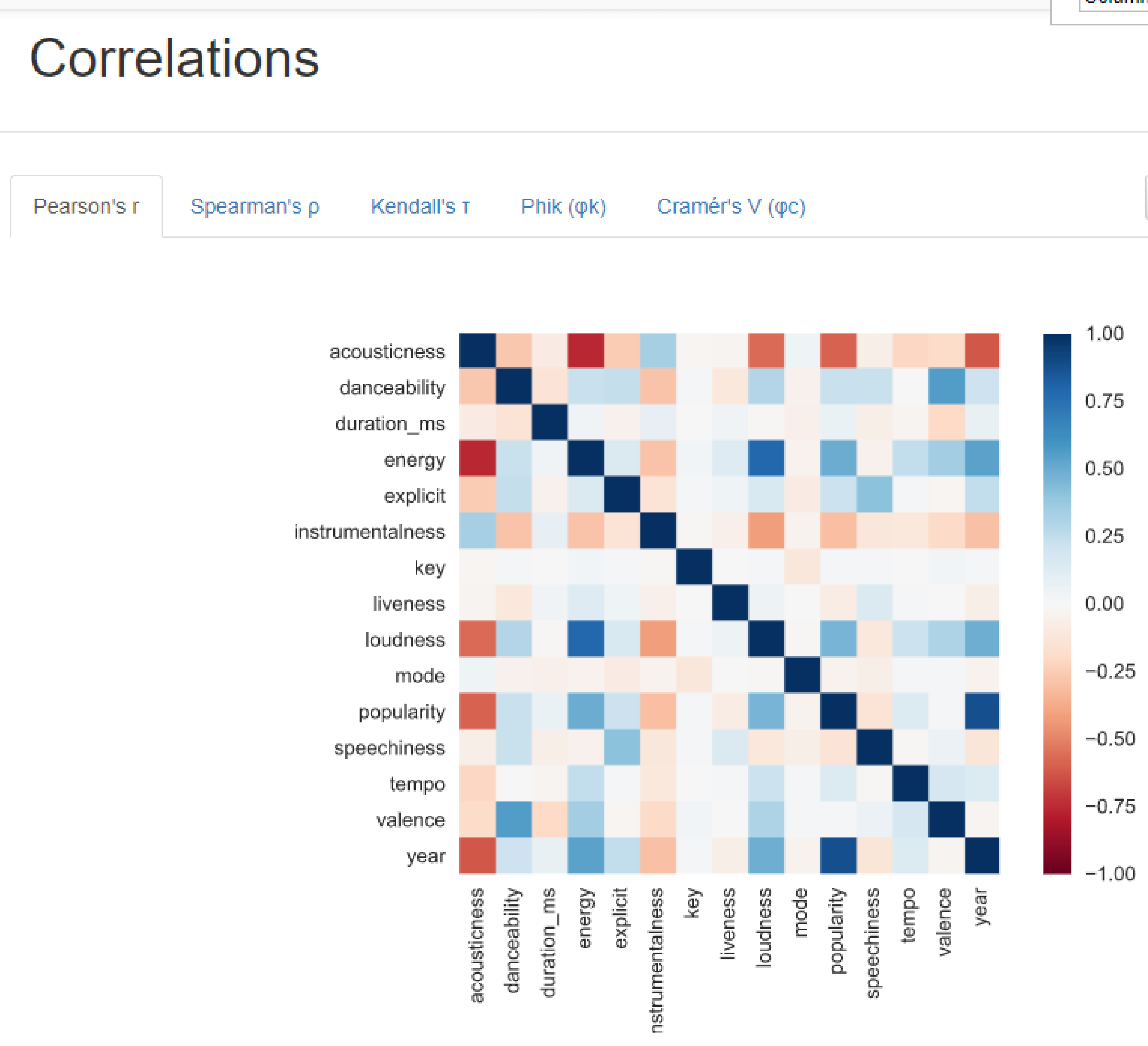


Missing values

Nullity matrix is a data-dense display which lets you quickly visually pick out patterns in data completion.

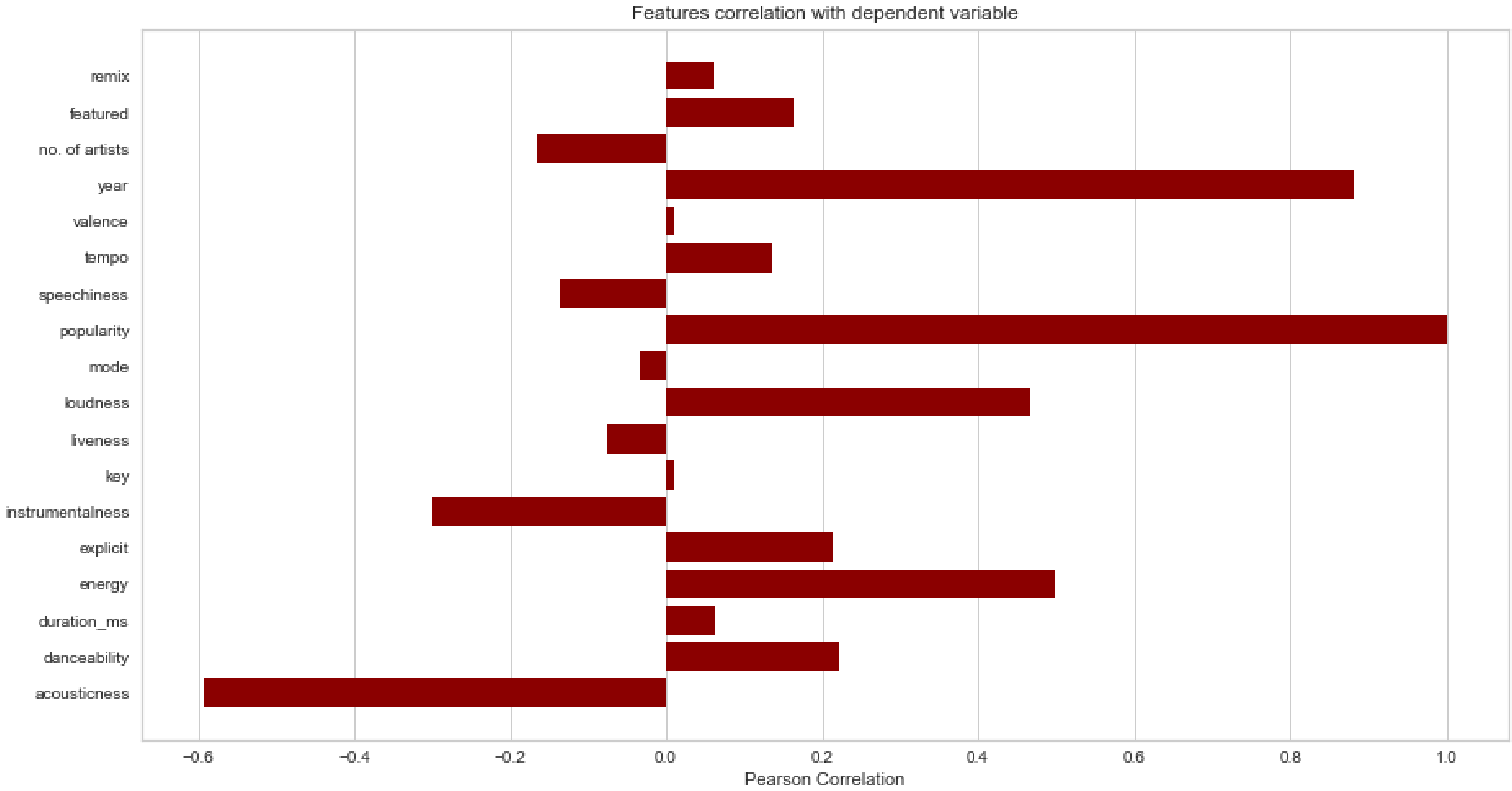
Yes!!

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING



Correlations

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING



from yellowbrick library:
Year, loudness, energy

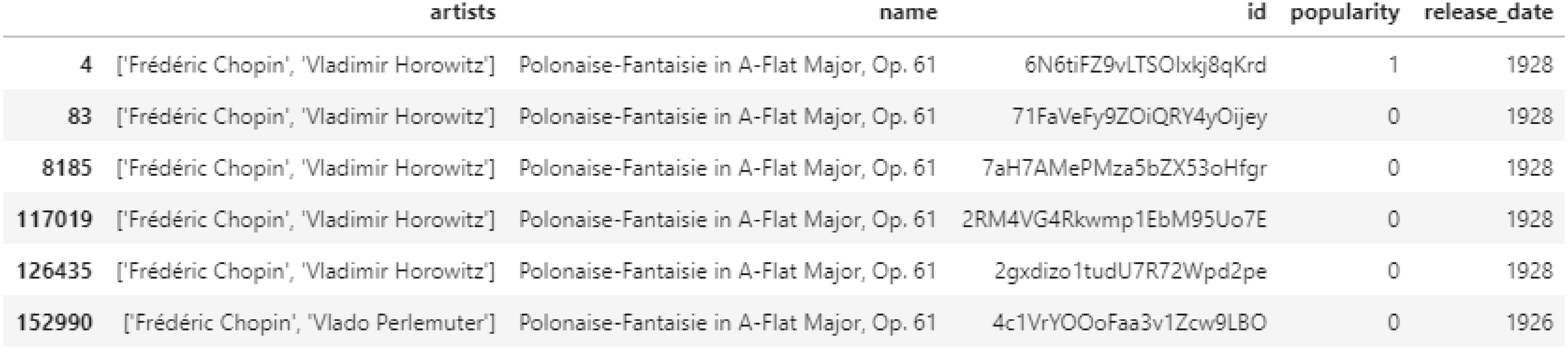
DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

- Exploration!

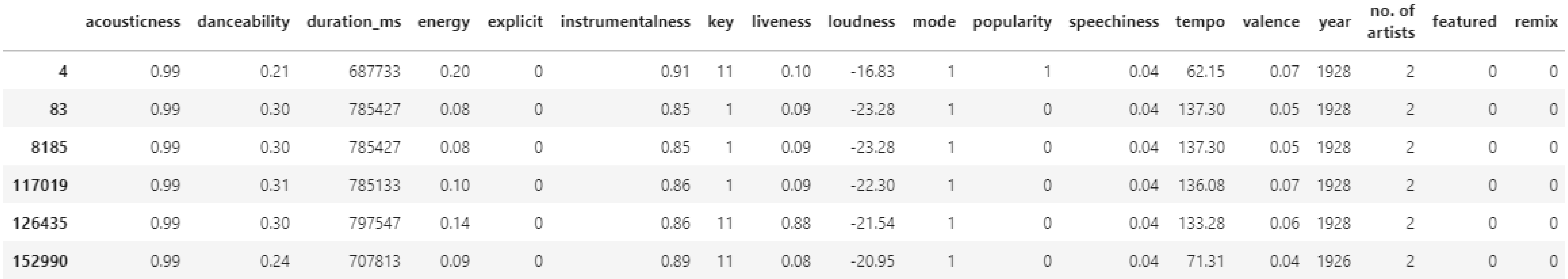
# CASE STUDY

## POTENTIALLY DUPLICATED SONG (EITHER LATEST OR MOST POPULAR?)

### SONG 1: POLONAISE-FANTAISIE IN A-FLAT MAJOR, OP. 61



	artists	name	id	popularity	release_date
4	['Frédéric Chopin', 'Vladimir Horowitz']	Polonaise-Fantaisie in A-Flat Major, Op. 61	6N6tiFZ9vLTSOIxkj8qKrd	1	1928
83	['Frédéric Chopin', 'Vladimir Horowitz']	Polonaise-Fantaisie in A-Flat Major, Op. 61	71FaVeFy9ZOiQRY4yOijey	0	1928
8185	['Frédéric Chopin', 'Vladimir Horowitz']	Polonaise-Fantaisie in A-Flat Major, Op. 61	7aH7AMePMza5bZX53oHfgr	0	1928
117019	['Frédéric Chopin', 'Vladimir Horowitz']	Polonaise-Fantaisie in A-Flat Major, Op. 61	2RM4VG4Rkwmp1EbM95Uo7E	0	1928
126435	['Frédéric Chopin', 'Vladimir Horowitz']	Polonaise-Fantaisie in A-Flat Major, Op. 61	2gxdizo1tudU7R72Wpd2pe	0	1928
152990	['Frédéric Chopin', 'Vlado Perlemuter']	Polonaise-Fantaisie in A-Flat Major, Op. 61	4c1VrYOOoFaa3v1Zcw9LBO	0	1926



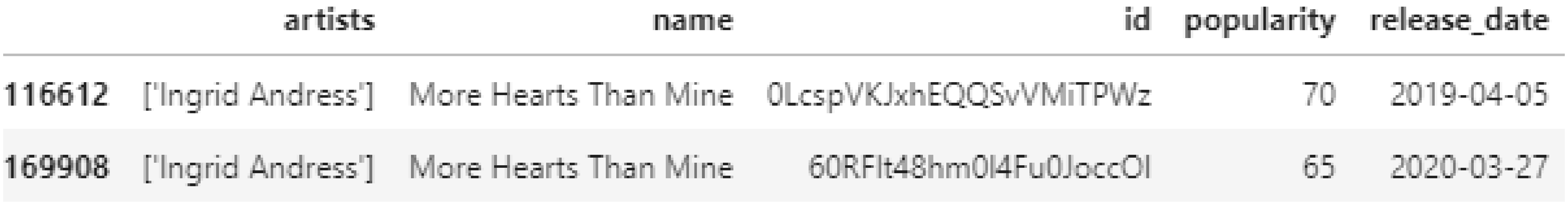
	acousticness	danceability	duration_ms	energy	explicit	instrumentalness	key	liveness	loudness	mode	popularity	speechiness	tempo	valence	year	no. of artists	featured	remix
4	0.99	0.21	687733	0.20	0	0.91	11	0.10	-16.83	1	1	0.04	62.15	0.07	1928	2	0	0
83	0.99	0.30	785427	0.08	0	0.85	1	0.09	-23.28	1	0	0.04	137.30	0.05	1928	2	0	0
8185	0.99	0.30	785427	0.08	0	0.85	1	0.09	-23.28	1	0	0.04	137.30	0.05	1928	2	0	0
117019	0.99	0.31	785133	0.10	0	0.86	1	0.09	-22.30	1	0	0.04	136.08	0.07	1928	2	0	0
126435	0.99	0.30	797547	0.14	0	0.86	11	0.88	-21.54	1	0	0.04	133.28	0.06	1928	2	0	0
152990	0.99	0.24	707813	0.09	0	0.89	11	0.08	-20.95	1	0	0.04	71.31	0.04	1926	2	0	0

# CASE STUDY
## POTENTIALLY DUPLICATED SONG (EITHER LATEST OR MOST POPULAR?)
### SONG 1: POLONAISE-FANTAISIE IN A-FLAT MAJOR, OP. 61

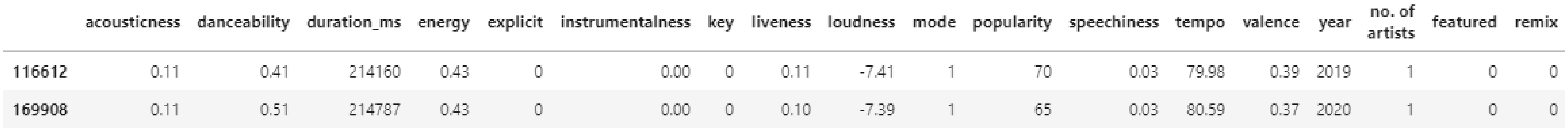
- #https://open.spotify.com/album/1n81HsE0rnviDNIIfX3fp0?highlight=spotify:track:6N6tiFZ9vLTSOIxkj8qKrd #disc3
- #https://open.spotify.com/album/1n81HsE0rnviDNIIfX3fp0?highlight=spotify:track:2RM4VG4Rkwmp1EbM95Uo7E #disc4
- #https://open.spotify.com/album/1n81HsE0rnviDNIIfX3fp0?highlight=spotify:track:2gxdizo1tudU7R72Wpd2pe #disc6
- #https://open.spotify.com/album/6P9bPQ1LDtgAB5V8Bt50ne?highlight=spotify:track:71FaVeFy9ZOiQRY4yOijey
- #https://open.spotify.com/album/27NrfgJFNdDIKJnSxHXcJt?highlight=spotify:track:7aH7AMePMza5bZX53oHfgr
- #https://open.spotify.com/album/2tBnuQsf1e2rXt6oW4Vy2N?highlight=spotify:track:4c1VrYOOoFaa3v1Zcw9LBO

- #individual songs probably played by different people
- Despite sounding almost exactly the same (Yes I actually listened to all 6 songs)
  - They have very different popularity!

# CASE STUDY
## POTENTIALLY DUPLICATED SONG (EITHER LATEST OR MOST POPULAR?)
### SONG 2: MORE HEARTS THAN MINE



	artists	name	id	popularity	release_date
116612	['Ingrid Andress']	More Hearts Than Mine	0LcspVKJxhEQQSvVMiTPWz	70	2019-04-05
169908	['Ingrid Andress']	More Hearts Than Mine	60RFlt48hm0l4Fu0JoccOI	65	2020-03-27



	acousticness	danceability	duration_ms	energy	explicit	instrumentalness	key	liveness	loudness	mode	popularity	speechiness	tempo	valence	year	no. of artists	featured	remix
116612	0.11	0.41	214160	0.43	0	0.00	0	0.11	-7.41	1	70	0.03	79.98	0.39	2019	1	0	0
169908	0.11	0.51	214787	0.43	0	0.00	0	0.10	-7.39	1	65	0.03	80.59	0.37	2020	1	0	0

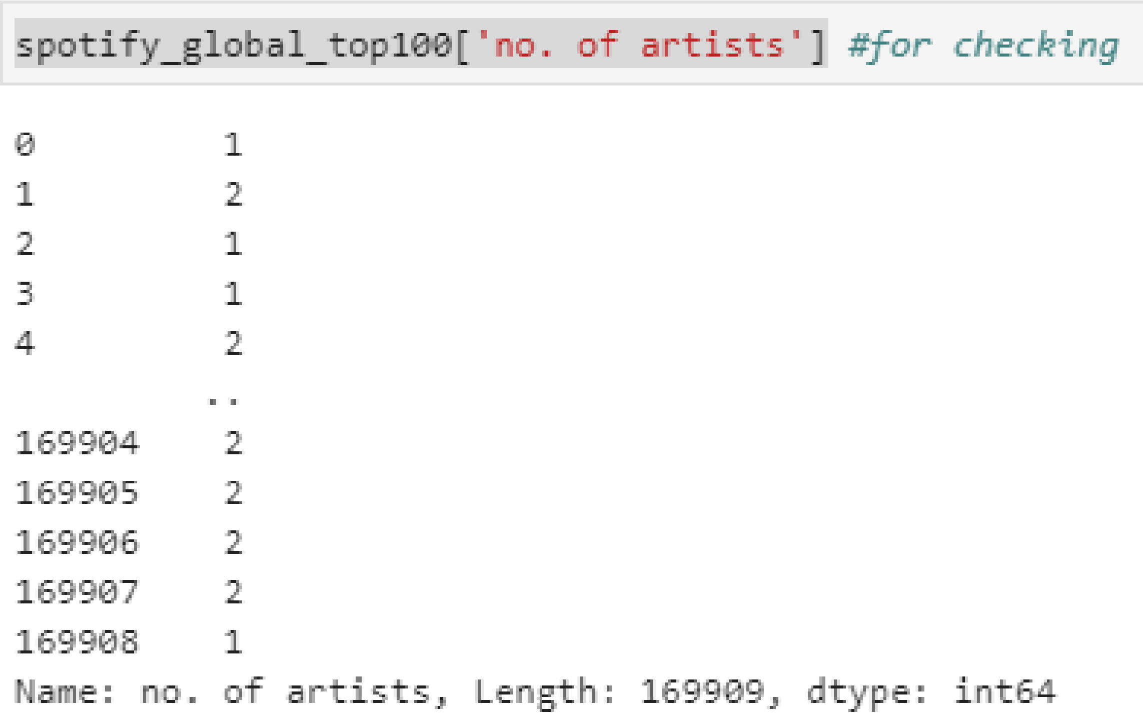
# CASE STUDY
## POTENTIALLY DUPLICATED SONG (EITHER LATEST OR MOST POPULAR?)
### SONG 2: MORE HEARTS THAN MINE

- # https://open.spotify.com/album/4VMYwWFqX9vUv9otWLRRF5?highlight=spotify:track:0LcspVKJxhEQQSvVMiTPWz released as single in 2019
- # https://open.spotify.com/album/6qon3hv0IhwK8o57PvVWZI?highlight=spotify:track:60RFIt48hm0I4Fu0JoccOI re-released as an album collection in 2020
- Despite being the same song, the timing released allowed a better performance for the later re-release

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

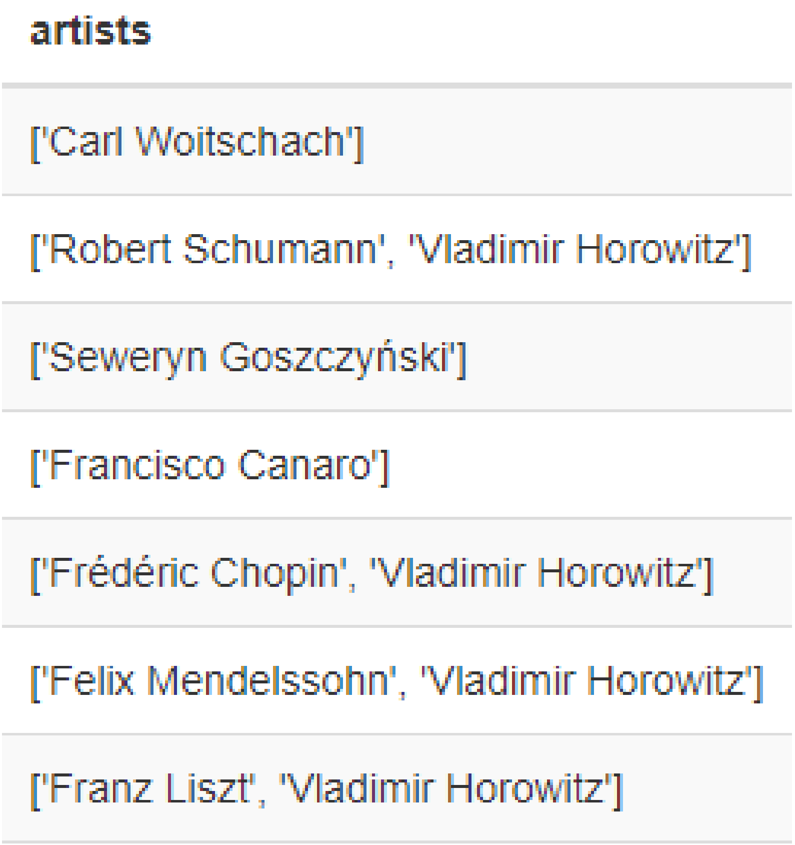
# FEATURE ENGINEERING AKA CREATING NEW COLUMNS

- ## 'no. of artists' - no. of artists in a song



```
spotify_global_top100['no. of artists'] #for checking
```

```
0         1
1         2
2         1
3         1
4         2
         ..
169904    2
169905    2
169906    2
169907    2
169908    1
Name: no. of artists, Length: 169909, dtype: int64
```

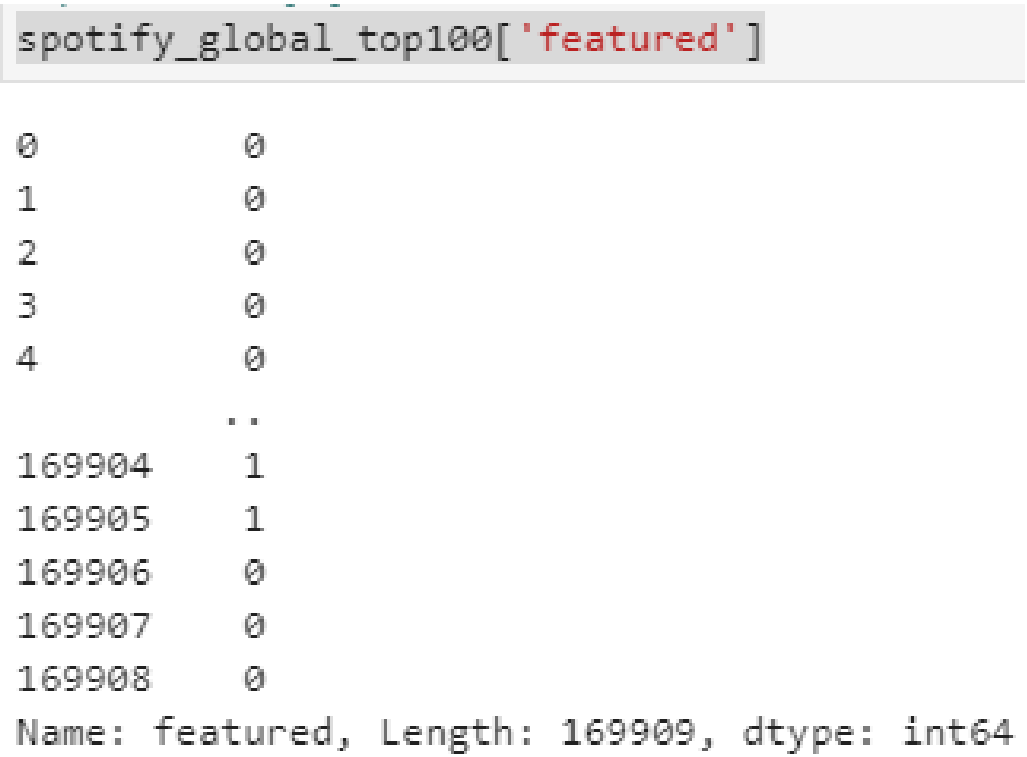


artists
['Carl Woitschach']
['Robert Schumann', 'Vladimir Horowitz']
['Seweryn Goszczyński']
['Francisco Canaro']
['Frédéric Chopin', 'Vladimir Horowitz']
['Felix Mendelssohn', 'Vladimir Horowitz']
['Franz Liszt', 'Vladimir Horowitz']

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

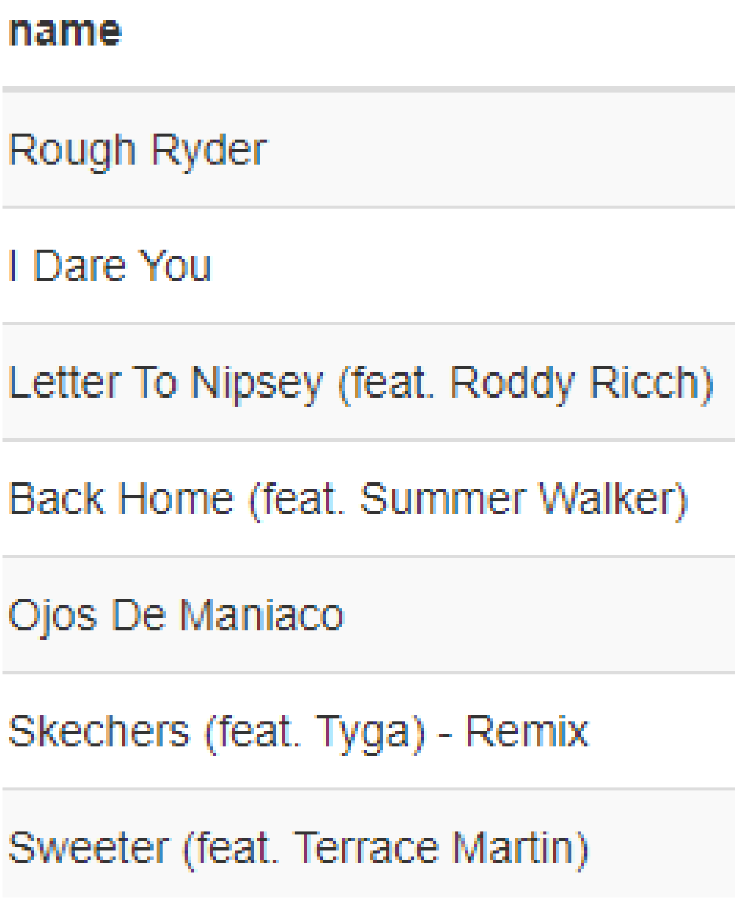
# FEATURE ENGINEERING AKA CREATING NEW COLUMNS

- ## 'featured' - whether or not the song has a feature



```
spotify_global_top100['featured']
```

```
0         0
1         0
2         0
3         0
4         0
         ..
169904    1
169905    1
169906    0
169907    0
169908    0
Name: featured, Length: 169909, dtype: int64
```

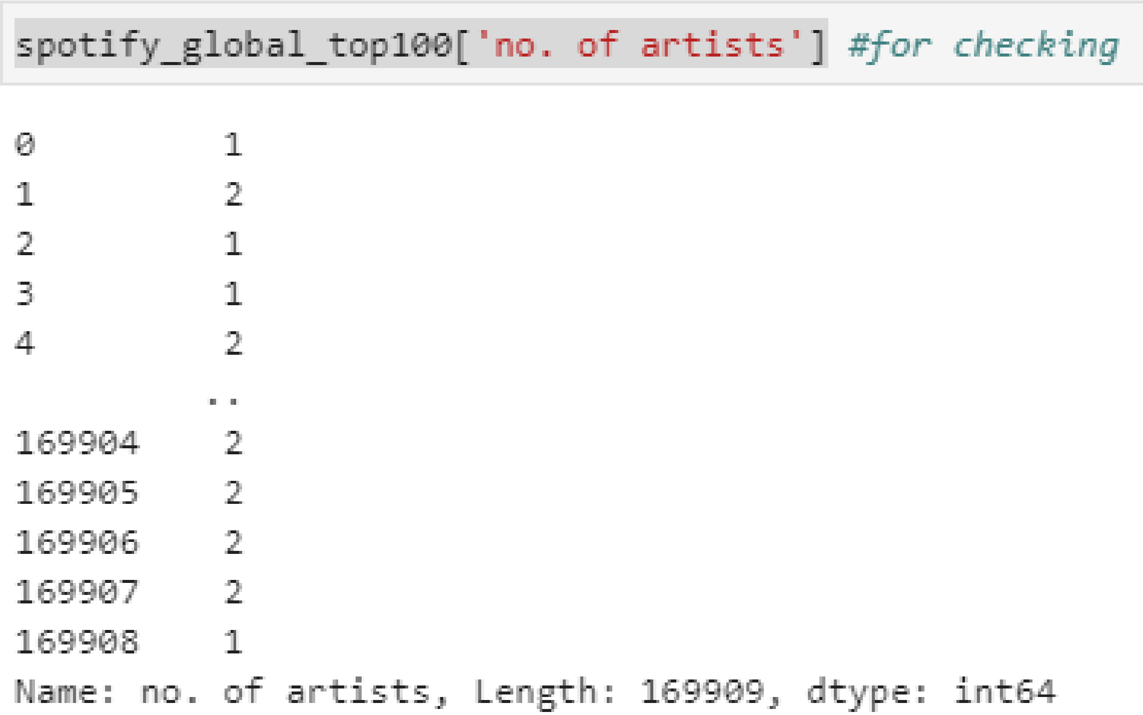


name
Rough Ryder
I Dare You
Letter To Nipsey (feat. Roddy Ricch)
Back Home (feat. Summer Walker)
Ojos De Maniaco
Skechers (feat. Tyga) - Remix
Sweeter (feat. Terrace Martin)

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

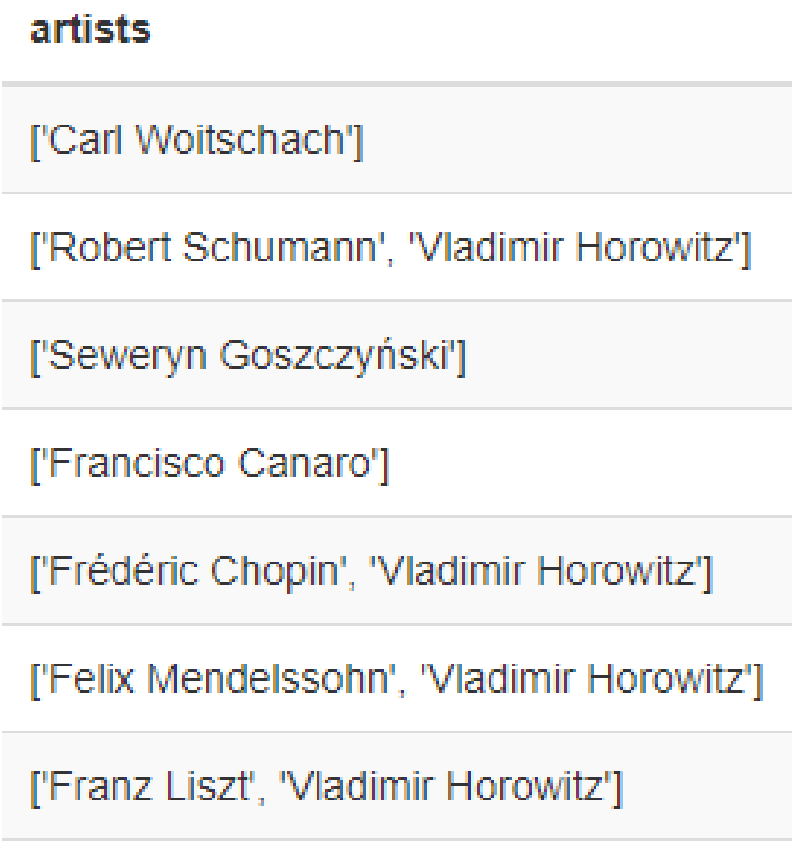
# FEATURE ENGINEERING AKA CREATING NEW COLUMNS

- ## 'no. of artists' - no. of artists in a song



```
spotify_global_top100['no. of artists'] #for checking
```

```
0         1
1         2
2         1
3         1
4         2
         ..
169904    2
169905    2
169906    2
169907    2
169908    1
Name: no. of artists, Length: 169909, dtype: int64
```

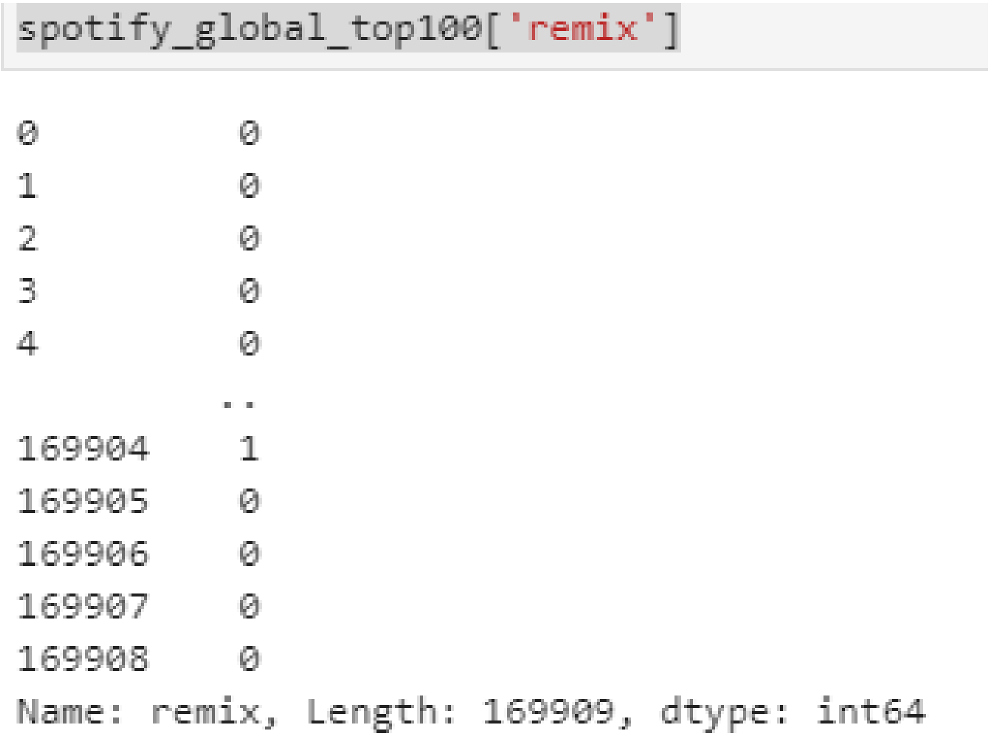


artists
['Carl Woitschach']
['Robert Schumann', 'Vladimir Horowitz']
['Seweryn Goszczyński']
['Francisco Canaro']
['Frédéric Chopin', 'Vladimir Horowitz']
['Felix Mendelssohn', 'Vladimir Horowitz']
['Franz Liszt', 'Vladimir Horowitz']

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

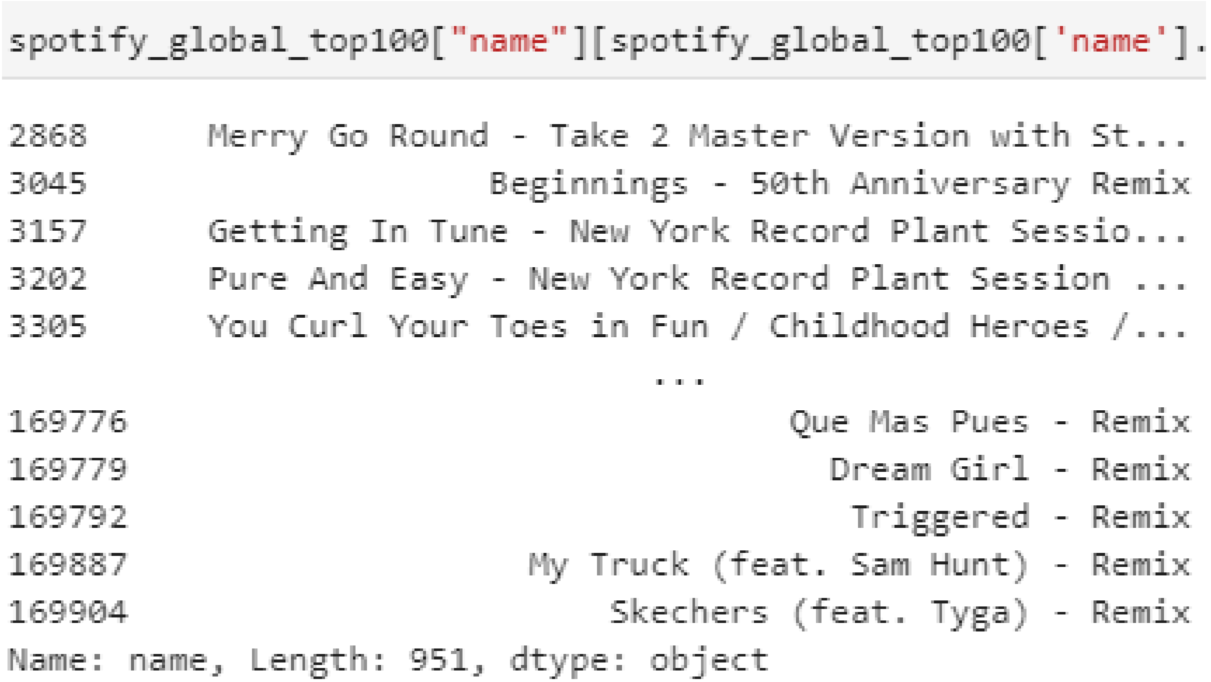
# FEATURE ENGINEERING AKA CREATING NEW COLUMNS

- ## 'no. of artists' - no. of artists in a song



```
spotify_global_top100['remix']
```

```
0         0
1         0
2         0
3         0
4         0
         ..
169904    1
169905    0
169906    0
169907    0
169908    0
Name: remix, Length: 169909, dtype: int64
```

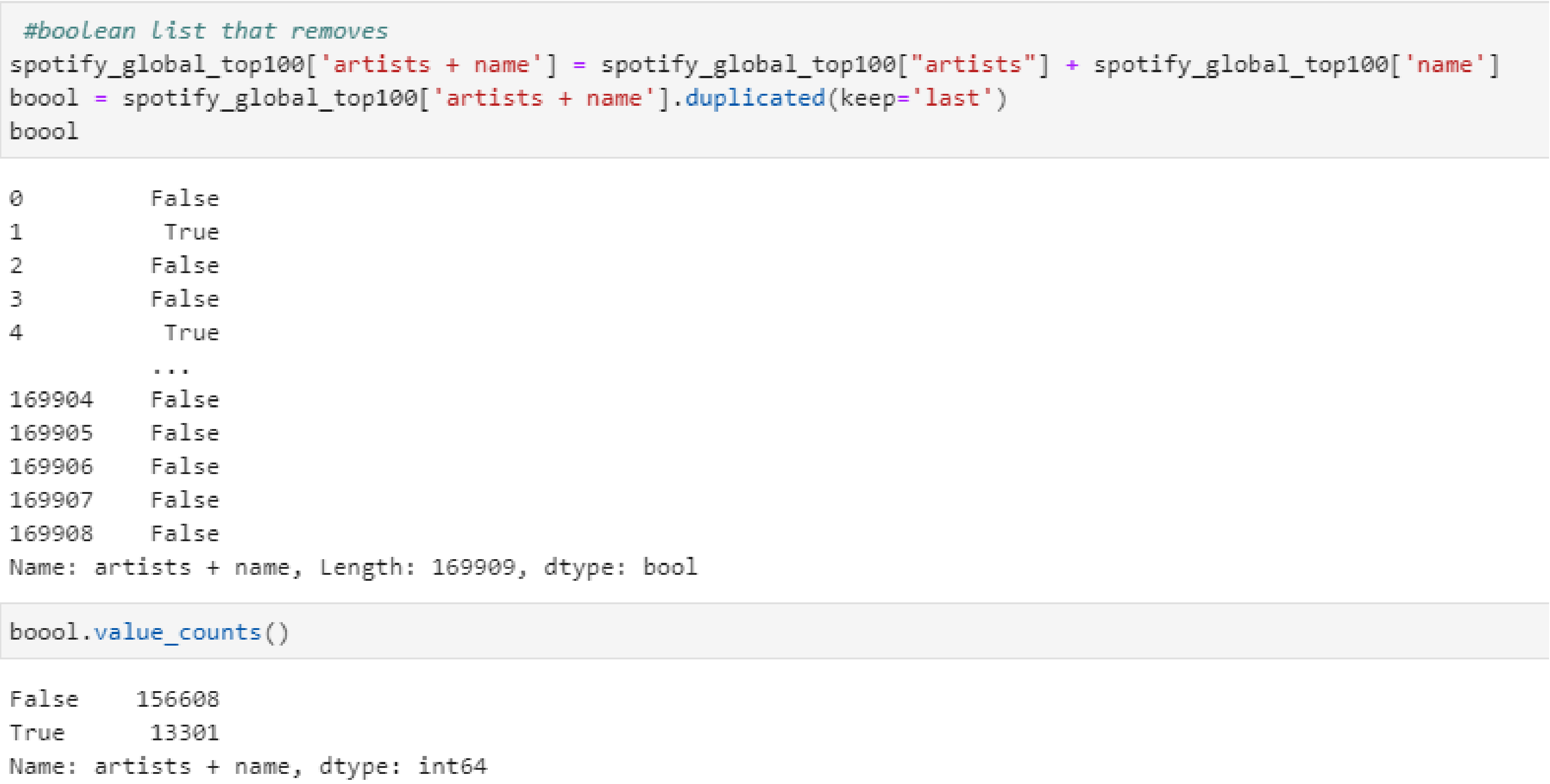


```
spotify_global_top100["name"][spotify_global_top100['name'].
```

```
2868      Merry Go Round - Take 2 Master Version with St...
3045                   Beginnings - 50th Anniversary Remix
3157      Getting In Tune - New York Record Plant Sessio...
3202      Pure And Easy - New York Record Plant Session ...
3305      You Curl Your Toes in Fun / Childhood Heroes /...
                                ...
169776                                 Que Mas Pues - Remix
169779                                   Dream Girl - Remix
169792                                    Triggered - Remix
169887                   My Truck (feat. Sam Hunt) - Remix
169904                        Skechers (feat. Tyga) - Remix
Name: name, Length: 951, dtype: object
```

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

# REMOVE "DUPES"



```
 #boolean list that removes
spotify_global_top100['artists + name'] = spotify_global_top100["artists"] + spotify_global_top100['name']
boool = spotify_global_top100['artists + name'].duplicated(keep='last')
boool
```

```
0         False
1          True
2         False
3         False
4          True
          ...
169904    False
169905    False
169906    False
169907    False
169908    False
Name: artists + name, Length: 169909, dtype: bool
```

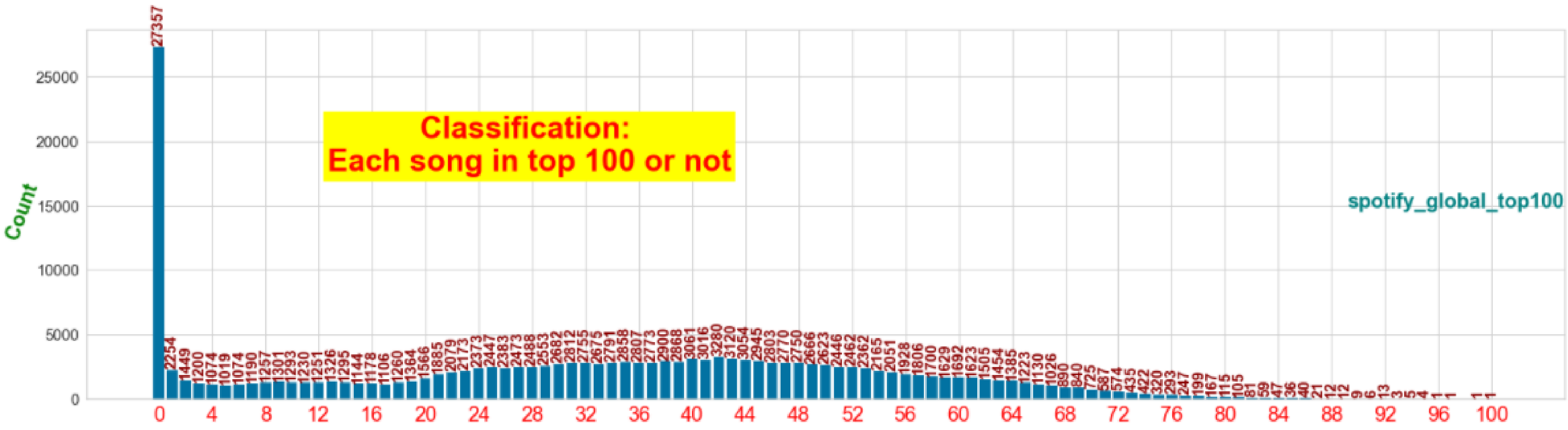
```
boool.value_counts()
```

```
False    156608
True      13301
Name: artists + name, dtype: int64
```

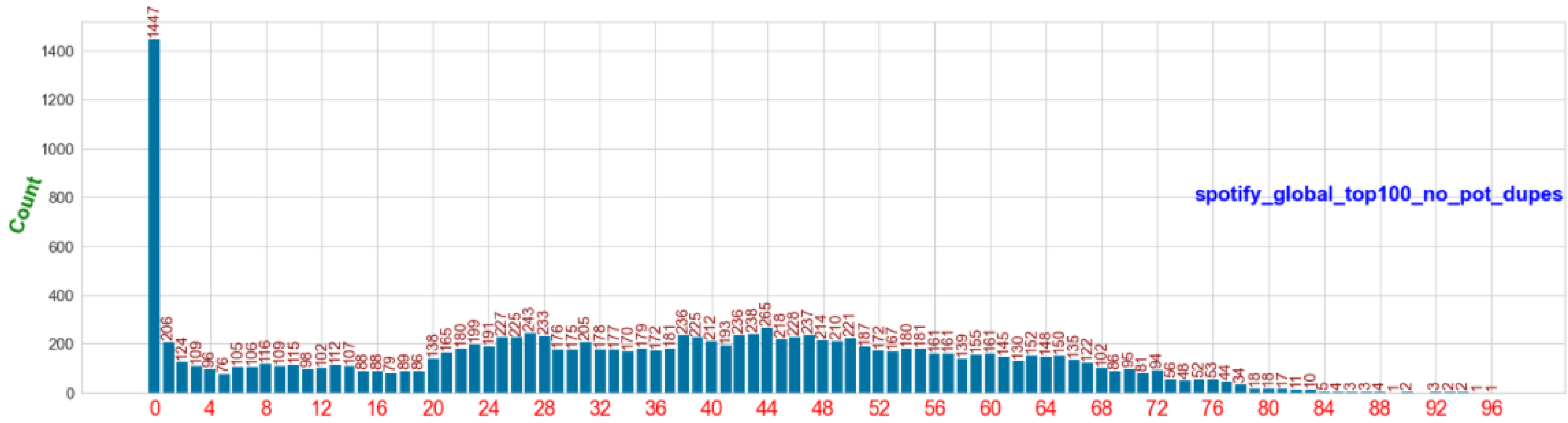
Data has truncated from 169909 to 13301

DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

# LABEL



Classification:
Each song in top 100 or not



A lot of 0s -> Not top 100

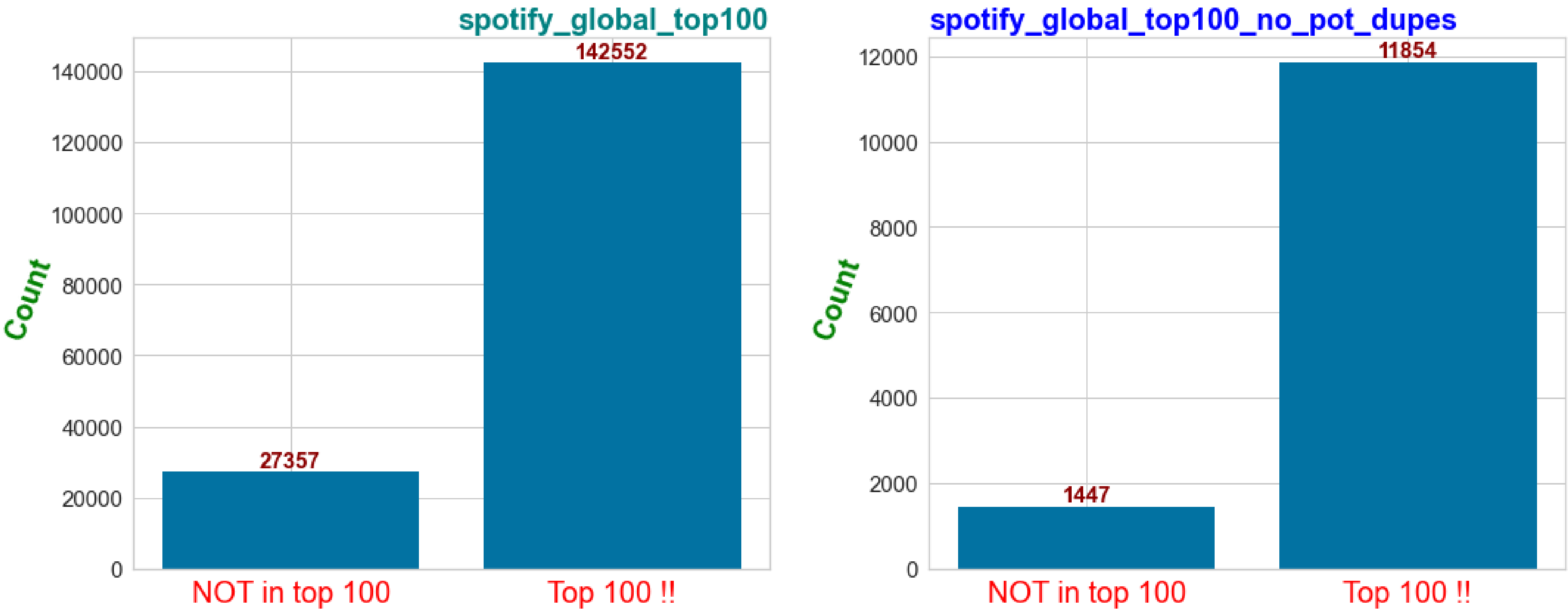
DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

# LABEL

Transform multiclass into Binary for simplicity sake

still A lot of 0s -> Not top 100

Classification (NOT BINNED):
No. of songs in top 100s VS top > 100



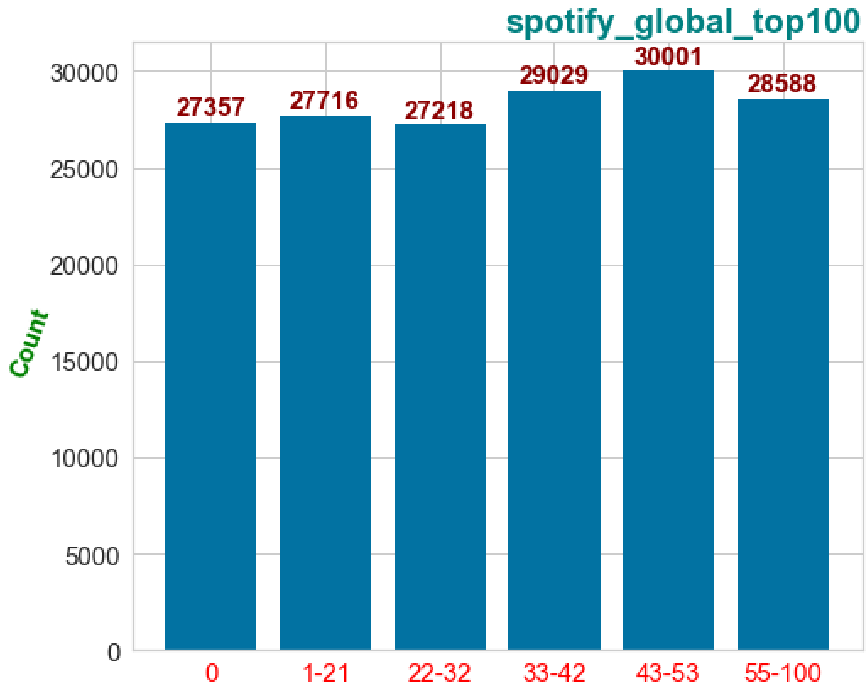
DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

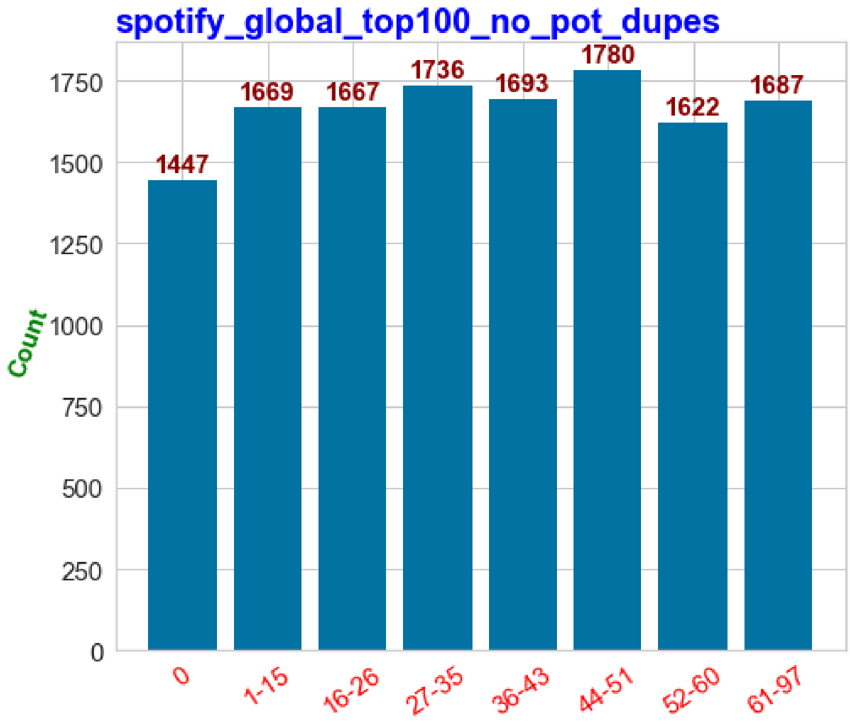
# LABEL

- Should I bin it? I could let it be and use other methods to solve it... but lets try binning to make it more balanced

...

Classification, BINNED: Each song in top 100 or not





- spotify_global_top100
  - top 1:21 -> 1
  - top 22:32 ->2
  - top 33:42 ->3
  - top 43:53 ->4
  - top 54:100 ->5
- spotify_global_top100_no_pot_dupes
  - top 1:15 ->1
  - top 16:26 ->2
  - top 27:35 ->3
  - top 36:43 ->4
  - top 44:51 ->5
  - top 52:61 ->6
  - top 62:96 ->7

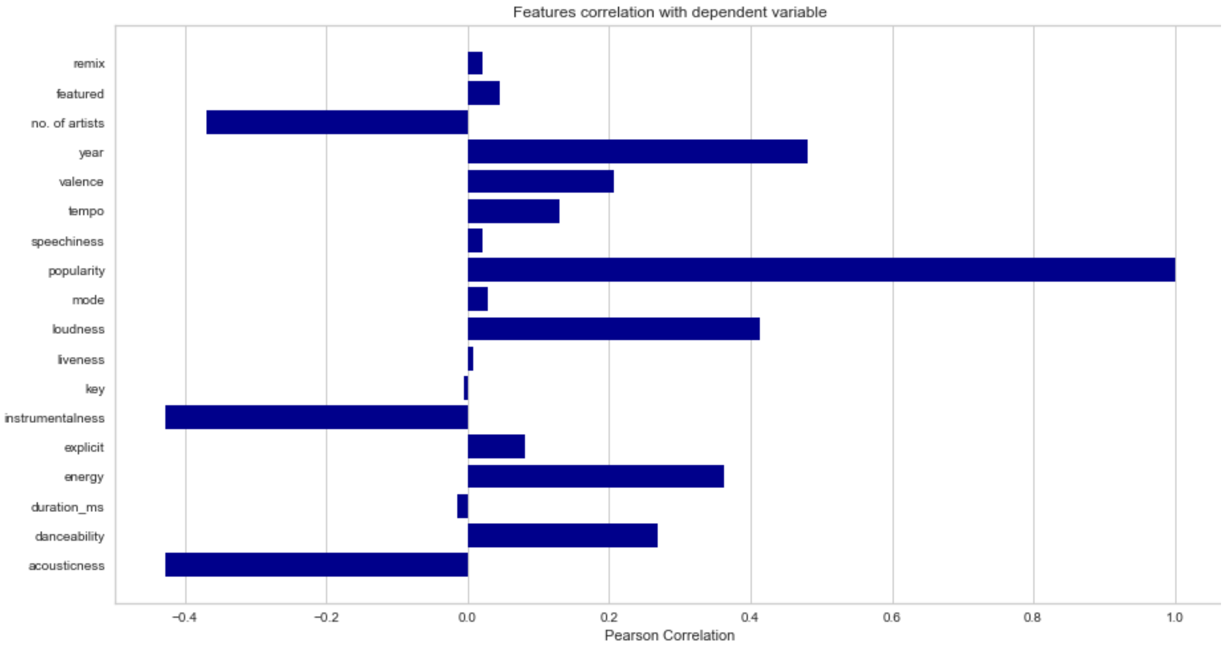
DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

# RE-UNDERSTAND

spotify_global_top100_no_pot_dupes

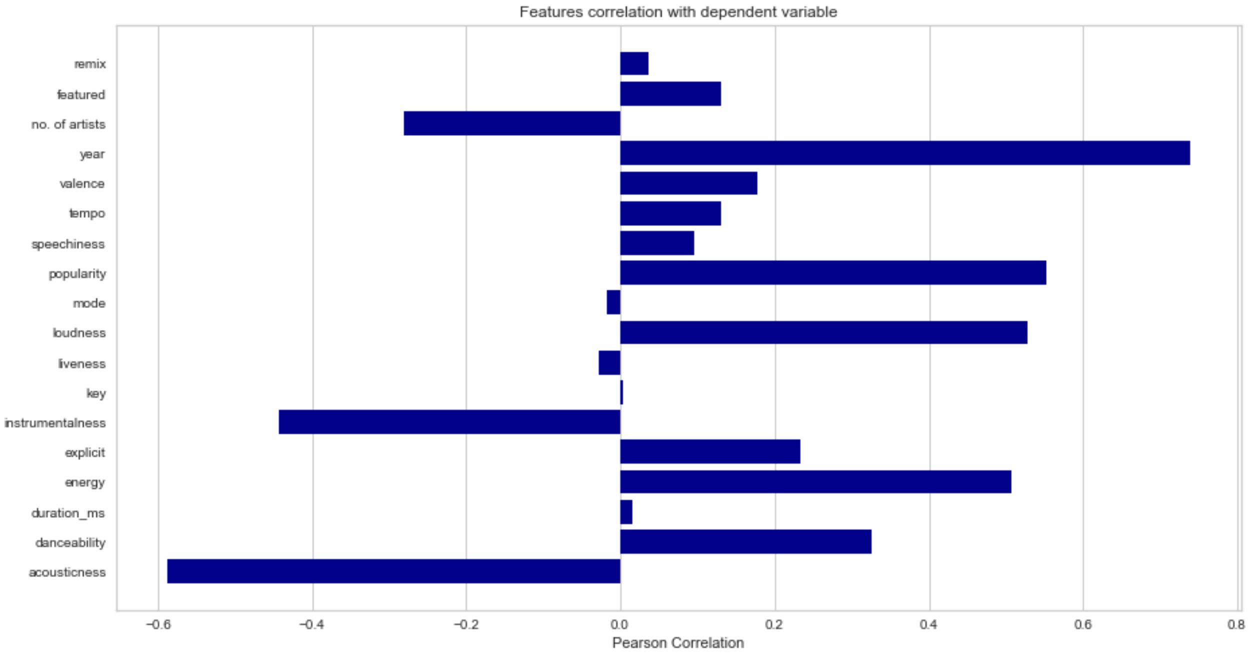
Feat. corre for popularity *NOT BINNED*

...



Feat. corre for Popularity in top 100 separately *BINNED*

...



Binning made the other positive features more positive

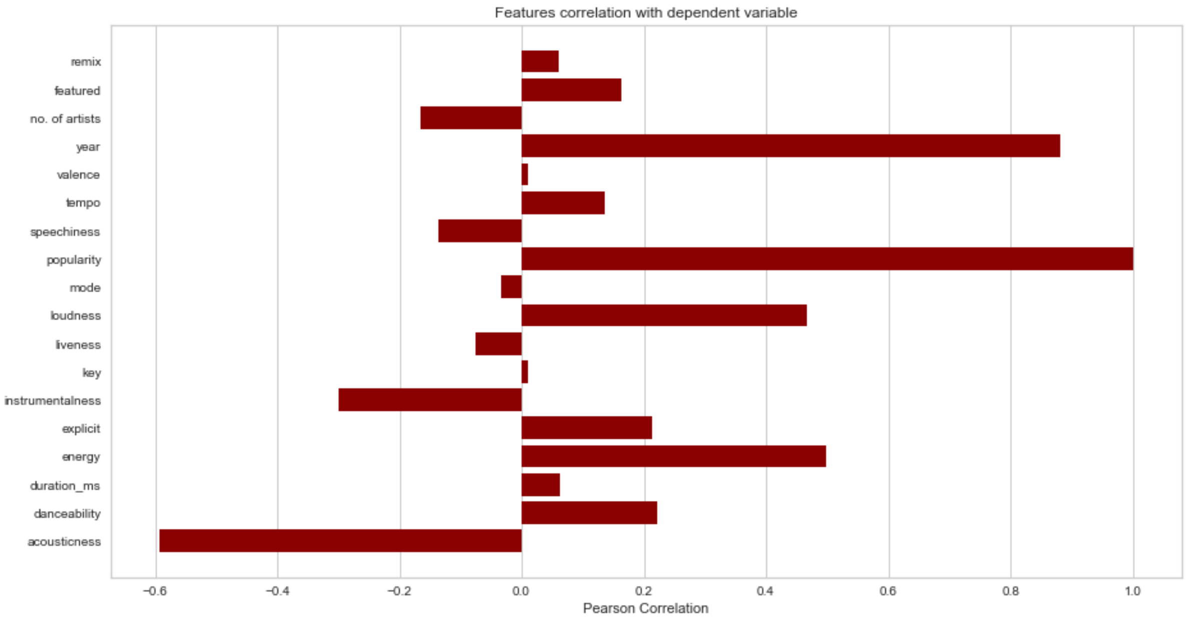
DATA UNDERSTANDING, EXPLORATION + PREPROCESSING

# RE-UNDERSTAND

spotify_global_top100

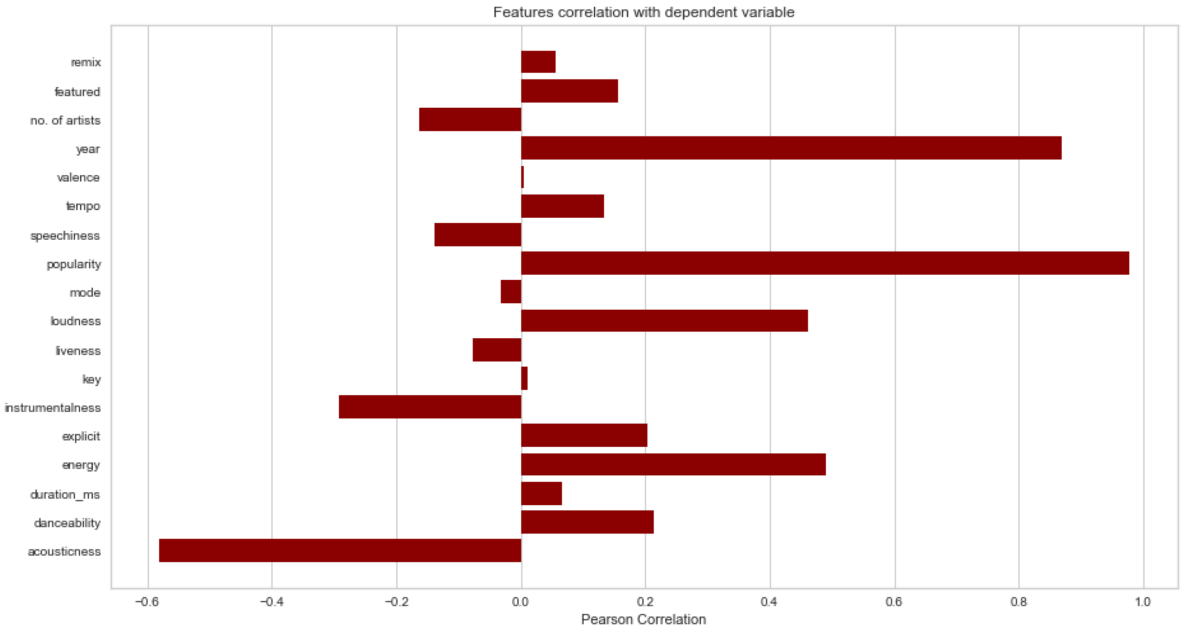
Feat. corre for popularity *NOT BINNED*

•••



Feat. corre for Popularity in top 100 separately *BINNED*

•••



Binning made the other positive features more positive

ML PORTION

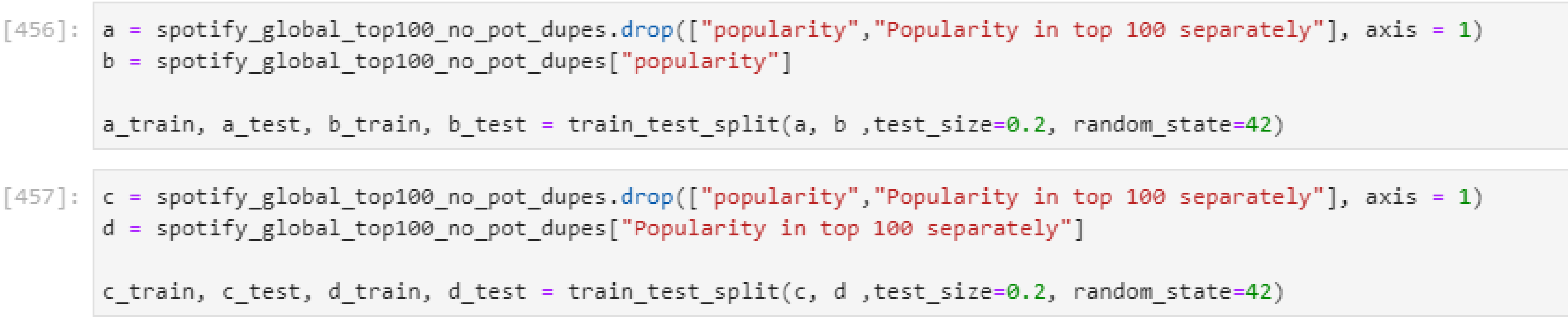
# GOAL // STRATEGY

TRAIN WITH THE NO_DUPES DATASET AND TEST IT AGAINST THE FULL DATASET

TO SEE HOW WELL IT DOES

ML: MODELS

# TRAIN_TEST_SPLIT



[456]:

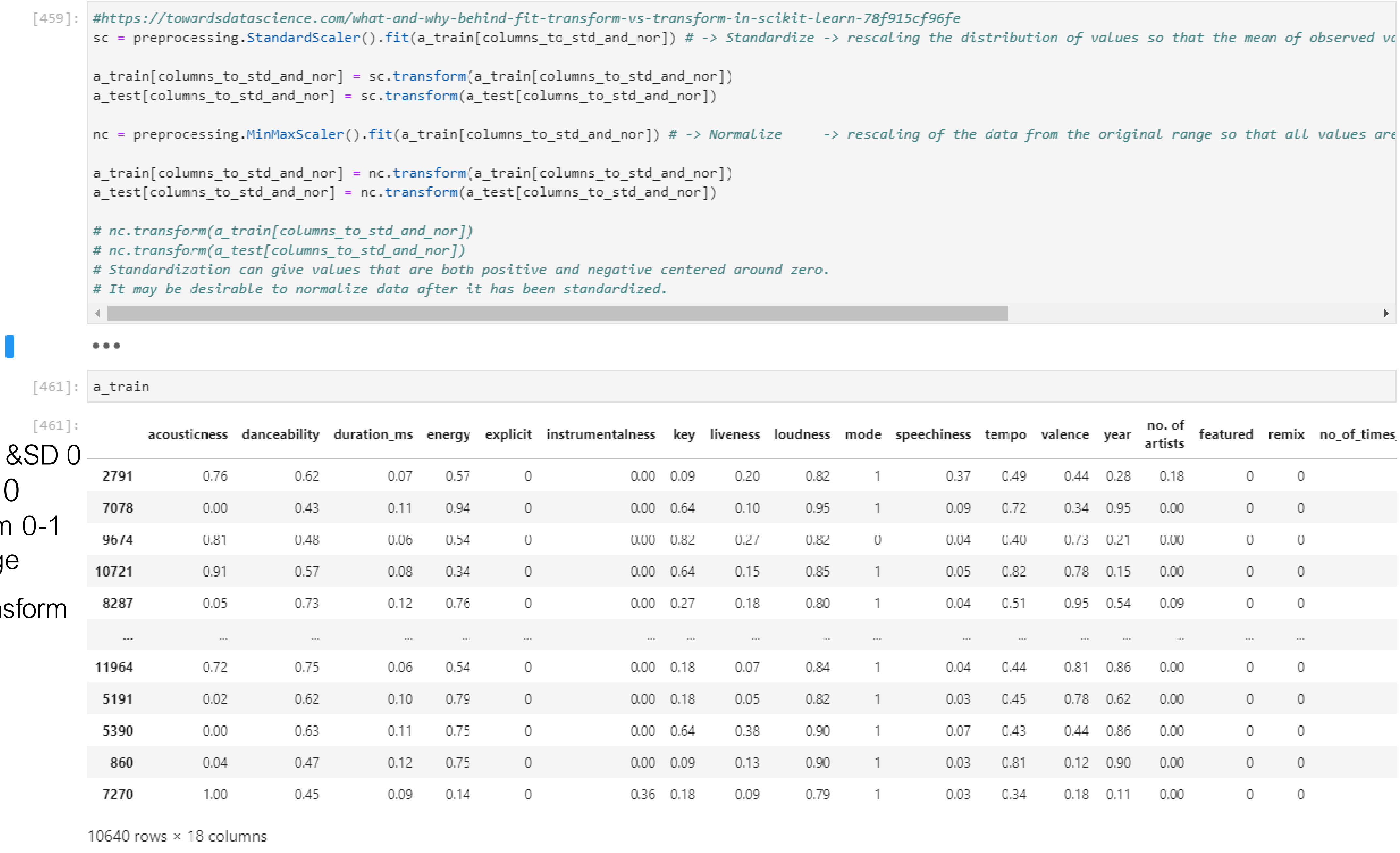
```
a = spotify_global_top100_no_pot_dupes.drop(["popularity","Popularity in top 100 separately"], axis = 1)
b = spotify_global_top100_no_pot_dupes["popularity"]

a_train, a_test, b_train, b_test = train_test_split(a, b ,test_size=0.2, random_state=42)
```

[457]:

```
c = spotify_global_top100_no_pot_dupes.drop(["popularity","Popularity in top 100 separately"], axis = 1)
d = spotify_global_top100_no_pot_dupes["Popularity in top 100 separately"]

c_train, c_test, d_train, d_test = train_test_split(c, d ,test_size=0.2, random_state=42)
```

ML: MODELS

# STANDARDISE & THEN NORMALIZE



```
[459]: #https://towardsdatascience.com/what-and-why-behind-fit-transform-vs-transform-in-scikit-learn-78f915cf96fe
       sc = preprocessing.StandardScaler().fit(a_train[columns_to_std_and_nor]) # -> Standardize -> rescaling the distribution of values so that the mean of observed va

       a_train[columns_to_std_and_nor] = sc.transform(a_train[columns_to_std_and_nor])
       a_test[columns_to_std_and_nor] = sc.transform(a_test[columns_to_std_and_nor])

       nc = preprocessing.MinMaxScaler().fit(a_train[columns_to_std_and_nor]) # -> Normalize     -> rescaling of the data from the original range so that all values are

       a_train[columns_to_std_and_nor] = nc.transform(a_train[columns_to_std_and_nor])
       a_test[columns_to_std_and_nor] = nc.transform(a_test[columns_to_std_and_nor])

       # nc.transform(a_train[columns_to_std_and_nor])
       # nc.transform(a_test[columns_to_std_and_nor])
       # Standardization can give values that are both positive and negative centered around zero.
       # It may be desirable to normalize data after it has been standardized.
```

•••

```
[461]: a_train
```

[461]:

	acousticness	danceability	duration_ms	energy	explicit	instrumentalness	key	liveness	loudness	mode	speechiness	tempo	valence	year	no. of artists	featured	remix	no_of_times_
2791	0.76	0.62	0.07	0.57	0	0.00	0.09	0.20	0.82	1	0.37	0.49	0.44	0.28	0.18	0	0	
7078	0.00	0.43	0.11	0.94	0	0.00	0.64	0.10	0.95	1	0.09	0.72	0.34	0.95	0.00	0	0	
9674	0.81	0.48	0.06	0.54	0	0.00	0.82	0.27	0.82	0	0.04	0.40	0.73	0.21	0.00	0	0	
10721	0.91	0.57	0.08	0.34	0	0.00	0.64	0.15	0.85	1	0.05	0.82	0.78	0.15	0.00	0	0	
8287	0.05	0.73	0.12	0.76	0	0.00	0.27	0.18	0.80	1	0.04	0.51	0.95	0.54	0.09	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
11964	0.72	0.75	0.06	0.54	0	0.00	0.18	0.07	0.84	1	0.04	0.44	0.81	0.86	0.00	0	0	
5191	0.02	0.62	0.10	0.79	0	0.00	0.18	0.05	0.82	1	0.03	0.45	0.78	0.62	0.00	0	0	
5390	0.00	0.63	0.11	0.75	0	0.00	0.64	0.38	0.90	1	0.07	0.43	0.44	0.86	0.00	0	0	
860	0.04	0.47	0.12	0.75	0	0.00	0.09	0.13	0.90	1	0.03	0.81	0.12	0.90	0.00	0	0	
7270	1.00	0.45	0.09	0.14	0	0.36	0.18	0.09	0.79	1	0.03	0.34	0.18	0.11	0.00	0	0	

10640 rows × 18 columns

Standardize: mean 0 &SD 0
-> AKA center ard 0
Normalize: range from 0-1
-> Force it into a range

Train set -> Fit & Transform
Test set -> Tranform

ML: MODELS

# STANDARDISE & THEN NORMALIZE

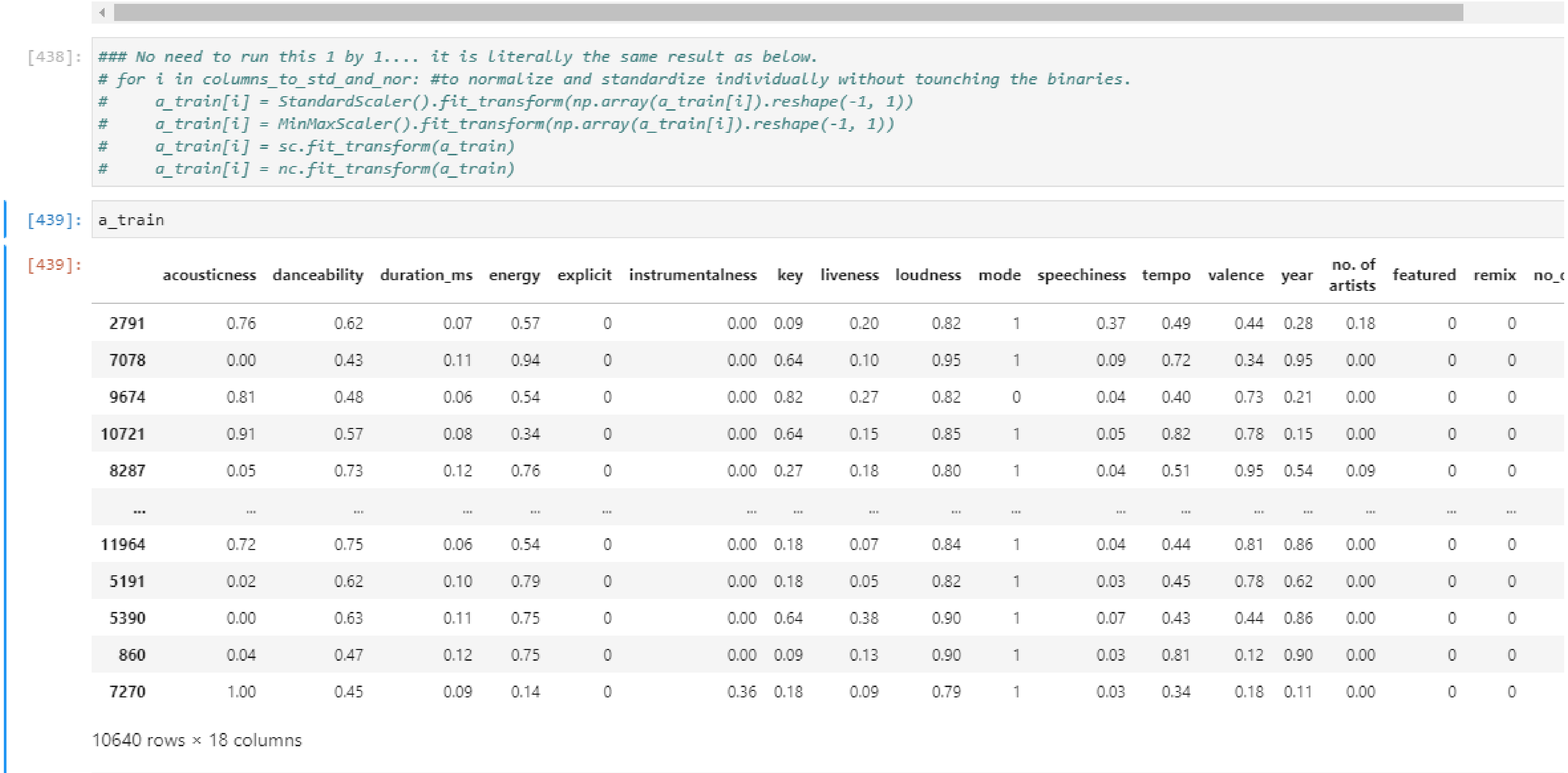
- Fit -> Calc. mean & var of each features present
- transform -> transforming all the features using the respective mean and variance.

- If we fit test data to test -> new mean and variance that is a new scale for each feature towards test and will let our model learn about our test data too

ML: MODELS

# STANDARDISE & THEN NORMALIZE

This is the column by column fit transform



```
[438]: ### No need to run this 1 by 1.... it is literally the same result as below.
       # for i in columns_to_std_and_nor: #to normalize and standardize individually without tounching the binaries.
       #     a_train[i] = StandardScaler().fit_transform(np.array(a_train[i]).reshape(-1, 1))
       #     a_train[i] = MinMaxScaler().fit_transform(np.array(a_train[i]).reshape(-1, 1))
       #     a_train[i] = sc.fit_transform(a_train)
       #     a_train[i] = nc.fit_transform(a_train)
```

```
[439]: a_train
```

[439]:

	acousticness	danceability	duration_ms	energy	explicit	instrumentalness	key	liveness	loudness	mode	speechiness	tempo	valence	year	no. of artists	featured	remix	no_c
2791	0.76	0.62	0.07	0.57	0	0.00	0.09	0.20	0.82	1	0.37	0.49	0.44	0.28	0.18	0	0	
7078	0.00	0.43	0.11	0.94	0	0.00	0.64	0.10	0.95	1	0.09	0.72	0.34	0.95	0.00	0	0	
9674	0.81	0.48	0.06	0.54	0	0.00	0.82	0.27	0.82	0	0.04	0.40	0.73	0.21	0.00	0	0	
10721	0.91	0.57	0.08	0.34	0	0.00	0.64	0.15	0.85	1	0.05	0.82	0.78	0.15	0.00	0	0	
8287	0.05	0.73	0.12	0.76	0	0.00	0.27	0.18	0.80	1	0.04	0.51	0.95	0.54	0.09	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
11964	0.72	0.75	0.06	0.54	0	0.00	0.18	0.07	0.84	1	0.04	0.44	0.81	0.86	0.00	0	0	
5191	0.02	0.62	0.10	0.79	0	0.00	0.18	0.05	0.82	1	0.03	0.45	0.78	0.62	0.00	0	0	
5390	0.00	0.63	0.11	0.75	0	0.00	0.64	0.38	0.90	1	0.07	0.43	0.44	0.86	0.00	0	0	
860	0.04	0.47	0.12	0.75	0	0.00	0.09	0.13	0.90	1	0.03	0.81	0.12	0.90	0.00	0	0	
7270	1.00	0.45	0.09	0.14	0	0.36	0.18	0.09	0.79	1	0.03	0.34	0.18	0.11	0.00	0	0	

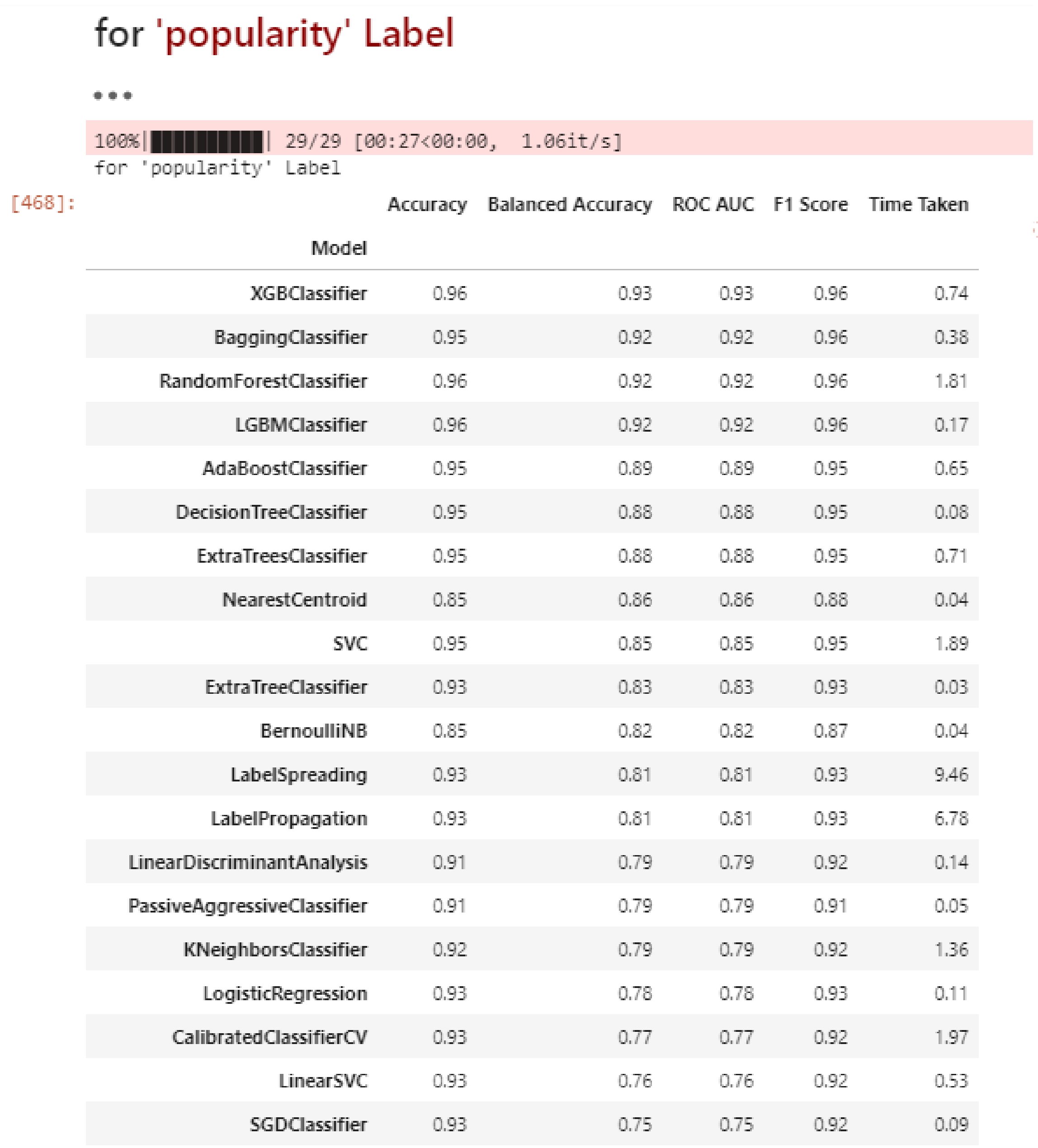
10640 rows × 18 columns

ML: MODELS

# LAZY

Okay not very sure how to deal with multiclass label ..

So I will stick with the Binary one!



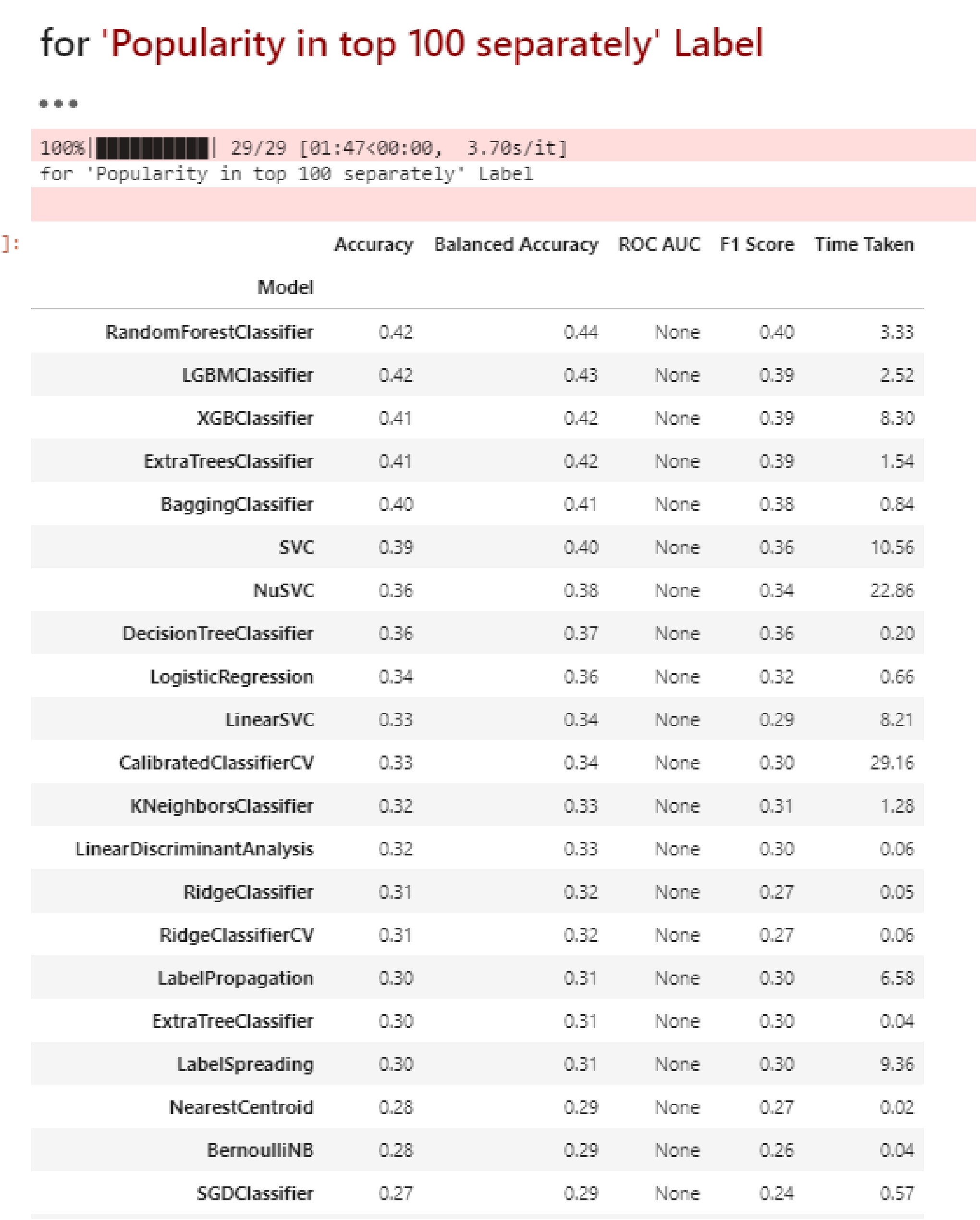
for 'popularity' Label

•••

```
100%|██████████| 29/29 [00:27<00:00,  1.06it/s]
for 'popularity' Label
```

[468]:

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score	Time Taken
XGBClassifier	0.96	0.93	0.93	0.96	0.74
BaggingClassifier	0.95	0.92	0.92	0.96	0.38
RandomForestClassifier	0.96	0.92	0.92	0.96	1.81
LGBMClassifier	0.96	0.92	0.92	0.96	0.17
AdaBoostClassifier	0.95	0.89	0.89	0.95	0.65
DecisionTreeClassifier	0.95	0.88	0.88	0.95	0.08
ExtraTreesClassifier	0.95	0.88	0.88	0.95	0.71
NearestCentroid	0.85	0.86	0.86	0.88	0.04
SVC	0.95	0.85	0.85	0.95	1.89
ExtraTreeClassifier	0.93	0.83	0.83	0.93	0.03
BernoulliNB	0.85	0.82	0.82	0.87	0.04
LabelSpreading	0.93	0.81	0.81	0.93	9.46
LabelPropagation	0.93	0.81	0.81	0.93	6.78
LinearDiscriminantAnalysis	0.91	0.79	0.79	0.92	0.14
PassiveAggressiveClassifier	0.91	0.79	0.79	0.91	0.05
KNeighborsClassifier	0.92	0.79	0.79	0.92	1.36
LogisticRegression	0.93	0.78	0.78	0.93	0.11
CalibratedClassifierCV	0.93	0.77	0.77	0.92	1.97
LinearSVC	0.93	0.76	0.76	0.92	0.53
SGDClassifier	0.93	0.75	0.75	0.92	0.09



for 'Popularity in top 100 separately' Label

•••

```
100%|██████████| 29/29 [01:47<00:00,  3.70s/it]
for 'Popularity in top 100 separately' Label
```

]:

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score	Time Taken
RandomForestClassifier	0.42	0.44	None	0.40	3.33
LGBMClassifier	0.42	0.43	None	0.39	2.52
XGBClassifier	0.41	0.42	None	0.39	8.30
ExtraTreesClassifier	0.41	0.42	None	0.39	1.54
BaggingClassifier	0.40	0.41	None	0.38	0.84
SVC	0.39	0.40	None	0.36	10.56
NuSVC	0.36	0.38	None	0.34	22.86
DecisionTreeClassifier	0.36	0.37	None	0.36	0.20
LogisticRegression	0.34	0.36	None	0.32	0.66
LinearSVC	0.33	0.34	None	0.29	8.21
CalibratedClassifierCV	0.33	0.34	None	0.30	29.16
KNeighborsClassifier	0.32	0.33	None	0.31	1.28
LinearDiscriminantAnalysis	0.32	0.33	None	0.30	0.06
RidgeClassifier	0.31	0.32	None	0.27	0.05
RidgeClassifierCV	0.31	0.32	None	0.27	0.06
LabelPropagation	0.30	0.31	None	0.30	6.58
ExtraTreeClassifier	0.30	0.31	None	0.30	0.04
LabelSpreading	0.30	0.31	None	0.30	9.36
NearestCentroid	0.28	0.29	None	0.27	0.02
BernoulliNB	0.28	0.29	None	0.26	0.04
SGDClassifier	0.27	0.29	None	0.24	0.57

ML: MODEL SELECTION

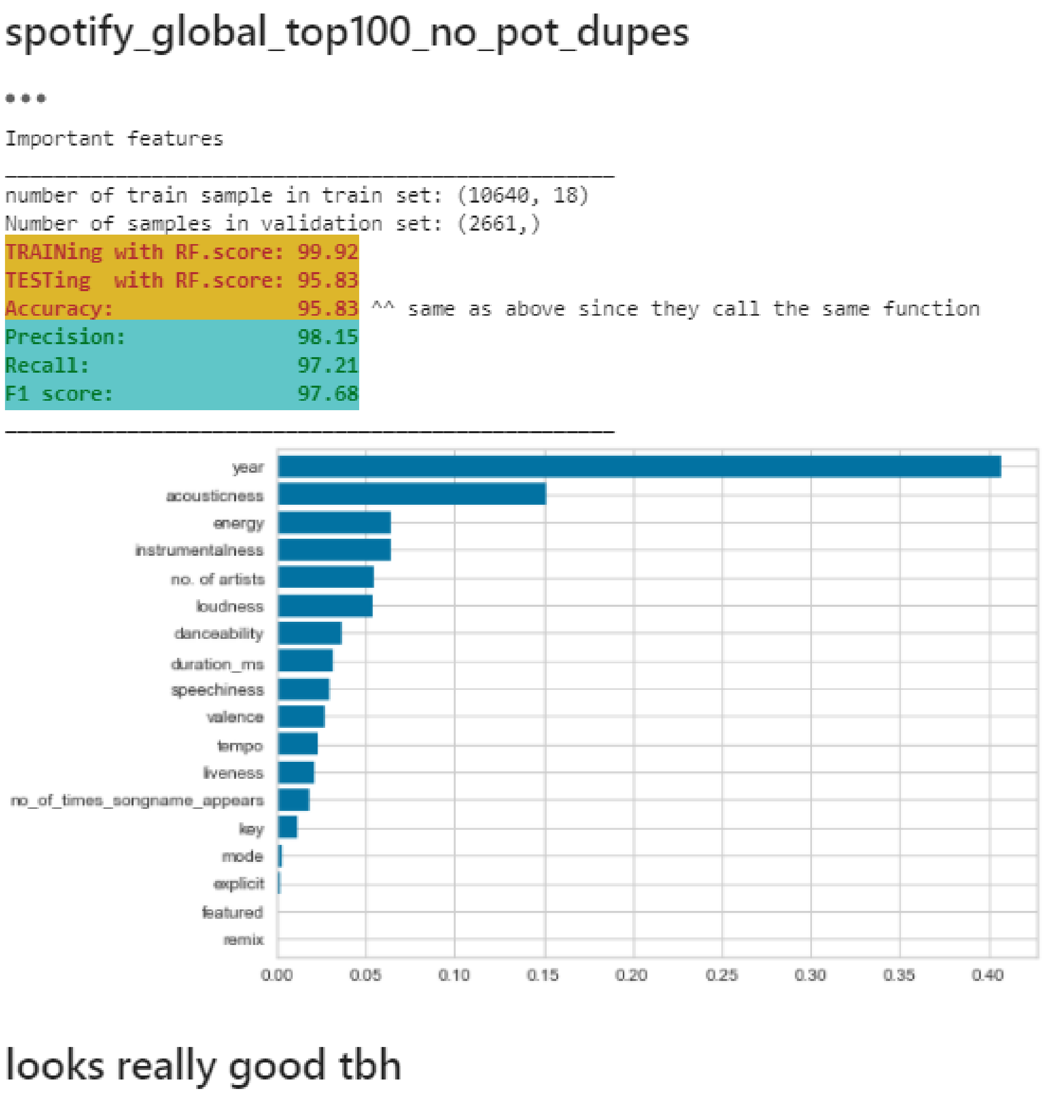
# RANDOM FOREST

Reasons:

- Lazy predict has very good accuracy, AUC & F1
- able to deal with imbalanced dataset with class_weight = "balanced"
- No sensitive to outliers (but I alrdy standardised and normalised)
- It is an ensemble of DTs -> Typically more depth -> Less overfitting
  -> AKA bagging -> reduce the complexity of models which will overfit.

ML: TRAINING

RANDOM FOREST



spotify_global_top100_no_pot_dupes

•••

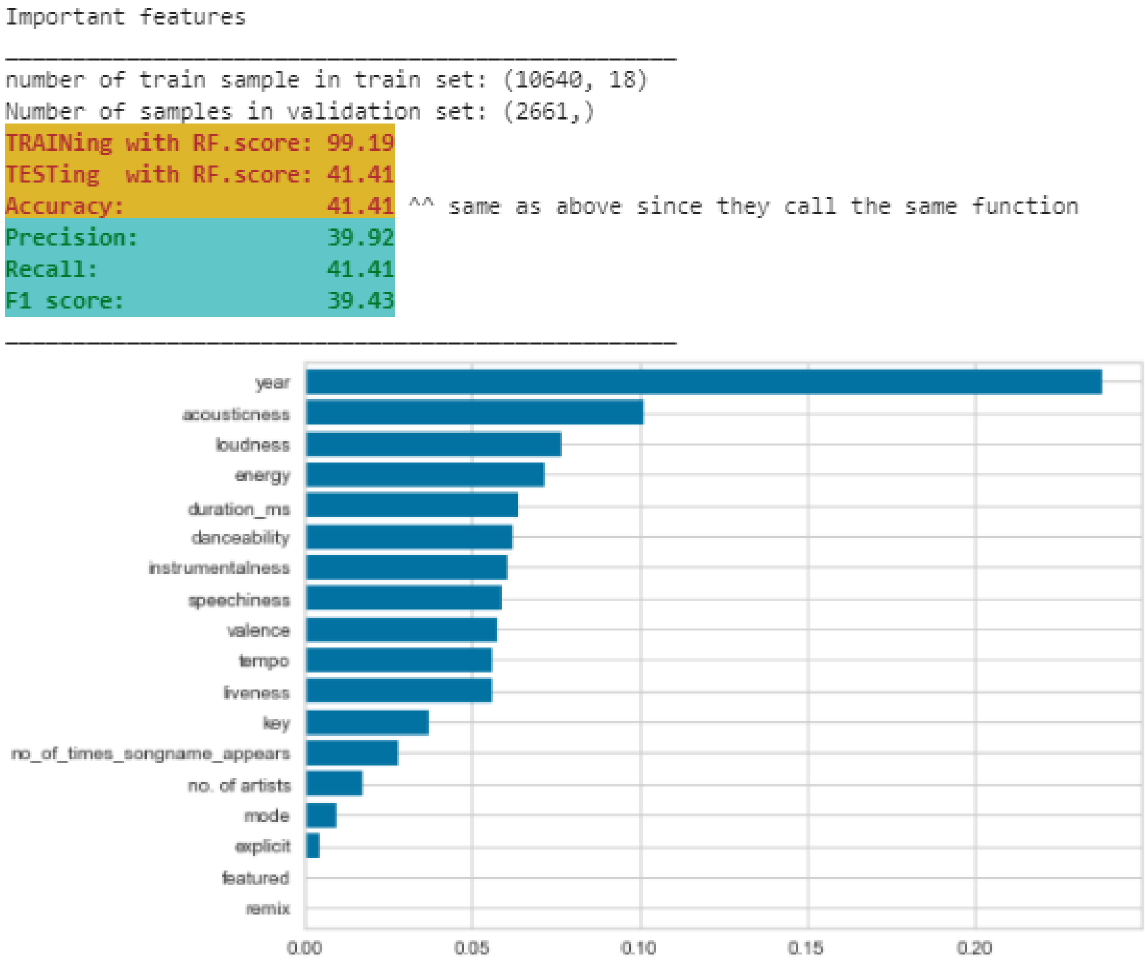
```
Important features

_________________________________________________
number of train sample in train set: (10640, 18)
Number of samples in validation set: (2661,)
TRAINing with RF.score: 99.92
TESTing  with RF.score: 95.83
Accuracy:               95.83 ^^ same as above since they call the same function
Precision:              98.15
Recall:                 97.21
F1 score:               97.68
_________________________________________________
```

looks really good tbh

Can proceed to tune

ML: TRAINING

# RANDOM FOREST



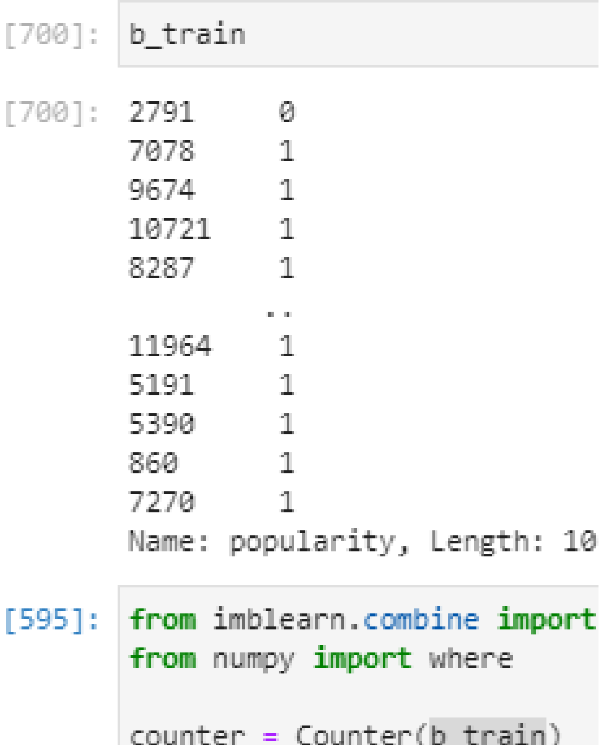
```
Important features

________________________________________________
number of train sample in train set: (10640, 18)
Number of samples in validation set: (2661,)
TRAINing with RF.score: 99.19
TESTing  with RF.score: 41.41
Accuracy:               41.41 ^^ same as above since they call the same function
Precision:              39.92
Recall:                 41.41
F1 score:               39.43
________________________________________________
```

Looks like overfitting.... lets abandon it as it takes too much time

ML: TRAINING

OVER AND UNDER SAMPLING

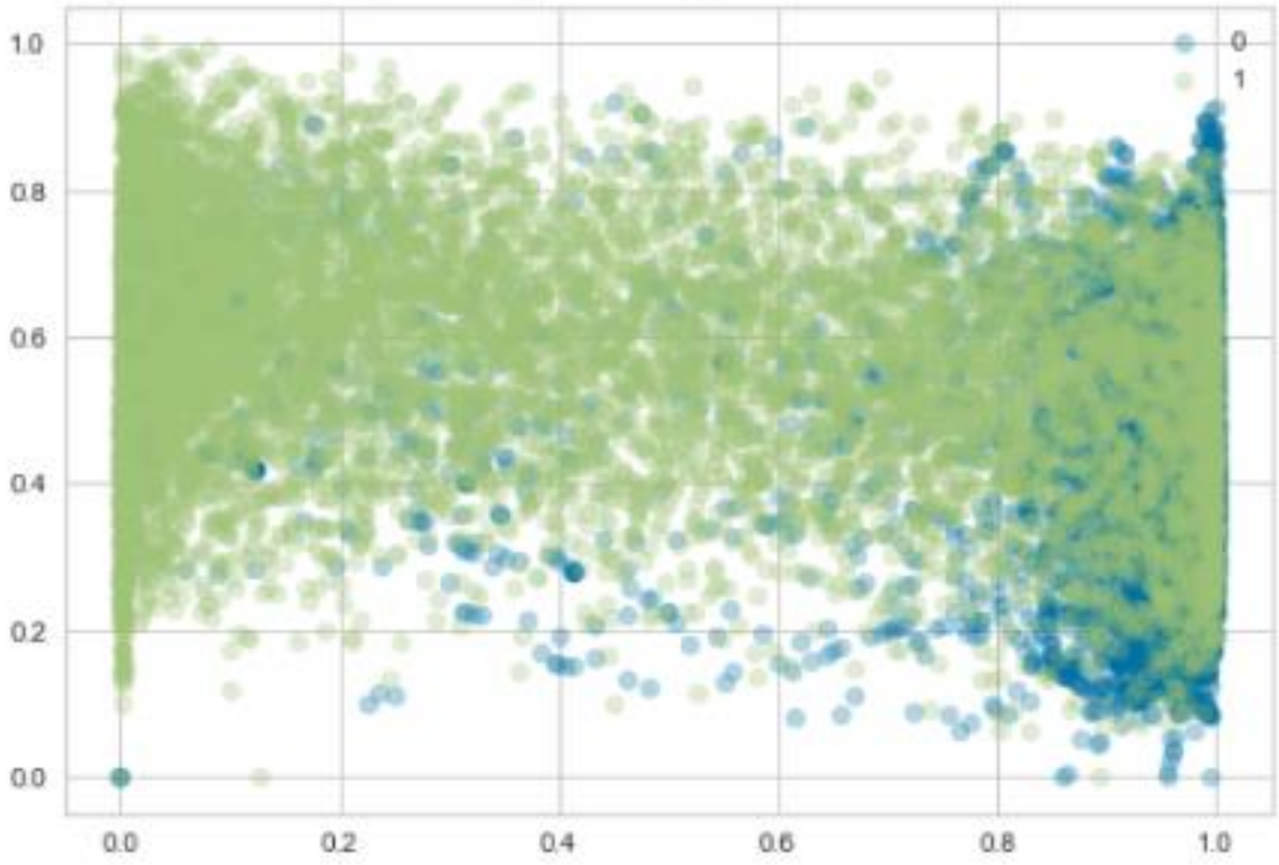
#SMOTE #TOMEK



```
[700]: b_train

[700]: 2791     0
       7078     1
       9674     1
       10721    1
       8287     1
               ..
       11964    1
       5191     1
       5390     1
       860      1
       7270     1
       Name: popularity, Length: 10

[595]: from imblearn.combine import
       from numpy import where

       counter = Counter(b_train)
```

Tomek links are the opposite class paired samples that are the closest neighbors to each other.

```
Before, the Counter({1: 9453, 0: 1187})
after, the Counter({0: 9449, 1: 9449})
```

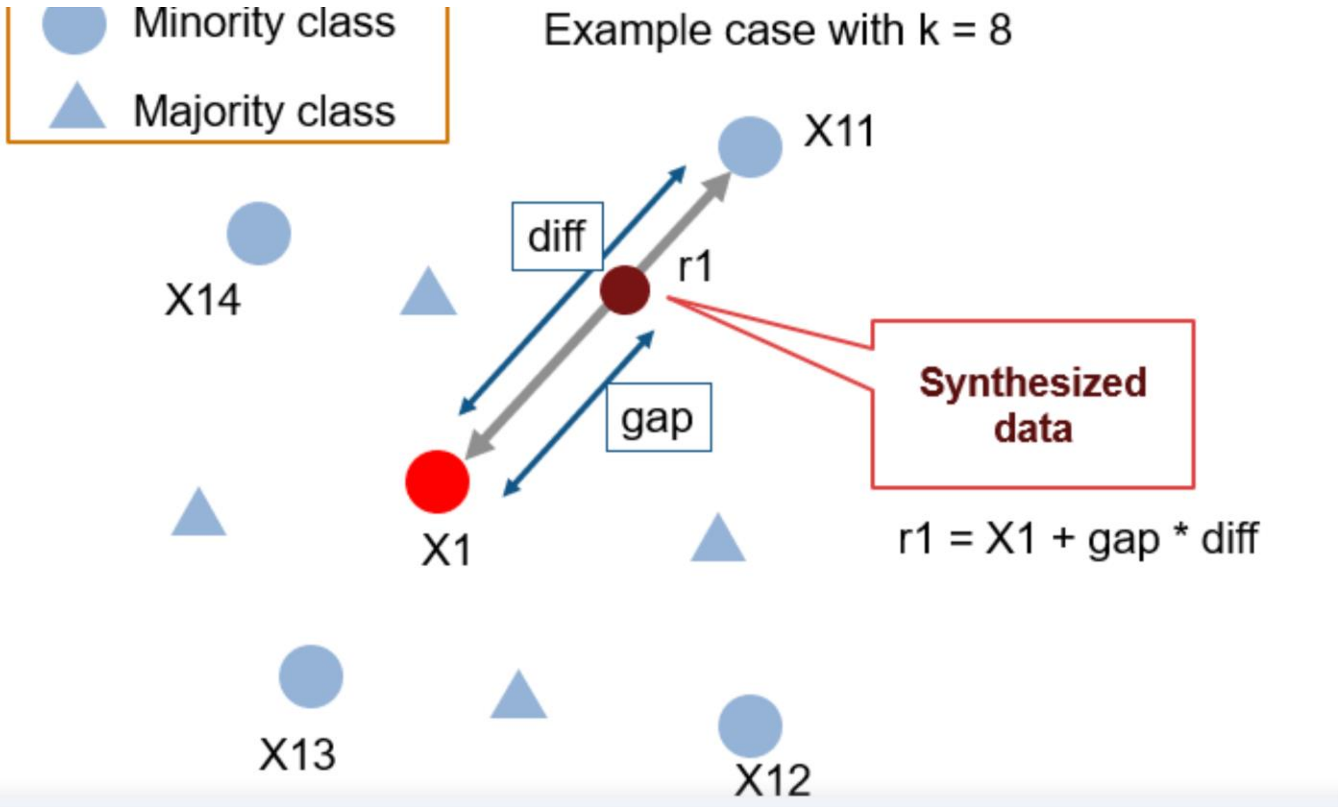


Smoting minority 1187 to 9453 and
Removing Tomek links on both classes to 9449 to prevent overfitting

ML: TRAINING

OVER AND UNDER SAMPLING

#SMOTE
#TOMEK

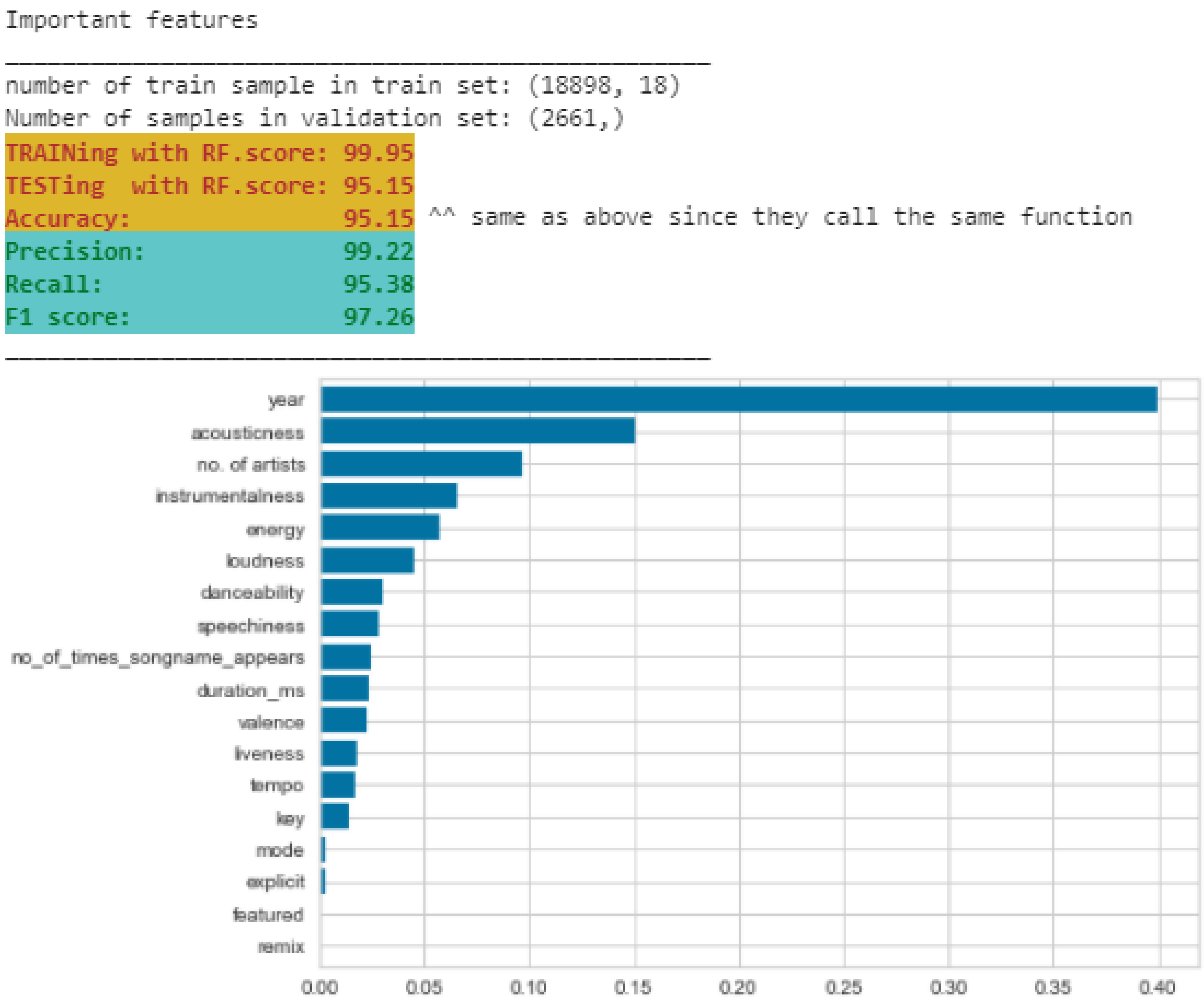


Pictorial on smoting specifically

ML: TRAINING

# OVER AND UNDER SAMPLING

#SMOTE
#TOMEK



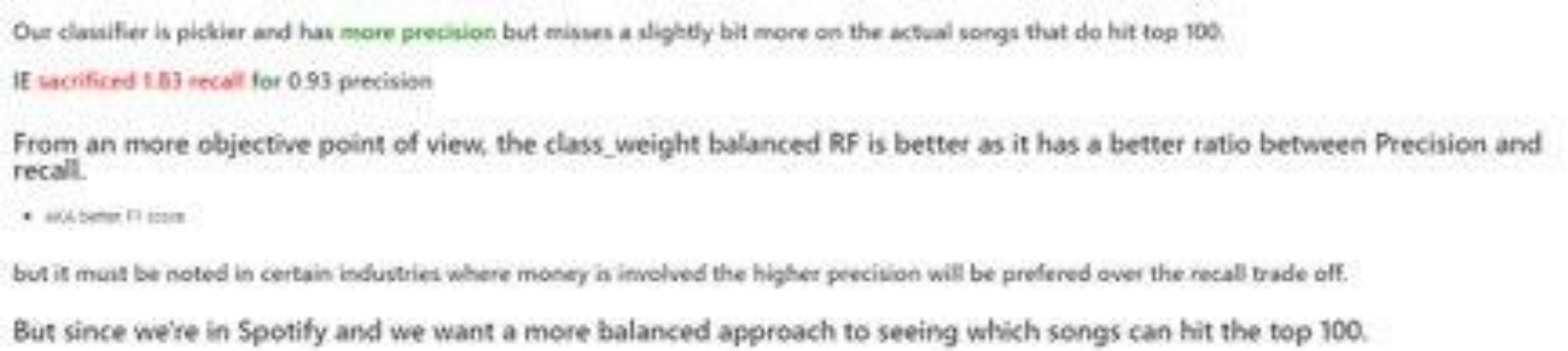
```
Important features

_____________________________________________________
number of train sample in train set: (18898, 18)
Number of samples in validation set: (2661,)
TRAINing with RF.score: 99.95
TESTing  with RF.score: 95.15
Accuracy:               95.15 ^^ same as above since they call the same function
Precision:              99.22
Recall:                 95.38
F1 score:               97.26
_____________________________________________________
```

ML: TRAINING

# OVER AND UNDER SAMPLING

#SMOTE
#TOMEK

Lets use the RF class weight balanced set



Our classifier is pickier and has more precision but misses a slightly bit more on the actual songs that do hit top 100.

IE sacrificed 1.83 recall for 0.93 precision

From an more objective point of view, the class_weight balanced RF is better as it has a better ratio between Precision and recall.

- AKA better F1 score

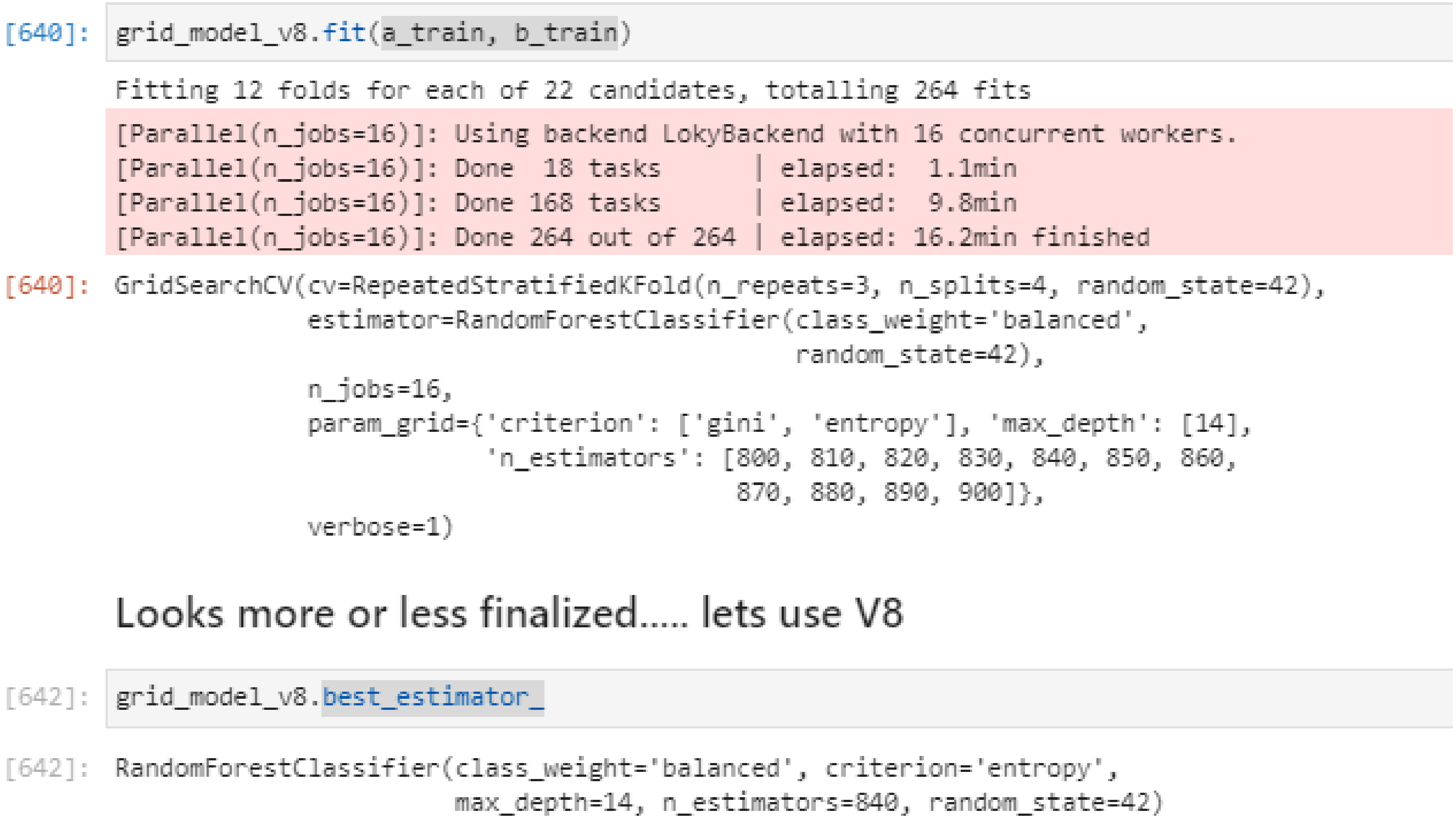
but it must be noted in certain industries where money is involved the higher precision will be prefered over the recall trade off.

But since we're in Spotify and we want a more balanced approach to seeing which songs can hit the top 100.

ML: TRAINING

# HYPER-PARAMETER TUNING

#GRIDSEARCHCV



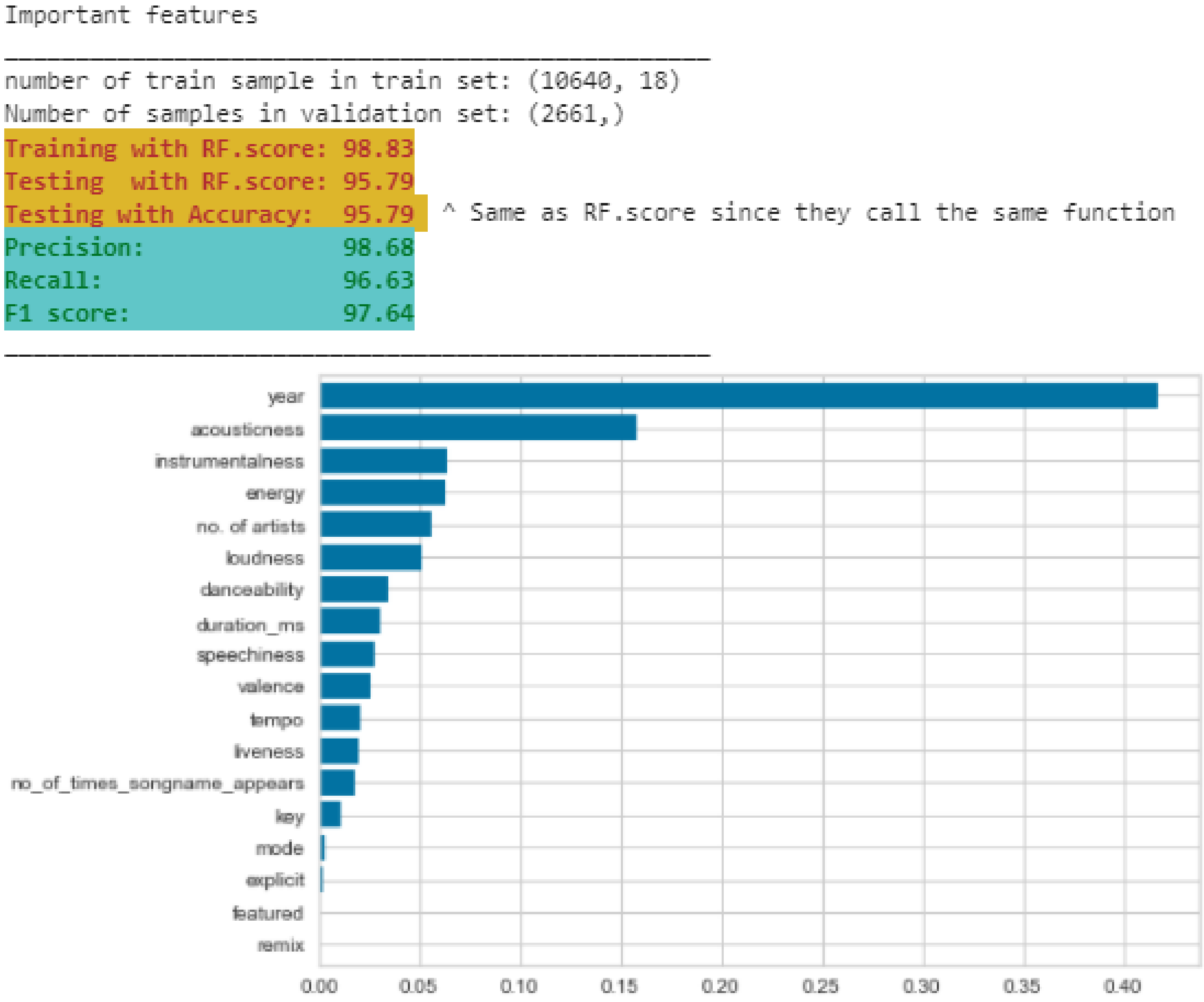
```
[640]: grid_model_v8.fit(a_train, b_train)

       Fitting 12 folds for each of 22 candidates, totalling 264 fits
       [Parallel(n_jobs=16)]: Using backend LokyBackend with 16 concurrent workers.
       [Parallel(n_jobs=16)]: Done  18 tasks      | elapsed:  1.1min
       [Parallel(n_jobs=16)]: Done 168 tasks      | elapsed:  9.8min
       [Parallel(n_jobs=16)]: Done 264 out of 264 | elapsed: 16.2min finished

[640]: GridSearchCV(cv=RepeatedStratifiedKFold(n_repeats=3, n_splits=4, random_state=42),
                    estimator=RandomForestClassifier(class_weight='balanced',
                                                     random_state=42),
                    n_jobs=16,
                    param_grid={'criterion': ['gini', 'entropy'], 'max_depth': [14],
                                'n_estimators': [800, 810, 820, 830, 840, 850, 860,
                                                 870, 880, 890, 900]},
                    verbose=1)
```

Looks more or less finalized..... lets use V8

```
[642]: grid_model_v8.best_estimator_

[642]: RandomForestClassifier(class_weight='balanced', criterion='entropy',
                              max_depth=14, n_estimators=840, random_state=42)
```

ML: TRAINING

# RUN AGAIN



```
Important features
__________________________________________________
number of train sample in train set: (10640, 18)
Number of samples in validation set: (2661,)
Training with RF.score: 98.83
Testing  with RF.score: 95.79
Testing with Accuracy:  95.79   ^ Same as RF.score since they call the same function
Precision:              98.68
Recall:                 96.63
F1 score:               97.64
__________________________________________________
```

ML: MODEL EVALUATION

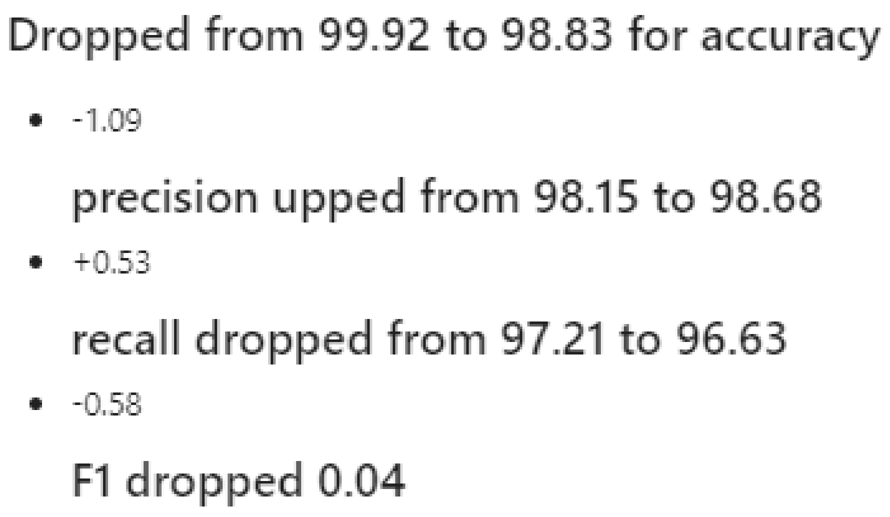
# ACCURACY
PRECISION,
RECALL,
F1

### Accuracy -> Correctness
- (tp + tn) / (p + n)

### Precision -> Exactness
- tp / (tp + fp)

### Recall -> Completeness
- tp / (tp + fn)

### F1 -> how complete & exact IE balance of precision and recall
- 2 tp / (2 tp + fp + fn)



Dropped from 99.92 to 98.83 for accuracy

- -1.09

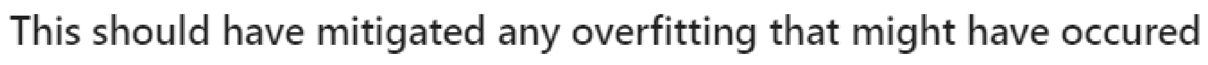
precision upped from 98.15 to 98.68

- +0.53

recall dropped from 97.21 to 96.63

- -0.58

F1 dropped 0.04



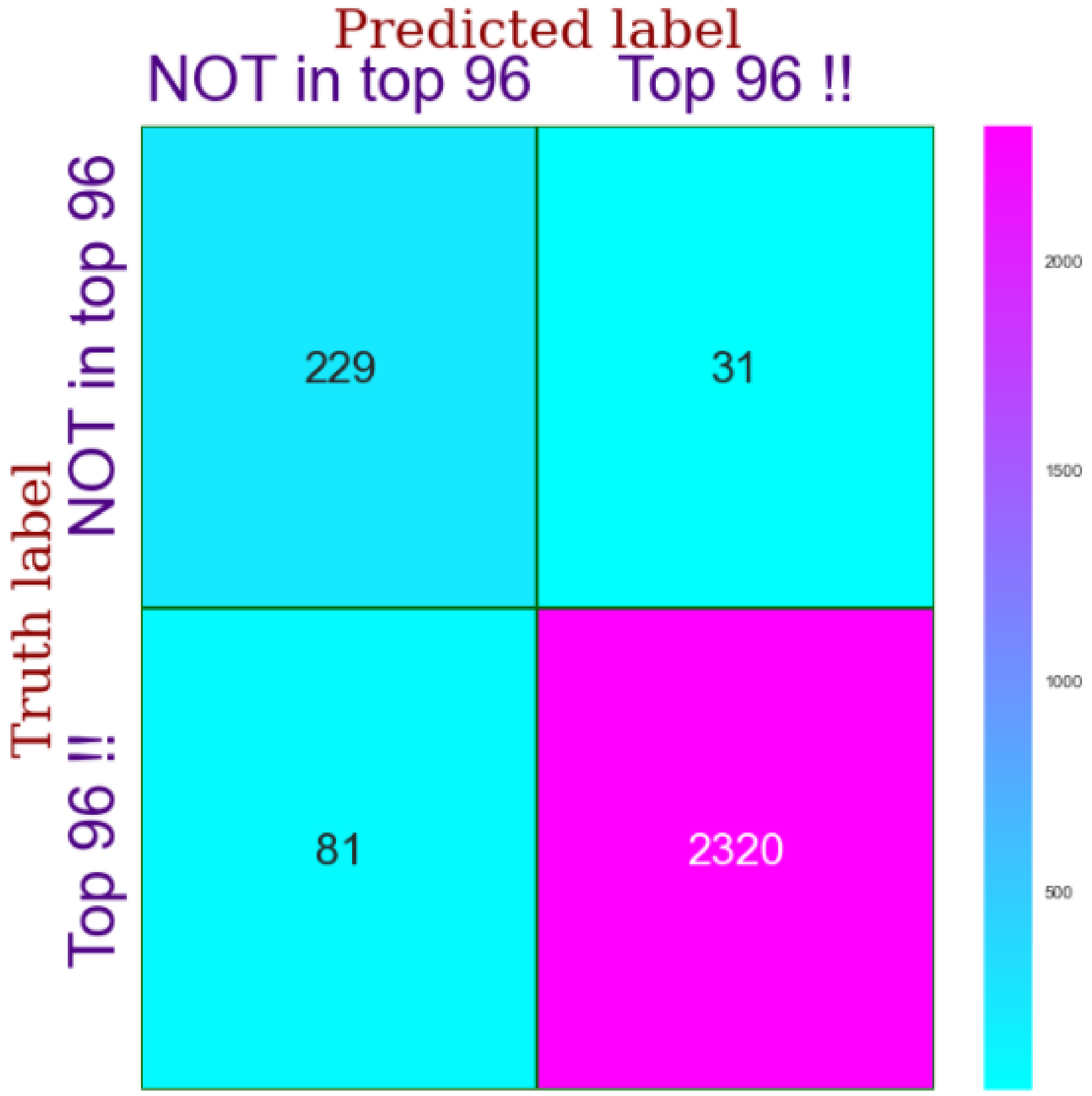
This should have mitigated any overfitting that might have occured

ML: MODEL EVALUATION

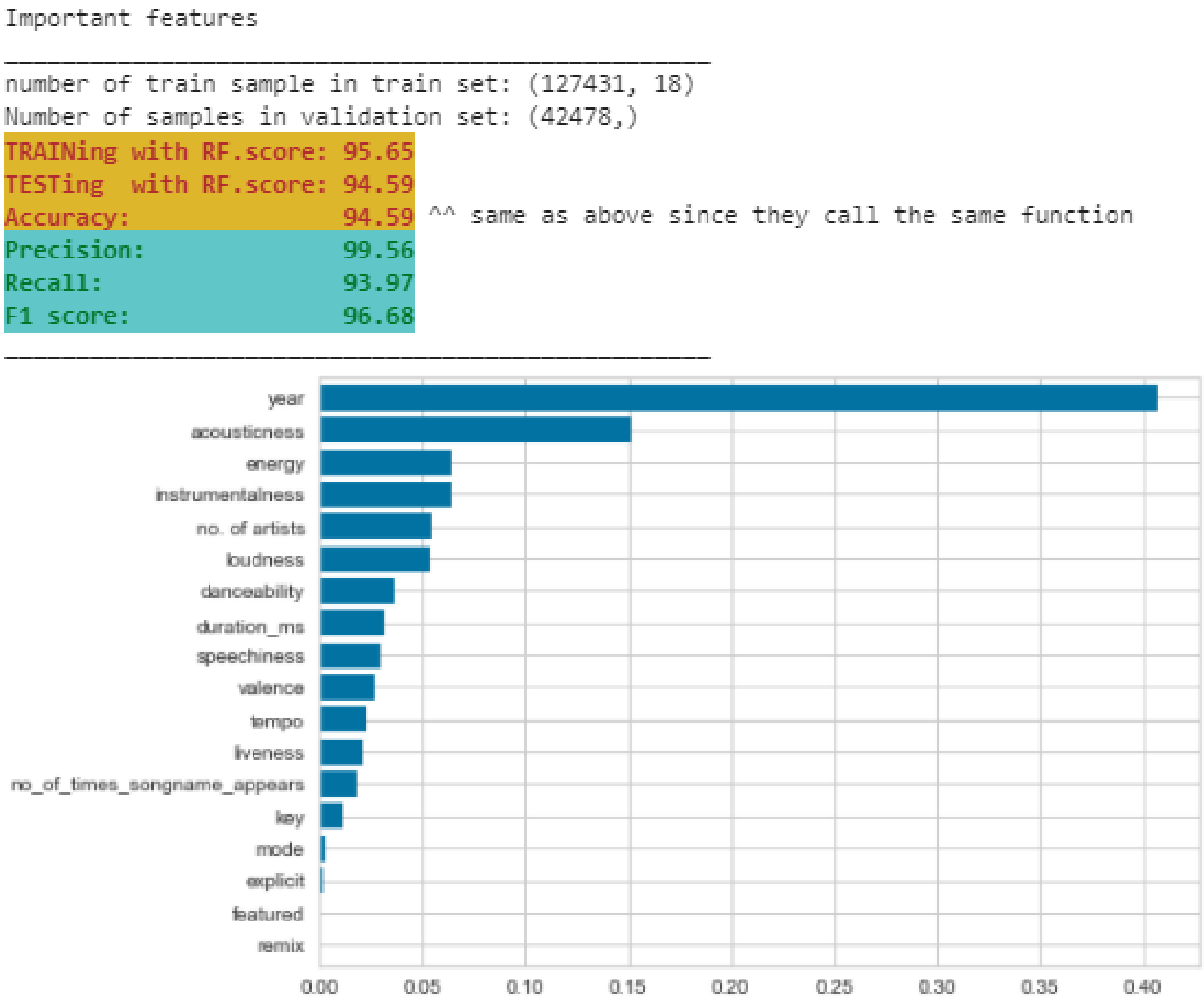
# ACCURACY PRECISION, RECALL, F1

Heat map of test data against predictions with test data

Very decent TNs & TPs



ML: TEST ON BIG SET



```
Important features

_________________________________________________
number of train sample in train set: (127431, 18)
Number of samples in validation set: (42478,)
TRAINing with RF.score: 95.65
TESTing  with RF.score: 94.59
Accuracy:               94.59 ^^ same as above since they call the same function
Precision:              99.56
Recall:                 93.97
F1 score:               96.68
_________________________________________________
```

Generalizes well! Very good!

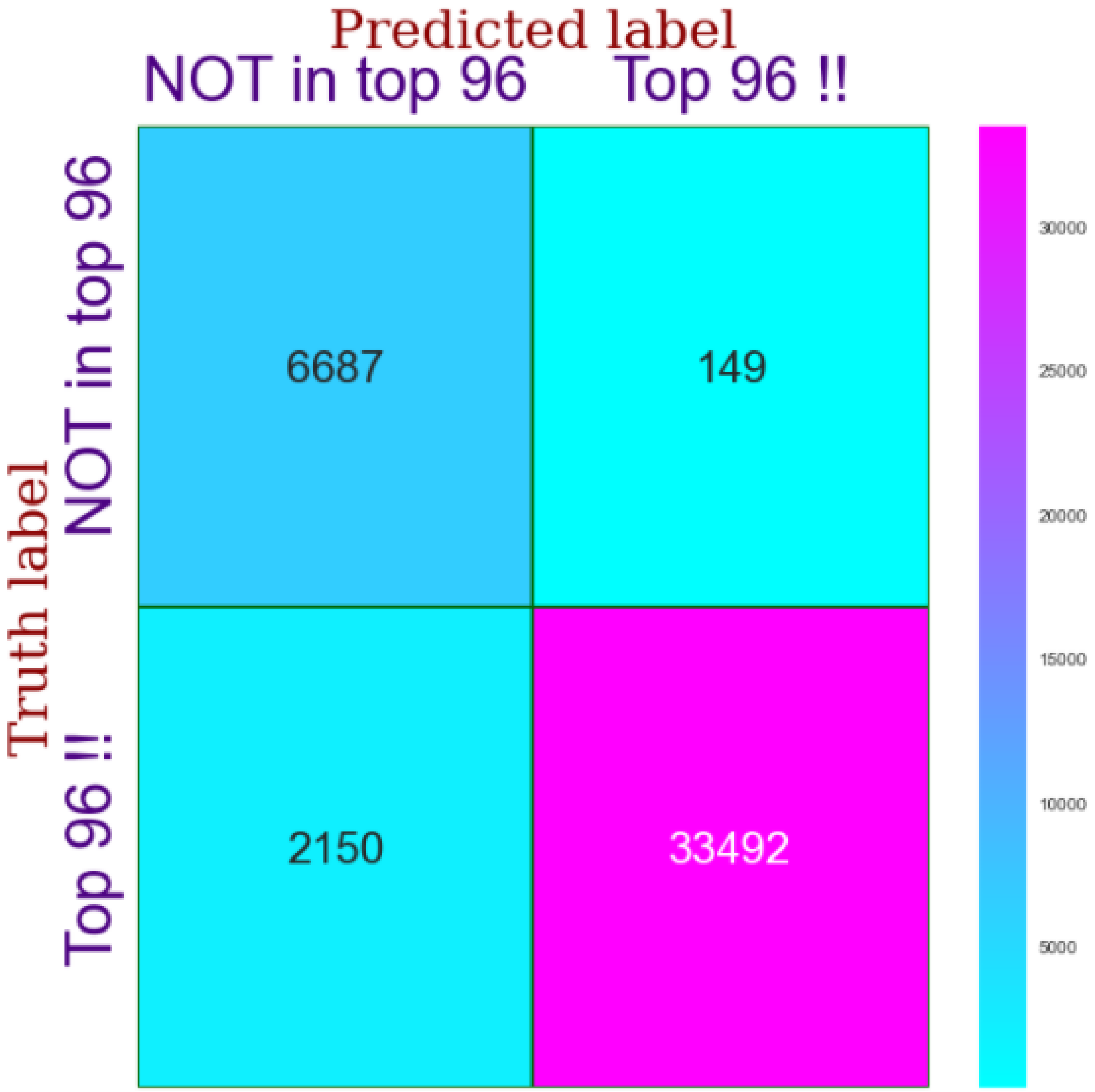
In hindsight I could have easily parsed out the no dupes set from the original 169k data set to make the results even more convincing.

ML: MODEL EVALUATION

# ACCURACY
PRECISION,
RECALL,
F1

Heat map of test data against predictions with test data

Still Very decent TNs & TPs



Spotify®

END OF PRESENTATION

https://github.com/lolasery/khdatasci

https://www.kaggle.com/ektanegi
/spotifydata-19212020