Music Recommendation

> I pledge my Honor that I have abided by the Stevens Honor System. - Mike DiGregorio & Joshua Schmidt

dataset

To download the dataset follow the instructions here:

- https://www.kaggle.com/c/kkbox-music-recommendation-challenge/data?select=members.csv.7z

If you are running archlinux:

- git clone https://aur.archlinux.org/kaggle-api.git
- cd kaggle-api
- makepkg -si
- Go to the first link and create a kaggle account and agree to the competition rules
- go to your account page on kaggle and create an api key and save the kaggle.json file in the folder ~/.kaggle/
- kaggle competitions download -c kkbox-music-recommendation-challenge

Import required dependencies

In [190…
```python
import os
import numpy as np
import pandas as pd
import tensorflow as tf
import tensorflow.data as tfd


from loguru import logger
from tqdm import tqdm

from typing import List, Any, Tuple, Optional, Dict
```

In [191…
```python
datapath: str = os.path.join('..', 'data')
```

In [192…
```python
def list_files(directory: str, extension: str) -> List[str]:
    all_files = os.listdir(directory)
    return [os.path.join(directory, file) for file in all_files if file.split('.')[-1] == extension]
```

In [193…
```python
datasets: Dict[str, pd.DataFrame] = dict()
for filepath in tqdm(list_files(datapath, 'csv'), ascii=True, desc="Loading data from disk"):
    datasets[os.path.basename(filepath).split('.')[0]] = pd.read_csv(filepath)
```

```
Loading data from disk: 100%|##########| 6/6 [00:15<00:00,  2.59s/it]
```

Some key metrics on dataset size

In [194…
```python
print(f"Loaded {len(datasets)} csv files")
for key, value in datasets.items():
    print(f"length of dataset {key} is {len(value)}")
```

```
Loaded 6 csv files
length of dataset songs is 2296320
length of dataset test is 2556790
length of dataset sample_submission is 2556790
length of dataset train is 7377418
length of dataset members is 34403
length of dataset song_extra_info is 2295971
```

In [195…
```python
# Let's remove the 'sample_submission' dataset
_ = datasets.pop('sample_submission')
```

Below is a more detailed analysis of the raw data, omitted for brevity

In [1]:
```python
# for key, value in datasets.items():
#     print(f"Information for dataset: {key}")
#     print("Description")
#     print(value.describe())
#     print('\n')
#     print("dataframe 'head'")
#     print(value.head())
#     print('\n\n-------------------------------------------------------\n\n')
```

"English' Description of the Dataset

- we have a list of users, their personal information, the songs that they liked and didnt like, and where they accesed the song
- we also have metadata about each song in the dataset

Dataset descriptions:

- members.csv
  - user ID, location, gender,
- song_extra_info + songs.csv
  - song_id, song name, artist name, composer, lyricist, genre id, song length, language
- train.csv:
  - userid, songid, where they found the song, whether they liked it or now

This will be used to create clusters of songs, or song groups

Recommendation dataset:

- userid, song rating, songs cluster, songs feature vector

Below is a preview of the raw curated 'songs' dataset

In [198…
```python
raw = pd.DataFrame()
# categorical variables
raw["artist_name"] = datasets["songs"]["artist_name"]
raw["composer"] = datasets["songs"]["composer"]
raw["lyricist"] = datasets["songs"]["lyricist"]
raw["genre_id"] = datasets["songs"]["genre_ids"]
raw["language"] = datasets["songs"]["language"]
raw["song_length"] = datasets["songs"]["song_length"]
raw["song_id"] = datasets["songs"]["song_id"]
```

In [199…
```python
raw
```

Out[199…

	artist_name	composer	lyricist	genre_id	language	song_length	song_id
0	張信哲 (Jeff Chang)	董貞	何啟弘	465	3.0	247640	CXoTN1eb7AI+DntdU1vbcwGRV4SCIDxZu+YD8JP8r4E=
1	BLACKPINK	TEDDY| FUTURE BOUNCE| Bekuh BOOM	TEDDY	444	31.0	197328	o0kFgae9QtnYgRkVPqLJwa05zIhRlUjfF7O1tDw0ZDU=
2	SUPER JUNIOR	NaN	NaN	465	31.0	231781	DwVvVurfpuz+XPuFvucclVQEyPqcpUkHR0ne1RQzPs0=
3	S.H.E	湯小康	徐世珍	465	3.0	273554	dKMBWoZyScdxSkihKG+Vf47nc18N9q4m58+b4e7dSSE=
4	貴族精選	Traditional	Traditional	726	52.0	140329	W3bqWd3T+VeHFzHAUfARgW9AvVRaF4N5Yzm4Mr6Eo/o=
...	...	...	...	...	...	...	...
2296315	Catherine Collard	Robert Schumann (1810-1856)	NaN	958	-1.0	20192	lg6rn7eV/ZNg0+P+x77kHUL7GDMfoL4eMtXxncseLNA=
2296316	紀文惠 (Justine Chi)	NaN	NaN	465	3.0	273391	nXi1lrSJe+gLoTTNky7If0mNPrIyCQCLwagwR6XopGU=
2296317	Various Artists	NaN	NaN	1609	52.0	445172	9KxSvljbJyJzfEVWnkMbgR6dyn6d54ot0N5FKyKqii8=
2296318	Peter Paul & Mary	NaN	NaN	465	52.0	172669	UO8Y2MR2sjOn2q/Tp8/IzZTGKmLEvwZ20oWanG4XnYc=
2296319	Kim Robertson	NaN	NaN	829	52.0	270466	V/9qPSUOGT0FeIGBhDIZRRz5Y5yyjdXC2Z/+bJExo5s=

2296320 rows × 7 columns

Here we begin cleaning the curated songs dataset for analysis

- This includes:
- removing na values
- removing unicode characters
- removing any songs classified under mutliple genres, artists, composers, or lyricists
- removing any purely instrumental songs

In [200…
```python
import re

def only_letters(tested_string):
    match = re.match("^[a-zA-Z]*$", str(tested_string))
    return match is not None
def only_numbers(tested_string):
    match = re.match("^[0-9]*$", str(tested_string))
    return match is not None
```

In [201…
```python
raw['artist_name'] = raw[raw['artist_name'].apply(only_letters)]['artist_name']
raw['lyricist'] = raw[raw['lyricist'].apply(only_letters)]['lyricist']
raw['composer'] = raw[raw['composer'].apply(only_letters)]['composer']
raw['genre_id'] = raw[raw['genre_id'].apply(only_numbers)]['genre_id']
```

We are working with a massive dataset, and to allocate enough memory to run an MCA on even just raw cat would take over 1.4 TiB so lets drop everything with an NA

In [203…
```python
raw.dropna(axis=0, how='any', inplace=True)
```

In [205…
```python
raw = raw[(raw.artist_name != 'Various Artists') & (raw.artist_name != 'Various')]
raw = raw[raw.language != -1]
```

One other way to reduce the number of categories for MCA is to filter our dataframe by the top 1000 artists

In [206…
```python
num_artists=100
num_composers=500
num_lyricists=500
num_genres=500
num_languages=3
```

In [208…
```python
raw = raw[raw.artist_name.isin(raw['artist_name'].value_counts(sort=True).index.tolist()[:num_artists])]
raw = raw[raw.composer.isin(raw['composer'].value_counts(sort=True).index.tolist()[:num_composers])]
raw = raw[raw.lyricist.isin(raw['lyricist'].value_counts(sort=True).index.tolist()[:num_lyricists])]
raw = raw[raw.genre_id.isin(raw['genre_id'].value_counts(sort=True).index.tolist()[:num_genres])]
raw = raw[raw.language.isin(raw['language'].value_counts(sort=True).index.tolist()[:num_languages])]
```

Below is a look at the artists, composers, lyricists, languages, and genres being preliminarily analyzed

In [210…
```python
raw.artist_name.unique()
```

Out[210…
```
array(['erica', 'Prince', 'Fromm', 'MISIA', 'Vitas', 'millstones', 'Mili',
       'keeno', 'YUI', 'Muna', 'Jain', 'Frost', 'Chumbawamba',
       'GARNiDELiA', 'supercell', 'SCANDAL', 'IA', 'SPYAIR', 'moumoon',
       'UVERworld', 'OOHYO', 'SALTNPAPER', 'EGOIST', 'Owlle', 'mothy',
       'MOT', 'Cranfield', 'wintermute', 'Versailles', 'LiSA', 'Soko',
       'VALSHE', 'LeeSSang', 'otetsu', 'Zeebra', 'GLAY', 'YK', 'Cocco',
       'NORIKIYO', 'Toraboruta', 'Mogwai', 'Royz', 'Yunomi', 'miwa',
       'PENICILLIN', 'Chara', 'Austra', 'Eels', 'DIV', 'Babyface',
       'INORAN', 'Eumlansonyeon', 'SYK', 'NIGHTMARE', 'Miliyah',
       'Lullaby', 'Chiquewa', 'Slowdive', 'Windycat', 'tofubeats',
       'dustbox', 'SALU', 'PolyphonicBranch', 'Hemenway', 'chay',
       'Marmozets', 'Lead', 'KAMIJO', 'DEPAPEPE', 'HIM', 'ryuryu',
       'Mastodon', 'Heavenz', 'Aquibird', 'SOiL', 'Candyman', 'ZORO',
       'Baekja', 'Korn', 'FACT', 'DATEKEN', 'Feldberg', 'Kreativgang',
       'Rio', 'Mucc', 'Djavan', 'Tellement', 'Shura', 'narry', 'Ken',
       'BOKKA', 'nyanyannya', 'Inmay', 'Gotttod', 'PIA', 'DELPHIC',
       'SKALAPPER', 'Sarantos', 'Megapuss'], dtype=object)
```

In [211…
```python
raw.composer.unique()
```

Out[211…
```
array(['nao', 'Prince', 'Fromm', 'Sinkiroh', 'Vitas', 'millstones',
       'Mili', 'keeno', 'YUI', 'MUNA', 'Jain', 'Frost', 'Chumbawamba',
       'toku', 'ryo', 'Scandal', 'Cloa', 'erica', 'UZ', 'YUKA', 'moumoon',
       'UVERworld', 'Oohyo', 'Myk', 'Owlle', 'mothy', 'Mot', 'TAKUYA',
       'Cranfield', 'wintermute', 'Hizaki', 'Kayoko', 'Soko', 'mito',
       'MYK', 'MINATO', 'Gil', 'otetsu', 'ZEEBRA', 'Takuro', 'Mami', 'Yk',
       'cocco', 'ALEX', 'Toraboruta', 'minato', 'Mogwai', 'TAKURO',
       'Royz', 'Yunomi', 'VALSHE', 'Cozzi', 'Miwa', 'PENICILLIN', 'Chara',
       'shuho', 'LiSA', 'kous', 'Austra', 'E', 'Takuya', 'DIV',
       'MASTERWORKS', 'Babyface', 'INORAN', 'Eumlansonyeon', 'Rina',
       'SYK', 'RUKA', 'Miliyah', 'Jiro', 'Traditional', 'Hisashi',
       'HAKUEI', 'Pandacchi', 'Sakoshin', 'Halstead', 'Windycat', 'Cocco',
       'yellowRubato', 'tofubeats', 'dustbox', 'BACHLOGIC',
       'PolyphonicBranch', 'Neru', 'Charm', 'Chay', 'Marmozets', 'AnDisM',
       'KAMIJO', 'Depapepe', 'Valo', 'ryuryu', 'Estra', 'Kamijo',
       'shinkiroh', 'Mastodon', 'YOOKEY', 'MOGWAI', 'Misia', 'Heavenz',
       'Aquibird', 'SOiL', 'Wowaka', 'Garry', 'chay', 'Candyman',
       'Tatsuhi', 'SHIBU', 'Baekja', 'Nhato', 'Korn', 'INOVADER', 'FACT',
       'Rika', 'DATEKEN', 'Teru', 'Feldberg', 'RYOSPEED', 'Kreativgang',
       'LMPSH', 'TERU', 'eAeon', 'Haruna', 'OHLD', 'HISASHI', 'OOHYO',
       'Rio', 'Tomomi', 'YUKIYOSHI', 'Kozhevnikov', 'GISHO', 'CHISA',
       'MASASHI', 'Jin', 'ORYO', 'YUKKE', 'Djavan', 'Taishi', 'HIZAKI',
       'Tellement', 'doriko', 'KNOXX', 'Isaac', 'Shura', 'narry',
       'Chiquewa', 'Ken', 'Bokka', 'NORIKIYO', 'dezzy', 'GODEES',
       'Dmitrii', 'nyanyannya', 'Inmay', 'Issac', 'Tetoteto', 'MAH',
       'Rado', 'chiquewa', 'Miya', 'Gotttod', 'herOism', 'ScareCrow',
       'Pia', 'YK', 'Delphic', 'myremy', 'Tatsuro', 'LEE', 'Kember',
       'HIDE', 'Yuya', 'NAGMATIC', 'nodoka', 'chobi', 'Cypher',
       'toraboruta', 'Versailles', 'SHINCO', 'T', 'ShiRai', 'Yohan',
       'JIGG', 'AnDism', 'satoshi', 'Hajimetal', 'Taizo', 'Sarantos',
       'Atsushi', 'DOITOKI', 'mabanua', 'KOYANMUSIC', 'SATOchi',
       'Megapuss', 'PATRON', 'Akira', 'Kentaro', 'TeddyLoid', 'SimZ',
       'Shinji', 'Joi', 'KEN', 'mooumoon', 'Saltwater', 'shogo',
       'Clankidd', 'RhymeTube', 'uz'], dtype=object)
```

In [212…
```python
raw.lyricist.unique()
```

Out[212…
```
array(['erica', 'Prince', 'Fromm', 'Misia', 'Vitas', 'millstones', 'Mili',
       'keeno', 'YUI', 'MUNA', 'Jain', 'Frost', 'Chumbawamba', 'MARiA',
       'ryo', 'Rina', 'Cloa', 'Momiken', 'YUKA', 'Takuya', 'Oohyo', 'Myk',
       'Owlle', 'mothy', 'Mot', 'TAKUYA', 'Cranfield', 'Scandal',
       'wintermute', 'Hizaki', 'LiSA', 'momocashew', 'Soko', 'mito',
       'MYK', 'VALSHE', 'Garry', 'otetsu', 'ZEEBRA', 'Takuro', 'Yk',
       'cocco', 'NORIKIYO', 'Toraboruta', 'Mogwai', 'TAKURO', 'Royz',
       'Yunomi', 'Miwa', 'Tomomi', 'HAKUEI', 'Chara', 'kous', 'Austra',
       'E', 'DIV', 'Babyface', 'INORAN', 'Kamijo', 'Eumlansonyeon', 'SYK',
       'RUKA', 'Hisashi', 'Miliyah', 'Traditional', 'Hinata', 'Aimi',
       'Chiquewa', 'Halstead', 'Windycat', 'Tablo', 'Cocco', 'chelly',
       'Mami', 'tofubeats', 'dustbox', 'SALU', 'PolyphonicBranch', 'Neru',
       'Charm', 'CHISA', 'Chay', 'Marmozets', 'AnDisM', 'KAMIJO',
       'Depapepe', 'Valo', 'ryuryu', 'Mastodon', 'MOGWAI', 'Heavenz',
       'Aquibird', 'SOiL', 'Wowaka', 'chay', 'Candyman', 'Ryuji', 'SHIBU',
       'Baekja', 'Nhato', 'Korn', 'toku', 'FACT', 'Rika', 'DATEKEN',
       'Feldberg', 'RYOSPEED', 'Kreativgang', 'LMPSH', 'JIRO', 'TERU',
       'eAeon', 'Haruna', 'HISASHI', 'OOHYO', 'Rio', 'minato', 'ORYO',
       'Tatsuro', 'Djavan', 'shogo', 'Taishi', 'ViCTiM', 'Tellement',
       'RUCCA', 'Isaac', 'MINATO', 'Shura', 'narry', 'chobi', 'Ken',
       'Bokka', 'dezzy', 'GODEES', 'nyanyannya', 'Inmay', 'Issac',
       'chiquewa', 'Gotttod', 'herOism', 'Pia', 'YK', 'Delphic', 'myremy',
       'Miya', 'LEE', 'Kember', 'Teru', 'HIDE', 'nodoka', 'Kyo',
       'toraboruta', 'ShiRai', 'flansowa', 'Yohan', 'AnDism', 'Hajimetal',
       'Sarantos', 'Megapuss', 'Pandacchi', 'Kentaro', 'TeddyLoid',
       'satoshi', 'Mao', 'KEN', 'uz'], dtype=object)
```

In [213…
```python
raw.genre_id.unique()
```

Out[213…
```
array(['437', '139', '465', '822', '1609', '359', '1259', '2022', '444',
       '352', '726', '1969', '242', '786', '1955', '921', '2072', '1616',
       '947', '2122', '691'], dtype=object)
```

In [214…
```python
raw.language.unique()
```

Out[214…
```
array([17., 52., 31.])
```

Scaling the song_length to the range [0, 1]. This is done because without this, the FAMD only discriminates based off of song lenth and tends to ignore the other factors in the analysis

In [215…
```python
from sklearn.preprocessing import MinMaxScaler
```

In [216…
```python
scaler = MinMaxScaler()
raw["song_length"] = scaler.fit_transform(raw["song_length"].values.reshape(-1, 1))
raw
```

Out[216…

	artist_name	composer	lyricist	genre_id	language	song_length	song_id
655	erica	nao	erica	437	17.0	0.213634	vK4072/9MUPsaoKaf8/9LmtNuVWz8i8D0sQmEAKO3W4=
1118	Prince	Prince	Prince	139	52.0	0.158879	cvRpobXTkdQa7Yxf2lAvYTrLj9RPck5FiHg0KOZSIw0=
1125	Fromm	Fromm	Fromm	465	31.0	0.182421	rh35a46NXpktCl3sm7Q/PNPecP1dNs1QEmhWQmLeWPg=
1742	MISIA	Sinkiroh	Misia	822	17.0	0.245873	FPIqsWBqpxx97+CSgXSCOaKkk1L2KgQ6eKKYhrgUg+o=
1852	Vitas	Vitas	Vitas	465	52.0	0.196119	AP3gCgZk4shAxlg4gYIT1mxwo+dqpDroopnT8CJKyLA=
...	...	...	...	...	...	...	...
2288152	otetsu	otetsu	otetsu	2022	17.0	0.219651	oR8alrUMYXBQc369cafFgK00gvdJzhiUho5+hIQGcqg=
2289954	PIA	Pia	Pia	2022	31.0	0.185472	8R2oKRnJFSfDn4QPJ2jPXYbkLRG19rCupuNU8m9SIO4=
2290742	Mogwai	Mogwai	Mogwai	2022	52.0	0.243366	E4F826L/3vBfaeY0s7KxW4f7Aj72vm6xKo6n2M8aIAM=
2293848	Djavan	Djavan	Djavan	465	52.0	0.134168	5nsiCaZnjJVlas/okuUm93rnD4ZViVTNCIQm2apBdAU=
2294539	Hemenway	Charm	Charm	2022	17.0	0.188683	nIifWfBBZVfklOKoH+78BgPRWEEtpkYTT71eWthlD/s=

2816 rows × 7 columns

Performing the FAMD

- FAMD (Factor Analysis of Mixed Data) is a technique to analyse a set of categorical and continuous data
- An MCA (Multiple Correspondence Analysis) is performed on all categorical variables
- A PCA (Principal Component Analysis) is performed on all continuous variables
- A PCA is performed on the outputs of the previous MCA and PCA, and the results of this are returned
- We pruned the dataset so heavily becuase MCA requires us to one-hot-encode our categorical variables. Becuase we are dealing with hundreds of classes and thousands of samples, the memory overhead is tremendous. The memory overhead of the entire dataset is 1.4TB!

In [217…
```python
from prince.famd import FAMD
famd = FAMD(
    n_components=3,
    n_iter=5,
    copy=True,
    check_input=True,
    engine='auto',
    random_state=42
)
famd = famd.fit(raw.drop(['song_id'], axis='columns'))
```

In [218…
```python
famd.row_coordinates(raw)
```

Out[218…

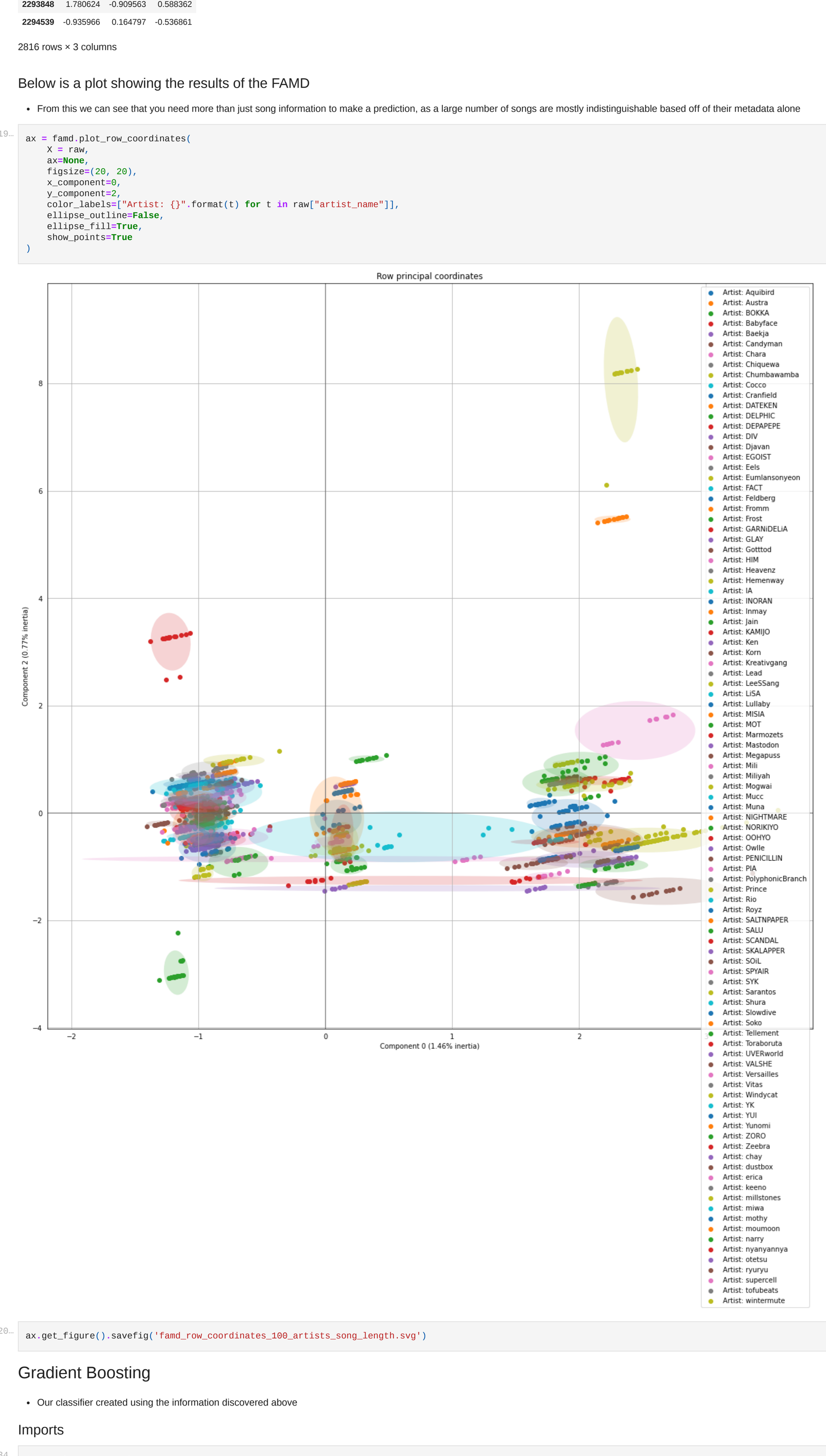
	0	1	2
655	-1.078767	0.795495	0.208250
1118	2.191764	-0.435968	0.502185
1125	0.188833	-0.748536	0.565635
1742	-0.989763	1.241269	-0.434505
1852	1.861413	-0.472608	0.570857
...	...	...	...
2288152	-0.916648	0.165201	-0.629373
2289954	0.083141	-0.373721	-0.539500
2290742	2.147080	1.246312	-0.501505
2293848	1.780624	-0.909563	0.588362
2294539	-0.935966	0.164797	-0.536861

2816 rows × 3 columns

Below is a plot showing the results of the FAMD

- From this we can see that you need more than just song information to make a prediction, as a large number of songs are mostly indistinguishable based off of their metadata alone

In [219…
```python
ax = famd.plot_row_coordinates(
    X = raw,
    ax=None,
    figsize=(20, 20),
    x_component=0,
    y_component=2,
    color_labels=["Artist: {}".format(t) for t in raw["artist_name"]],
    ellipse_outline=False,
    ellipse_fill=True,
    show_points=True
)
```



In [220…
```python
ax.get_figure().savefig('famd_row_coordinates_100_artists_song_length.svg')
```

Gradient Boosting

- Our classifier created using the information discovered above

Imports

In [234…
```python
import lightgbm as lgb
import gc
```

Read in the data

In [275…
```python
sei = pd.read_csv('../data/song_extra_info.csv')
members = pd.read_csv('../data/members.csv', parse_dates=['registration_init_time','expiration_date'])
songs = pd.read_csv('../data/songs.csv')
train = pd.read_csv('../data/train.csv')
test = pd.read_csv('../data/test.csv')
```

In [257…
```python
members['expiration_year'] = members['expiration_date'].dt.year
members.drop(columns = ['registration_init_time' , 'expiration_date'] , inplace = True)
members['membership_days'] = members['expiration_date'].subtract(members['registration_init_time']).dt.days.astype(int)
members['registration_year'] = members['registration_init_time'].dt.year
members.head()
```

Out[257…

	msno	city	bd	gender	registered_via	membership_days	registration_year	expiration_year
0	XQxgAYj3klVKjR3oxPPXYYFp4soD4TuBghkhMTD4oTw=	1	0	NaN	7	2223	2011	2017
1	UizsfmJb9mV54qE9hCYyU07Va97c0lCRLEQX3ae+ztM=	1	0	NaN	7	725	2015	2017
2	D8nEhsIOBSoE6VthTaqDX8U6lqjJ7dLdr72mOyLya2A=	1	0	NaN	4	457	2016	2017
3	mCuD+tZ1hERA/o5GPqk38e041J8ZsBaLcu7nGoIIvhI=	1	0	NaN	9	1	2015	2015
4	q4HRBfVSssAFS9iRfxWrohxuk9kCYMKjHOEagUMV6rQ=	1	0	NaN	4	138	2017	2017

Create a valid training and test set from combining the avalilable dataframes

In [258…
```python
train = train.merge(songs , on='song_id' , how='left')
train = train.merge(members , on = 'msno' , how='left')
train = train.merge(sei , on = 'song_id' , how='left')
test  = test.merge(songs , on='song_id' , how='left')
test = test.merge(members , on = 'msno' , how = 'left')
test =  test.merge(sei , on = 'song_id' , how = 'left')
```

Out[258…
```
3116
```

In [259…
```python
test['song_length'].fillna(test['song_length'].mean() , inplace = True)
test['song_length'] = test['song_length'].astype(np.uint32)
test['language'].fillna(test['language'].mode().values[0] , inplace= True)
test['language'] = test['language'].astype(np.int8)

train['song_length'].fillna(train['song_length'].mean() , inplace = True)
train['song_length'] = train['song_length'].astype(np.uint32)
train['language'].fillna(train['language'].mode().values[0] , inplace= True)
train['language'] = train['language'].astype(np.int8)

print(train.columns)
train.head()
```

```
False    0.999985
True     0.000015
Name: song_length, dtype: float64
False    0.99998
True     0.00002
Name: language, dtype: float64
Index(['msno', 'song_id', 'source_system_tab', 'source_screen_name',
       'source_type', 'target', 'song_length', 'genre_ids', 'artist_name',
       'composer', 'lyricist', 'language', 'city', 'bd', 'gender',
       'registered_via', 'membership_days', 'registration_year',
       'expiration_year', 'name', 'isrc', 'year'],
      dtype='object')
```

Out[259…

	msno	song_id	source_system_tab	source_screen_name	source_type	target	song_length	genre_ids	artist_name	composer	...	city	bd	gender	registered_via	membership_days	registration_year	expiration_year	name	isrc	year
0	FGtllVqz18RPiwJj/edr2gV78zirAiY/9SmYvia+kCg=	BBzumQNXUHKdEBOB7mAJuzok+IJA1c2Ryg/yzTF6tik=	explore	Explore	online-playlist	1	206471	359	Bastille	Dan Smith| Mark Crew	...	1	0	NaN	7	2103	2012	2017	Good Grief	GBUM71602854	2016.0
1	Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=	bhp/MpSNoqoxOIB+/l8WPqu6jldth4DIpCm3ayXnJqM=	my library	Local playlist more	local-playlist	1	284584	1259	Various Artists	NaN	...	13	24	female	9	2301	2011	2017	Lords of Cardboard	US3C69910183	1999.0
2	Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=	JNWfrrC7zNN7BdMpsISKa4Mw+xVJYNnxXh3/Epw7QgY=	my library	Local playlist more	local-playlist	1	225396	1259	Nas	N. Jones、W. Adams、J. Lordan、D. Ingle	...	13	24	female	9	2301	2011	2017	Hip Hop Is Dead(Album Version (Edited))	USUM70618761	2006.0
3	Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=	2A87tzfnJTSWqD7gIZHisolhe4DMdzkbd6LzO1KHjNs=	my library	Local playlist more	local-playlist	1	255512	1019	Soundway	Kwadwo Donkoh	...	13	24	female	9	2301	2011	2017	Disco Africa	GBUQH1000063	2010.0
4	FGtllVqz18RPiwJj/edr2gV78zirAiY/9SmYvia+kCg=	3qm6XTZ6MOCU11x8FIVbAGH5l5uMkT3/ZalWG1oo2Gc=	explore	Explore	online-playlist	1	187802	1011	Brett Young	Brett Young| Kelly Archer| Justin Ebach	...	1	0	NaN	7	2103	2012	2017	Sleep Without You	QM3E21606003	2016.0

5 rows × 22 columns

In [260…
```python
train['genre_ids'].fillna('no_genre_id' , inplace= True)
train['genre_ids_count'] = train['genre_ids'].apply(lambda x: genre_count(x)).astype(np.int8)
test['genre_ids'].fillna('no_genre_id' , inplace= True)
test['genre_ids_count'] = test['genre_ids'].apply(lambda x: genre_count(x)).astype(np.int8)
```

```
False    0.983944
True     0.016056
Name: genre_ids, dtype: float64
```

In [261…
```python
def artist_count(art) -> int:
    """
    get number of artists
    """
    return 0 if art == 'no_artist_name' else art.count('|')+art.count('/') + art.count('//') + art.count(';') + 1

train['artist_name'].isnull().value_counts()
train['artist_name'].fillna('no_artist_name' , inplace = True)
train['artist_count'] = train['artist_name'].apply(lambda x : artist_count(x)).astype(np.int8)
test['artist_name'].fillna('no_artist_name' , inplace = True)
test['artist_count'] = test['artist_name'].apply(lambda x : artist_count(x)).astype(np.int8)
```

In [277…
```python
train_col = list(train.columns)
test_col = list(test.columns)

label_encoded = ['source_system_tab', 'source_screen_name',
       'source_type','gender']
drop = ['msno', 'song_id' , 'isrc','artist_name',
       'composer', 'lyricist','name','genre_ids']
min_max_scaling = ['number_of_time_played', 'user_activity_msno','membership_days', 'song_length']

for feature in label_encoded:
    le = LabelEncoder()
    le.fit(train[feature].values + test[feature].values)
    train[f] = le.transform(list(train[feature].values))
    test[f] = le.transform(list(test[feature].values))

for feature in min_max_scaling:
    ms = MinMaxScaler()
    train[f] = ms.fit_transform(train[[feature]])
    test[f] = ms.transform(test[[feature]])
```

In [266…
```python
for col in train.columns:
    if train[col].dtype == object:
        train[col] = train[col].astype('category')
        test[col] = test[col].astype('category')
```

In [267…
```python
print(train.columns)
train.head(10)
```

```
Index(['msno', 'song_id', 'source_system_tab', 'source_screen_name',
       'source_type', 'target', 'song_length', 'genre_ids', 'artist_name',
       'composer', 'lyricist', 'language', 'city', 'bd', 'gender',
       'registered_via', 'membership_days', 'registration_year',
       'expiration_year', 'name', 'isrc', 'year', 'genre_ids_count',
       'artist_count', 'composer_count', 'lyricist_count',
       'number_of_time_played', 'user_activity_msno'],
      dtype='object')
```

Out[267…

	msno	song_id	source_system_tab	source_screen_name	source_type	target	song_length	genre_ids	artist_name	composer	...	expiration_year	name	isrc	year	genre_ids_count	artist_count	composer_count	lyricist_count	number_of_time_played	user_activity_msno
0	FGtllVqz18RPiwJj/edr2gV78zirAiY/9SmYvia+kCg=	BBzumQNXUHKdEBOB7mAJuzok+IJA1c2Ryg/yzTF6tik=	1	7	7	1	0.018901	359	Bastille	Dan Smith| Mark Crew	...	2017	Good Grief	GBUM71602854	2016.0	1	1	2	0	0.015316	0.896237
1	Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=	bhp/MpSNoqoxOIB+/l8WPqu6jldth4DIpCm3ayXnJqM=	3	8	4	1	0.026100	1259	Various Artists	no_composer	...	2017	Lords of Cardboard	US3C69910183	1999.0	1	1	0	0	0.000000	0.092360
2	Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=	JNWfrrC7zNN7BdMpsISKa4Mw+xVJYNnxXh3/Epw7QgY=	3	8	4	1	0.020645	1259	Nas	N. Jones、W. Adams、J. Lordan、D. Ingle	...	2017	Hip Hop Is Dead(Album Version (Edited))	USUM70618761	2006.0	1	1	1	0	0.000215	0.092360
3	Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=	2A87tzfnJTSWqD7gIZHisolhe4DMdzkbd6LzO1KHjNs=	3	8	4	1	0.023420	1019	Soundway	Kwadwo Donkoh	...	2017	Disco Africa	GBUQH1000063	2010.0	1	1	1	0	0.000000	0.092360
4	FGtllVqz18RPiwJj/edr2gV78zirAiY/9SmYvia+kCg=	3qm6XTZ6MOCU11x8FIVbAGH5l5uMkT3/ZalWG1oo2Gc=	1	7	7	1	0.017180	1011	Brett Young	Brett Young| Kelly Archer| Justin Ebach	...	2017	Sleep Without You	QM3E21606003	2016.0	1	1	3	0	0.029416	0.896237
5	FGtllVqz18RPiwJj/edr2gV78zirAiY/9SmYvia+kCg=	3Hg5kugV1S0wzEVLAEfqjIV5UHzb7bCrdBRQlGygLvU=	1	7	7	1	0.022710	1259	Desiigner	Sidney Selby| Adnan Khan	...	2017	Panda	USUM71601094	2016.0	1	1	2	0	0.079230	0.896237
6	Xumu+NIjS6QYVxDS4/t3SawvJ7viT9hPKXmf0RtLNx8=	VkILU0H1h3NMmk9MQrXouNudGk5n8Ls5cqRRuBxeTh4=	3	8	4	1	0.021068	465	BIGBANG TAEYANG	TEDDY| DEE.P| Rebecca Johnson	...	2017	眼| 鼻| 口 (Eyes| Nose| Lips)	TWA531400512	2014.0	1	1	3	2	0.276839	0.092360
7	FGtllVqz18RPiwJj/edr2gV78zirAiY/9SmYvia+kCg=	bPIvRTzfHxH5LgHrStll+tYwSQNVV8PySgA3M1PfTgc=	1	7	7	1	0.016564	1011	Thomas Rhett	Thomas Rhett| Rhett Akins| Ben Hayslip	...	2017	Star Of The Show	USLXJ1607334	2016.0	1	1	3	0	0.020470	0.896237
8	uHqAtShXTRXju5GE8ri3ITsVFepPf8jUoCF7ffNOuqE=	/bU6IRSK+YNlNbaTkxo7bhsb2EDLPrnksdX3ggcZNhI=	3	8	3	1	0.025582	2022	OneRepublic	Ryan Tedder	...	2018	Dreaming Out Loud	USUM70759544	2007.0	1	1	1	0	0.002147	0.106423
9	uHqAtShXTRXju5GE8ri3ITsVFepPf8jUoCF7ffNOuqE=	EbI7xoNxI+3QSsiHxL13zBdgHIJOwa3srHd7cDcnJ0g=	3	8	3	1	0.023592	465	OneRepublic	Ryan Tedder	...	2018	Counting Stars	USUM71301306	2013.0	1	1	1	0	0.052748	0.106423

10 rows × 28 columns

Below, the train an test set are fully defined

In [271…
```python
X_train = train.drop(columns = ['target'] , axis = 1)
Y_train = train['target'].values
X_test = test.drop(columns = ['id'] , axis = 1)

ids = test['id'].values
train_set = lgb.Dataset(X_train , Y_train)
```

Train the Gradient Boosting Algorithm for the final classification

In [272…
```python
model = lgb.train({
    'objective': 'binary',
    'metric': 'binary_logloss',
    'boosting': 'gbdt',
    'learning_rate': 0.3 ,
    'verbose': 0,
    'num_leaves': 108,
    'bagging_fraction': 0.95,
    'bagging_freq': 1,
    'bagging_seed': 1,
    'feature_fraction': 0.9,
    'feature_fraction_seed': 1,
    'max_bin': 256,
    'max_depth': 10,
    'num_rounds': 200,
    'metric' : 'auc'
}, train_set=train_set,  valid_sets=train_set, verbose_eval=5)
```

```
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead of testing was 0.856083 seconds.
You can set `force_col_wise=true` to remove the overhead.
[5]	training's auc: 0.736167
[10]	training's auc: 0.748005
[15]	training's auc: 0.754421
[20]	training's auc: 0.759233
[25]	training's auc: 0.762544
[30]	training's auc: 0.765713
[35]	training's auc: 0.768136
[40]	training's auc: 0.771355
[45]	training's auc: 0.773379
[50]	training's auc: 0.775447
[55]	training's auc: 0.777483
[60]	training's auc: 0.779126
[65]	training's auc: 0.780748
[70]	training's auc: 0.782426
[75]	training's auc: 0.784057
[80]	training's auc: 0.785748
[85]	training's auc: 0.787138
[90]	training's auc: 0.78843
[95]	training's auc: 0.789651
[100]	training's auc: 0.790847
[105]	training's auc: 0.791955
[110]	training's auc: 0.792972
[115]	training's auc: 0.793971
[120]	training's auc: 0.794948
[125]	training's auc: 0.795891
[130]	training's auc: 0.798364
[135]	training's auc: 0.799259
[140]	training's auc: 0.799988
[145]	training's auc: 0.800807
[150]	training's auc: 0.801528
[155]	training's auc: 0.802236
[160]	training's auc: 0.803045
[165]	training's auc: 0.803731
[170]	training's auc: 0.804531
[175]	training's auc: 0.805011
[180]	training's auc: 0.805644
[185]	training's auc: 0.806235
[190]	training's auc: 0.807032
[195]	training's auc: 0.807964
[200]	training's auc: 0.808508
CPU times: user 21min 9s, sys: 19.7 s, total: 21min 29s
Wall time: 3min 13s
```

A set of example predictions. This returns the probability that a user would enjoy a given song

In [276…
```python
predictions = model.predict(X_test)
print(predictions)
print('Saving Predictions')
submission = pd.DataFrame({
    'id': ids,
    'target': pred_test
})
submission['target'] = pred_test
submission.to_csv('submission.csv' , index = False , float_format ='%.5f' )
submission.head()
```

```
[0.38419875 0.31085878 0.19812878 ... 0.42768898 0.38944534 0.39090245]
Saving Predictions
```

Out[276…

	id	target
0	0	0.384199
1	1	0.310859
2	2	0.198129
3	3	0.119010
4	4	0.097116