WORKBOOK_WMCS_01

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GROUP COURSEWORK <p

MSIN0097 Predictive Analytics

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1 WORKBOOK INITIALIZATION

1.1 1. Load required libraries

Load initially required libraries which will cover most used functions.

[1]:
```
!pip install keras
```

```
Collecting keras
  Using cached Keras-2.3.1-py2.py3-none-any.whl (377 kB)
Requirement already satisfied: pyyaml in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from keras) (5.3.1)
Requirement already satisfied: keras-applications>=1.0.6 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from keras) (1.0.8)
Requirement already satisfied: keras-preprocessing>=1.0.5 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from keras) (1.1.0)
Requirement already satisfied: h5py in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from keras) (2.10.0)
Requirement already satisfied: numpy>=1.9.1 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from keras) (1.18.1)
Requirement already satisfied: scipy>=0.14 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from keras) (1.4.1)
Requirement already satisfied: six>=1.9.0 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from keras) (1.14.0)
Installing collected packages: keras
Successfully installed keras-2.3.1
```

[2]:
```
!pip install spotipy --upgrade
```

```
Collecting spotipy
  Using cached spotipy-2.11.1-py3-none-any.whl (18 kB)
Requirement already satisfied, skipping upgrade: requests>=2.20.0 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from spotipy) (2.23.0)
Requirement already satisfied, skipping upgrade: six>=1.10.0 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from spotipy) (1.14.0)
Requirement already satisfied, skipping upgrade:
urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
requests>=2.20.0->spotipy) (1.25.8)
Requirement already satisfied, skipping upgrade: chardet<4,>=3.0.2 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
requests>=2.20.0->spotipy) (3.0.4)
Requirement already satisfied, skipping upgrade: idna<3,>=2.5 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
requests>=2.20.0->spotipy) (2.9)
Requirement already satisfied, skipping upgrade: certifi>=2017.4.17 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
requests>=2.20.0->spotipy) (2019.11.28)
Installing collected packages: spotipy
Successfully installed spotipy-2.11.1
```

[3]:
```
import pandas as pd
import random

import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import sherlockml.filesystem as sfs
import random
from sklearn.model_selection import train_test_split
from IPython.display import display, Image

import keras
from keras.models import Sequential
from keras.layers import Dense
from IPython.display import display, Image

from matplotlib.ticker import (MultipleLocator, FormatStrFormatter,
                               AutoMinorLocator)

#deactivate warnings
#import warnings
#warnings.filterwarnings("ignore")
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/sherlockml/filesystem.py:21: UserWarning: sherlockml.filesystem has
been renamed sherlockml.datasets - please update your code to use the new import
location
  warnings.warn(_WARNING_MESSAGE)
Using TensorFlow backend.
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorflow/python/framework/dtypes.py:516: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorflow/python/framework/dtypes.py:517: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorflow/python/framework/dtypes.py:518: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorflow/python/framework/dtypes.py:519: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorflow/python/framework/dtypes.py:520: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorflow/python/framework/dtypes.py:525: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:541: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:542: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:543: FutureWarning:
```

```
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:544: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:545: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:550: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

[4]:
```
#Import custom functions from library, named 'spotfunc'
#import spotfunc as spotfunc_v2
```

[5]:
```
flatui = ['#1CE48C', "#213E68"]
flatui2 = ['#1CE48C', '#21556D','#21947B',"#213E68"]
#sns.palplot(sns.color_palette(flatui))
```

1.2 2. Read in Spotify dataset

Dataset containing >3mio streams on Spotify platform w/ a manifold of features for each individual stream.

[6]:
```
%%time
# Read in sampled data
data = pd.read_csv('DATA/cleaned_data.csv')
print('rows:',len(data))

# Keep a copy of original data in case of changes made to dataframe
df_music = data.copy()
```

```
<string>:2: DtypeWarning: Columns (2,13) have mixed types.Specify dtype option
on import or set low_memory=False.
```

```
rows: 3805499
CPU times: user 20 s, sys: 2.57 s, total: 22.5 s
Wall time: 22.5 s
```

1.3 3. Additional Datasource from Spotify API

Additional features for each stream (incl. audio features and genres) accessed via Spotify Developer API. Data was pre processed in seperate workbook (SECOND DATASOURCE_WMCS.ipynb) and is imported as csv-file here.

[7]:
```
import spotipy
from spotipy.oauth2 import SpotifyClientCredentials
```

[8]:
```
# Code that connects to the Spotify API, to be used to get the genre␣
↪information for artists.
# Credentials that provide access to the Spotify API
client_id='b360f940d7b649f79b9b790e2ff2c964'
client_secret='c734f14083044192a1bb7c0210f1a6a3'
client_credentials_manager = SpotifyClientCredentials(client_id=client_id,␣
↪client_secret=client_secret)

# Create Spotify object to access API
sp = spotipy.Spotify(client_credentials_manager=client_credentials_manager)
```

[9]:
```
%%time
# Read in sampled data
api_data = pd.read_csv('DATA/spotify_api_audio_features.csv')
print('rows:',len(api_data))

# Keep a copy of original data in case of changes made to dataframe
df_music_add = api_data.copy()
```

```
rows: 3556
CPU times: user 4 ms, sys: 0 ns, total: 4 ms
Wall time: 10.4 ms
```

1.4 3. Combine Datasources

Add new features from spotify API to original dataset.

[10]:
```
#add new features to main dataset: combine two main dataframes
df_music = pd.merge(df_music, df_music_add, on=['track_name'],how='outer')
```

1.5 —-

2 DATA EXPLORATION

2.1 1. Understanding the data

Each row in the data is a unique stream – every time a user streams a song in the Warner Music catalogue for at least 30 seconds it becomes a row in the database. Each stream counts as a 'transaction', the value of which is £0.0012, and accordingly, 1000 streams of a song count as a 'sale' (worth £1) for the artist. The dataset is comprised of listeners in Great Britain only.

Not all the columns provided are relevant to us. Lets take a look at some basic properties of the dataset, and identify the columns that are important for this study

A year's worth of Spotify streaming data in the WMG database amounts to approximately 50 billion rows of data i.e. 50 billion streams (1.5 to 2 terabytes worth), with a total of seven years of data stored altogether (2010 till today). For the purposes of this case study, we will be using a sample of this data. The dataset uploaded on the Faculty server is about 16GB, containing data from 2015 - 2017. Given the limits on RAM and cores, we will be taking a further sample of this data for purposes of this case study: a 10% random sample of the total dataset, saved as 'cleaned_data.csv'.

[11]:
```
#show all columns of dataframe (/dataset)
df_music.columns
```

[11]:
```
Index(['Unnamed: 0', 'Unnamed: 0.1', 'Unnamed: 0.1.1', 'day', 'log_time',
       'mobile', 'track_id', 'isrc', 'upc', 'artist_name', 'track_name',
       'album_name', 'customer_id', 'postal_code', 'access', 'country_code',
       'gender', 'birth_year', 'filename', 'region_code', 'referral_code',
       'partner_name', 'financial_product', 'user_product_type',
       'offline_timestamp', 'stream_length', 'stream_cached', 'stream_source',
       'stream_source_uri', 'stream_device', 'stream_os', 'track_uri',
       'track_artists', 'source', 'DateTime', 'hour', 'minute', 'week',
       'month', 'year', 'date', 'weekday', 'weekday_name', 'playlist_id',
       'playlist_name', 'danceability', 'acousticness', 'valence'],
      dtype='object')
```

The columns we will *focus* on for this case study are:

- Log Time – timestamp of each stream
- Artist Name(s) – some songs feature more than one artist
- Track Name
- ISRC - (Unique code identifier for that version of the song, i.e. radio edit, album version, remix etc.)
- Customer ID
- Birth Year
- Location of Customer
- Gender of Customer

- Stream Source URI – where on Spotify was the song played – unique playlist ID, an artist's page, an album etc.

2.2 2. Data Features

2.2.1 Descriptive Statistics .... hier noch eine bessere beschreibung finden

First, we take a look at the inculded variables in the dataset in order to get a general understanding of the data. We start by listing all included variables using. This reveals that 'cleaned_data.csv' contains 45 variables, which spread across numeric and non-numeric variables.

[12]:
```
df_music.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3805499 entries, 0 to 3805498
Data columns (total 48 columns):
 #   Column             Dtype
---  ------             -----
 0   Unnamed: 0         int64
 1   Unnamed: 0.1       int64
 2   Unnamed: 0.1.1     object
 3   day                int64
 4   log_time           object
 5   mobile             bool
 6   track_id           object
 7   isrc               object
 8   upc                float64
 9   artist_name        object
 10  track_name         object
 11  album_name         object
 12  customer_id        object
 13  postal_code        object
 14  access             object
 15  country_code       object
 16  gender             object
 17  birth_year         float64
 18  filename           object
 19  region_code        object
 20  referral_code      float64
 21  partner_name       object
 22  financial_product  object
 23  user_product_type  object
 24  offline_timestamp  float64
 25  stream_length      float64
 26  stream_cached      float64
 27  stream_source      object
 28  stream_source_uri  object
```

```
 29  stream_device       object
 30  stream_os           object
 31  track_uri           object
 32  track_artists       object
 33  source              float64
 34  DateTime            object
 35  hour                int64
 36  minute              int64
 37  week                int64
 38  month               int64
 39  year                int64
 40  date                object
 41  weekday             int64
 42  weekday_name        object
 43  playlist_id         object
 44  playlist_name       object
 45  danceability        float64
 46  acousticness        float64
 47  valence             float64
dtypes: bool(1), float64(10), int64(9), object(28)
memory usage: 1.4+ GB
```

While count, mean, min and max are mostly self-explanatory. The '.describe()'-function also inculdes standard deviation and different quantiles. As one can see these values only show up for numeric attributes (e.g., stream_length) not for non-numeric. Further, some interpretations are logically flawed (e.g., day). Therefore, '.describe()' allows us to assess the individual numeric values, however, is overall limited in its meaningfulness.

[13]:
```
df_music.describe()
```

[13]:
```
        Unnamed: 0  Unnamed: 0.1        day           upc    birth_year  \
count  3.805499e+06  3.805499e+06  3805499.0  3.805499e+06  3.795478e+06
mean   1.902749e+06  1.902750e+07       10.0  2.389062e+11  1.990107e+03
std    1.098553e+06  1.098553e+07        0.0  2.757391e+11  1.068282e+01
min    0.000000e+00  9.000000e+00       10.0  1.686134e+10  1.867000e+03
25%    9.513745e+05  9.513754e+06       10.0  7.567991e+10  1.987000e+03
50%    1.902749e+06  1.902750e+07       10.0  1.902958e+11  1.993000e+03
75%    2.854124e+06  2.854124e+07       10.0  1.902960e+11  1.997000e+03
max    3.805498e+06  3.805499e+07       10.0  5.414940e+12  2.017000e+03

       referral_code  offline_timestamp  stream_length  stream_cached  source  \
count            0.0                0.0   3.805499e+06            0.0     0.0
mean             NaN                NaN   1.891587e+02            NaN     NaN
std              NaN                NaN   6.105546e+01            NaN     NaN
min              NaN                NaN   3.000000e+01            NaN     NaN
25%              NaN                NaN   1.720000e+02            NaN     NaN
50%              NaN                NaN   2.000000e+02            NaN     NaN
75%              NaN                NaN   2.240000e+02            NaN     NaN
```

```
max                NaN                 NaN   9.000000e+02            NaN      NaN

                hour        minute          week         month          year  \
count   3.805499e+06  3.805499e+06  3.805499e+06  3.805499e+06  3.805499e+06
mean    1.373665e+01  2.254671e+01  2.316008e+01  5.970407e+00  2.016437e+03
std     5.400456e+00  1.675157e+01  1.320996e+01  3.036840e+00  5.964080e-01
min     0.000000e+00  0.000000e+00  1.000000e+00  1.000000e+00  2.014000e+03
25%     1.000000e+01  1.500000e+01  1.400000e+01  4.000000e+00  2.016000e+03
50%     1.400000e+01  3.000000e+01  2.300000e+01  6.000000e+00  2.016000e+03
75%     1.800000e+01  4.500000e+01  3.200000e+01  8.000000e+00  2.017000e+03
max     2.300000e+01  4.500000e+01  5.000000e+01  1.200000e+01  2.017000e+03

             weekday  danceability  acousticness       valence
count   3.805499e+06  3.083495e+06  3.083495e+06  3.083495e+06
mean    2.837800e+00  6.052237e-01  2.375802e-01  4.428670e-01
std     2.001057e+00  1.449020e-01  2.971150e-01  2.369624e-01
min     0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%     1.000000e+00  4.970000e-01  1.210000e-02  2.570000e-01
50%     3.000000e+00  6.200000e-01  8.120000e-02  4.400000e-01
75%     5.000000e+00  7.180000e-01  4.760000e-01  5.990000e-01
max     6.000000e+00  9.600000e-01  9.960000e-01  9.830000e-01
```

Let's continue by taking an extract out of the actual dataset leveraging '.head()'. This allows us to take a first loo into the different data formats and information contained in the data cells. Each row represents one unique stream. As we will see in the next step there are a total of 3.805.499 streams included in the given dataset.

[14]:
```
df_music.head(3)
```

[14]:
```
   Unnamed: 0  Unnamed: 0.1                  Unnamed: 0.1.1  day  \
0           0             9   ('small_artists_2016.csv', 9)   10
1           1            19  ('small_artists_2016.csv', 19)   10
2           2            29  ('small_artists_2016.csv', 29)   10

          log_time  mobile                          track_id         isrc  \
0  20160510T12:15:00    True  8f1924eab3804f308427c31d925c1b3f  USAT21600547
1  20160510T12:15:00    True  8f1924eab3804f308427c31d925c1b3f  USAT21600547
2  20160510T14:00:00    True  8f1924eab3804f308427c31d925c1b3f  USAT21600547

           upc       artist_name  … month  year        date weekday  \
0  7.567991e+10  Sturgill Simpson  …     5  2016  2016-05-10       1
1  7.567991e+10  Sturgill Simpson  …     5  2016  2016-05-10       1
2  7.567991e+10  Sturgill Simpson  …     5  2016  2016-05-10       1

  weekday_name playlist_id playlist_name  danceability acousticness valence
0      Tuesday         NaN           NaN         0.333      0.00198   0.607
1      Tuesday         NaN           NaN         0.333      0.00198   0.607
```

```
2       Tuesday          NaN              NaN           0.333       0.00198    0.607

[3 rows x 48 columns]
```

2.3 3. EXPLORATORY ANALYSIS

We continue to analyize patterns, that highlight on any potential uncertainties or peculiarities using figures, plots and visualization as necessar. Our approach is to look at one attribute at a time. Be aware there is a lot to learn.

2.3.1 Histograms

The Histograms provide a great deal of information. We will continue by discussing a some key insights from these.

[15]:
```
#histogram for all non-objects
df_histo = df_music

#dropped all non-numeric / logically flawed variables
df_histo = df_histo.drop(['Unnamed: 0','Unnamed: 0.1','Unnamed: 0.1.
↪1','log_time','mobile','track_id','isrc',
                           ␣
↪'track_name','album_name','customer_id','postal_code','access','country_code',
                           ␣
↪'gender','birth_year','filename','region_code','referral_code','partner_name',
                           ␣
↪'financial_product','user_product_type','stream_source','stream_source_uri',
                           ␣
↪'stream_device','stream_os','track_uri','track_artists','DateTime','date',
                           ␣
↪'weekday_name','playlist_id','playlist_name','offline_timestamp','source',
                            'stream_cached','upc','artist_name'], axis=1)

df_histo = df_histo.hist(figsize=(20, 25), bins=24, xlabelsize=9, ylabelsize=9,␣
↪color = '#1CE48C',
                           grid=False , edgecolor='grey', linewidth=1.2),plt.
↪tight_layout(rect=(0, 1, 1, 0))
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:14:
UserWarning: Tight layout not applied. The bottom and top margins cannot be made
large enough to accommodate all axes decorations.
```

Description - to be changed at given time: - Day: It appears that the dataset only contains one single value for day (=10). Further exploration will follow. - Hour: One can notice that over the 24h timespan of given days the number of plays differ drastically. While some users listen at any given time, the steep increase in plays starts after 5am and then continues throughout the day. Between 4-5pm Spotify reaches its maximum plays which then decrease again over the evening and eventually end up at the 5am starting point again. We will explore this in detail later on. - weekday: Intersting to notice is the distribution of streams across weekdays. One could assume that the weekends tend to have the most streams. As it appears users stream a lot on fridays and saturdays, the most streamed days is monday. Additioanlly, Wednesday has alot of plays (names gathered from weekday_name). Since this to me looks unintuitive, we will take a closer look at weekdays. - month/week: Further, there appears to be an interesting trend involving the streaming time over the year. The late spring / early summer month have the most streams. This trend is also visiable when looking at the weeks (Note: some weeks appear to be missing). Again, the summer time indicates the most plays while the winter time has a steady yet low number of plays. This is visualized and discussed later on. - year: When looking at the 'year' one first notices that there is data for 2015, 2016 and 2017. While there is a massive increase in streams between 2015 and 2016, the increase in the following year is only marginal. - stream length: Stream length which appears to be measured in seconds has a high at ~200sec. Which seems logical since songs tend to last around 3-4minutes. Further there are large number of streams with less than 200sec, these could be skipped/half-played songs. On the other, the long-tail is reasonably short since few songs last very long.

2.3.2 Variable Exploration

Will take a closer look at the following variable. 1. Log Time 2. Gender 3. Artists 4. Track Name 5. Stream Length 6. User Age 7. Geograpical Data 8. Stream Source 9. Playlists

---

(1)

2.4 Log Time

Variable Exploration

Description: We noticed that there is a dedicated variable for log time (i.e.,'log_time') during the general data understanding. We also noted that there are multiple time-relevant variables (e.g., 'DateTime'). Therefore, we start by looking at a sample output for log times.

[16]:
```
#attribute overview
df_music['log_time'].head(3)
```

[16]:
```
0    20160510T12:15:00
1    20160510T12:15:00
2    20160510T14:00:00
Name: log_time, dtype: object
```

[17]:
```
#attribute(s) overview
df_music[['log_time', 'DateTime', 'hour',␣
↪'minute','week','month','date','weekday','weekday_name']].head(3)
```

[17]:
```
            log_time            DateTime  hour  minute  week  month  \
0  20160510T12:15:00 2016-05-10 12:15:00    12      15    19      5
1  20160510T12:15:00 2016-05-10 12:15:00    12      15    19      5
2  20160510T14:00:00 2016-05-10 14:00:00    14       0    19      5
```

```
         date  weekday weekday_name
0  2016-05-10        1      Tuesday
1  2016-05-10        1      Tuesday
2  2016-05-10        1      Tuesday
```

[18]:
```python
#unique values for time relevant attributes
df_music[['log_time','DateTime','hour','minute','week','month','date'
          ,'weekday','weekday_name','year']].nunique()
```

[18]:
```
log_time        3257
DateTime        3257
hour              24
minute             4
week              22
month             12
date              38
weekday            7
weekday_name       7
year               4
dtype: int64
```

Insight: Comparing these attributes one quickly notices that all attributes refer to the same timestamp. All of them are sub-values of 'log_time' which combines them. Additionally, it is interesting that certain attributes are less frequent than expected. For example 'date', the dataset only contains 38 unique dates over the time horizon of 4 years. The same can be seen for 'week' which only records 22 unique weeks (see below). Hence, we are missing crucial data in order to get a complete picture.

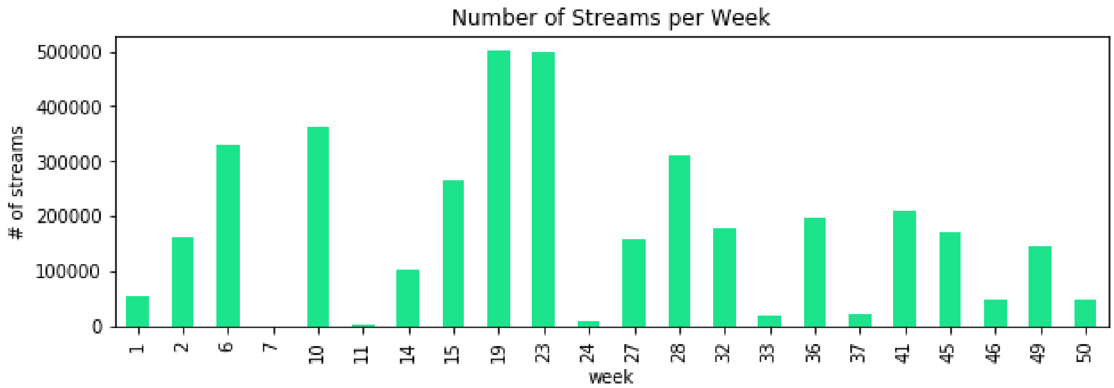
[19]:
```python
#look at all dates contained in the dataset
df_music['date'].value_counts()
```

[19]:
```
2017-05-10    349052
2017-06-10    328465
2017-07-10    298310
2017-04-10    260368
2017-03-10    252229
2017-02-10    220711
2016-09-10    196641
2016-10-10    184916
2016-08-10    178459
2016-11-10    171150
2016-06-10    170708
2017-01-10    162609
2016-07-10    158154
2016-12-10    146615
2016-05-10    142871
```

```
2016-03-10    111453
2016-02-10    108856
2016-04-10    103670
2016-01-10     53867
2015-12-10     48013
2015-11-10     47232
2015-10-10     25879
2015-09-10     23622
2015-08-10     20139
2015-07-10     10992
2015-05-10     10694
2015-06-10      9487
2015-04-10      4917
2015-03-10      3417
2014-12-10       687
2015-02-10       550
2015-01-10       351
2014-11-10       220
2014-06-10        86
2014-10-10        40
2014-07-10        30
2014-09-10        23
2014-08-10        16
Name: date, dtype: int64
```

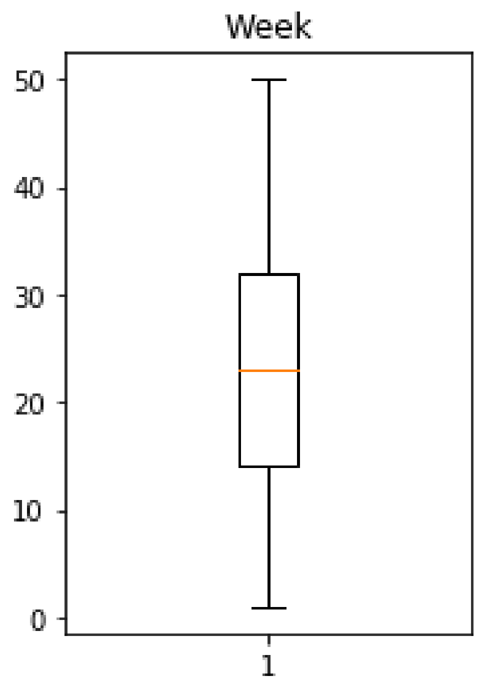
The detailed look at 'date' answers the question raised when looking at the histograms. The datapoints contained in the dataset have only been collected once a month (always on the 10th). One can still observe a strong increase of streams from the first to the last datapoint. As we've seen in the histogram, weekly streams vary quite a low and peak during the summer month. In general, winter and spring tend to have less streams. Since we're missing substantial amount of weeks we, however, shouldn't not draw final conclusions only based on 'week'.

[20]:
```
#bar chart number of streams per week; indicates missing weeks
ax = df_music.groupby('week').size().
 ↪plot(kind='bar',figsize=(10,3),title="Number of Streams per Week",␣
 ↪color='#1CE48C')
ax.set_ylabel("# of streams")
plt.show()
```



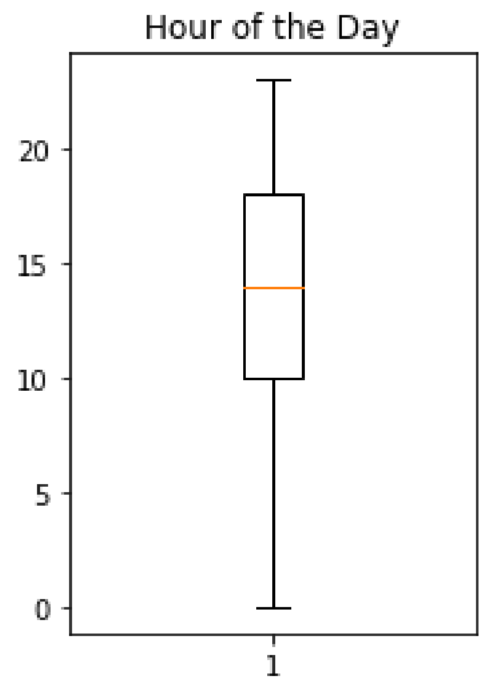
[21]:

```
#boxplot week (yearly basis)
fig = plt.figure()
ax1 = fig.add_subplot(121)

ax1.boxplot(df_music.week)

ax1.set_title('Week')
plt.show()
```

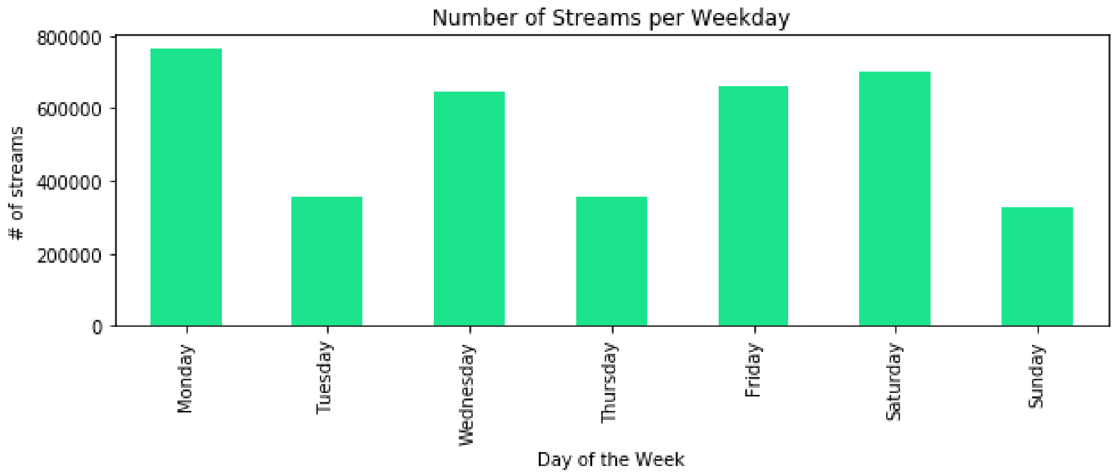


As seen when looking at the histograms, we notice a daily peak for streams. User tend to listen to music in the evening hours (e.g., after work or school). We continue by looking at this on a weekday basis.

[22]:
```
#boxplot number of streams at given daytime (hour)
fig = plt.figure()
ax1 = fig.add_subplot(121)

ax1.boxplot(df_music.hour)

ax1.set_title('Hour of the Day')
plt.show()
```



[23]:
```
#bar chart number of streams per weekday
ax = df_music.groupby('weekday').size().
 ↪plot(kind='bar',figsize=(10,3),title="Number of Streams per Weekday",␣
 ↪color='#1CE48C')
plt.xticks([0, 1, 2,3,4,5,6], ['Monday', 'Tuesday', 'Wednesday',"Thursday",␣
 ↪"Friday","Saturday", "Sunday"])
ax.set_ylabel("# of streams")
plt.xlabel('Day of the Week')
plt.show()
```

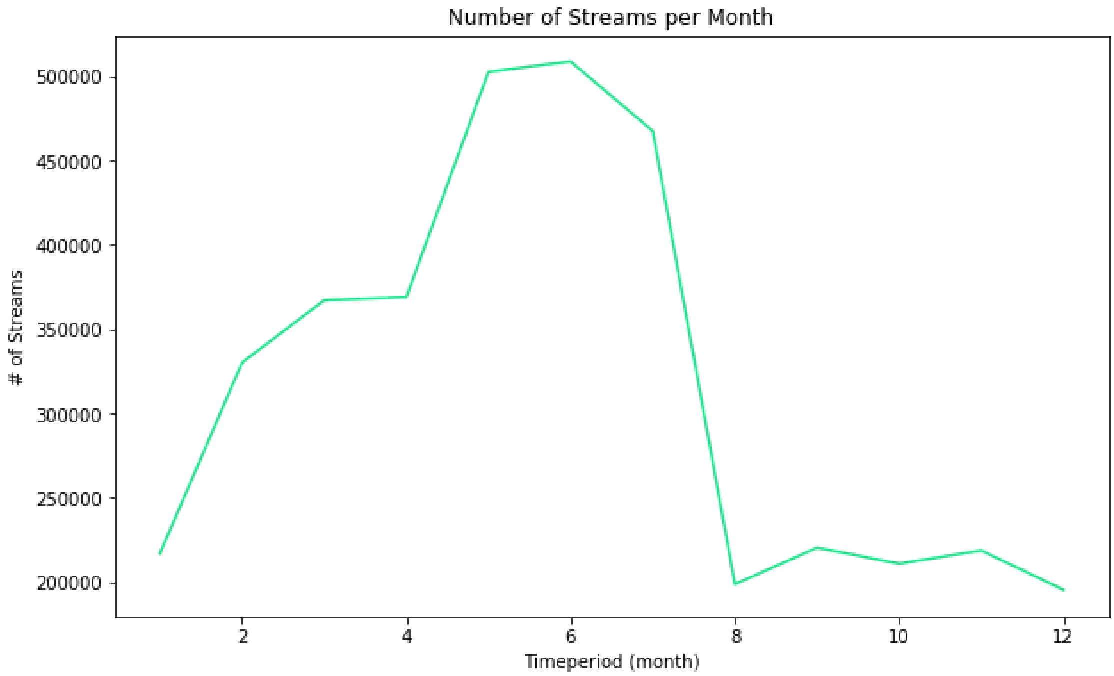


[24]:
```
df_music.weekday.value_counts(sort=False)
```

[24]:
```
0    763953
1    356765
2    646564
3    354268
4    659597
5    697951
6    326401
Name: weekday, dtype: int64
```

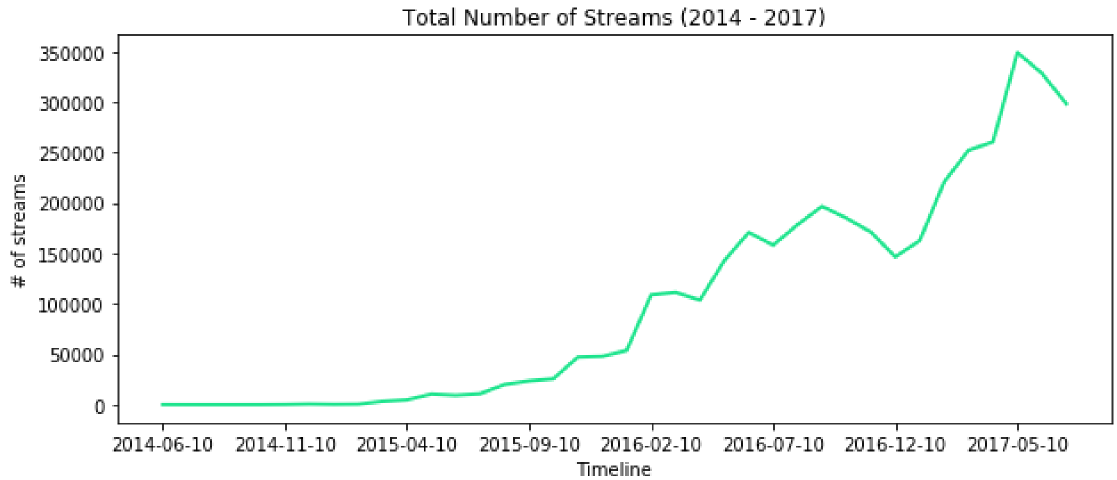
As previously outlined, there are major differences in number of streams per weekday. In absolute numbers (measured in streams) tuesdays, thursdays and sundays have comparably less streams. However, when counting the number of weekdays included in the dataset it becomes evident that these days are less frequently represented. Since data was only collected on the 10th of each month, some weekdays may be underrepresented. Now, we continue by looking at the yearly basis again.

[25]:
```
#bar chart streams monthly (one year)
df_music.groupby('month').size().plot(kind='line',figsize=(10,6),title="Number␣
↪of Streams per Month", color='#1CE48C')
plt.ylabel("# of Streams")
plt.xlabel('Timeperiod (month)')
plt.show()
```



It is apparent that users stream more songs out of our dataset in the late spring/ early summer month. One explanation for this is that people tend to spend more time outside and listen to music as well as the so called 'spring-mood' which could motivate people to listen to more music. This follows the same trend we've seen when looking at streams per week.

[26]:
```
#line chart streams over long time-period
ax = df_music.groupby('date')['customer_id'].size().plot(kind='line',␣
 ↪figsize=(10,4), title='Total Number of Streams (2014 - 2017)',  linewidth=2,␣
 ↪color='#1CE48C')
ax.set_xlabel('Timeline')
ax.set_ylabel('# of streams')
plt.show()
```



The same trend is evident when looking at a longer time horizon. While there is a increase in streams over time one still notices the spikes during the summer month.

---

(2)

2.5 Gender

Variable Exploration

As seen in the initial data review, the Spotify data also allows us to gain insights into gender of its customers.

[27]:
```
#rename female/male into numeric binary
df_music['gender'] = df_music['gender'].apply({'male':0, 'female':1}.get)

#map the binary value of mode to major/minor
gender_mapping = {1.0: "female", 0.0: "male"}
df_music['gender'] = df_music['gender'].map(gender_mapping)
```

[28]:
```
gender_mapping
```

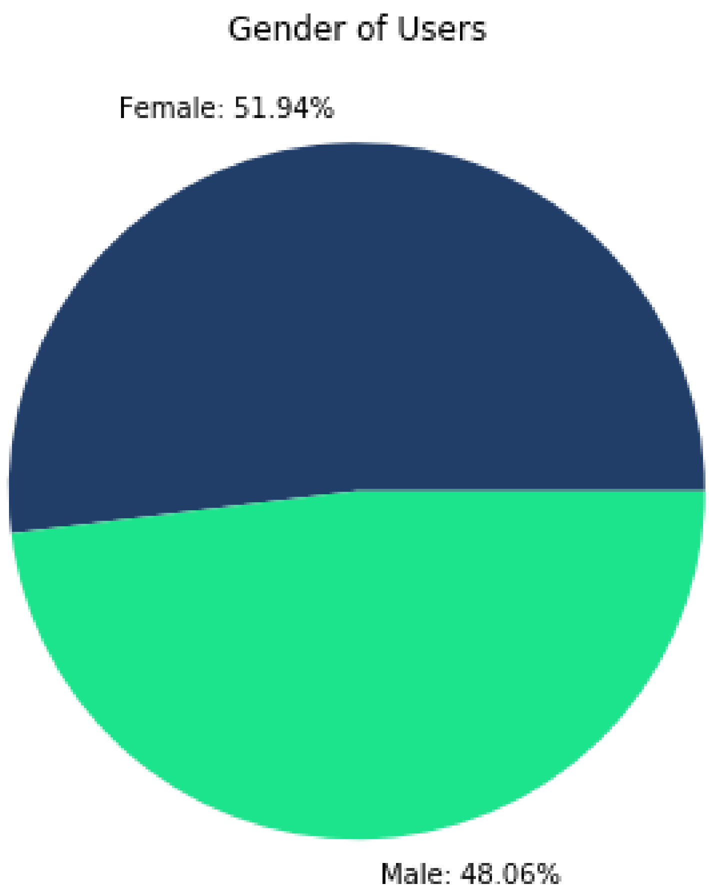
[28]:
```
{1.0: 'female', 0.0: 'male'}
```

[29]:
```
#user age



#important for later on


df_music['user_age'] = df_music['year'] - df_music['birth_year']
###
```

[ ]:

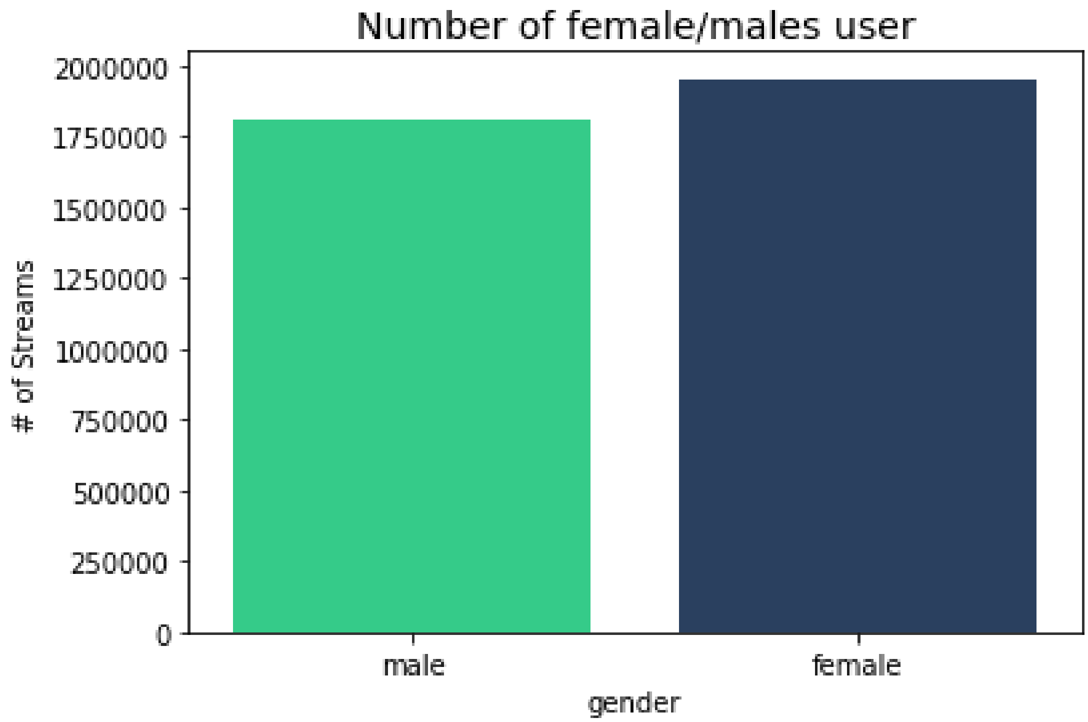
[30]:
```
count_female = int(df_music[df_music['gender']=='female'].
 ↪groupby(['gender'])['gender'].count())
count_male = int(df_music[df_music['gender']=='male'].
 ↪groupby(['gender'])['gender'].count())

female_quote = round(((count_female/(count_female+count_male))*100),2)
male_quote = round(((count_male/(count_female+count_male))*100),2)
```

[31]:
```
df_music.groupby('gender').size().plot(kind='pie',figsize=(10,6),title="Gender␣
 ↪of Users",
                                       labels=['Female: {}%'.
 ↪format(female_quote),'Male: {}%'.format(male_quote)],
                                       colors =[ "#213E68", '#1CE48C'])
plt.xlabel(None)
plt.ylabel(None)
plt.show()
```



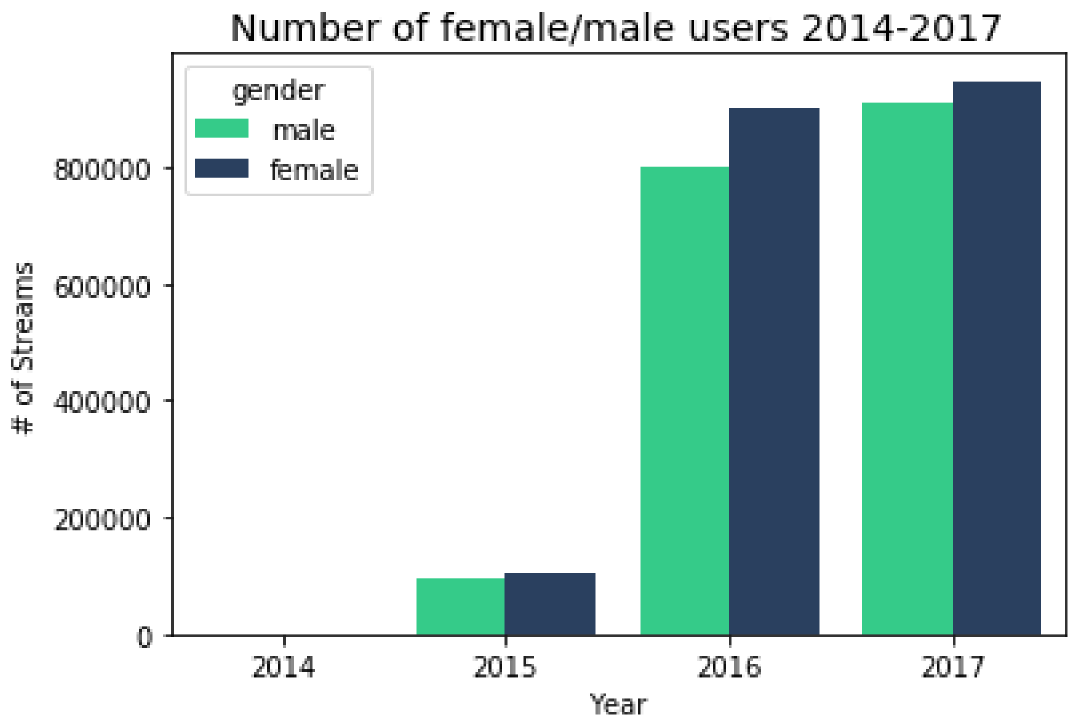
[32]:

```
#rename female/male into numeric binary
df_music['gender'] = df_music['gender'].apply({'male':0, 'female':1}.get)

#map the binary value of mode to major/minor
gender_mapping = {1.0: "female", 0.0: "male"}
df_music['gender'] = df_music['gender'].map(gender_mapping)

#draw a countplot of the values
sns.countplot(x ='gender', data=df_music, palette=flatui)
plt.title("Number of female/males user", size=14)
plt.ylabel("# of Streams")
plt.show()
```

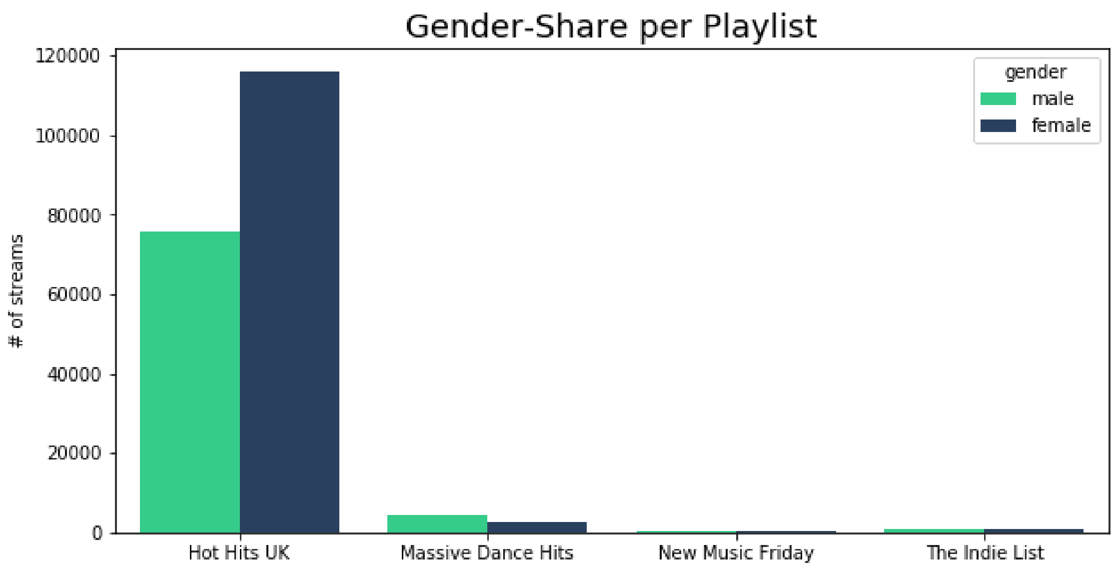


[33]:

```
sns.countplot(x="year", hue="gender",␣
 ↪data=df_music,palette=['#1CE48C',"#213E68"])
plt.title("Number of female/male users 2014-2017", size=14)
plt.xlabel("Year")
plt.ylabel("# of Streams")
plt.show()
```



[34]:
```
#generate dataframe focused on our four playlist; used again later on
df_playlist = df_music[(df_music['playlist_name']=='Hot Hits␣
↪UK')|(df_music['playlist_name']=='Massive Dance␣
↪Hits')|(df_music['playlist_name']=='The Indie␣
↪List')|(df_music['playlist_name']=='New Music Friday')]

#catplot gender share at individual playlists
a4_dims = (10,5)
fig, ax = plt.subplots(figsize=a4_dims)
ax = sns.countplot(x="playlist_name", hue="gender",data=df_playlist,␣
↪palette=flatui)
ax.set_title("Gender-Share per Playlist", size=18)
ax.set(xlabel=None, ylabel="# of streams")
plt.show()
```



When adding playlists as a additional dimension, the gender share appears to change. Notable is that 'Hot Hits UK' is mostly streamed by females while 'Massive Dance Hits' is more often streamed by males. Further analysis in the music taste and artist selection of both genders might be useful in the future.

[35]:
```
df_geo = df_music[df_music['country_code'] == 'GB'] #.columns
```

[36]:
```
df_geo = df_geo[df_geo['year'] == 2017]
```

[37]:
```
df_geo.shape
```

[37]:
```
(1871744, 49)
```

[ ]:
```

```

[38]:
```
##############################################################################################
```

[39]:
```
#alle groß schreiben
df_music['track_artists'] = df_music['track_artists'].str.upper()
df_music['artist_name'] = df_music['artist_name'].str.upper()
```

[40]:
```
df_music[['artist_name','track_artists']]
```

[40]:

	artist_name	track_artists
0	STURGILL SIMPSON	STURGILL SIMPSON
1	STURGILL SIMPSON	STURGILL SIMPSON
2	STURGILL SIMPSON	STURGILL SIMPSON
3	STURGILL SIMPSON	STURGILL SIMPSON

```
4        STURGILL SIMPSON  STURGILL SIMPSON
…               …                 …
3805494        ANNE-MARIE        ANNE-MARIE
3805495        ANNE-MARIE        ANNE-MARIE
3805496        ANNE-MARIE        ANNE-MARIE
3805497        ANNE-MARIE        ANNE-MARIE
3805498        ANNE-MARIE        ANNE-MARIE

[3805499 rows x 2 columns]
```

[41]:
```
df_music['buffer'] = 1
df_music['new'] = df_music['buffer'][(df_music['artist_name'] ==␣
↪df_music['track_artists'])]
1- df_music['new'].sum()/df_music['artist_name'].count()
```

[41]:
```
0.1075540947455248
```

[42]:
```
##################################################################################################
```

---

(3)

2.6 Artists

Variable Exploration

[43]:
```
#attribute overview
df_music['artist_name'].head(3)
```

[43]:
```
0    STURGILL SIMPSON
1    STURGILL SIMPSON
2    STURGILL SIMPSON
Name: artist_name, dtype: object
```

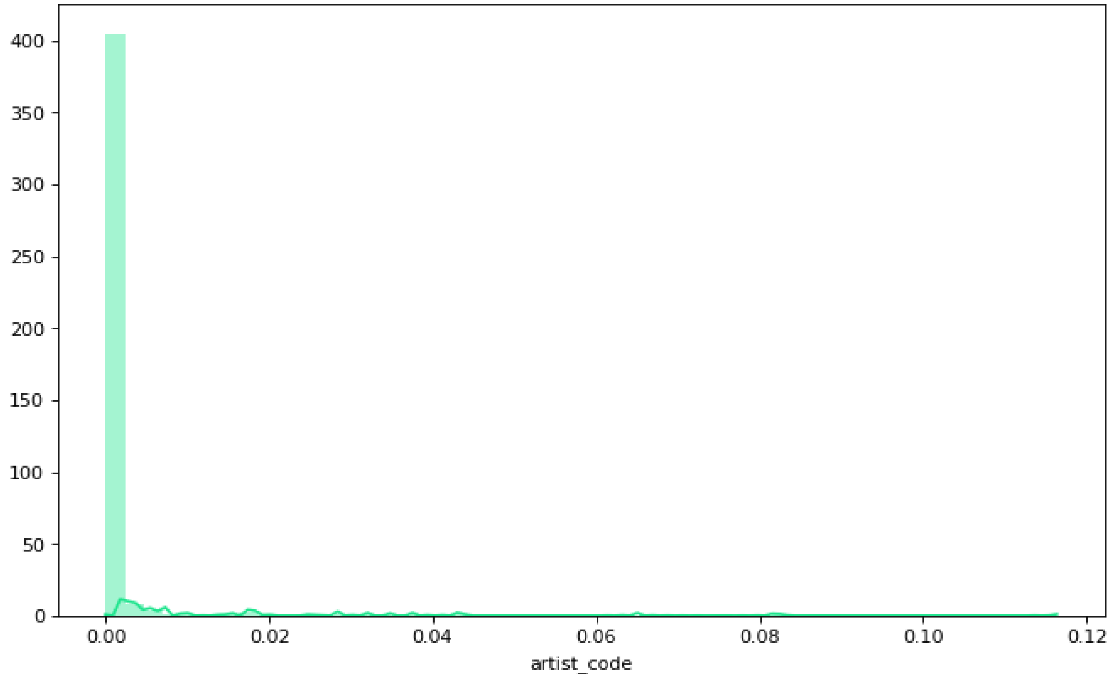
[44]:
```
#generate categorial variables
df_music['artist_code']=df_music['track_artists'].factorize()[0]
```

[45]:
```
print('Number of unique artists in training set: ',len(df_music['artist_code'].
↪value_counts()))
```

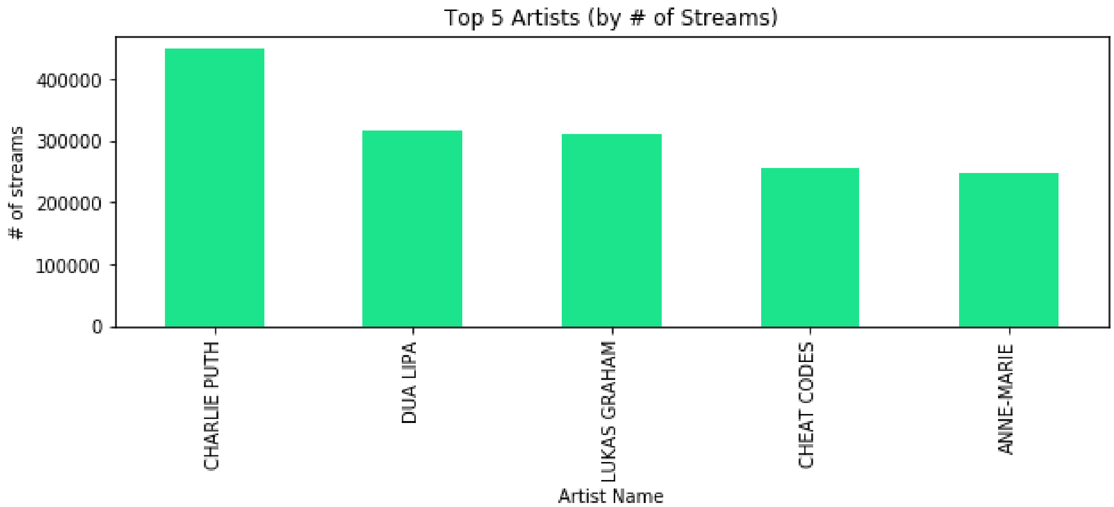
```
Number of unique artists in training set:  818
```

When analyzing the number of streams per artist, we noticed that the 'power law' is present. Few artists have a lot of streams while the long-tail of artists has very little number of streams. Therefore, we continued to explore the most popular artists (top 5).

[46]:
```
fig = plt.figure(figsize=(10,6),dpi=80)
fig = sns.distplot(df_music['artist_code'].
 ↪value_counts(normalize=True),color='#1CE48C')
```

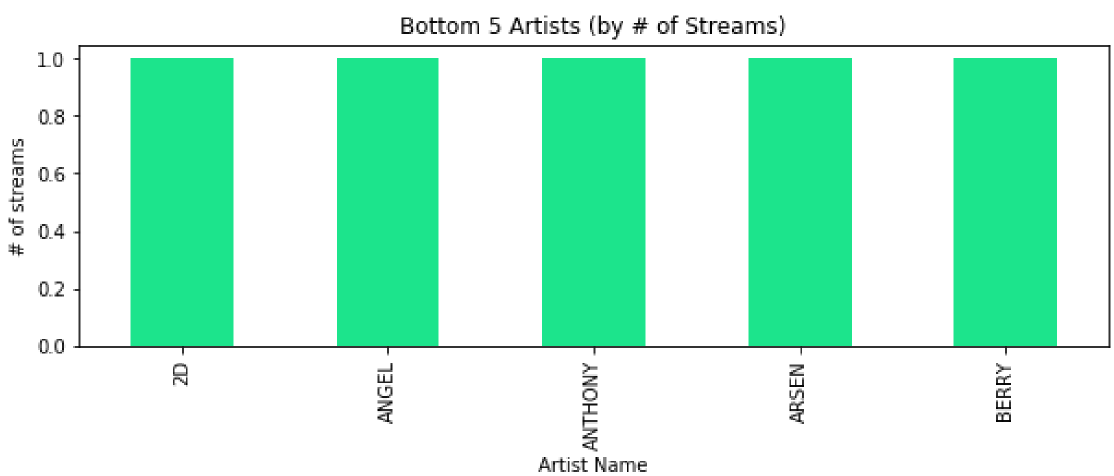


[47]:
```
#bar chart most popular artists
ax = df_music.groupby('artist_name').size().nlargest(5).
 ↪plot(kind='bar',figsize=(10,3),color='#1CE48C',fontsize=10, title='Top 5␣
 ↪Artists (by # of Streams)')
ax.set_ylabel("# of streams")
ax.set_xlabel("Artist Name")
plt.show()
```



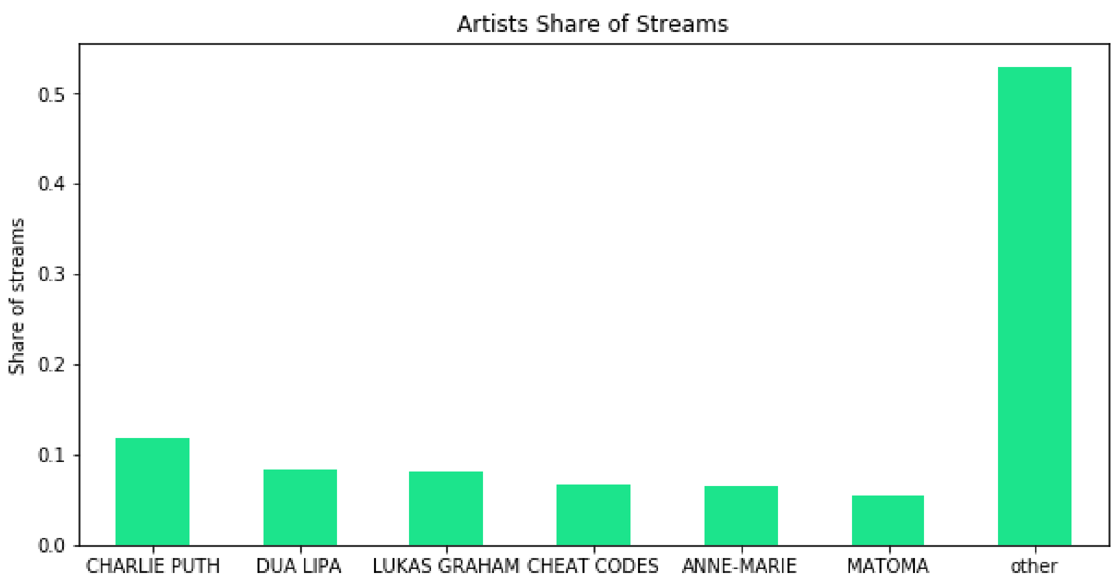
Especially when comparing the top 5 most streamed artists with the lowest 5 streamed artists you clearly see the difference. While 'Charlie Puth' has over 400.000 plays, the bottom five artists only have 1 stream each. Since this is commen when comparing top to bottom, we will now look at the magnitude in difference.

[48]:
```
#bar chart bottom artists
ax = df_music.groupby('artist_name').size().nsmallest(5).
 ↪plot(kind='bar',figsize=(10,3),color='#1CE48C',fontsize=10, title='Bottom 5␣
 ↪Artists (by # of Streams)')
ax.set_ylabel("# of streams", rotation=90)
ax.set_xlabel("Artist Name")
plt.show()
```



To visualise the magnitude of the difference between the few highly streamed artist and all others we applied a threshold to the top-artist graph. As seen below, 6 out of >800 artists (Charlie Puth, Dua Lipa, ...) are associated with nearly half of all streams. This underlines the beforementioned long-tail of artists in our dataset.

[49]:
```
#graph artists according to %-streams (w/threshold)
prob = df_music['artist_name'].value_counts(normalize=True)

#set threshold
threshold = 0.05

#mask threshold
mask = prob > threshold
tail_prob = prob.loc[~mask].sum()
prob = prob.loc[mask]
prob['other'] = tail_prob

#plot graph
prob.plot(kind='bar', color=["#1CE48C"], figsize=(10,5))
plt.xticks(rotation=0)
plt.title('Artists Share of Streams')
plt.ylabel("Share of streams")
plt.show()
```



(4)

2.7 Track Name

Variable Exploration

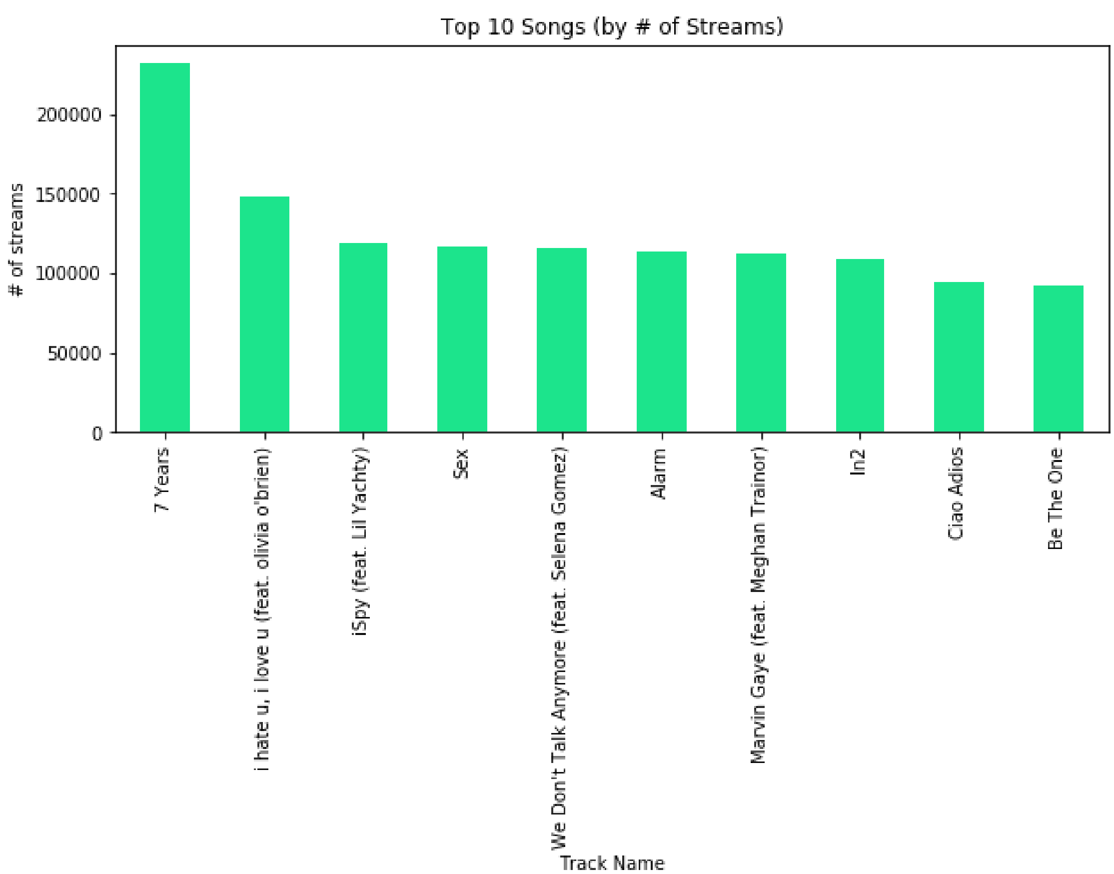
[50]:
```
#attribute(s) overview
df_music[['track_name','track_id']].head(3)
```

[50]:

	track_name	track_id
0	Call To Arms	8f1924eab3804f308427c31d925c1b3f
1	Call To Arms	8f1924eab3804f308427c31d925c1b3f
2	Call To Arms	8f1924eab3804f308427c31d925c1b3f

The same trend as for artists is present again, few songs are streamed frequently and most songs only a few times. Hence, we just took a look at the top 10 songs. We observe that '7 years' by Lukas Graham is the most streamed song out of our dataset.

[51]:
```
#bar chart top 10 songs
ax = df_music.groupby('track_name').size().nlargest(10).
 ↪plot(kind='bar',figsize=(10,4),color='#1CE48C',fontsize=10, title='Top 10␣
 ↪Songs (by # of Streams)')
ax.set_ylabel("# of streams")
ax.set_xlabel("Track Name")
plt.show()
```



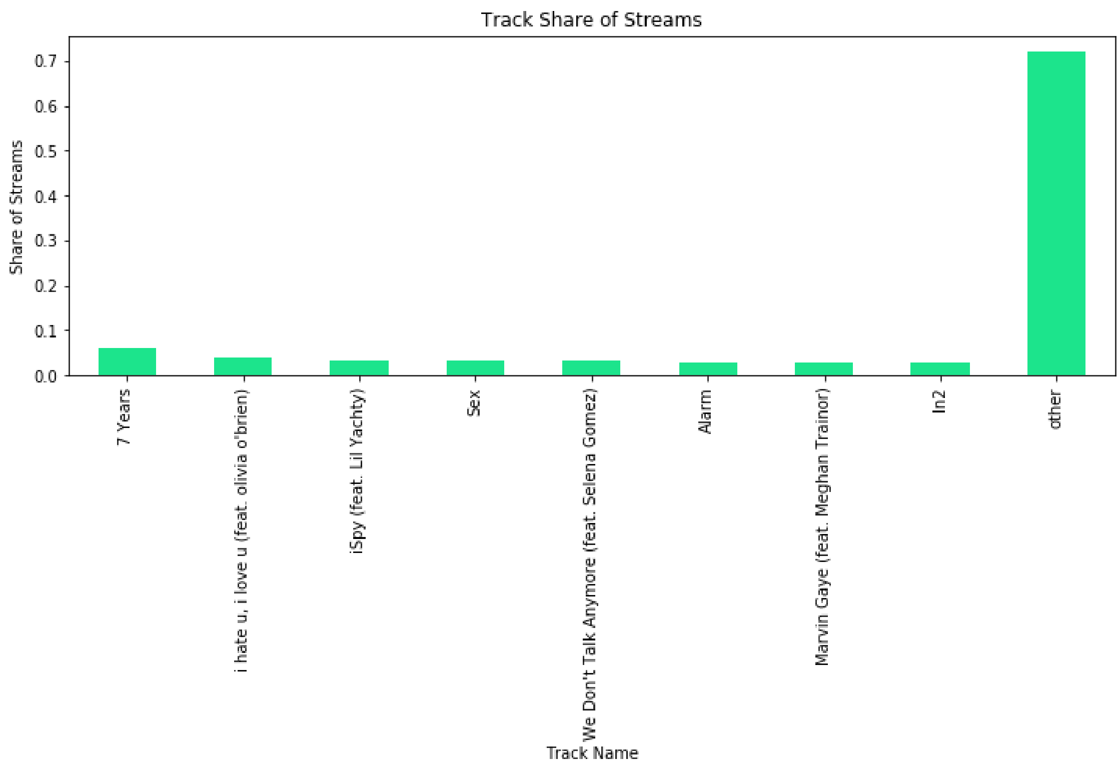
[52]:

```
#graphic top song in dataset
#display(Image(filename='./graphics/7 years_image.png', width=200, height=40))
```

Tracks follow a similar distribution as artists before. A couple of tracks (i.e., 8 tracks) cover nearly 30% of all streams. Logically, artists are even more central than tracks. In other words, artists produce a number of songs therefore one single song is less likely to account for a share of the total tracks. However, even for tracks there is the notion that the long-tail of tracks is only played few times.

[53]:

```
#graph tracks according to %-streams (w/threshold)
prob = df_music['track_name'].value_counts(normalize=True)

#set threshold
threshold = 0.025

#mask threshold
mask = prob > threshold
tail_prob = prob.loc[~mask].sum()
prob = prob.loc[mask]
prob['other'] = tail_prob

#plot graph
prob.plot(kind='bar', color=["#1CE48C"],figsize=(12,4))
plt.xticks(rotation=90)
plt.title('Track Share of Streams')
plt.xlabel("Track Name")
plt.ylabel("Share of Streams")
plt.show()
```



ACTION: Interpretation is missing

(5)

2.8 Stream Length

Variable Exploration

[54]:
```
#attribute overview
df_music['stream_length'].head(3)
```

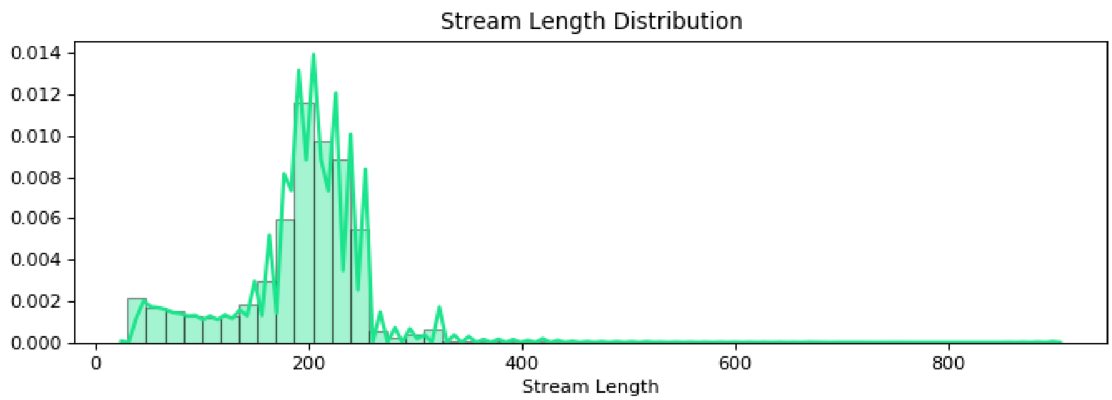
[54]:
```
0    277.0
1     53.0
2    326.0
Name: stream_length, dtype: float64
```

[55]:
```
print('Average Stream Length: ',df_music['stream_length'].mean())
```

```
Average Stream Length:  189.15867853335396
```

As the mean stream length suggested the distribution peaks at around 200 seconds. This can be explained with the common song length of 3-4minutes. Further, on can observe that only few users stop the stream after they have crossed 30sec (min. to be recorded). As well as only few datapoints having a stream length >300 since only a couple of songs last that long.

[56]:
```
fig = plt.figure(figsize=(10,3), dpi=80)
fig = sns.distplot(df_music['stream_length'],color='#1CE48C',␣
↪hist_kws={'edgecolor':'black'}, kde_kws={'linewidth': 2})
fig.set_title('Stream Length Distribution')
fig.set(xlabel='Stream Length')
plt.show()
```



There appears to be a long-tail of users streaming less songs while some users tend to stream a lot. This is even more evident when looking at 'powerusers' (see below) and the average number of streams per user. While some users stream above 100 tracks the average for the training data is close to 1.68 tracks. The total number of streams as well as the avg. streams per user seems rather small. As mentioned before, the datapoints are collected over 38 dates. Hence, it only provides partial picture of the total user-activity.

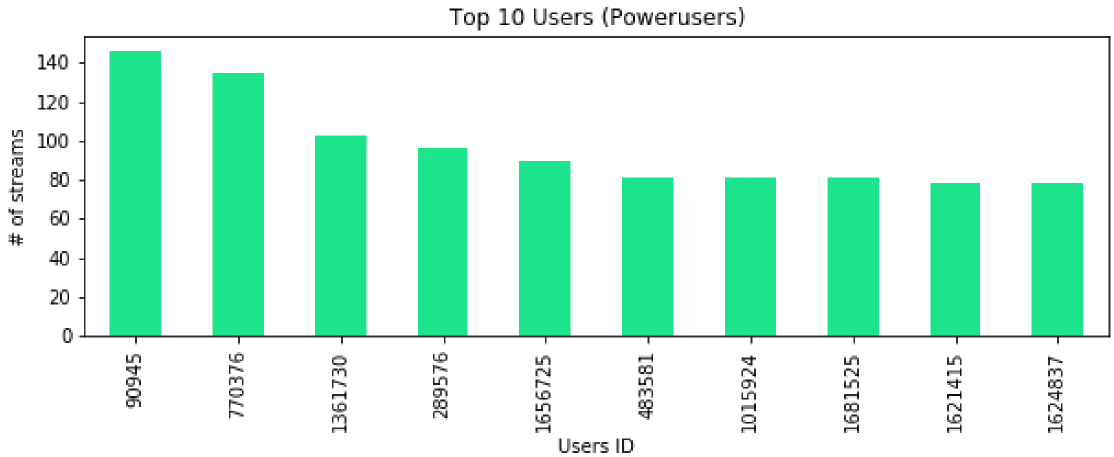
[57]:
```
#calculation average # of streams per user
df_music['customer_id']=df_music['customer_id'].factorize()[0]
print('Average number of streamed songs: ',df_music['customer_id'].
↪value_counts().mean())
```

```
Average number of streamed songs:  1.8198168084072641
```

Insights: There are certain 'power-users' within our data. These are users who frequently stream songs, accumulating as amany as 140 streams during the sampled time period compared to the baseline of 1.8 streams/user.

[58]:
```
#bar chart top 10 users (poweruser)
ax = df_music.groupby('customer_id').size().nlargest(10).
↪plot(kind='bar',figsize=(10,3),color='#1CE48C',fontsize=10, title='Top 10␣
↪Users (Powerusers)')
x_axis = ax.axes.get_xaxis()
x_axis.set_visible(True)
ax.set_ylabel("# of streams")
ax.set_xlabel("Users ID")
```

```
plt.show()
```



(6)

2.9 User Age

Variable Exploration

[59]:
```
#function to get use of device per age group
def age_device_breakdown(data):
    #again, define actual age using 'year' and 'birth-year'
    data['age'] = round(data['year'] - data['birth_year'], 0)

    #add 'age_bin' column to the dataframe with labels for each bin
    data["age_bin"] = pd.cut(x=data["age"], bins=[0, 20, 30, 40, 50, 60, 70,␣
↪80, 90, 100, 1000],
                             labels=['<20','20s', '30s', '40s', '50s', '60s',␣
↪'70s', '80s', '90s', '>100'])

    #generate the output by creating a matrix
    result = pd.DataFrame(pd.crosstab(data['stream_device'],data['age_bin']).
↪apply(lambda r: (r/r.sum())*100, axis=0))

    return result #data
```

[60]:
```
#apply function
age_device_breakdown(df_music)
```

[60]:
```
age_bin              <20        20s        30s        40s        50s  \
stream_device
```

```
desktop         19.084715  22.708768  27.103755  27.617323  28.998460
mobile          69.299265  69.863530  62.495526  59.589458  57.223863
tablet          11.616020   7.427702  10.400719  12.793219  13.777677

age_bin               60s        70s        80s        90s       >100
stream_device
desktop         34.417829  32.967464  24.326599  26.867749  29.094013
mobile          46.919373  46.569973  52.356902  60.556845  59.248872
tablet          18.662798  20.462564  23.316498  12.575406  11.657115
```

Insight: Usage of devices differs between age groups as one would expect. The younger generation tends to stream most via mobile and tablet, while the desktop regains significance with older people.

Explanation: The year of birth provides great value for our further analysis. Especially when thinking about targeting users with the right music. It is widely assumed that music taste follows the age, therefore, we need to consider this factor during our playlist analysis. Note that we decided to cut the birth year in 2003 since Spotify regulations does not allow users younger than 14 years old (latest datapoint in 2017).

[61]:
```python
#attribute overview
df_music['birth_year'].head(3)
```

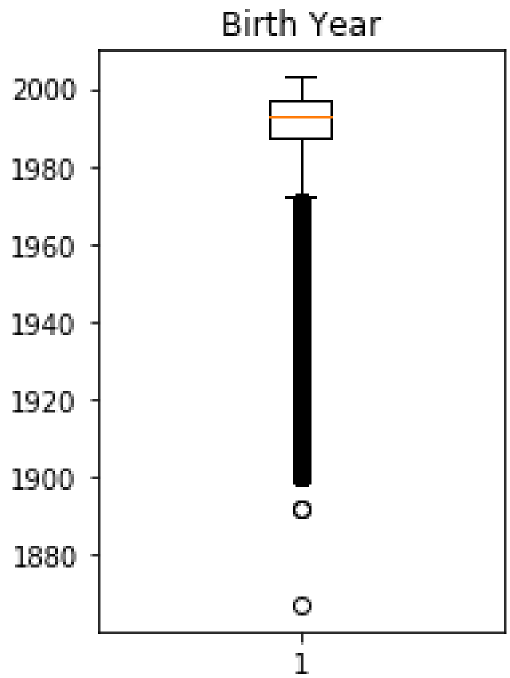
[61]:
```
0    1968.0
1    1968.0
2    1995.0
Name: birth_year, dtype: float64
```

[62]:
```python
print('Average birth year: ',round(df_music['birth_year'].mean(),0))
```

```
Average birth year:  1990.0
```

[63]:
```python
#cut allowed birth age (sperate dataframe to keep datapoints for other␣
 ↪attributes)
df_birthyear = df_music[df_music['birth_year'] <= 2003]
```

[64]:
```python
#boxplot bithyear
fig = plt.figure()
ax = fig.add_subplot(121)

ax.boxplot(df_birthyear.birth_year)

ax.set_title('Birth Year')
plt.show()
```

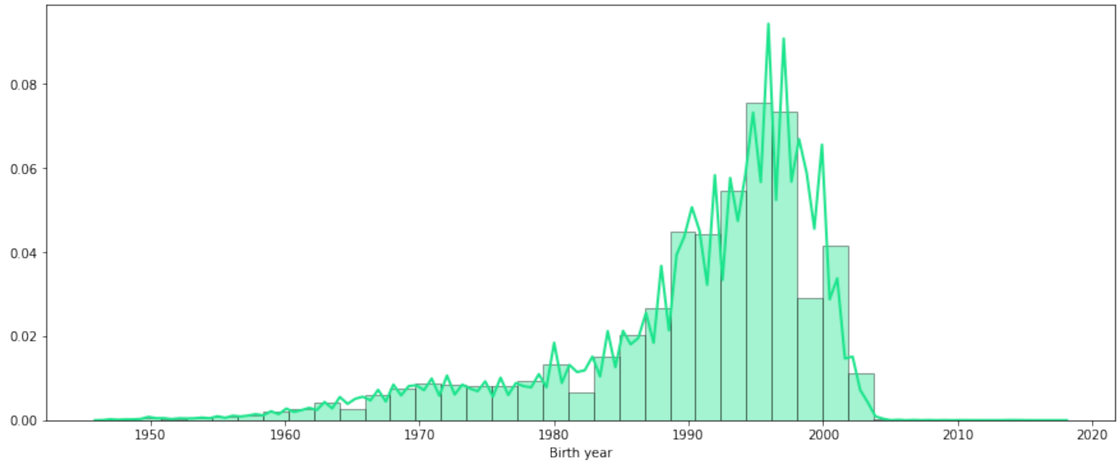


One can directly notice that the large focus group of users appaer to be born around 1990. This seems logical considering that Spotify is a trendy tech-product targted to young people. Additionally, one has to note that there a large amounts of outliers dating back even before 1880. This is obviously unrealistic and leads to the assumption that users may have entered fake ages. Therefore for further analysis we decided to assume that the maximum birth year within in the analysis (playlist targeted to young people) is set to 1947 (70 years old at max).

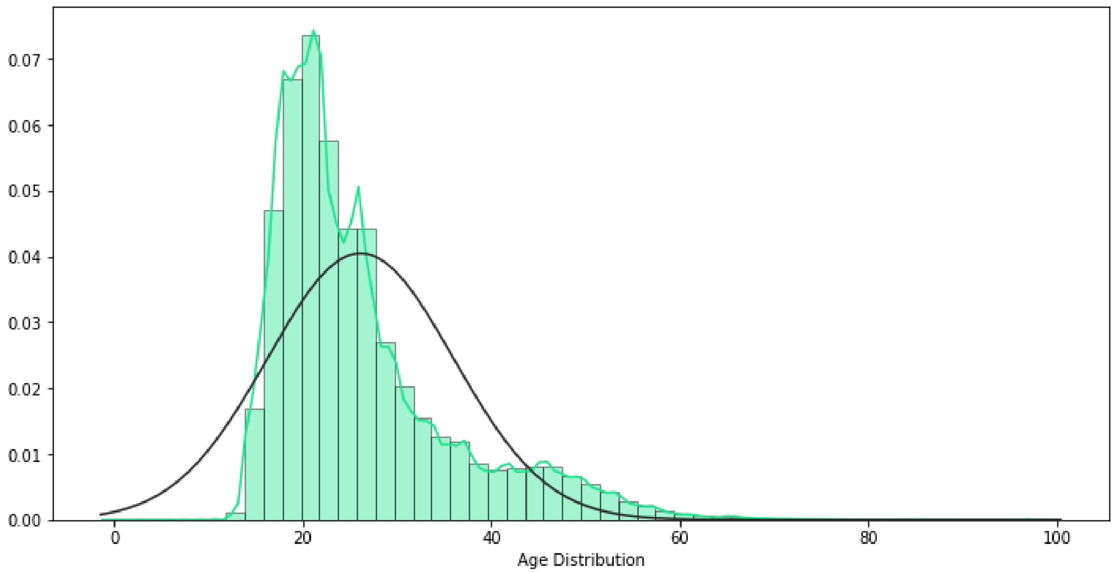
[65]:
```
#cut birth age according to outliers
df_birthyear = df_music[df_music['birth_year'] >= 1947]
```

Description: Next, we take a closer look at the actual number of streams included at given birth years. The same trend as before becomes evident: The large mass of users are born between 1990 and 2000. In more detail, there is a spike in users in 1990 and again in the years between 1995 - 1998. Since nearly all age-groups use Spotify, the long-tail of users is the older generation. And, based on the age restrictions set beforehand there are no observations after 2003/ before 1947.

[66]:
```
#plot distribution of observations
plt.figure(figsize=(15, 6))
sns.distplot(df_birthyear['birth_year'], hist=True, kde=True, bins=int(150/4),␣
↪color = '#1CE48C', hist_kws={'edgecolor':'black'}, kde_kws={'linewidth': 2})
plt.xlabel("Birth year")
plt.show()
```



[67]:
```
# Age Distribution
def get_age(df):
    df.birth_year = np.float64(df.birth_year)
    df = df.dropna(subset = ['birth_year'])
    #df = df[(df.birth_year!='male') & (df.birth_year!='female')]
    age = df.year - df.birth_year
    return age
all_artists_age = get_age(df_music)
all_artists_age_cleaned= pd.
 ↪Series(all_artists_age[all_artists_age<100],name="Age Distribution")
plt.figure(figsize=(12,6))
from scipy.stats import norm
sns.distplot(all_artists_age_cleaned,fit=norm,␣
 ↪color="#1CE48C",hist_kws={'edgecolor':'black'})
plt.show()
```

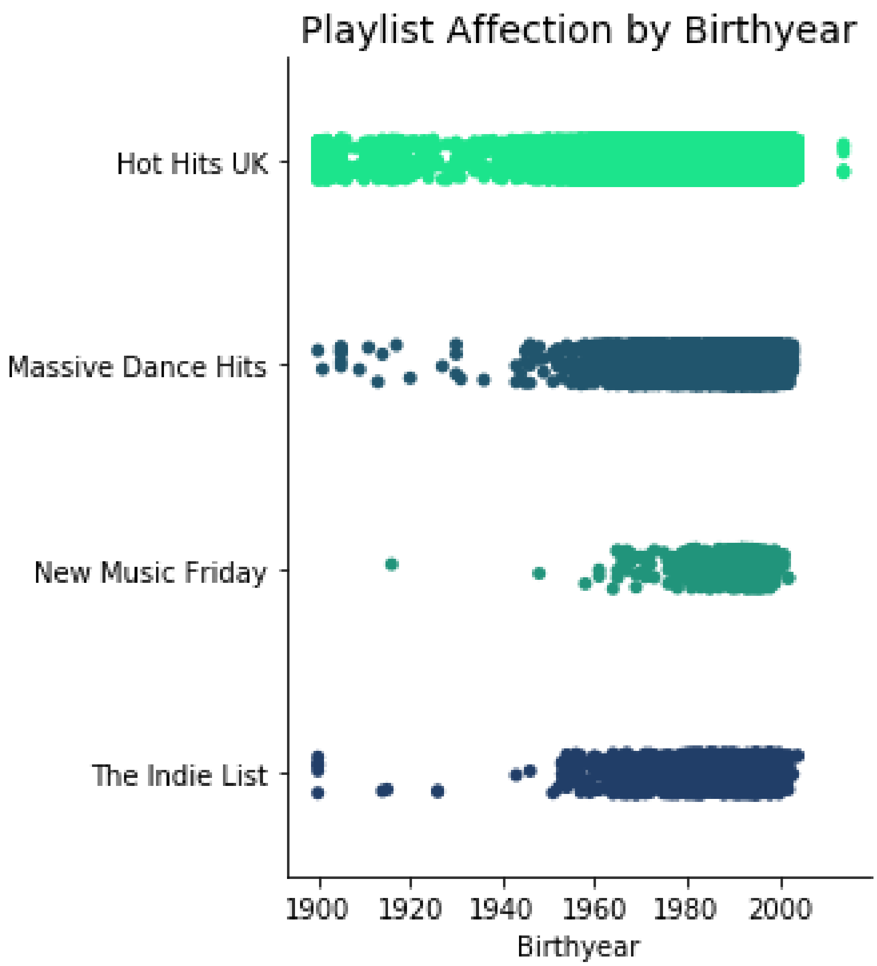


Insights: Interstingly the normalized age distribution peaks just before 'age == 30', while the spike in age groups appears to be much earlier (close to age == 20). This can be explained with the long-tail of users ranging into age groups >100.

[68]:
```
#generate dataframe focused on our four playlist; used again later on
df_playlist = df_music[(df_music['playlist_name']=='Hot Hits␣
↪UK')|(df_music['playlist_name']=='Massive Dance␣
↪Hits')|(df_music['playlist_name']=='The Indie␣
↪List')|(df_music['playlist_name']=='New Music Friday')]
```

Insights: Comparing the playlists with age reveals that 'Hot Hits UK' is popular across all ages groups, 'New Music Friday' is mostly listend to by younger audience and 'Massive Dance Hits' and 'The Indie List' have a young audience yet also older people listening to these songs. Considering the content of the individual playlists this distribution seems reasonable. However, note that due to the unbalance between streams in all four playlists this might not hold true for a larger population.

[69]:
```
#catplot birthyear and playlist streams

fig = sns.catplot(x="birth_year",y="playlist_name",data=df_playlist,␣
↪palette=flatui2)
plt.title('Playlist Affection by Birthyear', size=14)
plt.xlabel('Birthyear')
plt.ylabel(None)
plt.show()
```



(7)

2.10 Geograpical Data

Variable Exploration

Explanation: The provided information tells us that all streams occured in the UK. Hence, we can focus on a narrow customer location. First, we verify this information by looking at the 'country_code' provided before we look at a sample location output to better understand the provided data.

[70]:
```
#share of UK users
print(df_music.country_code[df_music['country_code'] == 'GB'].count()/
 ↪df_music['country_code'].count()*100, '%')
```

```
100.0 %
```

[71]:
```
#attribute(s) overview
df_music[['country_code','postal_code','region_code']].head(3)
```

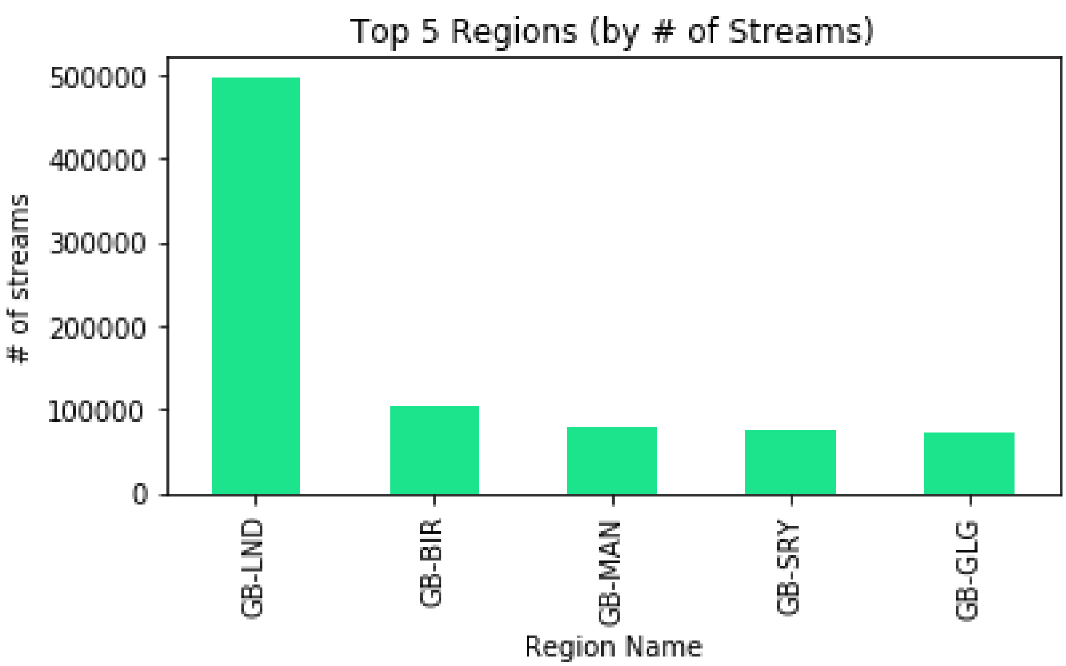
[71]:

	country_code	postal_code	region_code
0	GB	NE	GB-DUR
1	GB	NE	GB-DUR
2	GB	1	GB-ESS

Insights: One can observe that 'GB-LDN' is the region with the most streams by far. LDN represents London, which seems only logical that London would have the most streams. London is followed by 'GB-BIR'(Birmingham) and 'GB-MAN' (Manchester), which are the 2nd and 3rd largest cities in GB.
London – 9,750,500. Birmingham – 2,453,700. Manchester – 1,903,100.

Source: https://www.citymetric.com/skylines/where-are-largest-cities-britain-1404

[72]:
```
#bar chart top 5 regions (by # of streams)
ax = df_music.groupby('region_code').size().nlargest(5).
↪plot(kind='bar',figsize=(6,3),color='#1CE48C',fontsize=10, title='Top 5␣
↪Regions (by # of Streams)')
ax.set_ylabel("# of streams")
ax.set_xlabel("Region Name")
plt.show()
```



Lastly, we leveraged Tableau in order to generate a map pin-pointing the locations. As noted before, this gives a visual representation of the trend. London appears to be the city with the most streams by far, followed by other mayor GB cities. Since Spotify targets young cosmopolitan customers they are heavily centered in larger metropolitan areas. Interesting to see is 'Glasgow' (up north) since it is in Scottland, which however is still part of GB.

[73]:
```
df_music.columns
```

[73]:
```
Index(['Unnamed: 0', 'Unnamed: 0.1', 'Unnamed: 0.1.1', 'day', 'log_time',
       'mobile', 'track_id', 'isrc', 'upc', 'artist_name', 'track_name',
       'album_name', 'customer_id', 'postal_code', 'access', 'country_code',
       'gender', 'birth_year', 'filename', 'region_code', 'referral_code',
       'partner_name', 'financial_product', 'user_product_type',
       'offline_timestamp', 'stream_length', 'stream_cached', 'stream_source',
       'stream_source_uri', 'stream_device', 'stream_os', 'track_uri',
       'track_artists', 'source', 'DateTime', 'hour', 'minute', 'week',
       'month', 'year', 'date', 'weekday', 'weekday_name', 'playlist_id',
       'playlist_name', 'danceability', 'acousticness', 'valence', 'user_age',
       'buffer', 'new', 'artist_code', 'age', 'age_bin'],
      dtype='object')
```

[74]:
```
#grwoth in streams in top 5 UK regions (2015-2016); since these are the only␣
↪'full' recorded years

#streams in either 2015 and 2017
df_2015 = pd.DataFrame(df_music[df_music['year']==2015].groupby('region_code').
↪size().nlargest(5),columns=['2015'])
df_2016 = pd.DataFrame(df_music[df_music['year']==2016].groupby('region_code').
↪size().nlargest(5),columns=['2016'])

#dataframe creation
df_location = pd.concat([df_2015, df_2016], axis=1, sort=False)
df_location['growth-factor'] = df_location['2016']/df_location['2015']

#show results
df_location
```

[74]:

region_code	2015	2016	growth-factor
GB-LND	18546	290857	15.683004
GB-BIR	2398	42785	17.841952
GB-MAN	2143	38224	17.836678
GB-SRY	2067	37964	18.366715
GB-GLG	1753	34942	19.932687

[75]:
```
### please add comment on growth of certain regions
```

[76]:
```
#display(Image(filename='./graphics/Stream Location Map_image.jpg'))
```

(8)

2.11 Stream Source

Variable Exploration

[77]:
```
#share of stream source
print('stream_source_uri: ',round(df_music['stream_source_uri'].count()/
↪df_music['day'].count()*100,2),'%')
print('stream_source: ',round(df_music['stream_source'].count()/df_music['day'].
↪count()*100,2),'%')

df_music[['stream_source_uri','stream_source']].head(3)
```

```
stream_source_uri:  27.43 %
stream_source:  100.0 %
```

[77]:

	stream_source_uri	stream_source
0	NaN	album
1	NaN	album
2	NaN	collection

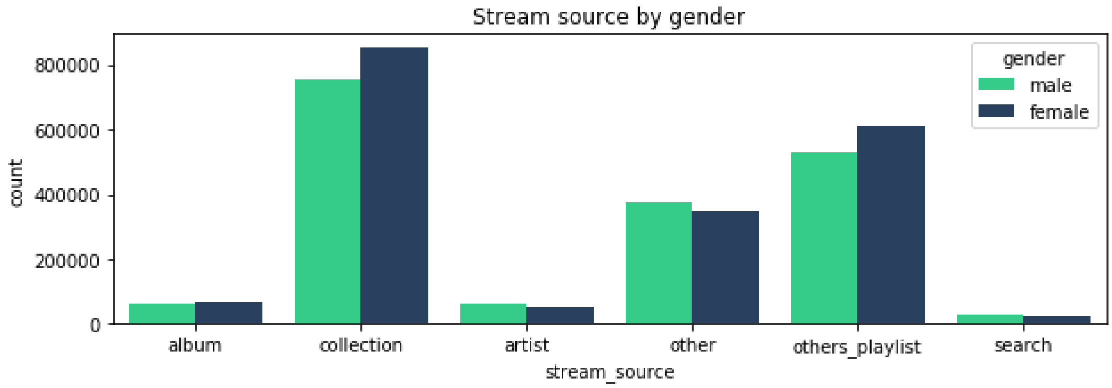
[78]:
```
#preperation pie chart; data formatting
count_album = df_music.stream_source[df_music['stream_source']=='album'].count()
count_collection = df_music.
↪stream_source[df_music['stream_source']=='collection'].count()
count_artist = df_music.stream_source[df_music['stream_source']=='artist'].
↪count()
count_other = df_music.stream_source[df_music['stream_source']=='other'].count()
count_other_playlist = df_music.
↪stream_source[df_music['stream_source']=='others_playlist'].count()
count_search = df_music.stream_source[df_music['stream_source']=='search'].
↪count()
```

[79]:
```
#dataframe as basis for chart
data = [['Album', count_album], ['Collection', count_collection], ['Artist',␣
↪count_artist], ['other', count_other], ['others_playlist',␣
↪count_other_playlist], ['search', count_search]]
df_count = pd.DataFrame(data, columns=['Source','Count'])
df_count = df_count.set_index('Source')
```

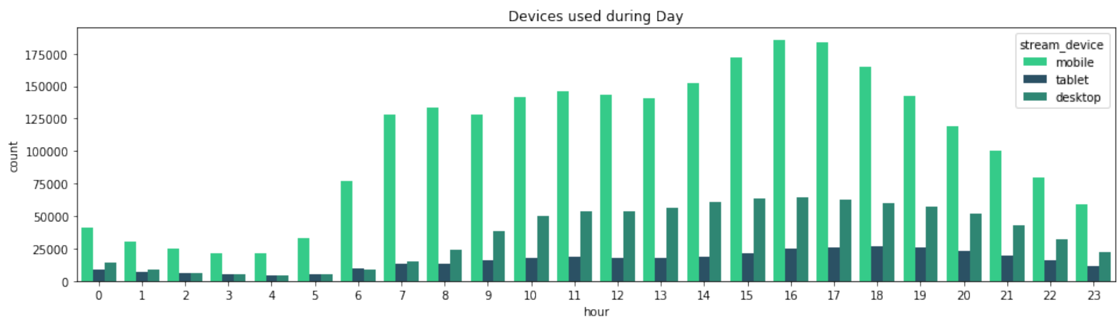
Insights: The source of the streams appears to be largely from ‘Collection(s)’, which are several separate recordings by either one or several artists and ‘others_playlist’. Notable is that only few streams are from ‘Artist(s)’ or ‘Album(s)’.

[80]:
```
#Plot stream source by gender
plt.figure(figsize=(10,3))
sns.countplot(x="stream_source", hue="gender", data=df_music,palette= flatui).
↪set_title('Stream source by gender')
```

```
plt.show()
```



[81]:
```
#Plot Operating system per year
plt.figure(figsize=(16,4))
sns.countplot(x="hour", hue="stream_device",data=df_music,palette= flatui2).
 ↪set_title('Devices used during Day')
plt.show()
```



(9)

2.12 Playlist

Variable Exploration

Explanation: With the knowledge about different individual attributes in mind, we can continue by looking at our four playlists in detail. Let's start analyzing the number of streams for each of the playlists. - Hot Hits UK - Massive Dance Hits - The Indie List - New Music Friday

[82]:
```
#attribute(s) overview
df_music[['playlist_name','playlist_id']].head(3)
```

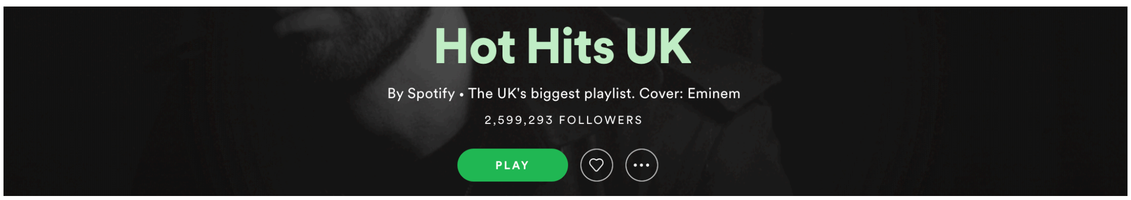
[82]:
```
  playlist_name playlist_id
0           NaN         NaN
1           NaN         NaN
2           NaN         NaN
```

[83]:
```
#count playlist name and id; notice difference
df_music[['playlist_name','playlist_id']].count()
```

[83]:
```
playlist_name     979110
playlist_id      1043871
dtype: int64
```

Description: Note that not all streams appear to be assigned to playlists. Some, however, are assigned to a 'playlist_id' yet lack the matching 'playlist_name'. This should be further investigated later on.

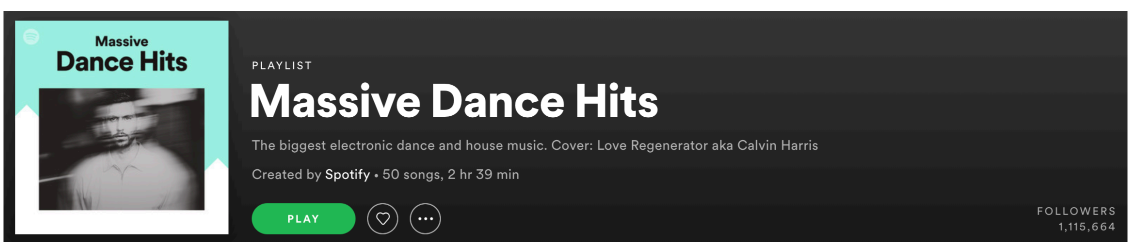
[84]:
```
display(Image(filename='./GRAPHICS/Hot Hits UK_playlist.png'))
```



[85]:
```
count_HotHits = df_music.playlist_name[df_music['playlist_name']=='Hot Hits␣
↪UK'].count()
count_HotHits
```

[85]: 193654

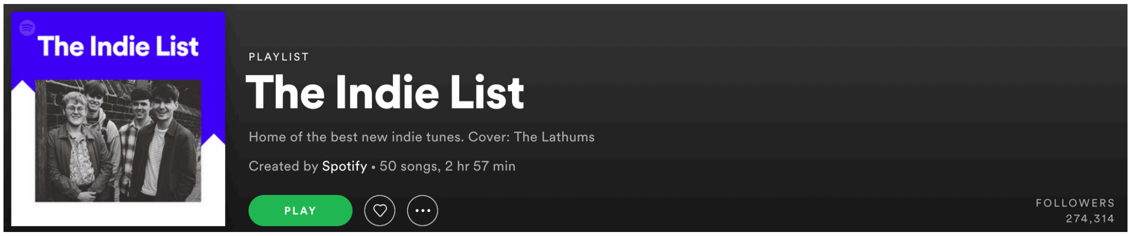
[86]:
```
display(Image(filename='./GRAPHICS/Massive Dance Hits_playlist.png'))
```



[87]:
```
count_Dancehits = df_music.playlist_name[df_music['playlist_name']=='Massive␣
↪Dance Hits'].count()
count_Dancehits
```

[87]: 7087

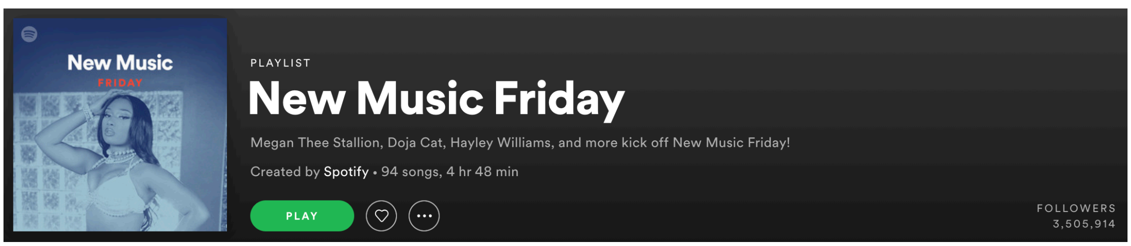
[88]:
```
display(Image(filename='./GRAPHICS/The Indie List_playlist.png'))
```



[89]:
```
count_Indie = df_music.playlist_name[df_music['playlist_name']=='The Indie␣
↪List'].count()
count_Indie
```

[89]: 1572

[90]:
```
display(Image(filename='./GRAPHICS/New Music Friday_playlist.png'))
```



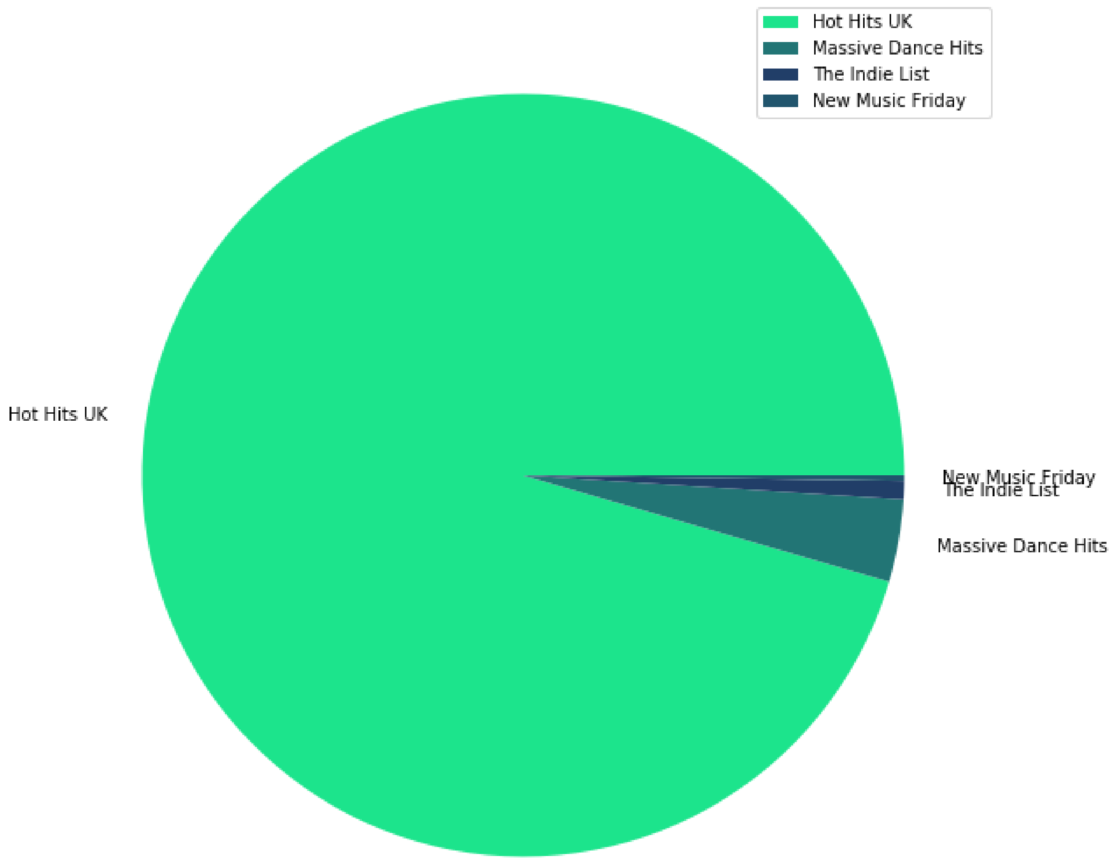
[91]:
```
count_NewMusic = df_music.playlist_name[df_music['playlist_name']=='New Music␣
↪Friday'].count()
count_NewMusic
```

[91]: 466

Description: As the above counts indicate 'Hot Hits UK' has the most streams out of the four given playlists. In order to better visualise the distribution between the playlist we created the below pie-chart.

[92]:
```
#pie chart playlist distribution (by # of streams)

#combining sums from counting
data_in = [['Hot Hits UK', count_HotHits], ['Massive Dance Hits',␣
↪count_Dancehits],['The Indie List', count_Indie],['New Music␣
↪Friday',count_NewMusic]]
```

```
#generating new dataframe
df_count = pd.DataFrame(data_in, columns=['Source','Count'])
df_count = df_count.set_index('Source')
df_count.plot.pie(y='Count', figsize=(10, 10),colors=['#1CE48C','#227575',␣
↪'#213E68',  '#21556D', '#21947B' ])
plt.ylabel(None)
plt.show()
```



Insights: As previously mentioned the four selected playlists only contain a fraction of the total streams. Out of all streams labeled with a playlist 20.71% are in the four playlists (or not assigned to a playlist at all). Others are scattered across different playlists. As seen in the graph below, nearly all of these are then accounted for by 'Hot Hits UK'.

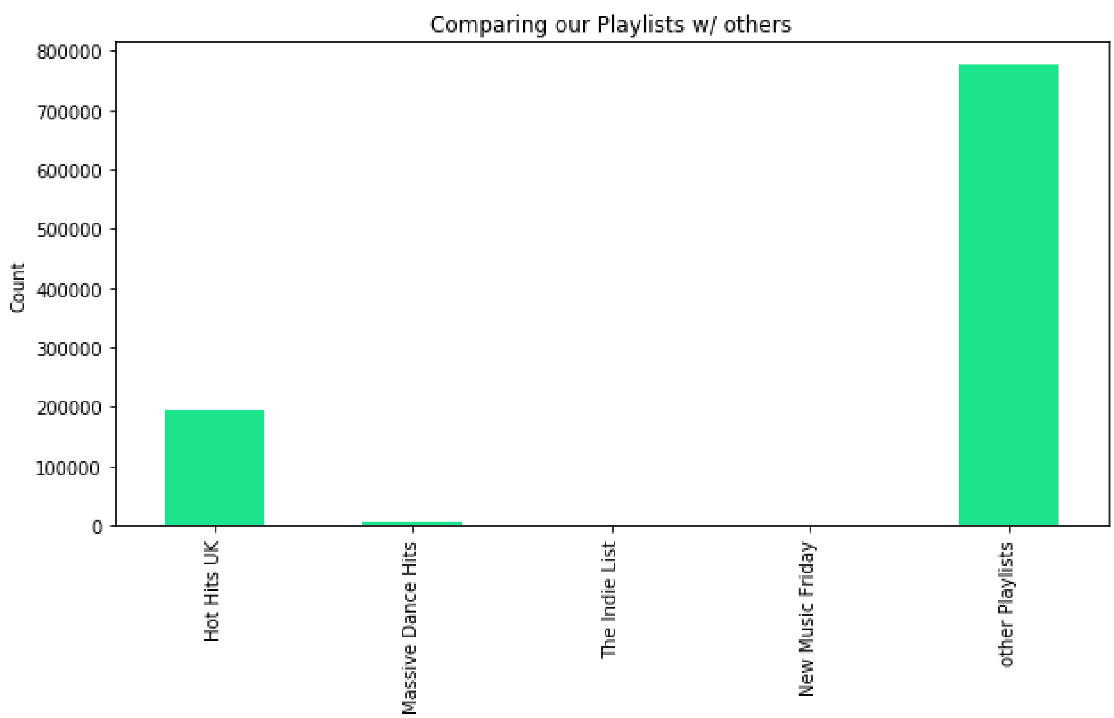
[93]:
```
#count number of streams in 'other' (not the main 4) playlists
count_total = df_music.playlist_name.count()
```

```
count_other = df_music.playlist_name.
 ↪count()-count_HotHits-count_Dancehits-count_Indie-count_NewMusic
```

[94]:
```
print('Streams included in selected playlists',round((count_total-count_other)/
 ↪count_total*100,2),'%')
```

```
Streams included in selected playlists 20.71 %
```

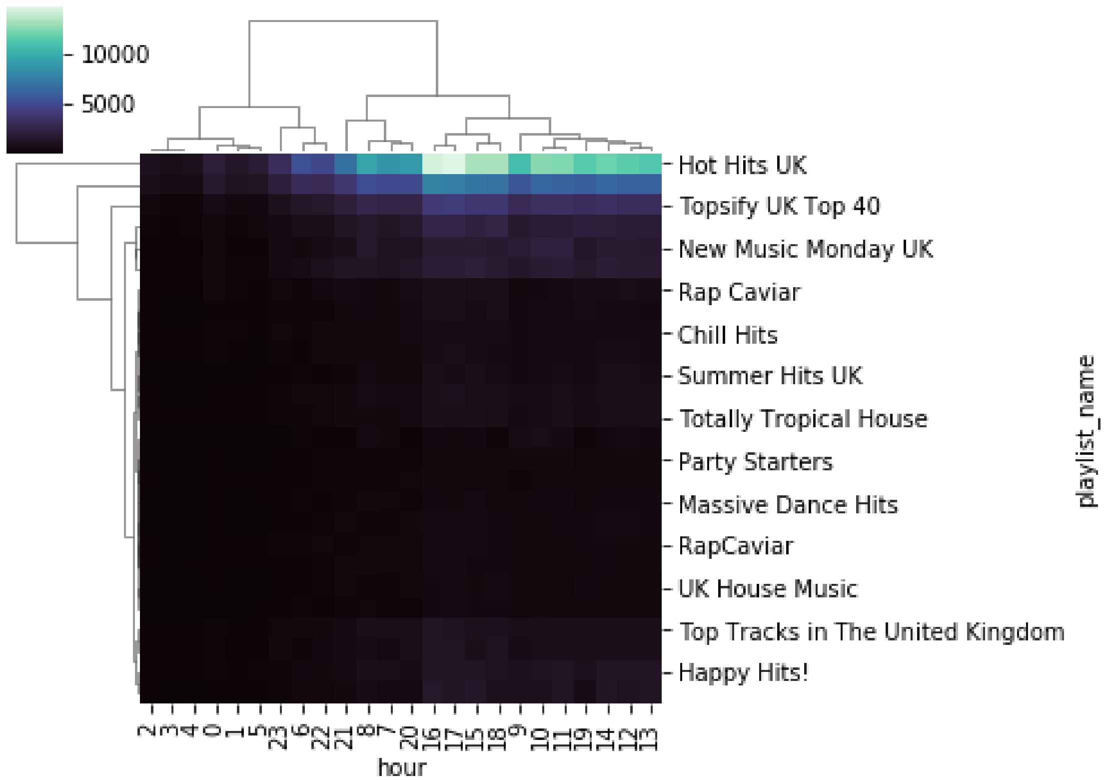
[95]:
```
#bar chart comparing streams per playlist
data_in = [['Hot Hits UK', count_HotHits], ['Massive Dance Hits',␣
 ↪count_Dancehits],['The Indie List', count_Indie],['New Music␣
 ↪Friday',count_NewMusic],['other Playlists',count_other]]
df_count = pd.DataFrame(data_in, columns=['Source','Count'])

ax = df_count.plot(kind='bar',figsize=(10,5),color='#1CE48C',fontsize=10,␣
 ↪title='Comparing our Playlists w/ others')
#ax.set_yscale('log')
ax.set_xticklabels(df_count['Source'], minor=False)
plt.ylabel("Count")
ax.get_legend().remove()
plt.show()
```



Insights: The cluster-plot below gives us an idea of the most popular playlists in the data and how their stream counts compare to the other playlists in our dataset.

[96]:
```
# Keep a copy of original data in case of changes made to dataframe
all_artists = data.copy()

# Load laylist data
playlist_ids_and_titles = pd.read_csv('DATA/playlists_ids_and_titles.
↪csv',encoding = 'latin-1',error_bad_lines=False,warn_bad_lines=False)

# Keep only those with 22 characters (data cleaning)
playlist_mapper = playlist_ids_and_titles[playlist_ids_and_titles.id.str.
↪len()==22].drop_duplicates(['id'])
```

[97]:
```
def plot_cluster(t,figsize=None):
    cg = sns.clustermap(t,figsize=(7, 5),cmap="mako")
    plt.setp(cg.ax_heatmap.yaxis.get_majorticklabels(), rotation=0)
#     plt.axes().set_title('ClusterMap')
    return cg

df = df_music.copy()
df['playlist_name'] = df.stream_source_uri.astype(str).str[-22:].
↪map(playlist_mapper.set_index('id')['name'])
filter_playlists = df.stream_source_uri.value_counts().head(30).keys().tolist()
t = df[df.stream_source_uri.isin(filter_playlists)]
t = t.groupby(['playlist_name','hour']).size().unstack().fillna(0)
plot_cluster(t)
plt.show()
```



2.13 —-

3 Data Preperation and Feature Engineering

From our business understanding, we know that our criteria for success is whether or not an artist has been on one of 4 key playlists. The column 'stream_source_uri', contains data about the source of the stream – whether it was from an artist's page, an album, a playlist etc.

For streams coming from different playlists, only the Spotify URI code is provided. To make sense of this column and identify our key playlists, we can use the additional table provided that we cleaned above and named 'playlist_mapper'.

We can being by out data preperation by subsetting the 4 key playlists we are interested in and creating our dependent variable:

3.0.1 Dependent Variable

[98]:
```
#create dependent variable
#set up the problem as one of classification, selecting the relevant playlists␣
↪as the variable we are trying to model

#define 4 key playlists
keyplaylists = ['Hot Hits UK','Massive Dance Hits','The Indie List','New Music␣
↪Friday']

#define dependent variable and assign values
df_music['success'] = 0
df_music.success[df_music['playlist_name'].isin(keyplaylists)] = 1
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:9:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[99]:
```
#(example) test to ensure that 'success' was assigned
df_music[df_music['success']==1].head(3)
```

[99]:
```
       Unnamed: 0  Unnamed: 0.1                        Unnamed: 0.1.1  day  \
3727          633          6339  ('small_artists_2016.csv', 6339)   10
52862     2831656      28316569       ('matoma_early.csv', 233444)   10
52870     2831664      28316649       ('matoma_early.csv', 233524)   10

                 log_time  mobile                          track_id  \
3727   20160410T12:45:00   False  db62b1d507bc4fd1bc8b4785d82d6356
52862  20160810T15:00:00    True  ef017af7dc9b4c59802fa54458988ac4
52870  20160810T09:45:00    True  ef017af7dc9b4c59802fa54458988ac4

               isrc           upc   artist_name  … danceability  \
3727   USAT21601204  7.567991e+10  VINYL ON HBO  …        0.000
52862  GBAYE1601052  1.902959e+11        MATOMA  …        0.592
52870  GBAYE1601052  1.902959e+11        MATOMA  …        0.592

      acousticness  valence user_age buffer new artist_code   age age_bin  \
3727         0.795    0.000     24.0      1 NaN          21  24.0     20s
52862        0.172    0.424     25.0      1 NaN         167  25.0     20s
52870        0.172    0.424     25.0      1 NaN         167  25.0     20s

      success
3727        1
52862       1
```

```
52870        1

[3 rows x 55 columns]
```

[100]:
```
#successful artists
def get_successful_artists(data):
    result = data[data['success']==1].groupby('artist_name').count()
    result.success = 1
    result = pd.DataFrame(result['success'])
    result = result.rename(columns = {'success': 'artist_success'})
    return result
```

[101]:
```
#test function
get_successful_artists(df_music).shape
```

[101]:
```
(82, 1)
```

[102]:
```
#combine success attributes into one dataframe for merging of features later on
df_success_combined = get_successful_artists(df_music)
df_success_combined = df_success_combined.fillna(0)
df_success_combined.head(10)
```

[102]:
```
                        artist_success
artist_name
A BOOGIE WIT DA HOODIE               1
A R I Z O N A                        1
ABSOFACTO                            1
ALL TVVINS                           1
AMIR                                 1
ANNE-MARIE                           1
ARMAN CEKIN                          1
AXSHN                                1
BASIC TAPE                           1
BETSY                                1
```

Now that we have created our dependent variable – whether an artist is successful or not, we can look at generating a set of features, based on the columns within our dataset, that we think might best explain the reasons for this success.

3.0.2 Feature Engineering

There are a large number of factors that could have an impact on the success of an artist, such as the influence of a playlist, or the popularity of an artist in a certain geographical region. To build a predictive model for this problem, we first need to turn these (largely qualitative) factors into measurable quantities. Characteristics like 'influence' and 'popularity' need to be quantified and standardized for all artists, to allow for a fair comparison. The accurateness of these numerical estimates will be the fundamental driver of success for any model we build. There are many approaches one might take to generate features. Based on the data columns available to us, a sensible approach is to divide our feature set into three groups:

1. Artist Features
2. Playlist Features
3. User Features

Description: The following code-blocks focus on generating useful functions to determine artist features. In order to get a sense of the number of successful artists we start by looking at the number of (unique) successful artists applying the function defined beforehand.

[103]:
```
#number of successful artists
len(get_successful_artists(df_music))
```

[103]:
```
82
```

(1)

3.1 Artist Feature

Feature Engineering

The following artist features have been created: - Streams per Artist 2. User Count per Artist 3. Artist Passion Score 4. Artist Danceability 5. Artist Acousticness 6. Artist Valance 7. Artists avg. Streamlength 8. Artists Number of Tracks 9. Artists Number of Albums 10. Artists Playlist Count

3.1.1 1.1. Streams per Artist

[104]:
```
#define function for stream count per artist
def stream_per_artist_count(data):
    res = data[data['success']==1]
    res = res.groupby('artist_name').count()
    return res['success']
```

Description: In order to verify each function we tested each function. This appraoch will be seen troughout the notebook.

[105]:
```
#test function
stream_per_artist_count(df_music).sum(), stream_per_artist_count(df_music).shape
```

[105]:
```
(202779, (82,))
```

[106]:
```
#pd.DataFrame(stream_per_artist_count(df_music)).
 ↪sort_values(by='success',ascending=False)
```

[107]:
```
#define function for stream count per artist

#female
```

```
def stream_per_artist_count_female(data):
    res = data[(data['success']==1) & (data['gender']=='female')]
    res = res.groupby('artist_name').count()
    return res['success']
```

[108]:
```
#test function
stream_per_artist_count_female(df_music).sum(),␣
 ↪stream_per_artist_count_female(df_music).shape
```

[108]: (119588, (67,))

[109]:
```
#define function for stream count per artist

#male
def stream_per_artist_count_male(data):
    res = data[(data['success']==1) & (data['gender']=='male')]
    res = res.groupby('artist_name').count()
    return res['success']
```

[110]:
```
#test function
stream_per_artist_count_male(df_music).sum(),␣
 ↪stream_per_artist_count_male(df_music).shape
```

[110]: (81052, (70,))

3.1.2 1.2. User Count per Artist

[111]:
```
#number of unique users
df_music['customer_id'].nunique()
```

[111]: 2091144

[112]:
```
#define function for (unique) user count per artist

#general
def user_per_artist_count(data):
    res = data[data['success']==1]
    res = res.groupby('artist_name').customer_id.nunique()
    return res
```

[113]:
```
#test function
user_per_artist_count(df_music).shape
```

[113]: (82,)

[114]:
```
#define function for (unique) user count per artist

#female
def user_per_artist_count_female(data):
    res = data[(data['success']==1) & (data['gender']=='female')]
    res = res.groupby('artist_name').customer_id.nunique()
    return res

#male
def user_per_artist_count_male(data):
    res = data[(data['success']==1) & (data['gender']=='male')]
    res = res.groupby('artist_name').customer_id.nunique()
    return res
```

[115]:
```
#test function
user_per_artist_count_female(df_music).sum(),␣
↪user_per_artist_count_male(df_music).shape
```

[115]:
```
(114628, (70,))
```

3.1.3 1.3. Artist Passion Score

[116]:
```
#passion score (number of stream divided by the total number of users)
def passion_score(data):
    return stream_per_artist_count(data)/user_per_artist_count(data)

def passion_score_female(data):
    return stream_per_artist_count_female(data)/
↪user_per_artist_count_female(data)

def passion_score_male(data):
    return stream_per_artist_count_male(data)/user_per_artist_count_male(data)
```

3.1.4 1.4. Artist Danceability

[117]:
```
#average danceability per artist
def danceability_per_artist_avg(data):
    data = data.groupby('artist_name')[['danceability']].mean()
    return data
```

[118]:
```
df_danceability = danceability_per_artist_avg(df_music)
df_danceability = df_danceability.set_axis(['artist_danceability'], axis=1,␣
↪inplace=False)
df_danceability.head()
```

[118]:
```
              artist_danceability
artist_name
#90S UPDATE                0.6430
17 MEMPHIS                 0.3890
2D                         0.4910
3JS                        0.6534
99 PERCENT                 0.3610
```

3.1.5 1.5. Artist Acousticness

[119]:
```
#average acousticness per artist
def acousticness_per_artist_avg(data):
    data = data.groupby('artist_name')[['acousticness']].mean()
    return data
```

[120]:
```
df_acousticness = acousticness_per_artist_avg(df_music)
df_acousticness = df_acousticness.set_axis(['artist_acousticness'], axis=1,␣
↪inplace=False)
df_acousticness.head()
```

[120]:
```
              artist_acousticness
artist_name
#90S UPDATE              0.015300
17 MEMPHIS               0.001930
2D                       0.258000
3JS                      0.431128
99 PERCENT               0.879000
```

3.1.6 1.6. Artist Valence

Valence describes the musical positiveness conveyed by a track. Tracks with high valence sound more positive (happy, cheerful, euphoric), while tracks with low valence sound more negative (sad, depressed, angry). SOURCE: https://developer.spotify.com/documentation/web-api/reference/tracks/get-several-audio-features/

[121]:
```
#average valence per artist
def valence_per_artist_avg(data):
```

```
    data = data.groupby('artist_name')[['valence']].mean()
    return data
```

[122]:
```
df_valence = valence_per_artist_avg(df_music)
df_valence = df_valence.set_axis(['artist_valence'], axis=1, inplace=False)
df_valence.head()
```

[122]:
```
                 artist_valence
artist_name
#90S UPDATE              0.0983
17 MEMPHIS               0.6770
2D                       0.9590
3JS                      0.4768
99 PERCENT               0.1280
```

3.1.7 1.7. Artists avg. Streamlength

[123]:
```
#average stream length per artist
def streamlength_per_artist_avg(data):
    data = data.groupby('artist_name')[['stream_length']].mean()
    return data
```

[124]:
```
#test function
df_streamlength = streamlength_per_artist_avg(df_music)
df_streamlength = df_streamlength.set_axis(['artist_stream_length'], axis=1,␣
 ↪inplace=False)
df_streamlength.head()
```

[124]:
```
                 artist_stream_length
artist_name
#90S UPDATE                 133.68750
17 MEMPHIS                  177.25000
2D                           81.00000
3JS                         234.00000
99 PERCENT                  154.10457
```

3.1.8 1.8. Artists Number of Tracks

[125]:
```
#number of tracks per artist
def tracks_per_artist_count(data):
    data = data.groupby('artist_name')[['track_name']].nunique()
```

```
    return data
```

[126]:
```
#test function
df_artist_tracks = tracks_per_artist_count(df_music)
df_artist_tracks = df_artist_tracks.set_axis(['artist_track_count'], axis=1,␣
↪inplace=False)
df_artist_tracks.head()
```

[126]:
```
                 artist_track_count
artist_name
#90S UPDATE                       1
17 MEMPHIS                        1
2D                                1
3JS                               4
99 PERCENT                        2
```

3.1.9 1.9. Artists Number of Albums

[127]:
```
#number of albums per artist
def albums_per_artist_count(data):
    #data = data[data['success']==1]
    data = data.groupby('artist_name')[['album_name']].nunique()
    return data
```

[128]:
```
#test function
df_artist_albums = albums_per_artist_count(df_music)
df_artist_albums = df_artist_albums.set_axis(['artist_album_count'], axis=1,␣
↪inplace=False)
df_artist_albums.head()
```

[128]:
```
                 artist_album_count
artist_name
#90S UPDATE                       1
17 MEMPHIS                        1
2D                                1
3JS                               2
99 PERCENT                        2
```

3.1.10 1.10. Artists Playlist Count

[129]:
```
df_artist_playlist_count = pd.DataFrame(df_music.
 ↪groupby('artist_name')['playlist_name'].value_counts())
df_artist_playlist_count = df_artist_playlist_count.reset_index(level=1,␣
 ↪drop=True).reset_index().groupby('artist_name').count()
df_artist_playlist_count = df_artist_playlist_count.
 ↪rename(columns={"playlist_name":'artist_count_playlist'})
```

[130]:
```
df_artist_playlist_count.head()
```

[130]:
```
                        artist_count_playlist
artist_name
#90S UPDATE                                 2
17 MEMPHIS                                  1
99 PERCENT                                 18
A BOOGIE WIT DA HOODIE                    148
A R I Z O N A                             347
```

3.1.11 Combining Artists Features

[131]:
```
#dataframe merging for above functions

#for artist stream count
df_stream_count = pd.concat([stream_per_artist_count(df_music),␣
 ↪stream_per_artist_count_female(df_music),
                               stream_per_artist_count_male(df_music)],axis=1,␣
 ↪sort=False)
df_stream_count = df_stream_count.fillna(0)
df_stream_count = df_stream_count.set_axis(['artist_stream_count_general',
                                            'artist_stream_count_female',
                                            'artist_stream_count_male'],␣
 ↪axis=1, inplace=False)

#for artist user count
df_user_count = pd.concat([user_per_artist_count(df_music),␣
 ↪user_per_artist_count_female(df_music),
                           user_per_artist_count_male(df_music)],axis=1,␣
 ↪sort=False)
df_user_count = df_user_count.fillna(0)
df_user_count = df_user_count.set_axis(['artist_user_count_general',
                                        'artist_user_count_female',
                                        'artist_user_count_male'], axis=1,␣
 ↪inplace=False)
```

```
#for artist passion score
df_passion_score = pd.concat([passion_score(df_music),␣
↪passion_score_female(df_music),
                              passion_score_male(df_music)],axis=1, sort=False)
df_passion_score = df_passion_score.fillna(1)
df_passion_score = df_passion_score.set_axis(['artist_passion_score_general',
                                              'artist_passion_score_female',
                                              'artist_passion_score_male'],␣
↪axis=1, inplace=False)
```

[132]:
```
#combine artist features into one dataframe for merging of features later on
df_artist_combined = pd.concat([df_stream_count,df_user_count,df_passion_score,
                                df_streamlength, df_artist_tracks,␣
↪df_artist_albums,
                                df_danceability, df_acousticness, df_valence,
                                df_artist_playlist_count],axis=1, sort=False)
df_artist_combined.head(5)
```

[132]:
```
                        artist_stream_count_general  \
A BOOGIE WIT DA HOODIE                          1.0
A R I Z O N A                                 937.0
ABSOFACTO                                       1.0
ALL TVVINS                                      4.0
AMIR                                            1.0

                        artist_stream_count_female  artist_stream_count_male  \
A BOOGIE WIT DA HOODIE                         1.0                       0.0
A R I Z O N A                                344.0                     588.0
ABSOFACTO                                      1.0                       0.0
ALL TVVINS                                     1.0                       3.0
AMIR                                           0.0                       1.0

                        artist_user_count_general  artist_user_count_female  \
A BOOGIE WIT DA HOODIE                        1.0                       1.0
A R I Z O N A                               926.0                     340.0
ABSOFACTO                                     1.0                       1.0
ALL TVVINS                                    4.0                       1.0
AMIR                                          1.0                       0.0

                        artist_user_count_male  artist_passion_score_general  \
A BOOGIE WIT DA HOODIE                     0.0                      1.000000
A R I Z O N A                            581.0                      1.011879
ABSOFACTO                                  0.0                      1.000000
ALL TVVINS                                 3.0                      1.000000
AMIR                                       1.0                      1.000000
```

```
                         artist_passion_score_female  \
A BOOGIE WIT DA HOODIE                      1.000000
A R I Z O N A                               1.011765
ABSOFACTO                                   1.000000
ALL TVVINS                                  1.000000
AMIR                                        1.000000

                         artist_passion_score_male  artist_stream_length  \
A BOOGIE WIT DA HOODIE                    1.000000            163.245813
A R I Z O N A                             1.012048            189.223565
ABSOFACTO                                 1.000000            193.956522
ALL TVVINS                                1.000000            195.473674
AMIR                                      1.000000            187.587127

                         artist_track_count  artist_album_count  \
A BOOGIE WIT DA HOODIE                   20                   8
A R I Z O N A                            33                  13
ABSOFACTO                                 2                   2
ALL TVVINS                               15                   7
AMIR                                     22                   7

                         artist_danceability  artist_acousticness  \
A BOOGIE WIT DA HOODIE              0.638510             0.052206
A R I Z O N A                       0.676498             0.326743
ABSOFACTO                           0.376841             0.910188
ALL TVVINS                          0.639840             0.220745
AMIR                                0.573425             0.091298

                         artist_valence  artist_count_playlist
A BOOGIE WIT DA HOODIE         0.540364                  148.0
A R I Z O N A                  0.404002                  347.0
ABSOFACTO                      0.251232                    6.0
ALL TVVINS                     0.399729                   79.0
AMIR                           0.510780                   39.0
```

---

(2)

3.2 Playlist Feature

Feature Engineering

The following playlist features have been created: - Average Stream Count per Playlist - Average Number of Users per Playlist - Average Playlist Passion Score

Description: Understanding an artist's growth as a function of his/her movement across different playlists is potentially key to understanding how to identify and breakout new artists on Spotify.

Given that we have over 19,000 playlists in our dataset or 600 artists, using the playlists each artist has featured on, as categorical variables would lead to too many features and a very large, sparse matrix. Instead, we need to think of ways to summarize the impact of these playlists. We decided to take a closer look at the top 20 playlists as defined below.

3.2.1 2.1 Average Stream Count per Playlist

[133]:
```
#define list of top 20 overall playlists measured by stream counts
list_abs_top20 = dict(df_music['playlist_name'].value_counts().nlargest(20))
list_female_top20 = dict(df_music.playlist_name[df_music['gender']=='female'].
 ↪value_counts().nlargest(20))
list_male_top20 = dict(df_music.playlist_name[df_music['gender']=='male'].
 ↪value_counts().nlargest(20))
```

[134]:
```
#average stream counts in top 20 playlists by artist

#define function
def playlist_avg_stream_counts(data, liste):
    #create new column indicating if stream is in top 20 playlist
    data['top20_playlist'] = 0
    data.top20_playlist[data['playlist_name'].isin(liste)] = 1

    #cut dataframe to top 20 playlist
    data = data[data['top20_playlist']==1]

    #generate output by grouping along artists and number of streams (divided␣
 ↪by #of playlists)
    data = data.groupby(['artist_name'])[['top20_playlist']].count()/20
    data = data.rename(columns = {'top20_playlist': 'score'})

    return data
```

[135]:
```
#test function
playlist_avg_stream_counts(df_music, list_abs_top20).head()
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[135]:
```
                        score
artist_name
A BOOGIE WIT DA HOODIE  156.60
A R I Z O N A           733.85
ALL TVVINS                3.35
```

```
AMIR                          0.05
ANNABEL JONES                 6.50
```

3.2.2 2.2 Average Number of Users per Playlist

[136]:
```
#average user count in top 20 playlists by artist

#define function
def playlist_avg_number_of_users(data, liste):
    #create new column indicating if stream is in top 20 playlist
    data['top20_playlist'] = 0
    data.top20_playlist[data['playlist_name'].isin(liste)] = 1

    #cut dataframe to top 20 playlist
    data = data[data['top20_playlist']==1]

    #generate output by grouping along artists and filter for unique customer␣
↪ids (divided by #of playlists)
    data = pd.DataFrame(data.groupby(['artist_name']).customer_id.nunique()/20)
    data = data.rename(columns = {'customer_id': 'score'})

    return data
```

[137]:
```
#test function
playlist_avg_number_of_users(df_music, list_abs_top20).head()
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[137]:

artist_name	score
A BOOGIE WIT DA HOODIE	147.55
A R I Z O N A	707.45
ALL TVVINS	3.25
AMIR	0.05
ANNABEL JONES	5.90

3.2.3 2.3 Average Playlist Passion Score

[138]:
```
#def playlist_avg_passion_score(data)

#define function
def playlist_avg_passion_score(data, liste):
    return playlist_avg_stream_counts(data, liste)/
 ↪playlist_avg_number_of_users(data, liste)
```

[139]:
```
#test function
playlist_avg_passion_score(df_music, list_abs_top20).head()
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[139]:
```
                          score
artist_name
A BOOGIE WIT DA HOODIE  1.061335
A R I Z O N A           1.037317
ALL TVVINS              1.030769
AMIR                    1.000000
ANNABEL JONES           1.101695
```

3.2.4 Combining Artists Features

[140]:
```
#dataframe merging for above functions

#for playlist stream count
df_playlist_stream_count = pd.concat([playlist_avg_stream_counts(df_music,␣
 ↪list_abs_top20),
                                      playlist_avg_stream_counts(df_music,␣
 ↪list_female_top20),
                                      playlist_avg_stream_counts(df_music,␣
 ↪list_male_top20)],axis=1, sort=False)
df_playlist_stream_count = df_playlist_stream_count.fillna(0)
df_playlist_stream_count = df_playlist_stream_count.
 ↪set_axis(['playlist_stream_count_general',
                                                                    ␣
 ↪'playlist_stream_count_female',
```

```
↪'playlist_stream_count_male'], axis=1, inplace=False)

#for playlist user count
df_playlist_user_count = pd.concat([playlist_avg_number_of_users(df_music,␣
↪list_abs_top20),
                                   playlist_avg_number_of_users(df_music,␣
↪list_female_top20),
                                   playlist_avg_number_of_users(df_music,␣
↪list_male_top20)],axis=1, sort=False)
df_playlist_user_count = df_playlist_user_count.fillna(0)
df_playlist_user_count = df_playlist_user_count.
↪set_axis(['playlist_user_count_general',
                                                                         ␣
↪'playlist_user_count_female',
                                                                         ␣
↪'playlist_user_count_male'], axis=1, inplace=False)

#for playlist passion score
df_playlist_passion_score = pd.concat([playlist_avg_passion_score(df_music,␣
↪list_abs_top20),
                                       playlist_avg_passion_score(df_music,␣
↪list_female_top20),
                                       playlist_avg_passion_score(df_music,␣
↪list_male_top20)],axis=1, sort=False)
df_playlist_passion_score = df_playlist_passion_score.fillna(1)
df_playlist_passion_score = df_playlist_passion_score.
↪set_axis(['playlist_passion_score_general',
                                                                               ␣
↪'playlist_passion_score_female',
                                                                               ␣
↪'playlist_passion_score_male'], axis=1, inplace=False)
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[141]:
```
#combine artist features into one dataframe for merging of features later on
df_playlist_combined = pd.concat([df_playlist_stream_count,
                                  df_playlist_user_count,
                                  df_playlist_passion_score],axis=1, sort=False)
df_playlist_combined.head()
```

[141]:

```
                          playlist_stream_count_general  \
A BOOGIE WIT DA HOODIE                           156.60
A R I Z O N A                                    733.85
ALL TVVINS                                         3.35
AMIR                                               0.05
ANNABEL JONES                                      6.50

                          playlist_stream_count_female  \
A BOOGIE WIT DA HOODIE                            0.10
A R I Z O N A                                   734.10
ALL TVVINS                                        3.35
AMIR                                              0.05
ANNABEL JONES                                     6.50

                          playlist_stream_count_male  \
A BOOGIE WIT DA HOODIE                        156.65
A R I Z O N A                                 684.55
ALL TVVINS                                      3.40
AMIR                                            0.05
ANNABEL JONES                                   6.50

                          playlist_user_count_general  \
A BOOGIE WIT DA HOODIE                         147.55
A R I Z O N A                                  707.45
ALL TVVINS                                       3.25
AMIR                                             0.05
ANNABEL JONES                                    5.90

                          playlist_user_count_female  playlist_user_count_male  \
A BOOGIE WIT DA HOODIE                          0.10                    147.60
A R I Z O N A                                 707.65                    659.90
ALL TVVINS                                      3.25                      3.30
AMIR                                            0.05                      0.05
ANNABEL JONES                                   5.90                      5.90

                          playlist_passion_score_general  \
A BOOGIE WIT DA HOODIE                          1.061335
A R I Z O N A                                   1.037317
ALL TVVINS                                      1.030769
AMIR                                            1.000000
ANNABEL JONES                                   1.101695

                          playlist_passion_score_female  \
A BOOGIE WIT DA HOODIE                         1.000000
A R I Z O N A                                  1.037377
ALL TVVINS                                     1.030769
AMIR                                           1.000000
```

```
ANNABEL JONES                                 1.101695

                        playlist_passion_score_male
A BOOGIE WIT DA HOODIE                    1.061314
A R I Z O N A                             1.037354
ALL TVVINS                                1.030303
AMIR                                      1.000000
ANNABEL JONES                             1.101695
```

(3)

3.3 User-base Feature

Feature Engineering

The following playlist features have been created: - User Gender Breakdown - User Age Breakdown - PCA Features

3.3.1 3.1 User Gender Breakdown

[142]:
```
#gender breakdown

#define function for gender breakdown
def gender_breakdown(data):
    dummies = pd.get_dummies(data['gender'],prefix='gender')
    df_gender = pd.concat([data,dummies],axis=1)
    result = pd.crosstab(df_gender['artist_name'],df_gender['gender']).
↪apply(lambda r: (r/r.sum()), axis=1)
    return result
```

[143]:
```
#test function
gender_breakdown(df_music)
```

[143]:

gender artist_name	female	male
#90S UPDATE	0.437500	0.562500
17 MEMPHIS	0.666667	0.333333
2D	0.000000	1.000000
3JS	0.200000	0.800000
99 PERCENT	0.677926	0.322074
…	…	…
ZAK ABEL	0.530072	0.469928
ZAKOPOWER	0.000000	1.000000
ZARCORT	0.200000	0.800000
ZBIGNIEW KURTYCZ	0.000000	1.000000
ZION & LENNOX	0.537685	0.462315

```
[638 rows x 2 columns]
```

[144]:
```
#dataframe for combining into single dataframe at the end
df_gender = gender_breakdown(df_music)
```

3.3.2 3.2 User Age Breakdown

[145]:
```
#age breakdown

#define sub-dataframe
df_age = df_music

#set age as year (of stream) minus birth year
df_age['age_mean'] = round(df_age['year'] - df_age['birth_year'], 0)

#calculate average user age per artist
df_age = df_age.groupby('artist_name').mean()
df_age = pd.DataFrame(df_age['age_mean'])
df_age.head(5)
```

[145]:
```
              age_mean
artist_name
#90S UPDATE  29.250000
17 MEMPHIS   25.750000
2D           14.000000
3JS          36.200000
99 PERCENT   23.825545
```

Description: In order to gain more insights from the age analysis, we continued by generating age bin and the respective percentage of users in each bin.

[146]:
```
#age breakdown (in age bins)

#define function for age bin breakdown
def age_breakdown(data):
    #again, define actual age using 'year' and 'birth-year'
    data['age'] = round(data['year'] - data['birth_year'], 0)

    #add 'age_bin' column to the dataframe with labels for each bin
    data["age_bin"] = pd.cut(x=data["age"], bins=[0, 20, 30, 40, 50, 60, 70,␣
↪80, 90, 100, 1000],
                             labels=['<20','20s', '30s', '40s', '50s', '60s',␣
↪'70s', '80s', '90s', '>100'])

    #generate the output by creating a matrix
```

```
    result = pd.DataFrame(pd.crosstab(data['artist_name'],data['age_bin']).
↪apply(lambda r: (r/r.sum())*100, axis=1))

    return result
```

[147]:
```
#test function
age_breakdown(df_music)
```

[147]:
```
age_bin                   <20        20s         30s        40s       50s  \
artist_name
#90S UPDATE          6.250000  50.000000   37.500000   6.250000  0.000000
17 MEMPHIS          16.666667  75.000000    0.000000   0.000000  8.333333
2D                 100.000000   0.000000    0.000000   0.000000  0.000000
3JS                  0.000000  40.000000    0.000000  60.000000  0.000000
99 PERCENT          52.881620  29.517134    6.464174   8.255452  2.336449
…                         …         …          …         …         …
ZAK ABEL            22.337537  51.426552   15.098761   6.989547  3.340401
ZAKOPOWER            0.000000   0.000000  100.000000   0.000000  0.000000
ZARCORT             24.000000  44.000000   24.000000   4.000000  4.000000
ZBIGNIEW KURTYCZ     0.000000   0.000000  100.000000   0.000000  0.000000
ZION & LENNOX       16.378424  59.848556   16.191456   4.870524  1.785547

age_bin                 60s       70s       80s       90s      >100
artist_name
#90S UPDATE        0.000000  0.000000  0.000000  0.000000  0.000000
17 MEMPHIS         0.000000  0.000000  0.000000  0.000000  0.000000
2D                 0.000000  0.000000  0.000000  0.000000  0.000000
3JS                0.000000  0.000000  0.000000  0.000000  0.000000
99 PERCENT         0.155763  0.077882  0.077882  0.077882  0.155763
…                       …        …        …        …        …
ZAK ABEL           0.491017  0.055797  0.037198  0.029759  0.193431
ZAKOPOWER          0.000000  0.000000  0.000000  0.000000  0.000000
ZARCORT            0.000000  0.000000  0.000000  0.000000  0.000000
ZBIGNIEW KURTYCZ   0.000000  0.000000  0.000000  0.000000  0.000000
ZION & LENNOX      0.523511  0.046742  0.093484  0.074787  0.186968

[639 rows x 10 columns]
```

3.3.3 Combine initial User Features

[148]:
```
#generate inclusive age dataframe for combining into single dataframe at the end
df_age_combined = age_breakdown(df_music)
df_age_combined.columns = df_age_combined.columns.add_categories(['mean'])
df_age_combined['mean'] = df_age['age_mean']

#add prefix 'age' for easy identification
```

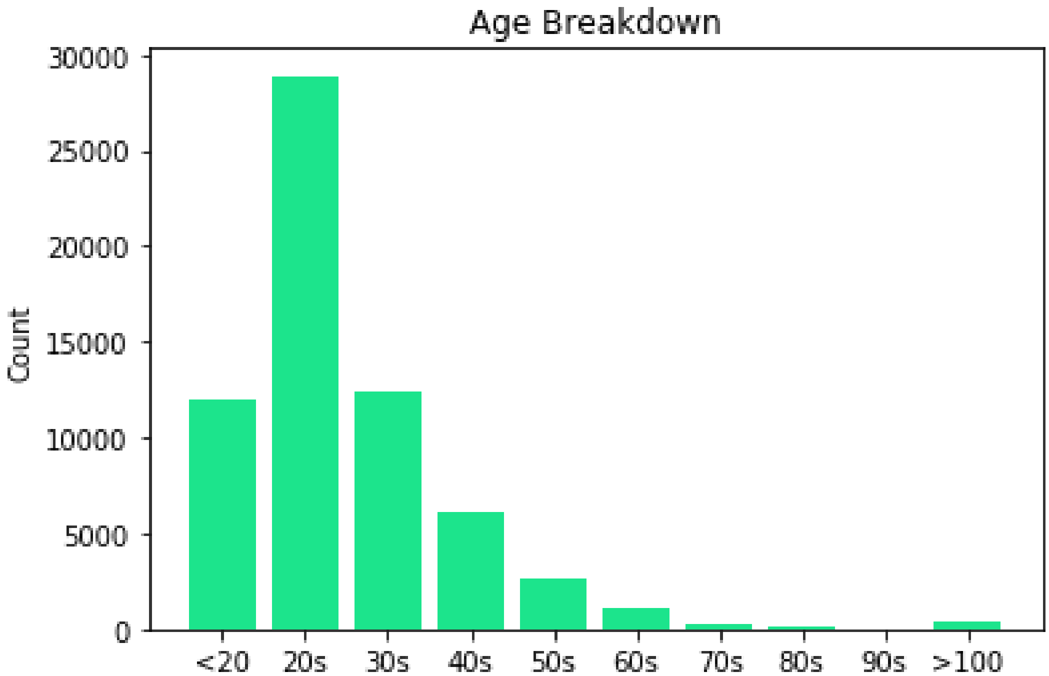
```
df_age_combined = df_age_combined.add_prefix('age_')
```

[149]:
```
#combine user features into one dataframe for merging of features later on
df_user_combined = df_age_combined
df_user_combined['gender_female_share'] = df_gender['female']
df_user_combined['gender_male_share'] = df_gender['male']

#showcase result w/ '.head()'
df_user_combined.head(3)
```

[149]:
```
age_bin         age_<20  age_20s  age_30s  age_40s   age_50s  age_60s  \
artist_name
#90S UPDATE    6.250000     50.0     37.5     6.25  0.000000      0.0
17 MEMPHIS    16.666667     75.0      0.0     0.00  8.333333      0.0
2D           100.000000      0.0      0.0     0.00  0.000000      0.0

age_bin      age_70s  age_80s  age_90s  age_>100  age_mean  \
artist_name
#90S UPDATE      0.0      0.0      0.0       0.0     29.25
17 MEMPHIS       0.0      0.0      0.0       0.0     25.75
2D               0.0      0.0      0.0       0.0     14.00

age_bin      gender_female_share  gender_male_share
artist_name
#90S UPDATE             0.437500           0.562500
17 MEMPHIS              0.666667           0.333333
2D                      0.000000           1.000000
```

Insights: To further add detail to the analysis, we continued by visualizing the age bins leveraging the previously defined function. As expected the peak of users is centered aroud '20s', with a rather young user base in general.

[150]:
```
#visualization of age bins

#generate new dataframe leveraging previously defined function
age_visual = age_breakdown(df_music)

#list of sums for each columns (or age bin)
age_visual_dict = dict(age_visual.sum())

#plot the above sums in bar chart
plt.bar(range(len(age_visual_dict)), list(age_visual_dict.values()),␣
 ↪align='center', color="#1CE48C")
plt.xticks(range(len(age_visual_dict)), list(age_visual_dict.keys()))
plt.title('Age Breakdown')
plt.ylabel("Count")
plt.show()
```



Principle Component Analysis

The data also contains a partial region code of the listener. We might want to consider including the regional breakdown of streams per artist as a feature of our model, to know if streams for certain regions are particularly influential on the future performance of an artist.

However, we have over 400 unique regions and like playlists, including them all would lead to too many features and a large sparse matrix. One way in which to extract relevant 'generalized' features of each region would be to incorporate census and demographic data, from publicly available datasets.

This is however beyond the scope of this courswork. Instead, a better way to summarize the impact of regional variation in streams is to use dimensionality reduction techniques. Here we will use Principle Component Analysis (PCA) to capture the regional variation in stream count.

PCA captures the majority of variation in the original feature set and represents it as a set of new orthogonal variables. Each 'component' of PCA is a linear combination of every feature, i.e. playlist in the dataset. Use `scikit-learn`'s PCA module (Pedregosa, et al., 2011) for generating PCA components.

For a comprehensive understanding of how sklearn's PCA module works, please refer to the sklearn documentation. We will using 10 components of PCA in our model.

Note: We could also apply a similar method to condense variation in stream across the 19,600 different playlists in our dataset.

3.3.4 3.3 PCA Features

[151]:
```
#import additional library
from sklearn import decomposition
from sklearn.preprocessing import StandardScaler
```

Description: The following code transformes the original dataframe into a matrix of artist names and region codes. This will allow us to start our dimension reduction on region codes.
Note: 'ACTION: PCA features' refers to features from region and artists, rather than the stated users.

[152]:
```
#generate dataframe matrix of artist names (y-axis) and region codes (x-axis)
df_pca = pd.crosstab(index=df_music['artist_name'], columns =␣
 ↪df_music['region_code'])
df_pca.head()
```

[152]:
```
region_code  0  500  501  502  504  505  506  508  510  511  …  SE-G  SE-H  \
artist_name                                                  …
#90S UPDATE  0    0    0    0    0    0    0    0    0    0  …     0     0
17 MEMPHIS   0    0    0    0    0    0    0    0    0    0  …     0     0
2D           0    0    0    0    0    0    0    0    0    0  …     0     0
3JS          0    0    0    0    0    0    0    0    0    0  …     0     0
99 PERCENT   0    0    0    0    0    0    0    0    0    0  …     0     0

region_code  SE-M  SE-N  SE-O  SE-S  SE-T  SE-W  SE-Y  SE-Z
artist_name
#90S UPDATE     0     0     0     0     0     0     0     0
17 MEMPHIS      0     0     0     0     0     0     0     0
2D              0     0     0     0     0     0     0     0
3JS             0     0     0     0     0     0     0     0
99 PERCENT      0     0     0     0     0     0     0     0

[5 rows x 514 columns]
```

[153]:
```
#standardize the features onto unit scale (mean = 0 and variance = 1) using␣
 ↪'StandardScaler()'
x = pd.DataFrame(StandardScaler().fit_transform(df_pca))
```

[154]:
```
#check whether the normalized data has a mean of zero and a standard deviation␣
 ↪of one
np.mean(x).mean(), np.std(x).mean()
```

[154]:
```
(-2.9798244323391765e-17, 1.000000000000001)
```

[155]:
```
#applies PCA to reduce the dimensionality of the dataset down to n=10 dimensions
pca_10 = decomposition.PCA(n_components=10)
```

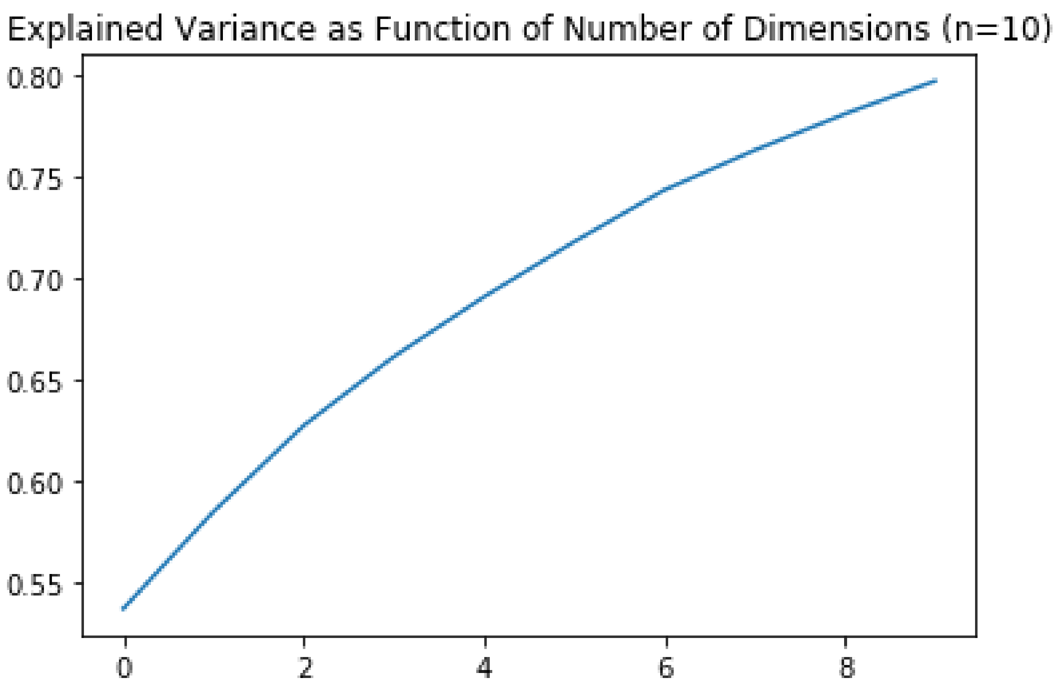
```
#fitting the PCA transformer to the dataframe
principalComponents = pca_10.fit_transform(x)

#project the original data to n=10 components
pca_regions_output_10 = pd.DataFrame(data = principalComponents, index = df_pca.
 ↪index)
```

[156]:
```
#calculate cummulative sum of explained variance
cumsum_10 = np.cumsum(pca_10.explained_variance_ratio_)
print(cumsum_10)
```

```
[0.5374452  0.58517171 0.6275547  0.66156358 0.69096755 0.71811673
 0.74363042 0.76324137 0.78105943 0.79724434]
```

[157]:
```
#explained variance as a function of the number of dimensions (n=10); note: no␣
 ↪'elbow' visible
plt.plot(cumsum_10)
plt.title('Explained Variance as Function of Number of Dimensions (n=10)')
```

[157]: `Text(0.5, 1.0, 'Explained Variance as Function of Number of Dimensions (n=10)')`



Check the PCA feature table to make sure the dataframe looks as expected. Comment on anything the looks important.

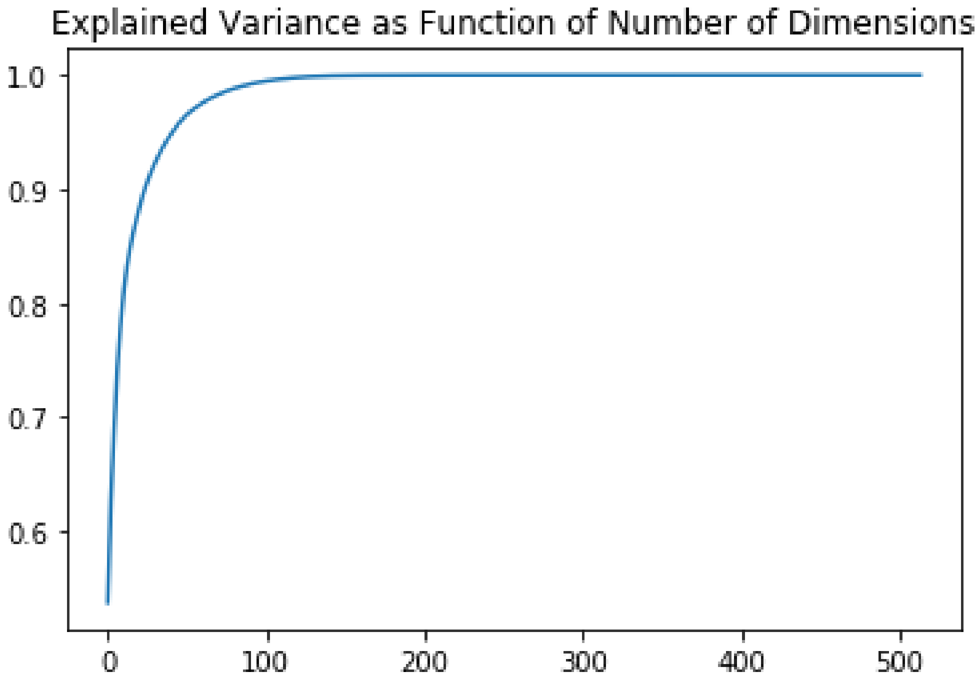
[158]:
```
#rename columns
pca_regions_output_10 = pca_regions_output_10.add_prefix('pca_')

#output dataframe dimension reduction ('pca_regions_output')
pca_regions_output_10.head(5)
```

[158]:
```
                pca_0     pca_1     pca_2     pca_3     pca_4     pca_5  \
artist_name
#90S UPDATE -3.043846  0.140668 -0.217304 -0.000919  0.116564 -0.081906
17 MEMPHIS  -3.042596  0.140827 -0.218421 -0.001649  0.115620 -0.082876
2D          -3.048887  0.141179 -0.216041 -0.000494  0.117797 -0.082681
3JS         -3.046863  0.140735 -0.216914 -0.000552  0.117404 -0.083273
99 PERCENT  -2.480358  0.083553 -0.439889 -0.089710 -0.010249 -0.061247

                pca_6     pca_7     pca_8     pca_9
artist_name
#90S UPDATE -0.217640 -0.003046  0.021729 -0.006441
17 MEMPHIS  -0.218215 -0.002824  0.020448 -0.007463
2D          -0.217613 -0.003185  0.021763 -0.006678
3JS         -0.217438 -0.003190  0.021561 -0.006822
99 PERCENT  -0.246259  0.031792 -0.039059 -0.040060
```

Insights: As we have seen above, applying n=10 yields in reasonable results. However, we are unable to draw conclusions about the 'elbow' of the curve. IN other words, we are not yet sure how many components to include to reach the optimal ration between '#components' and 'explained variance'. Therefore, we now plot showcasing all possible values of 'n_components'.

[159]:
```
#standardize the features onto unit scale (mean = 0 and variance = 1) using␣
↪'StandardScaler()'
x = pd.DataFrame(StandardScaler().fit_transform(df_pca))

#now, we do not specify a upper border for 'n_components'
pca_all = decomposition.PCA()

#fitting the PCA transformer to the dataframe
principalComponents = pca_all.fit_transform(x)

#project the original data onto new components
pca_regions_output = pd.DataFrame(data = principalComponents)

#calculate cumsum of variance
cumsum_all = np.cumsum(pca_all.explained_variance_ratio_)

#plot the cumsum
plt.plot(cumsum_all)
plt.title('Explained Variance as Function of Number of Dimensions')
```

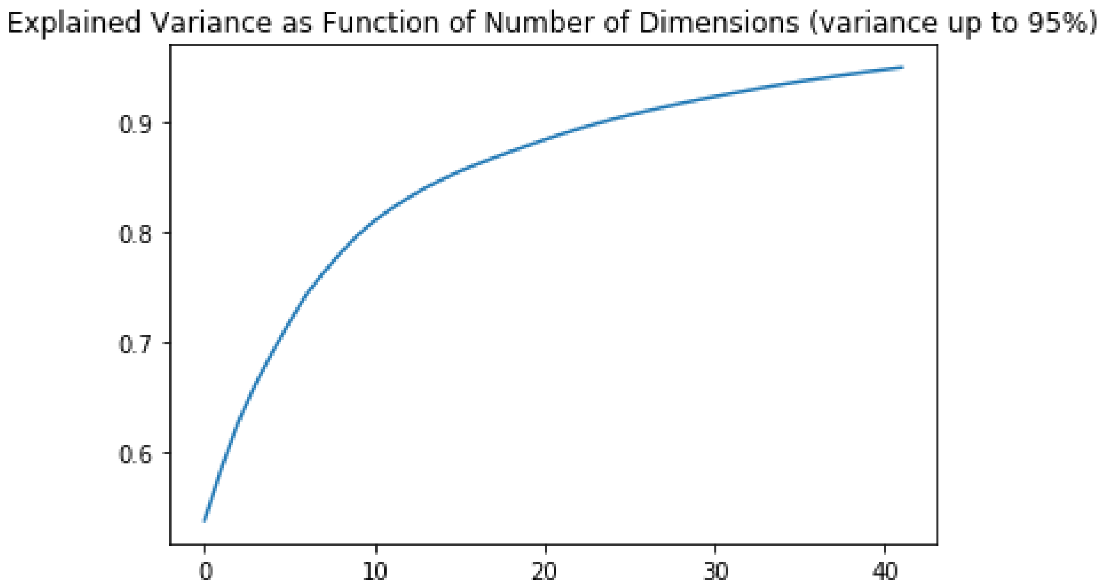
[159]: Text(0.5, 1.0, 'Explained Variance as Function of Number of Dimensions')



Insights: As one can notice there is a sharp 'elbpow' somewhere around n=50. Let's further investigate this by looking at the 95% explained variable in the following graph.

[160]:
```
#again, standardize the features onto unit scale (mean = 0 and variance = 1)␣
↪using 'StandardScaler()'
x = pd.DataFrame(StandardScaler().fit_transform(df_pca))

#specify the 95% variance for 'n_components'
pca_095 = decomposition.PCA(0.95)

#fitting the PCA transformer to the dataframe
principalComponents = pca_095.fit_transform(x)

#project the original data onto new components
pca_regions_output = pd.DataFrame(data = principalComponents)

#calculate cumsum of variance
cumsum_095 = np.cumsum(pca_095.explained_variance_ratio_)

#plot the cumsum
plt.plot(cumsum_095)
plt.title('Explained Variance as Function of Number of Dimensions (variance up␣
↪to 95%)')
```

[160]: Text(0.5, 1.0, 'Explained Variance as Function of Number of Dimensions (variance up to 95%)')



Insights: We can see that 95% of the variance can be explained with (roughly) n=40. Since, however, n=40 is quite a large number of components one has to make a decision on the aimed reduction. As previously shown and seen in the above graph n=10 is able to explain nearly 80% of variance (0.7972185) while the number of components is still reasonably low.

3.3.5 Data Transformation

The final step is to decide whether or not to normalize/transform any of the features.

We should normalize data if we are more interested in the relative rather than absolute differences between variables. Given that all the numerical features in our dataset (centrality, lift, influence, gender breakdown, age breakdown) were meaningful, i.e. distances did make a difference)

We will explore the following steps: 1. Feature Transformation 2. Preprocessing 3. Multi-Colinearity 4. Class Balance

Now we can combine all of our features that we generated above, into a dataframe that can be processed by a machine learning algorithm:

[161]:
```
#The following gives an overview of all previously defined dataframes which␣
↪will be merged into the final dataframe:
    #df_success_combined
    #df_artist_combined
    #df_playlist_combined
    #df_user_combined
```

```
    #pca_regions_output_10

df_success_combined.shape, df_artist_combined.shape, df_playlist_combined.
 ↪shape, df_user_combined.shape, pca_regions_output_10.shape
```

[161]: ((82, 1), (639, 16), (128, 9), (639, 13), (628, 10))

---

[162]:
```
#generate combined dataframe for all self defined features
df_combined = pd.concat([df_success_combined,df_artist_combined,
                          df_playlist_combined,df_user_combined,
                          pca_regions_output_10],axis=1, sort=False)
df_combined.columns
```

[162]:
```
Index(['artist_success', 'artist_stream_count_general',
       'artist_stream_count_female', 'artist_stream_count_male',
       'artist_user_count_general', 'artist_user_count_female',
       'artist_user_count_male', 'artist_passion_score_general',
       'artist_passion_score_female', 'artist_passion_score_male',
       'artist_stream_length', 'artist_track_count', 'artist_album_count',
       'artist_danceability', 'artist_acousticness', 'artist_valence',
       'artist_count_playlist', 'playlist_stream_count_general',
       'playlist_stream_count_female', 'playlist_stream_count_male',
       'playlist_user_count_general', 'playlist_user_count_female',
       'playlist_user_count_male', 'playlist_passion_score_general',
       'playlist_passion_score_female', 'playlist_passion_score_male',
       'age_<20', 'age_20s', 'age_30s', 'age_40s', 'age_50s', 'age_60s',
       'age_70s', 'age_80s', 'age_90s', 'age_>100', 'age_mean',
       'gender_female_share', 'gender_male_share', 'pca_0', 'pca_1', 'pca_2',
       'pca_3', 'pca_4', 'pca_5', 'pca_6', 'pca_7', 'pca_8', 'pca_9'],
      dtype='object')
```

[163]:
```
#generate csv file as working start for further analysis
df_combined.to_csv(r'final_pre_feature_transformation.csv',index=True)
```

[164]:
```
#re-load csv file; required due to limited sever capcity
df_combined = pd.read_csv('final_pre_feature_transformation.csv')
print('rows:',len(df_combined))
df_combined = df_combined.rename(columns={'Unnamed: 0':'artist_name'}).
 ↪set_index('artist_name')
```

```
rows: 639
```

(1)

3.4 Feature Transformation

Data Transformation

Description: As machine learning algorithms perform poorly if the numercial attributes have different scales, we need to transform features.

[165]:
```
#import further libraries
from sklearn.preprocessing import MinMaxScaler
from sklearn import preprocessing
from matplotlib.pyplot import figure
```

[166]:
```
#creating sub-dataframe for this task
df_scale_input = df_combined

#drop binary success factors as we have no interest in scaling them
df_scale_input = df_scale_input.drop(['artist_success'], axis=1)
df_scale_input.shape
```

[166]:
```
(639, 48)
```

Description: The MinMaxScaler scales and translates each feature individually such that it is in the given range on the dataset. In detail, it rescales the data set such that all feature values are in the range [0, 1]. One has to note that both StandardScaler & MinMaxScaler are very sensitive to the presence of outliers - however, our dataset appears to be suited for them.

[167]:
```
#apply min-max scaling method
scaler = preprocessing.MinMaxScaler()
scaled_df = scaler.fit_transform(df_scale_input)
scaled_df = pd.DataFrame(scaled_df, columns=df_scale_input.columns)
scaled_df = scaled_df.set_index(df_scale_input.index)
```

[168]:
```
#combining trnasformed values with binary indicators of success again
df_combined = pd.concat([df_success_combined,scaled_df], axis=1, sort=False)

#showcase initial output
df_combined.head()
```

[168]:
```
                        artist_success  artist_stream_count_general  \
A BOOGIE WIT DA HOODIE             1.0                     0.000000
A R I Z O N A                      1.0                     0.025296
ABSOFACTO                          1.0                     0.000000
ALL TVVINS                         1.0                     0.000081
AMIR                               1.0                     0.000000

                        artist_stream_count_female  artist_stream_count_male  \
A BOOGIE WIT DA HOODIE                    0.000046                  0.000000
A R I Z O N A                             0.015701                  0.040068
```

```
ABSOFACTO                                          0.000046                    0.000000
ALL TVVINS                                         0.000046                    0.000204
AMIR                                               0.000000                    0.000068

                        artist_user_count_general  artist_user_count_female  \
A BOOGIE WIT DA HOODIE                   0.000000                  0.000048
A R I Z O N A                            0.026456                  0.016398
ABSOFACTO                                0.000000                  0.000048
ALL TVVINS                               0.000086                  0.000048
AMIR                                     0.000000                  0.000000

                        artist_user_count_male  artist_passion_score_general  \
A BOOGIE WIT DA HOODIE                0.000000                      0.000000
A R I Z O N A                         0.041989                      0.137833
ABSOFACTO                             0.000000                      0.000000
ALL TVVINS                            0.000217                      0.000000
AMIR                                  0.000072                      0.000000

                        artist_passion_score_female  \
A BOOGIE WIT DA HOODIE                     0.000000
A R I Z O N A                              0.155234
ABSOFACTO                                  0.000000
ALL TVVINS                                 0.000000
AMIR                                       0.000000

                        artist_passion_score_male  …     pca_0     pca_1  \
A BOOGIE WIT DA HOODIE                   0.000000  …  0.057738  0.359824
A R I Z O N A                            0.114706  …  0.225731  0.348240
ABSOFACTO                                0.000000  …  0.000477  0.353765
ALL TVVINS                               0.000000  …  0.017327  0.351219
AMIR                                     0.000000  …  0.005723  0.352058

                           pca_2     pca_3     pca_4     pca_5     pca_6  \
A BOOGIE WIT DA HOODIE  0.450353  0.434261  0.313680  0.333464  0.388308
A R I Z O N A           0.593046  0.508063  0.637305  0.166161  0.788682
ABSOFACTO               0.362831  0.451610  0.382688  0.303450  0.413819
ALL TVVINS              0.354427  0.450127  0.374883  0.304513  0.411047
AMIR                    0.360971  0.453275  0.382373  0.303659  0.412796

                           pca_7     pca_8     pca_9
A BOOGIE WIT DA HOODIE  0.493920  0.491524  0.300189
A R I Z O N A           1.000000  0.000000  0.207787
ABSOFACTO               0.483222  0.401963  0.295637
ALL TVVINS              0.485614  0.397625  0.294896
AMIR                    0.483549  0.398285  0.291655

[5 rows x 49 columns]
```

[169]:
```
df_combined.columns
```

[169]:
```
Index(['artist_success', 'artist_stream_count_general',
       'artist_stream_count_female', 'artist_stream_count_male',
       'artist_user_count_general', 'artist_user_count_female',
       'artist_user_count_male', 'artist_passion_score_general',
       'artist_passion_score_female', 'artist_passion_score_male',
       'artist_stream_length', 'artist_track_count', 'artist_album_count',
       'artist_danceability', 'artist_acousticness', 'artist_valence',
       'artist_count_playlist', 'playlist_stream_count_general',
       'playlist_stream_count_female', 'playlist_stream_count_male',
       'playlist_user_count_general', 'playlist_user_count_female',
       'playlist_user_count_male', 'playlist_passion_score_general',
       'playlist_passion_score_female', 'playlist_passion_score_male',
       'age_<20', 'age_20s', 'age_30s', 'age_40s', 'age_50s', 'age_60s',
       'age_70s', 'age_80s', 'age_90s', 'age_>100', 'age_mean',
       'gender_female_share', 'gender_male_share', 'pca_0', 'pca_1', 'pca_2',
       'pca_3', 'pca_4', 'pca_5', 'pca_6', 'pca_7', 'pca_8', 'pca_9'],
      dtype='object')
```

(2)

3.5 Preprocessing

Data Transformation

Description: Before we can run any models on our dataset, we must make sure it is prepared and cleaned to avoid errors in results. This stage is generally refered to as preprocessing.

To begin with, we need to deal with missing data in the dataframe - the ML algorithm will not be able to process NaN or missing values.

For this study, we will be imputing missing numerical values, and filling any one which we were not able to imput, with 0.

[170]:
```
#import further libraries

from sklearn.impute import SimpleImputer
#from sklearn.preprocessing import Imputer
```

Description: We leverage the imputer to fill missing values. In detail, apllying 'constant' as a strategy for the missing values and the fill value of '0'. The result can be seen in the below table.

[171]:
```
#apply imputer to treat missing values
imp = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value= 0)
df_combined = pd.DataFrame(imp.fit_transform(df_combined), index = df_combined.
 ↪index, columns = df_combined.columns)
df_combined.head(5)
```

[171]:

```
                       artist_success  artist_stream_count_general  \
A BOOGIE WIT DA HOODIE             1.0                     0.000000
A R I Z O N A                      1.0                     0.025296
ABSOFACTO                          1.0                     0.000000
ALL TVVINS                         1.0                     0.000081
AMIR                               1.0                     0.000000

                       artist_stream_count_female  artist_stream_count_male  \
A BOOGIE WIT DA HOODIE                   0.000046                  0.000000
A R I Z O N A                            0.015701                  0.040068
ABSOFACTO                                0.000046                  0.000000
ALL TVVINS                               0.000046                  0.000204
AMIR                                     0.000000                  0.000068

                       artist_user_count_general  artist_user_count_female  \
A BOOGIE WIT DA HOODIE                  0.000000                  0.000048
A R I Z O N A                           0.026456                  0.016398
ABSOFACTO                               0.000000                  0.000048
ALL TVVINS                              0.000086                  0.000048
AMIR                                    0.000000                  0.000000

                       artist_user_count_male  artist_passion_score_general  \
A BOOGIE WIT DA HOODIE               0.000000                      0.000000
A R I Z O N A                        0.041989                      0.137833
ABSOFACTO                            0.000000                      0.000000
ALL TVVINS                           0.000217                      0.000000
AMIR                                 0.000072                      0.000000

                       artist_passion_score_female  \
A BOOGIE WIT DA HOODIE                    0.000000
A R I Z O N A                             0.155234
ABSOFACTO                                 0.000000
ALL TVVINS                                0.000000
AMIR                                      0.000000

                       artist_passion_score_male  …     pca_0     pca_1  \
A BOOGIE WIT DA HOODIE                  0.000000  …  0.057738  0.359824
A R I Z O N A                           0.114706  …  0.225731  0.348240
ABSOFACTO                               0.000000  …  0.000477  0.353765
ALL TVVINS                              0.000000  …  0.017327  0.351219
AMIR                                    0.000000  …  0.005723  0.352058

                          pca_2     pca_3     pca_4     pca_5     pca_6  \
A BOOGIE WIT DA HOODIE 0.450353  0.434261  0.313680  0.333464  0.388308
A R I Z O N A          0.593046  0.508063  0.637305  0.166161  0.788682
ABSOFACTO              0.362831  0.451610  0.382688  0.303450  0.413819
ALL TVVINS             0.354427  0.450127  0.374883  0.304513  0.411047
```

```
AMIR                     0.360971  0.453275  0.382373  0.303659  0.412796

                            pca_7     pca_8     pca_9
A BOOGIE WIT DA HOODIE   0.493920  0.491524  0.300189
A R I Z O N A            1.000000  0.000000  0.207787
ABSOFACTO                0.483222  0.401963  0.295637
ALL TVVINS               0.485614  0.397625  0.294896
AMIR                     0.483549  0.398285  0.291655

[5 rows x 49 columns]
```

[172]:

```python
df_combined.columns
```

[172]:

```
Index(['artist_success', 'artist_stream_count_general',
       'artist_stream_count_female', 'artist_stream_count_male',
       'artist_user_count_general', 'artist_user_count_female',
       'artist_user_count_male', 'artist_passion_score_general',
       'artist_passion_score_female', 'artist_passion_score_male',
       'artist_stream_length', 'artist_track_count', 'artist_album_count',
       'artist_danceability', 'artist_acousticness', 'artist_valence',
       'artist_count_playlist', 'playlist_stream_count_general',
       'playlist_stream_count_female', 'playlist_stream_count_male',
       'playlist_user_count_general', 'playlist_user_count_female',
       'playlist_user_count_male', 'playlist_passion_score_general',
       'playlist_passion_score_female', 'playlist_passion_score_male',
       'age_<20', 'age_20s', 'age_30s', 'age_40s', 'age_50s', 'age_60s',
       'age_70s', 'age_80s', 'age_90s', 'age_>100', 'age_mean',
       'gender_female_share', 'gender_male_share', 'pca_0', 'pca_1', 'pca_2',
       'pca_3', 'pca_4', 'pca_5', 'pca_6', 'pca_7', 'pca_8', 'pca_9'],
      dtype='object')
```

[173]:

```python
#test for 'nan'/missing values in the dataframe after applying imputer
np.isnan(df_combined)
```

[173]:

```
                        artist_success  artist_stream_count_general  \
A BOOGIE WIT DA HOODIE           False                        False
A R I Z O N A                    False                        False
ABSOFACTO                        False                        False
ALL TVVINS                       False                        False
AMIR                             False                        False
…                                  …                            …
ZAC BROWN                        False                        False
ZAK & DIEGO                      False                        False
ZAKOPOWER                        False                        False
ZARCORT                          False                        False
ZBIGNIEW KURTYCZ                 False                        False
```

```
                        artist_stream_count_female  artist_stream_count_male  \
A BOOGIE WIT DA HOODIE                       False                     False
A R I Z O N A                                False                     False
ABSOFACTO                                    False                     False
ALL TVVINS                                   False                     False
AMIR                                         False                     False
…                                            …                       …
ZAC BROWN                                    False                     False
ZAK & DIEGO                                  False                     False
ZAKOPOWER                                    False                     False
ZARCORT                                      False                     False
ZBIGNIEW KURTYCZ                             False                     False

                        artist_user_count_general  artist_user_count_female  \
A BOOGIE WIT DA HOODIE                      False                     False
A R I Z O N A                               False                     False
ABSOFACTO                                   False                     False
ALL TVVINS                                  False                     False
AMIR                                        False                     False
…                                           …                       …
ZAC BROWN                                   False                     False
ZAK & DIEGO                                 False                     False
ZAKOPOWER                                   False                     False
ZARCORT                                     False                     False
ZBIGNIEW KURTYCZ                            False                     False

                        artist_user_count_male  artist_passion_score_general  \
A BOOGIE WIT DA HOODIE                   False                         False
A R I Z O N A                            False                         False
ABSOFACTO                                False                         False
ALL TVVINS                               False                         False
AMIR                                     False                         False
…                                        …                           …
ZAC BROWN                                False                         False
ZAK & DIEGO                              False                         False
ZAKOPOWER                                False                         False
ZARCORT                                  False                         False
ZBIGNIEW KURTYCZ                         False                         False

                        artist_passion_score_female  \
A BOOGIE WIT DA HOODIE                        False
A R I Z O N A                                 False
ABSOFACTO                                     False
ALL TVVINS                                    False
AMIR                                          False
…                                             …
ZAC BROWN                                     False
```

```
ZAK & DIEGO                                        False
ZAKOPOWER                                          False
ZARCORT                                            False
ZBIGNIEW KURTYCZ                                   False

                        artist_passion_score_male  …  pca_0  pca_1  pca_2  \
A BOOGIE WIT DA HOODIE                      False  …  False  False  False
A R I Z O N A                               False  …  False  False  False
ABSOFACTO                                   False  …  False  False  False
ALL TVVINS                                  False  …  False  False  False
AMIR                                        False  …  False  False  False
…                                             …  …    …     …     …
ZAC BROWN                                   False  …  False  False  False
ZAK & DIEGO                                 False  …  False  False  False
ZAKOPOWER                                   False  …  False  False  False
ZARCORT                                     False  …  False  False  False
ZBIGNIEW KURTYCZ                            False  …  False  False  False

                        pca_3  pca_4  pca_5  pca_6  pca_7  pca_8  pca_9
A BOOGIE WIT DA HOODIE  False  False  False  False  False  False  False
A R I Z O N A           False  False  False  False  False  False  False
ABSOFACTO               False  False  False  False  False  False  False
ALL TVVINS              False  False  False  False  False  False  False
AMIR                    False  False  False  False  False  False  False
…                         …    …     …     …     …     …     …
ZAC BROWN               False  False  False  False  False  False  False
ZAK & DIEGO             False  False  False  False  False  False  False
ZAKOPOWER               False  False  False  False  False  False  False
ZARCORT                 False  False  False  False  False  False  False
ZBIGNIEW KURTYCZ        False  False  False  False  False  False  False

[639 rows x 49 columns]
```

Next, we need to make sure that none of the variables going into the model are collinear, and if so, we need to remove those variables that are highly correlated.

(3)

3.6 Multi-collinearity

Data Transformation

Description: Check and deal with multi-collinearity in your feature set. Let's start by looking at the correlation matrix of our final datafarme ('df_combined'). In order to draw conclusions we continue by visualizing the present multi-collinearity.

[174]:
```
#check for multicollinearity within in dataframe (showcase matrix)
df_combined.corr().head(10)
```

[174]:
```
                             artist_success  artist_stream_count_general  \
artist_success                     1.000000                     0.333788
artist_stream_count_general        0.333788                     1.000000
artist_stream_count_female         0.329644                     0.999656
artist_stream_count_male           0.339925                     0.999233
artist_user_count_general          0.335060                     0.999922
artist_user_count_female           0.330795                     0.999420
artist_user_count_male             0.341348                     0.999260
artist_passion_score_general       0.422494                     0.770246
artist_passion_score_female        0.424064                     0.793008
artist_passion_score_male          0.408694                     0.725018

                             artist_stream_count_female  \
artist_success                                 0.329644
artist_stream_count_general                    0.999656
artist_stream_count_female                     1.000000
artist_stream_count_male                       0.997874
artist_user_count_general                      0.999718
artist_user_count_female                       0.999926
artist_user_count_male                         0.998003
artist_passion_score_general                   0.765401
artist_passion_score_female                    0.787372
artist_passion_score_male                      0.721311

                             artist_stream_count_male  \
artist_success                               0.339925
artist_stream_count_general                  0.999233
artist_stream_count_female                   0.997874
artist_stream_count_male                     1.000000
artist_user_count_general                    0.998979
artist_user_count_female                     0.997427
artist_user_count_male                       0.999911
artist_passion_score_general                 0.775853
artist_passion_score_female                  0.799708
artist_passion_score_male                    0.729062

                             artist_user_count_general  \
artist_success                                0.335060
artist_stream_count_general                   0.999922
artist_stream_count_female                    0.999718
artist_stream_count_male                      0.998979
artist_user_count_general                     1.000000
artist_user_count_female                      0.999632
artist_user_count_male                        0.999168
artist_passion_score_general                  0.768229
artist_passion_score_female                   0.791003
artist_passion_score_male                     0.723015
```

```
                               artist_user_count_female  \
artist_success                                 0.330795
artist_stream_count_general                    0.999420
artist_stream_count_female                     0.999926
artist_stream_count_male                       0.997427
artist_user_count_general                      0.999632
artist_user_count_female                       1.000000
artist_user_count_male                         0.997709
artist_passion_score_general                   0.763666
artist_passion_score_female                    0.785511
artist_passion_score_male                      0.719761

                               artist_user_count_male  \
artist_success                               0.341348
artist_stream_count_general                  0.999260
artist_stream_count_female                   0.998003
artist_stream_count_male                     0.999911
artist_user_count_general                    0.999168
artist_user_count_female                     0.997709
artist_user_count_male                       1.000000
artist_passion_score_general                 0.773237
artist_passion_score_female                  0.797312
artist_passion_score_male                    0.726200

                               artist_passion_score_general  \
artist_success                                     0.422494
artist_stream_count_general                        0.770246
artist_stream_count_female                         0.765401
artist_stream_count_male                           0.775853
artist_user_count_general                          0.768229
artist_user_count_female                           0.763666
artist_user_count_male                             0.773237
artist_passion_score_general                       1.000000
artist_passion_score_female                        0.990993
artist_passion_score_male                          0.989809

                               artist_passion_score_female  \
artist_success                                    0.424064
artist_stream_count_general                       0.793008
artist_stream_count_female                        0.787372
artist_stream_count_male                          0.799708
artist_user_count_general                         0.791003
artist_user_count_female                          0.785511
artist_user_count_male                            0.797312
artist_passion_score_general                      0.990993
artist_passion_score_female                       1.000000
artist_passion_score_male                         0.963484
```

```
                             artist_passion_score_male  …    pca_0  \
artist_success                                0.408694  …  0.427924
artist_stream_count_general                   0.725018  …  0.879173
artist_stream_count_female                    0.721311  …  0.879596
artist_stream_count_male                      0.729062  …  0.877282
artist_user_count_general                     0.723015  …  0.879421
artist_user_count_female                      0.719761  …  0.879843
artist_user_count_male                        0.726200  …  0.877382
artist_passion_score_general                  0.989809  …  0.805505
artist_passion_score_female                   0.963484  …  0.810015
artist_passion_score_male                     1.000000  …  0.777784

                                pca_1     pca_2     pca_3     pca_4  \
artist_success               0.002313  0.071337  0.031841 -0.012352
artist_stream_count_general -0.086707 -0.063567  0.104992  0.031773
artist_stream_count_female  -0.085448 -0.063302  0.101897  0.036777
artist_stream_count_male    -0.087496 -0.062199  0.109729  0.025078
artist_user_count_general   -0.083170 -0.063607  0.104785  0.034044
artist_user_count_female    -0.082199 -0.063046  0.101383  0.038948
artist_user_count_male      -0.083392 -0.062714  0.110074  0.027442
artist_passion_score_general -0.114925  0.027851 -0.096451 -0.166778
artist_passion_score_female -0.111989  0.011252 -0.084592 -0.156610
artist_passion_score_male   -0.118137  0.051873 -0.111566 -0.172120

                                pca_5     pca_6     pca_7     pca_8     pca_9
artist_success               0.059525  0.101234  0.046472  0.029436  0.045544
artist_stream_count_general -0.125610  0.062083 -0.029725  0.087213 -0.021640
artist_stream_count_female  -0.123241  0.063260 -0.032906  0.089622 -0.014233
artist_stream_count_male    -0.129698  0.062384 -0.025847  0.084334 -0.032898
artist_user_count_general   -0.124443  0.065505 -0.031120  0.086821 -0.019079
artist_user_count_female    -0.122145  0.066377 -0.034311  0.089385 -0.011372
artist_user_count_male      -0.128441  0.066306 -0.027187  0.083745 -0.030844
artist_passion_score_general -0.132695  0.011467  0.001682 -0.012449 -0.062735
artist_passion_score_female -0.126782  0.017765  0.001521 -0.027397 -0.072111
artist_passion_score_male   -0.137728  0.003248  0.001422  0.006329 -0.047341

[10 rows x 49 columns]
```

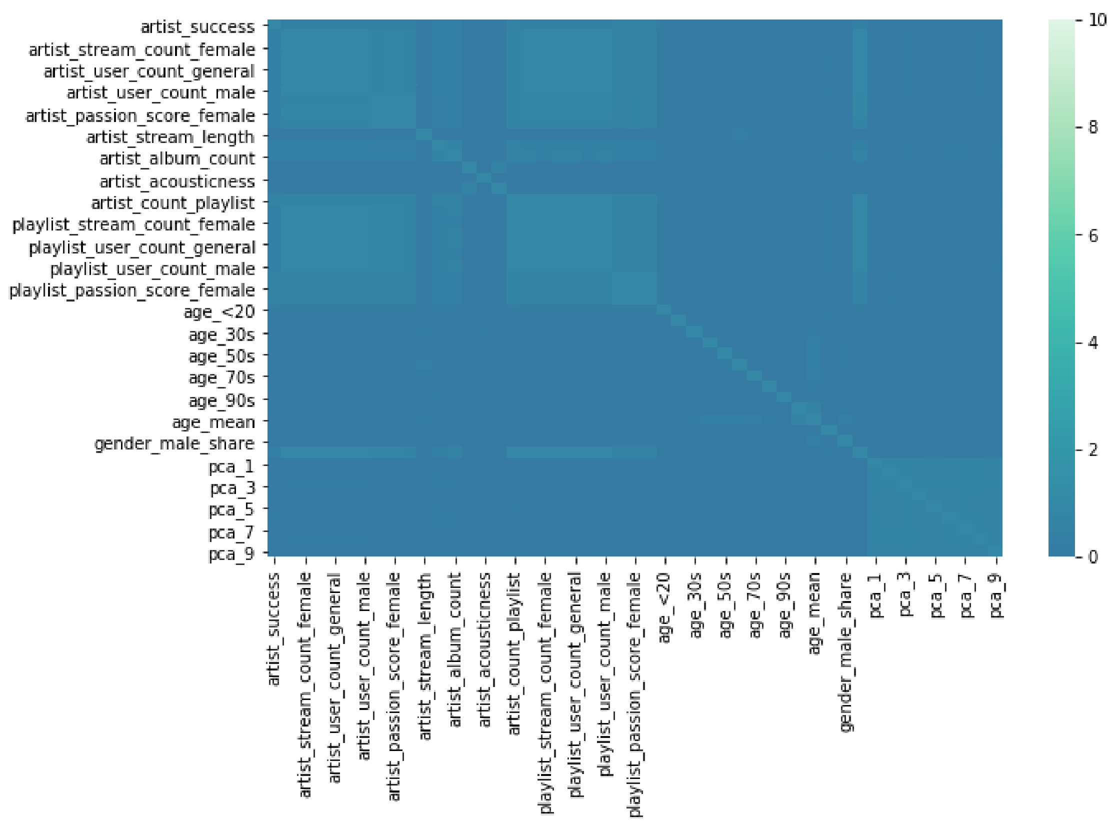
[175]:
```
df_combined.corr().columns
```

[175]:
```
Index(['artist_success', 'artist_stream_count_general',
       'artist_stream_count_female', 'artist_stream_count_male',
       'artist_user_count_general', 'artist_user_count_female',
       'artist_user_count_male', 'artist_passion_score_general',
       'artist_passion_score_female', 'artist_passion_score_male',
       'artist_stream_length', 'artist_track_count', 'artist_album_count',
```

```
'artist_danceability', 'artist_acousticness', 'artist_valence',
'artist_count_playlist', 'playlist_stream_count_general',
'playlist_stream_count_female', 'playlist_stream_count_male',
'playlist_user_count_general', 'playlist_user_count_female',
'playlist_user_count_male', 'playlist_passion_score_general',
'playlist_passion_score_female', 'playlist_passion_score_male',
'age_<20', 'age_20s', 'age_30s', 'age_40s', 'age_50s', 'age_60s',
'age_70s', 'age_80s', 'age_90s', 'age_>100', 'age_mean',
'gender_female_share', 'gender_male_share', 'pca_0', 'pca_1', 'pca_2',
'pca_3', 'pca_4', 'pca_5', 'pca_6', 'pca_7', 'pca_8', 'pca_9'],
dtype='object')
```

[176]:
```
fig, ax = plt.subplots(figsize=(10,6))
sns.heatmap(df_combined.corr(), center=0, cmap="mako", vmin=0, vmax=10)
```

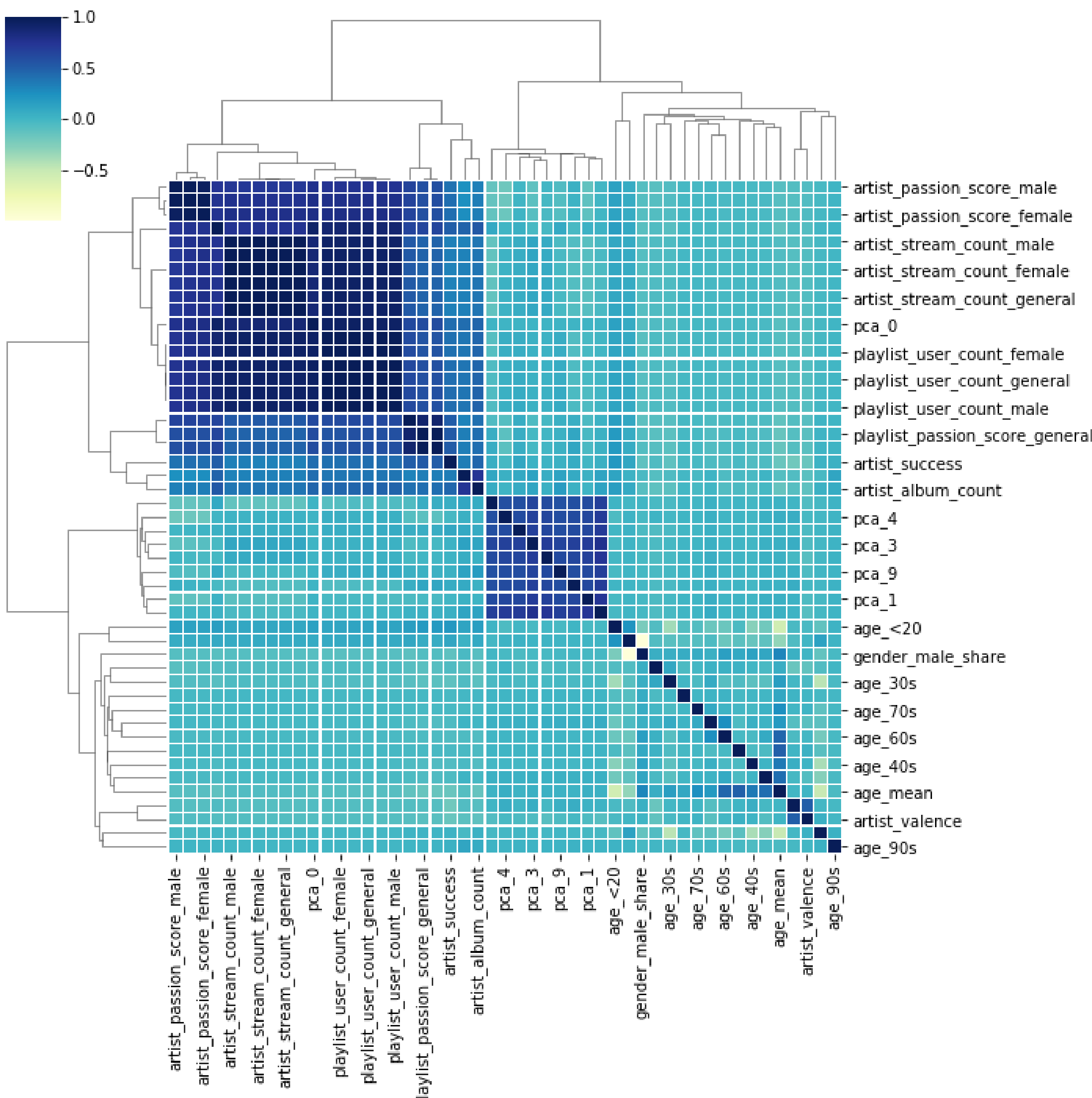
[176]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f93bc6b5eb8>
```



Description: We continue by clustering the correlation matrix using seaborns ‘clustermap’. This allows us to directly identify highly correlated areas; imporatant step towards removing highly correlated features.

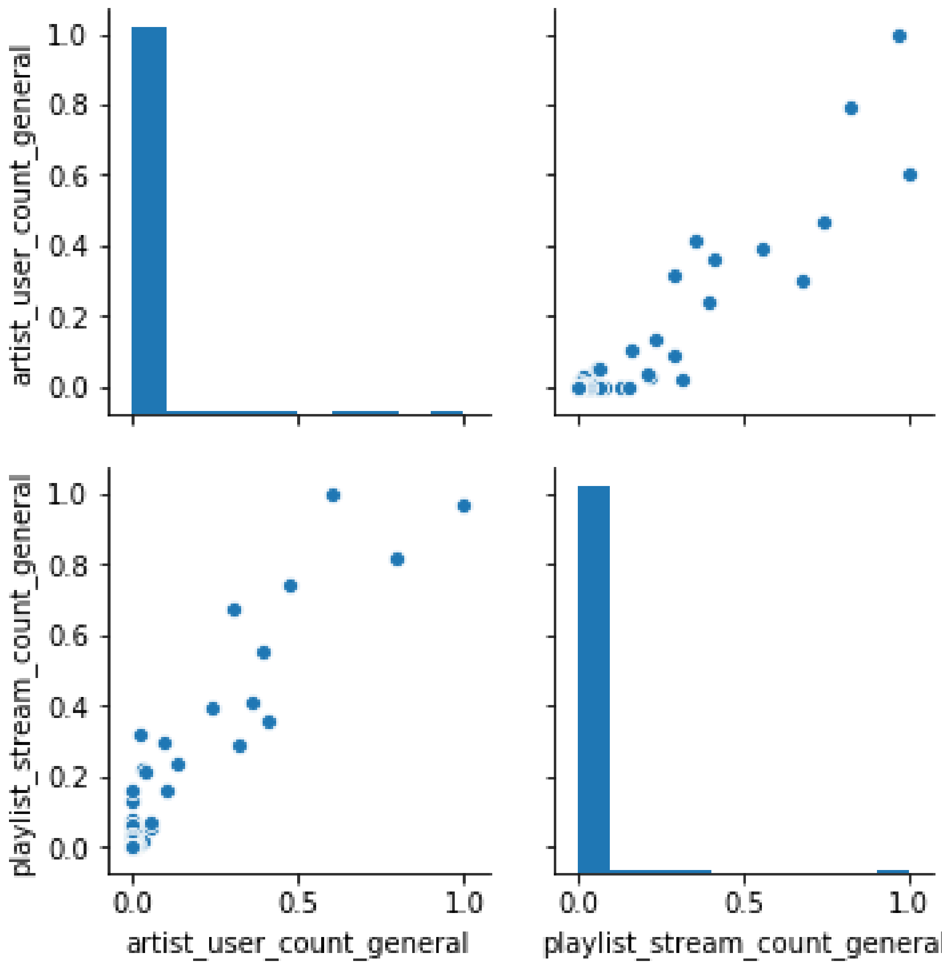
[177]:
```python
#clustered correlation matrix

#define correlation matrix
corr_matrix = df_combined.corr()

#build seaborn clustermap
clustermap = sns.clustermap(corr_matrix, cmap ="YlGnBu", linewidths = 0.1);
plt.setp(clustermap.ax_heatmap.yaxis.get_majorticklabels(), rotation = 0)

clustermap
```

[177]:
```
<seaborn.matrix.ClusterGrid at 0x7f931d533128>
```



Insights: From the above matrix we are already able to draw conclusions on correlations. It appears that artist and playlist features tend to be highly correlated as well as certain pca codes. Before we look at the exact correlation value and accordingly drop features, we first take a look at one example to further visualize the correlation (artist_user_count <> playlist_stream_count). This helps to understand the magnitude of correlation.

[178]:
```
#visualize correlation between 'artist_user_count' and 'playlist_stream_count'
sns.
 ↪pairplot(df_combined[['artist_user_count_general','playlist_stream_count_general']],␣
 ↪palette= flatui)
plt.show()
```



[179]:
```
#define function to get diagonal and lower triangular pairs of correlation␣
 ↪matrix
def get_redundant_pairs(df):
    pairs_to_drop = set()
    cols = df.columns
```

```
    for i in range(0, df.shape[1]):
        for j in range(0, i+1):
            pairs_to_drop.add((cols[i], cols[j]))
    return pairs_to_drop

#define function to get top absolute correlations from the previously defined␣
↪matrix
def get_top_abs_correlations(df, n=5):
    au_corr = df.corr().abs().unstack()
    labels_to_drop = get_redundant_pairs(df)
    au_corr = au_corr.drop(labels=labels_to_drop).sort_values(ascending=False)
    return au_corr[0:n]
```

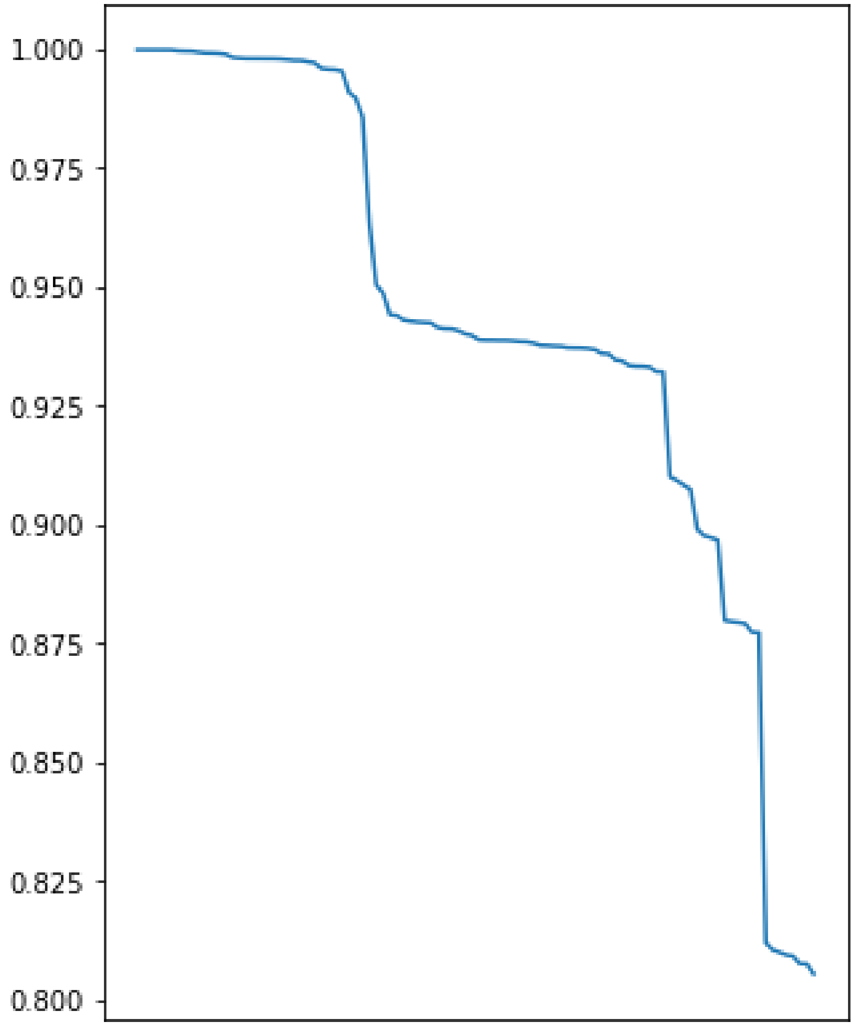
Description: One can observe that various features are highly correlated (above 99%). Therefore, we have to handle these correlations. In order to get a better understanding, we decided to visualize the correlations. Since one can notice a sharp drops just below '0.95' and '0.75' (see graph below), we decided to drop all features with correlations higher than '0.75'.

[180]:
```
#output top absolute correlations
print("Top Absolute Correlations")
print(get_top_abs_correlations(df_combined, 10))
```

```
Top Absolute Correlations
playlist_stream_count_female   playlist_user_count_female     0.999939
playlist_stream_count_general  playlist_user_count_general    0.999938
playlist_stream_count_male     playlist_user_count_male       0.999931
artist_stream_count_female     artist_user_count_female       0.999926
artist_stream_count_general    artist_user_count_general      0.999922
artist_stream_count_male       artist_user_count_male         0.999911
artist_stream_count_female     artist_user_count_general      0.999718
artist_stream_count_general    artist_stream_count_female     0.999656
artist_user_count_general      artist_user_count_female       0.999632
artist_stream_count_general    artist_user_count_female       0.999420
dtype: float64
```

[181]:
```
fig = get_top_abs_correlations(df_combined, 100)
plt.xticks([])
fig.plot(figsize=(5,7))
```

[181]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9342fe5d68>



Description: We start by dropping 'playlist__passion_score' and 'artist__passion_score' for both genders only leaving the combined attribute in as well as certain pca features, since all of these are highly correlated.

[182]:
```
#assign to new dataframe, which will be used for dropping attributes based on␣
↪correlation
df_combined_corr = df_combined.corr()
df_combined_corr.shape
```

[182]: (49, 49)

[183]:
```
#define function to drop single attributes
def drop_corr_attribute(data, attribute):
    data = data.drop(attribute, 1).drop(attribute)
    return data
```

[184]:
```
#drop the beforementioned attributes and print the new shape of the correlation␣
↪matrix

#playlist passion score feature
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'playlist_passion_score_female')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'playlist_passion_score_male')

#atrist passion score feature
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'artist_passion_score_female')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'artist_passion_score_male')
```

[185]:
```
#drop the beforementioned 'pca' attributes and print the new shape of the␣
↪correlation matrix

df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_2')
df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_5')
df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_4')
df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_7')
df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_8')

print(get_top_abs_correlations(df_combined_corr, 2))
df_combined_corr.shape
```

```
playlist_stream_count_general  playlist_user_count_general    0.999998
playlist_stream_count_female   playlist_user_count_female     0.999998
dtype: float64
```

[185]:
```
(40, 40)
```

Description: Stepwise reduction of correlation - the methodolgy was to alwys eliminate the two highest correlated features, re-calculate the correlation and repeat the step. The was done until the correlation was below 0.80 for all remaining (and non-related to success).

[186]:
```
#step-wise reduction
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'playlist_stream_count_general')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'playlist_stream_count_female')

#re-calculate and print correlation
print(get_top_abs_correlations(df_combined_corr, 2))

#return shape to check if features were dropped
```

```
df_combined_corr.shape
```

```
playlist_stream_count_male  playlist_user_count_male    0.999998
artist_stream_count_female  artist_user_count_female    0.999997
dtype: float64
```

[186]: (38, 38)

[187]:
```
#step-wise reduction
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'playlist_stream_count_male')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'artist_stream_count_female')

print(get_top_abs_correlations(df_combined_corr, 2))
df_combined_corr.shape
```

```
artist_stream_count_general  artist_user_count_general    0.999997
artist_stream_count_male     artist_user_count_male       0.999996
dtype: float64
```

[187]: (36, 36)

[188]:
```
#step-wise reduction
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'artist_stream_count_male')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'artist_user_count_female')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'artist_user_count_male')

print(get_top_abs_correlations(df_combined_corr, 2))
df_combined_corr.shape
```

```
artist_stream_count_general  artist_user_count_general     0.999996
playlist_user_count_general  playlist_user_count_female    0.999919
dtype: float64
```

[188]: (33, 33)

[189]:
```
#step-wise reduction
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'playlist_user_count_female')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'playlist_user_count_male')

print(get_top_abs_correlations(df_combined_corr, 2))
```

```
df_combined_corr.shape
```

```
artist_stream_count_general  artist_user_count_general    0.999995
gender_female_share          gender_male_share            0.999666
dtype: float64
```

[189]: (31, 31)

[190]:
```
#step-wise reduction
df_combined_corr = drop_corr_attribute(df_combined_corr, 'gender_male_share')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'playlist_user_count_general')

print(get_top_abs_correlations(df_combined_corr, 2))
df_combined_corr.shape
```

```
artist_stream_count_general  artist_user_count_general    0.999995
artist_count_playlist        pca_0                        0.991977
dtype: float64
```

[190]: (29, 29)

[191]:
```
#step-wise reduction
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'artist_user_count_general')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
↪'artist_passion_score_general')

print(get_top_abs_correlations(df_combined_corr, 2))
df_combined_corr.shape
```

```
artist_count_playlist        pca_0    0.992311
artist_stream_count_general  pca_0    0.981847
dtype: float64
```

[191]: (27, 27)

[192]:
```
#step-wise reduction
df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_0')
df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_1')
df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_3')
#df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_6')
#df_combined_corr = drop_corr_attribute(df_combined_corr, 'pca_9')

print(get_top_abs_correlations(df_combined_corr, 3))
df_combined_corr.shape
```

```
artist_track_count           artist_album_count                0.957073
```

```
artist_stream_count_general  artist_count_playlist            0.951415
artist_count_playlist        playlist_passion_score_general   0.918417
dtype: float64
```

[192]:
```
(24, 24)
```

[193]:
```
#step-wise reduction
df_combined_corr = drop_corr_attribute(df_combined_corr, 'artist_album_count')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'playlist_passion_score_general')
df_combined_corr = drop_corr_attribute(df_combined_corr,␣
 ↪'artist_count_playlist')
#df_combined_corr = drop_corr_attribute(df_combined_corr, 'artist_valence')

print(get_top_abs_correlations(df_combined_corr, 3))
df_combined_corr.shape
```

```
pca_6                 pca_9             0.861338
artist_danceability   artist_valence    0.791867
age_<20               age_mean          0.738325
dtype: float64
```

[193]:
```
(21, 21)
```

[194]:
```
#final overview of correlation
print(get_top_abs_correlations(df_combined_corr, 10))
```

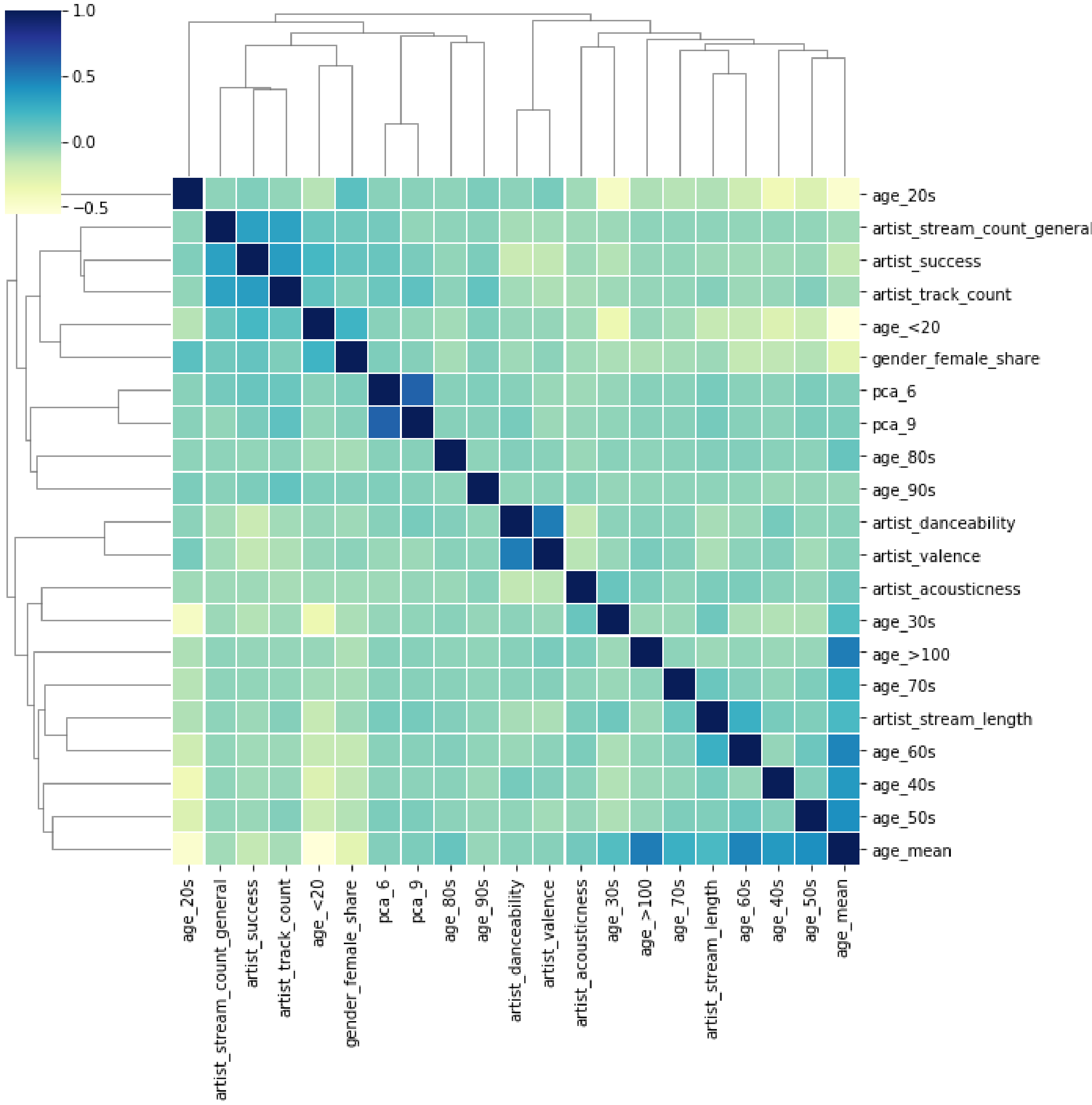
```
pca_6                        pca_9                         0.861338
artist_danceability          artist_valence                0.791867
age_<20                      age_mean                      0.738325
age_20s                      age_mean                      0.680871
age_mean                     gender_female_share           0.653856
artist_success               artist_track_count            0.645170
age_60s                      age_mean                      0.631365
artist_success               artist_stream_count_general   0.621741
age_50s                      age_mean                      0.602298
artist_stream_count_general  artist_track_count            0.601220
dtype: float64
```

Description: The above table was then visualized into the clustered matrix again. The graph below showcases the 'new' correlation matrix excluding the dropped features. One can directly notice that the overall correlation was lowered drastically. We continue to investigate the features by looking at the feature importance. Feature importance gives you a score for each feature of your data, the higher the score more important or relevant is the feature towards your output variable.

[195]:
```
#clustered correlation matrix

#define correlation matrix
```

```
corr_matrix = df_combined_corr

#build seaborn clustermap
clustermap = sns.clustermap(corr_matrix, cmap ="YlGnBu", linewidths = 0.1);
plt.setp(clustermap.ax_heatmap.yaxis.get_majorticklabels(), rotation = 0)

clustermap
```

[195]: <seaborn.matrix.ClusterGrid at 0x7f9340fe4390>



Description: Since we decided to drop features in the correlation dataframe and recalculate the correlation in the setpwise reduction on the same dataframe, we now have to convert this methodology to our 'main' dataframe. Please find the according code below.

[196]:
```
#drop columns in 'original' dataframe; based on selected features from␣
↪multi-corr

#list of remaining columns
list_combined_corr = list(df_combined_corr.columns)

#list of all orginal columns
list_combined = list(df_combined.columns)

#subtraction between the two lists: list_combined - list_combined_corr
df_combined_drop = list(set(list_combined) - set(list_combined_corr))

#delete subtraction list features from original dataframe
df_combined = df_combined.drop(df_combined_drop, axis=1)
print(df_combined.shape)

#showcase main dataframe
df_combined.head()
```

```
(639, 21)
```

[196]:
```
                        artist_success  artist_stream_count_general  \
A BOOGIE WIT DA HOODIE             1.0                     0.000000
A R I Z O N A                      1.0                     0.025296
ABSOFACTO                          1.0                     0.000000
ALL TVVINS                         1.0                     0.000081
AMIR                               1.0                     0.000000

                        artist_stream_length  artist_track_count  \
A BOOGIE WIT DA HOODIE              0.170420            0.351852
A R I Z O N A                       0.203896            0.592593
ABSOFACTO                           0.209996            0.018519
ALL TVVINS                          0.211951            0.259259
AMIR                                0.201788            0.388889

                        artist_danceability  artist_acousticness  \
A BOOGIE WIT DA HOODIE             0.619462             0.052496
A R I Z O N A                      0.668847             0.328698
ABSOFACTO                          0.279292             0.915680
ALL TVVINS                         0.621191             0.222057
AMIR                               0.534852             0.091825

                        artist_valence   age_<20   age_20s   age_30s  …  \
A BOOGIE WIT DA HOODIE        0.535004  0.431220  0.424176  0.065647  …
A R I Z O N A                 0.383541  0.264019  0.476183  0.148069  …
ABSOFACTO                     0.213853  0.210145  0.536232  0.173913  …
ALL TVVINS                    0.378795  0.237308  0.478942  0.176538  …
```

```
AMIR                              0.502144  0.303185  0.417224  0.150610  …

                         age_50s   age_60s   age_70s   age_80s   age_90s  \
A BOOGIE WIT DA HOODIE  0.018799  0.002809  0.000735  0.001556  0.015428
A R I Z O N A           0.029195  0.004221  0.000699  0.000466  0.018643
ABSOFACTO               0.014493  0.000000  0.000000  0.000000  0.152174
ALL TVVINS              0.024615  0.004038  0.000673  0.001923  0.006058
AMIR                    0.022414  0.007865  0.000000  0.000000  0.016516

                        age_>100  age_mean  gender_female_share     pca_6  \
A BOOGIE WIT DA HOODIE  0.003976  0.102707             0.299505  0.388308
A R I Z O N A           0.002372  0.131707             0.521963  0.788682
ABSOFACTO               0.000000  0.131367             0.405797  0.413819
ALL TVVINS              0.002019  0.135689             0.322149  0.411047
AMIR                    0.004719  0.133327             0.463366  0.412796

                           pca_9
A BOOGIE WIT DA HOODIE  0.300189
A R I Z O N A           0.207787
ABSOFACTO               0.295637
ALL TVVINS              0.294896
AMIR                    0.291655

[5 rows x 21 columns]
```

Finally, we want to take a look out the class balance in our dependent variable.

Given the natural bias in our data, i.e. there are more cases of failure than of success in the training and test sets; there is a strong bias toward predicting 'failure'. Based on our complete (unbalanced classes) training sample, if the model only predicted 'failure', we would achieve an accuracy of 88.8%.

To give us a more even class balance, without losing too much data, we will sample data from the bigger class to achive a class balance closer to 60-40.

There is another way to determine the accuracy of our predictions using a confusion matrix and ROC curve, but more on that later. For now, we will go ahead with sampling the bigger class:

(4)

3.7 Class Balance

Data Transformation

[197]:
```
# Class balance
p1 = df_combined[df_combined.artist_success == True]
p2 = df_combined[df_combined.artist_success == False].sample(round(len(p1)*2))
p3 = pd.concat([p1,p2])
df_sampled = p3[:]
```

```python
print(df_sampled.artist_success.value_counts())
```

```
0.0    164
1.0     82
Name: artist_success, dtype: int64
```

[198]:
```python
df_sampled.head()
```

[198]:
```
                        artist_success  artist_stream_count_general  \
A BOOGIE WIT DA HOODIE             1.0                     0.000000
A R I Z O N A                      1.0                     0.025296
ABSOFACTO                          1.0                     0.000000
ALL TVVINS                         1.0                     0.000081
AMIR                               1.0                     0.000000

                        artist_stream_length  artist_track_count  \
A BOOGIE WIT DA HOODIE              0.170420            0.351852
A R I Z O N A                       0.203896            0.592593
ABSOFACTO                           0.209996            0.018519
ALL TVVINS                          0.211951            0.259259
AMIR                                0.201788            0.388889

                        artist_danceability  artist_acousticness  \
A BOOGIE WIT DA HOODIE             0.619462             0.052496
A R I Z O N A                      0.668847             0.328698
ABSOFACTO                          0.279292             0.915680
ALL TVVINS                         0.621191             0.222057
AMIR                               0.534852             0.091825

                        artist_valence   age_<20   age_20s   age_30s  …  \
A BOOGIE WIT DA HOODIE        0.535004  0.431220  0.424176  0.065647  …
A R I Z O N A                 0.383541  0.264019  0.476183  0.148069  …
ABSOFACTO                     0.213853  0.210145  0.536232  0.173913  …
ALL TVVINS                    0.378795  0.237308  0.478942  0.176538  …
AMIR                          0.502144  0.303185  0.417224  0.150610  …

                         age_50s   age_60s   age_70s   age_80s   age_90s  \
A BOOGIE WIT DA HOODIE  0.018799  0.002809  0.000735  0.001556  0.015428
A R I Z O N A           0.029195  0.004221  0.000699  0.000466  0.018643
ABSOFACTO               0.014493  0.000000  0.000000  0.000000  0.152174
ALL TVVINS              0.024615  0.004038  0.000673  0.001923  0.006058
AMIR                    0.022414  0.007865  0.000000  0.000000  0.016516

                        age_>100  age_mean  gender_female_share     pca_6  \
A BOOGIE WIT DA HOODIE  0.003976  0.102707             0.299505  0.388308
A R I Z O N A           0.002372  0.131707             0.521963  0.788682
ABSOFACTO               0.000000  0.131367             0.405797  0.413819
```

```
ALL TVVINS               0.002019  0.135689            0.322149  0.411047
AMIR                     0.004719  0.133327            0.463366  0.412796

                            pca_9
A BOOGIE WIT DA HOODIE   0.300189
A R I Z O N A            0.207787
ABSOFACTO                0.295637
ALL TVVINS               0.294896
AMIR                     0.291655

[5 rows x 21 columns]
```

[199]:
```
#mid-way file save
df_sampled.to_csv(r'df_sampled.csv', index = False)
```

3.8 —-

4 Evaluate alogrithms

There are number of classification models available to us via the **scikit-learn** package, and we can rapidly experiment using each of them to find the optimal model.

Below is an outline of the steps we will take to arrive at the best model:

- Split data into training and validation (hold-out) set
- Use cross-validation to fit different models to training set
- Select model with the highest cross-validation score as model of choice
- Tune hyper parameters of chosen model.
- Use ensemble models to combine insights from different models.
- Test the model on hold-out set

In detail, we will vist the following steps: 1. Data Sampling 2. Explore Variety of Models 3. Spotcheck Algorithms 4. Ensemble Learning Model / Model Fine-Tuning 5. Spotcheck Neuronal Network 6. Model Selection Summary

Description: We start by reminding us where we left of. Below we see the features (i.e., columns) of our final dataframe.

[200]:
```
#output our current dataframe after sampling
df_sampled.columns
```

[200]:
```
Index(['artist_success', 'artist_stream_count_general', 'artist_stream_length',
       'artist_track_count', 'artist_danceability', 'artist_acousticness',
       'artist_valence', 'age_<20', 'age_20s', 'age_30s', 'age_40s', 'age_50s',
       'age_60s', 'age_70s', 'age_80s', 'age_90s', 'age_>100', 'age_mean',
       'gender_female_share', 'pca_6', 'pca_9'],
      dtype='object')
```

(1)

4.1 Data Sampling

Model Selection

[201]:
```
#import required library
from sklearn.model_selection import train_test_split
```

Explanation: As mentioned, we usually split our data into two sub-sets: training data and testing data, and fit our model on the train data, in order to make predictions on the test data. Sample Datasets:

- Training: The actual dataset that we use to train the model (weights and biases in the case of Neural Network). The model sees and learns from this data.
- Validation: The sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyperparameters.

[202]:
```
#generate training and validation datasets

#split into train and test datasets
X_train_artist, X_test_artist, y_train, y_test  = train_test_split(df_sampled,
                                                      df_sampled.artist_success,
                                                      stratify=df_sampled.
 ↪artist_success,
                                                      random_state = 42,
                                                      test_size = 0.20)

#NOTE: splitting appears to be highly sensible to random_state value
```

[203]:
```
#required to re-asign atrists for test metrics later on
X_train = X_train_artist.drop(columns = 'artist_success')
X_test = X_test_artist.drop(columns = 'artist_success')
```

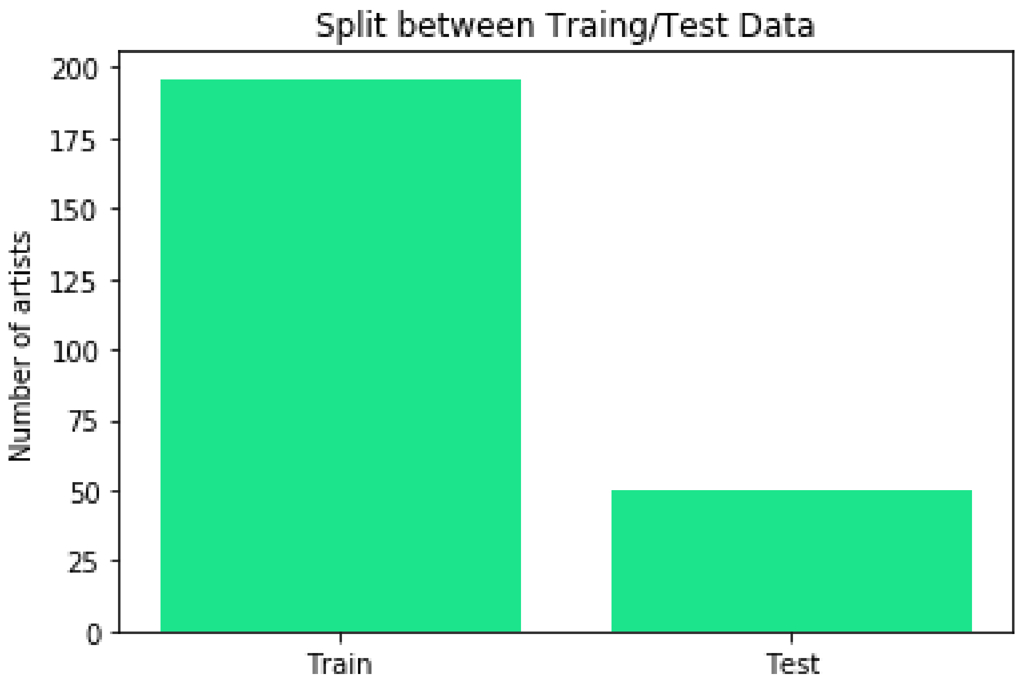
[204]:
```
print('This results in a test set with {0} artists and respectively a train set␣
 ↪including {1} artists.'
      .format(len(y_test),len(y_train)))
```

```
This results in a test set with 50 artists and respectively a train set
including 196 artists.
```

Insights: As seen we derive a training dataset of 199 artists and a test dataset containing 50 artists. Please find a visual representation of this below.

[205]:
```
#bar chart visualizing training/test split

#value definitions for bar-chart
height = [len(X_train), len(X_test)]
```

```
bars = ('Train', 'Test')
y_pos = np.arange(len(bars))

#create bars
plt.bar(y_pos, height, color= '#1CE48C')

#labeling
plt.xticks(y_pos, bars)
plt.title('Split between Traing/Test Data')
plt.ylabel("Number of artists")

#show graphic
plt.show()
```



(2)

4.2 Explore Variety of Models

Model Selection

Explanation: Before building a classification model, we build a so-called'Dummy Classifier' to determine the baseline performance. This answers the question — 'What would be the success rate of the model, if one were simply guessing?' The below dummy classifier will simply predict the majority class. The accuracy of the model is 66%; since the model does not classify any success case correctly, the recall and precision metrics are 0.

4.2.1 2.1. Dummy Classifier

[206]:
```
#import required libraries for dummy classifier
from sklearn.dummy import DummyClassifier
from sklearn.metrics import accuracy_score, recall_score, precision_score,␣
↪f1_score
```

[207]:
```
#Dummy Classifier

#predict 'DummyClassifier'
model = DummyClassifier(strategy= 'most_frequent')
model.fit(X_train,y_train)
y_pred = model.predict(X_test)

#return evaluation metrics of dummy classifier
print('METRICS'), print('-'*10)
print('Accuracy Score : ' + str(accuracy_score(y_test,y_pred)))
print('Precision Score : ' + str(precision_score(y_test,y_pred)))
print('Recall Score : ' + str(recall_score(y_test,y_pred)))
print('F1 Score : ' + str(f1_score(y_test,y_pred)))
```

```
METRICS
----------
Accuracy Score : 0.66
Precision Score : 0.0
Recall Score : 0.0
F1 Score : 0.0
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-
packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

4.2.2 2.2. Variety of Models

[208]:
```
#import required libraries for individual models

#library for Logistic Regression
from sklearn.linear_model import LogisticRegression
#library for Random Forrest
from sklearn.ensemble import RandomForestClassifier as RFC

#library for K-Neighbot
from sklearn.neighbors import KNeighborsClassifier
```

```
#libraries for decision tree
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
#libraries for GaussianNB
from sklearn.naive_bayes import GaussianNB
from sklearn.gaussian_process import GaussianProcessClassifier
#libraries for Quadratic Discriminant
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
#libraries for ExtraTreesClassifier
from sklearn.ensemble import ExtraTreesClassifier
#libraries for RidgeClassifier
from sklearn.linear_model import RidgeClassifier
#libraries for AdaBoostClassifier
from sklearn.ensemble import AdaBoostClassifier
#libraries for BaggingClassifier
from sklearn.ensemble import BaggingClassifier
#libraries for GradientBoostingClassifier
from sklearn.ensemble import GradientBoostingClassifier

#libraries for SVC
from sklearn.svm import SVC
#libraries for Stochastic Gradient Descent
from sklearn.linear_model import SGDClassifier

#libraries for cross validation
from sklearn.model_selection import cross_val_predict
from sklearn.model_selection import cross_val_score

#turn off warnings for the model output
import warnings
warnings.filterwarnings('ignore')
```

Explanation: After extensive research, the following models were selected for our predictive modeling task. The below dictionary shows them together. We believe that this list of models is suffiecient for our task (models discussed in class and beyond); yet not exhaustice since there are more models out there. Considering the future of this project one should consider predicting even more models. For now we start with the following.

[209]:
```
#dictionary of all models used within our model selection
model_dict = {'LogisticRegression':LogisticRegression,
              'RFC':RFC,
              'tree.DecisionTreeClassifier':tree.DecisionTreeClassifier,
              'ExtraTreesClassifier':ExtraTreesClassifier,
              'RidgeClassifier':RidgeClassifier,
              'KNeighborsClassifier':KNeighborsClassifier,
              'GaussianNB':GaussianNB,
              'QuadraticDiscriminantAnalysis':QuadraticDiscriminantAnalysis,
```

```
            'AdaBoostClassifier':AdaBoostClassifier,
            'BaggingClassifier':BaggingClassifier,
            'GradientBoostingClassifier':GradientBoostingClassifier,
            #New
            'Support Vector Machines':SVC,
            'Stochastic Gradient Descent':SGDClassifier

           }
```

Explanation: Started by building a generic function to test a variety of different models in fast and elegant way.

[210]:
```
#define generic function to apply variety of predictive models

#inputs selected model and train/test data
def generic_model_func(model, X_train, X_test, y_train, y_test):
    name = str(model)
    var = model()
    var.fit(X_train,y_train)

    folds = 10

    #predict actual model
    y_pred = cross_val_predict(var, X_train, y_train, cv=folds)

    #calculate accuracy
    acc_score_train = accuracy_score(y_train,y_pred)
    #acc_score_test = accuracy_score(y_test,var.predict(X_test))
    acc_score_test = accuracy_score(y_test,cross_val_predict(var, X_test,
 ↪y_test, cv=folds))

    #generate X/y samples from whole dataset
    X = df_sampled.drop(columns = 'artist_success')
    y = df_sampled.artist_success

    #calculate cross validation scores
    cv = cross_val_score(var, X, y, cv=folds)
    avg_cv = cv.mean()
    sd_cv = np.std(cv)

    #calculate further model metrics
    precision = precision_score(y_train,y_pred)
    recall = recall_score(y_train,y_pred)
    f1 = f1_score(y_train,y_pred)

    #put together output dataframe
    data = [[name, acc_score_train, acc_score_test,
```

```
            precision, recall, f1,
            avg_cv, sd_cv, cv]]

    res = pd.DataFrame(data, columns=['Model','Train Accuracy Score','Test␣
↪Accuracy Score',
                                     'Precision Score', 'Recall Score', 'F1␣
↪Score',
                                     'CV (avgerage)', 'CV (sd. deviation)',␣
↪'CV'])

    return res
```

(3)

4.3 Spotcheck Algorithms

Model Selection

Insights: The output dataframe includes all of our predicted models and combines different evaluation metrics for each model (i.e., accuracy, precision, recall, CV score, …). This ultimately allows us to chose our go-to model for the following analysis. Based on best parctices we continue to rank models according to the highest cross-validation score. Therefore, our model of choice is the 'Random Forrest Classifier'. Please note that there appears to be changes in the range of +/- 2% for each model; after multiple runs RFC proofed to score high most consistently. Further, RFC appears to have the lowest standard deviation.

[266]:
```
#comparison of model performance in one comprehensive dataframe

#set df columns as base
df_models = pd.DataFrame(columns=['Model','Train Accuracy Score','Test Accuracy␣
↪Score',
                                  'Precision Score', 'Recall Score', 'F1 Score',
                                  'CV (avgerage)', 'CV (sd. deviation)', 'CV'])

#loop through all outlined models
for i in model_dict:
    #apply function to generate test/train accuracy and CV scores
    df_add = generic_model_func(model_dict[i], X_train, X_test, y_train, y_test)
    df_models = df_models.append(df_add)

#adjust and return daraframe output
df_models['Model'] = df_models['Model'].str.slice(16,-2)
df_models.set_index(['Model'], inplace=True)
df_models
```

[266]:
```
                                                    Train Accuracy Score  \
Model
```

```
linear_model._logistic.LogisticRegression                        0.770408
ensemble._forest.RandomForestClassifier                          0.933673
tree._classes.DecisionTreeClassifier                             0.913265
ensemble._forest.ExtraTreesClassifier                            0.887755
linear_model._ridge.RidgeClassifier                              0.780612
neighbors._classification.KNeighborsClassifier                   0.785714
naive_bayes.GaussianNB                                           0.857143
discriminant_analysis.QuadraticDiscriminantAnal…               0.668367
ensemble._weight_boosting.AdaBoostClassifier                     0.918367
ensemble._bagging.BaggingClassifier                              0.933673
ensemble._gb.GradientBoostingClassifier                          0.938776
svm._classes.SVC                                                 0.801020
linear_model._stochastic_gradient.SGDClassifier                  0.709184

                                                    Test Accuracy Score  \
Model
linear_model._logistic.LogisticRegression                          0.72
ensemble._forest.RandomForestClassifier                            0.82
tree._classes.DecisionTreeClassifier                               0.84
ensemble._forest.ExtraTreesClassifier                              0.86
linear_model._ridge.RidgeClassifier                                0.74
neighbors._classification.KNeighborsClassifier                     0.78
naive_bayes.GaussianNB                                             0.82
discriminant_analysis.QuadraticDiscriminantAnal…                 0.66
ensemble._weight_boosting.AdaBoostClassifier                       0.76
ensemble._bagging.BaggingClassifier                                0.86
ensemble._gb.GradientBoostingClassifier                            0.70
svm._classes.SVC                                                   0.70
linear_model._stochastic_gradient.SGDClassifier                    0.62

                                                    Precision Score  \
Model
linear_model._logistic.LogisticRegression                  0.812500
ensemble._forest.RandomForestClassifier                    0.906250
tree._classes.DecisionTreeClassifier                       0.852941
ensemble._forest.ExtraTreesClassifier                      0.830769
linear_model._ridge.RidgeClassifier                        0.823529
neighbors._classification.KNeighborsClassifier             0.661972
naive_bayes.GaussianNB                                     0.717647
discriminant_analysis.QuadraticDiscriminantAnal…         0.000000
ensemble._weight_boosting.AdaBoostClassifier               0.876923
ensemble._bagging.BaggingClassifier                        0.919355
ensemble._gb.GradientBoostingClassifier                    0.907692
svm._classes.SVC                                           0.861111
linear_model._stochastic_gradient.SGDClassifier            0.555556

                                                    Recall Score  F1 Score  \
```

```
Model
linear_model._logistic.LogisticRegression              0.400000  0.536082
ensemble._forest.RandomForestClassifier                0.892308  0.899225
tree._classes.DecisionTreeClassifier                   0.892308  0.872180
ensemble._forest.ExtraTreesClassifier                  0.830769  0.830769
linear_model._ridge.RidgeClassifier                    0.430769  0.565657
neighbors._classification.KNeighborsClassifier         0.723077  0.691176
naive_bayes.GaussianNB                                 0.938462  0.813333
discriminant_analysis.QuadraticDiscriminantAnal…     0.000000  0.000000
ensemble._weight_boosting.AdaBoostClassifier           0.876923  0.876923
ensemble._bagging.BaggingClassifier                    0.876923  0.897638
ensemble._gb.GradientBoostingClassifier                0.907692  0.907692
svm._classes.SVC                                       0.476923  0.613861
linear_model._stochastic_gradient.SGDClassifier        0.615385  0.583942

                                                    CV (avgerage)  \
Model
linear_model._logistic.LogisticRegression               0.772833
ensemble._forest.RandomForestClassifier                 0.927000
tree._classes.DecisionTreeClassifier                    0.857500
ensemble._forest.ExtraTreesClassifier                   0.882333
linear_model._ridge.RidgeClassifier                     0.780833
neighbors._classification.KNeighborsClassifier          0.756833
naive_bayes.GaussianNB                                  0.821500
discriminant_analysis.QuadraticDiscriminantAnal…      0.666667
ensemble._weight_boosting.AdaBoostClassifier            0.890167
ensemble._bagging.BaggingClassifier                     0.915000
ensemble._gb.GradientBoostingClassifier                 0.906833
svm._classes.SVC                                        0.809833
linear_model._stochastic_gradient.SGDClassifier         0.677833

                                                    CV (sd. deviation)  \
Model
linear_model._logistic.LogisticRegression                    0.068961
ensemble._forest.RandomForestClassifier                      0.056405
tree._classes.DecisionTreeClassifier                         0.063163
ensemble._forest.ExtraTreesClassifier                        0.057755
linear_model._ridge.RidgeClassifier                          0.076472
neighbors._classification.KNeighborsClassifier               0.100287
naive_bayes.GaussianNB                                       0.141173
discriminant_analysis.QuadraticDiscriminantAnal…           0.014606
ensemble._weight_boosting.AdaBoostClassifier                 0.070724
ensemble._bagging.BaggingClassifier                          0.068158
ensemble._gb.GradientBoostingClassifier                      0.067369
svm._classes.SVC                                             0.070208
linear_model._stochastic_gradient.SGDClassifier              0.118136
```

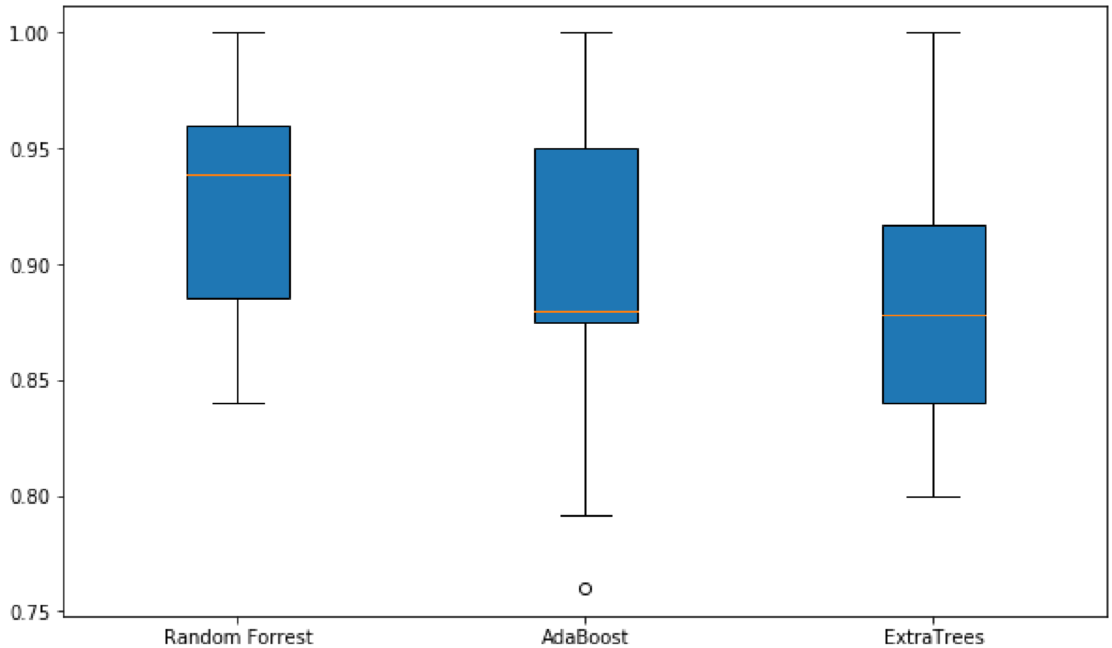
```
                                                                                                CV
Model
linear_model._logistic.LogisticRegression           [0.76, 0.64, 0.76, 0.72,
0.88, 0.76, 0.75, 0.8…
ensemble._forest.RandomForestClassifier             [0.84, 0.84, 0.96, 0.96,
1.0, 0.92, 0.95833333…
tree._classes.DecisionTreeClassifier                [0.8, 0.88, 0.84, 0.92, 1.0,
0.76, 0.833333333…
ensemble._forest.ExtraTreesClassifier               [0.84, 0.8, 0.92, 0.84, 1.0,
0.84, 0.833333333…
linear_model._ridge.RidgeClassifier                 [0.76, 0.64, 0.8, 0.72,
0.88, 0.8, 0.75, 0.875…
neighbors._classification.KNeighborsClassifier      [0.72, 0.64, 0.84, 0.72,
0.88, 0.56, 0.8333333…
naive_bayes.GaussianNB                              [0.64, 0.84, 0.88, 1.0,
0.96, 0.52, 0.79166666…
discriminant_analysis.QuadraticDiscriminantAnal…  [0.64, 0.64, 0.68, 0.68,
0.68, 0.68, 0.6666666…
ensemble._weight_boosting.AdaBoostClassifier        [0.88, 0.92, 0.88, 0.96,
0.96, 0.76, 1.0, 0.87…
ensemble._bagging.BaggingClassifier                 [0.76, 0.96, 0.88, 0.88,
1.0, 0.92, 0.95833333…
ensemble._gb.GradientBoostingClassifier             [0.84, 0.84, 0.96, 0.92,
1.0, 0.8, 1.0, 0.875,…
svm._classes.SVC                                    [0.76, 0.68, 0.8, 0.72,
0.88, 0.8, 0.833333333…
linear_model._stochastic_gradient.SGDClassifier     [0.76, 0.6, 0.64, 0.72, 0.8,
0.8, 0.7916666666…
```

Insights: The following five models appear to perform best (measured by model metrics in table above) and consistantly result in high predictive scores. Please note that during the duration of this week the models were run quite often which allows for this conclusion. - Random Forrest - DecisionTree
- GaussianNB - Bagging - Boosting

Insights: The below boxplot compares the CV scores of the five best performing models from before. It appears that the trees and GaussianNB have the best scores, with RandomForrestClassifier resulting in the highest average CV score. As seen in the table above RFC also has one of the lowest standard deviations. These boxplots further support our model selection process and again indicate that RFC should be our model of choice.

[267]:
```
#boxplot of Cross-Validation for different models

#set values for boxplot as cross value scores from above dataframe
value1 = df_models['CV'].iloc[1]  #RFC
value2 = df_models['CV'].iloc[8]  #AdaBoost
value3 = df_models['CV'].iloc[3]  #ExtraTrees
```

```
#plot data into boxplot
figure(figsize=(10, 6))
box_plot_data=[value1,value2,value3]
plt.boxplot(box_plot_data,patch_artist=True,labels=['Random Forrest','AdaBoost',
                                                    'ExtraTrees'])


plt.show()
```



Note: Further analiysis would allow to check voting or stacking algorithms for multiple combined models. At this stage of the course and outlines task we decided to stick with one model which will be optimized/ fine-tuned in the following steps.

(4)

4.4 Ensemble Learning Model

Model Selection

Description: Ensemble learning uses multiple machine learning models to try to make better predictions on a dataset. An ensemble model works by training different models on a dataset and having each model make predictions individually. The predictions of these models are then combined in the ensemble model to make a final prediction.

[268]:
```
from sklearn.model_selection import GridSearchCV
```

Note: At this stage we are aiming to fine-tune our chosen model; this would also allow to fine-tune multiple models and select the best one afterwards. However, following the task structure and limited computing power (focus: GridSearch) we decided to stick to one model resulting from the above section and optimize only this one model.

[269]:
```
#define function to fit models for ensemble
def model_fit_ensemble(model, param_grid, folds):
    model_gs = GridSearchCV(model, param_grid, cv=folds)

    #fit model to training data
    model_gs.fit(X_train, y_train)

    #save best model
    model_best = model_gs.best_estimator_

    y_pred = cross_val_predict(model_best, X_train, y_train, cv=folds)

    model_precision = precision_score(y_train,y_pred)
    model_recall = recall_score(y_train,y_pred)
    model_f1 = f1_score(y_train,y_pred)

    #output scores
    print('Precision: ', model_precision, ', Recall: ', model_recall, ', F1: ',␣
↪model_f1)

    return model_best
```

Explanation: For the Random Forrest Classifier we check all available parameters for modification. Based on bets practices we decided to optimize: - n_estimators - max_features - max_depth

4.4.1 4.1. Ensemble 1. Model: Random Forrest Classifier

[270]:
```
model = RFC()
param_grid = [{'n_estimators': [200,250,300,350,400], 'max_features': ['auto'],␣
↪'max_depth': [30,50,70]}]
folds = 5

#save best model for RFC
rfc_best = model_fit_ensemble(model, param_grid, folds)
```

```
Precision:  0.9047619047619048 , Recall:  0.8769230769230769 , F1:  0.890625
```

Insights: The below case model will be retrained 75 times. = 5x(n_estimator) * 1x(max_features) * 3x(max_depth) * 5x(cv runs) = 75

4.4.2 4.2. Ensemble 2. Model: Ada Boost Classifier

[320]:
```
model = AdaBoostClassifier()
param_grid = [{'n_estimators': [200,250,300]}]
folds = 5

#save best model for RFC
abc_best = model_fit_ensemble(model, param_grid, folds)
```

```
Precision:  0.8923076923076924 , Recall:  0.8923076923076924 , F1:
0.8923076923076924
```

4.4.3 4.3. Ensemble 3. Model: Extra Trees Classifier

[321]:
```
model = ExtraTreesClassifier()
param_grid = [{'n_estimators': [200,250,300], 'max_depth': [30,50,70]}]
folds = 5

#save best model for RFC
etc_best = model_fit_ensemble(model, param_grid, folds)
```

```
Precision:  0.8636363636363636 , Recall:  0.8769230769230769 , F1:
0.8702290076335878
```

4.4.4 4.4. Voting Classifier

[322]:
```
from sklearn.ensemble import VotingClassifier

#create a dictionary of our models

voting_clf=[('rfc', rfc_best), ('abc', abc_best), ('etc', etc_best)]
#create our voting classifier, inputting our models
voting_clf = VotingClassifier(voting_clf, voting='soft')

#fit model to training data
voting_clf.fit(X_train, y_train)

#save best model
voting_best = voting_clf
```

[323]:
```
#accuracy scores for all models within ensemble
print('-'*5,'Accuracy Scores','-'*5)

for clf in (rfc_best, abc_best, etc_best, voting_best):
    y_pred = cross_val_predict(clf, X_train, y_train, cv=5)
```

```
    print(clf.__class__.__name__, accuracy_score(y_train,y_pred))
```

```
----- Accuracy Scores -----
RandomForestClassifier 0.9285714285714286
AdaBoostClassifier 0.9285714285714286
ExtraTreesClassifier 0.9081632653061225
VotingClassifier 0.9183673469387755
```

Insights: Our ensemble model performed better than our individual models! We've now built an ensemble model to combine individual models.

[324]:
```
#further metrics for ensamble voting classifier
print('-'*5,'Voting Classifier','-'*5)

print('precision_score ', precision_score(y_train,y_pred))
print('recall_score ', recall_score(y_train,y_pred))
print('f1_score ', f1_score(y_train,y_pred))
```

```
----- Voting Classifier -----
precision_score  0.8769230769230769
recall_score  0.8769230769230769
f1_score  0.8769230769230769
```

4.4.5 4.5. Percision and Recall

Explanation: Precision and recall are two extremely important model evaluation metrics. While precision refers to the percentage of your results which are relevant, recall refers to the percentage of total relevant results correctly classified by your algorithm. Unfortunately, it is not possible to maximize both these metrics at the same time, as one comes at the cost of another. For simplicity, there is another metric available, called F-1 score, which is a harmonic mean of precision and recall. Used Resources (non-exhaustive): - LINK: https://towardsdatascience.com/fine-tuning-a-classifier-in-scikit-learn-66e048c21e65

[276]:
```
from sklearn.metrics import precision_recall_curve
```

[277]:
```
#score that gives the probability [0,1] that each sample belongs to class 1
y_scores = voting_best.predict_proba(X_test)[::,1]
```

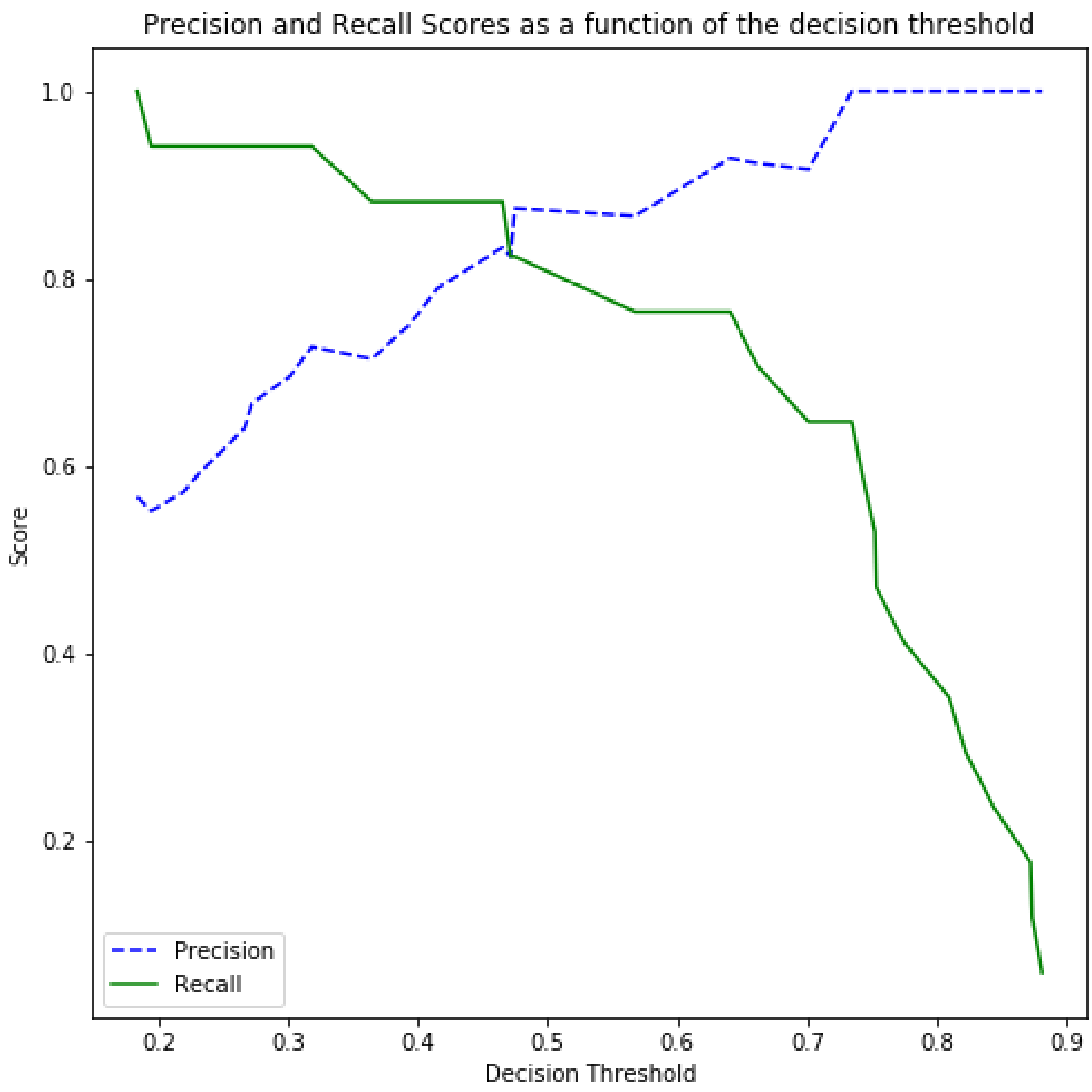
[278]:
```
#generate the precision recall curve
p, r, thresholds = precision_recall_curve(y_test, y_scores)
```

[279]:
```
#function to visualize relationship between precision/recall
def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.figure(figsize=(8, 8))
    plt.title("Precision and Recall Scores as a function of the decision␣
 ↪threshold")
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision")
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall")
```

```
    plt.ylabel("Score")
    plt.xlabel("Decision Threshold")
    plt.legend(loc='best')
```

Insights: One way to view the tradeoff between precision and recall is to plot them together as a function of the decision threshold. This is pretty intuitive. If you have to recall everything, you will have to keep generating results which are not accurate, hence lowering your precision.

[280]:
```
#plot percision/recall - to evaluate threshold
plot_precision_recall_vs_threshold(p, r, thresholds)
```



(5)

4.5 Spotcheck Neuronal Network

Model Selection

[281]:
```
#import required library
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import Dense
from sklearn.preprocessing import OneHotEncoder
```

[282]:
```
#Changing pandas dataframe to numpy array
X_n = df_sampled.iloc[:,1:21].values
y_n = df_sampled.iloc[:,:1].values
```

[283]:
```
ohe = OneHotEncoder()
y_n = ohe.fit_transform(y_n).toarray()
print('One hot encoded array:')
print(y_n[0:1])
```

```
One hot encoded array:
[[0. 1.]]
```

[284]:
```
#Train test split of model
from sklearn.model_selection import train_test_split
X_train_n,X_test_n,y_train_n,y_test_n = train_test_split(X_n,y_n,test_size = 0.
↪2,random_state = 0)
```

[285]:
```
model = keras.models.Sequential()
model.add(Dense(4, input_dim=20, activation='relu'))
model.add(Dense(2, activation='softmax'))
```

[286]:
```
#To visualize neural network
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_2 (Dense)              (None, 4)                 84
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 10
=================================================================
Total params: 94
Trainable params: 94
Non-trainable params: 0
_________________________________________________________________
```

[287]:
```
model.compile(loss=tf.keras.losses.BinaryCrossentropy(), optimizer="sgd",␣
↪metrics=['accuracy']) #optimizer='adam' #keras.optimizer.SGD(lr=1e-3)
```

[288]:
```
history = model.fit(X_train_n, y_train_n, epochs=80, batch_size=32,␣
↪validation_data=(X_test_n, y_test_n))
```

```
Train on 196 samples, validate on 50 samples
Epoch 1/80
196/196 [==============================] - 0s 520us/sample - loss: 0.7988 - acc:
0.3469 - val_loss: 0.8242 - val_acc: 0.2800
Epoch 2/80
196/196 [==============================] - 0s 47us/sample - loss: 0.7780 - acc:
0.3520 - val_loss: 0.8027 - val_acc: 0.3000
Epoch 3/80
196/196 [==============================] - 0s 46us/sample - loss: 0.7627 - acc:
0.3520 - val_loss: 0.7842 - val_acc: 0.3000
Epoch 4/80
196/196 [==============================] - 0s 44us/sample - loss: 0.7494 - acc:
0.3520 - val_loss: 0.7659 - val_acc: 0.2800
Epoch 5/80
196/196 [==============================] - 0s 46us/sample - loss: 0.7365 - acc:
0.3622 - val_loss: 0.7501 - val_acc: 0.2600
Epoch 6/80
196/196 [==============================] - 0s 45us/sample - loss: 0.7256 - acc:
0.3622 - val_loss: 0.7365 - val_acc: 0.2600
Epoch 7/80
196/196 [==============================] - 0s 46us/sample - loss: 0.7164 - acc:
0.3265 - val_loss: 0.7265 - val_acc: 0.2800
Epoch 8/80
196/196 [==============================] - 0s 46us/sample - loss: 0.7095 - acc:
0.3469 - val_loss: 0.7175 - val_acc: 0.4000
Epoch 9/80
196/196 [==============================] - 0s 44us/sample - loss: 0.7037 - acc:
0.3776 - val_loss: 0.7112 - val_acc: 0.4200
Epoch 10/80
196/196 [==============================] - 0s 47us/sample - loss: 0.6996 - acc:
0.4184 - val_loss: 0.7039 - val_acc: 0.5000
Epoch 11/80
196/196 [==============================] - 0s 45us/sample - loss: 0.6950 - acc:
0.5255 - val_loss: 0.6956 - val_acc: 0.5000
Epoch 12/80
196/196 [==============================] - 0s 45us/sample - loss: 0.6900 - acc:
0.6020 - val_loss: 0.6864 - val_acc: 0.5200
Epoch 13/80
196/196 [==============================] - 0s 41us/sample - loss: 0.6848 - acc:
0.6224 - val_loss: 0.6831 - val_acc: 0.6200
Epoch 14/80
```

```
196/196 [==============================] - 0s 45us/sample - loss: 0.6825 - acc:
0.6276 - val_loss: 0.6752 - val_acc: 0.6800
Epoch 15/80
196/196 [==============================] - 0s 45us/sample - loss: 0.6780 - acc:
0.6429 - val_loss: 0.6683 - val_acc: 0.6800
Epoch 16/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6742 - acc:
0.6480 - val_loss: 0.6655 - val_acc: 0.6800
Epoch 17/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6726 - acc:
0.6480 - val_loss: 0.6609 - val_acc: 0.6800
Epoch 18/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6702 - acc:
0.6531 - val_loss: 0.6588 - val_acc: 0.7000
Epoch 19/80
196/196 [==============================] - 0s 45us/sample - loss: 0.6690 - acc:
0.6531 - val_loss: 0.6558 - val_acc: 0.7000
Epoch 20/80
196/196 [==============================] - 0s 40us/sample - loss: 0.6672 - acc:
0.6531 - val_loss: 0.6519 - val_acc: 0.7000
Epoch 21/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6652 - acc:
0.6531 - val_loss: 0.6491 - val_acc: 0.7000
Epoch 22/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6638 - acc:
0.6531 - val_loss: 0.6446 - val_acc: 0.7200
Epoch 23/80
196/196 [==============================] - 0s 41us/sample - loss: 0.6614 - acc:
0.6531 - val_loss: 0.6414 - val_acc: 0.7200
Epoch 24/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6598 - acc:
0.6531 - val_loss: 0.6375 - val_acc: 0.7200
Epoch 25/80
196/196 [==============================] - 0s 42us/sample - loss: 0.6578 - acc:
0.6531 - val_loss: 0.6365 - val_acc: 0.7200
Epoch 26/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6572 - acc:
0.6531 - val_loss: 0.6341 - val_acc: 0.7200
Epoch 27/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6558 - acc:
0.6531 - val_loss: 0.6318 - val_acc: 0.7200
Epoch 28/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6547 - acc:
0.6531 - val_loss: 0.6312 - val_acc: 0.7200
Epoch 29/80
196/196 [==============================] - 0s 41us/sample - loss: 0.6542 - acc:
0.6531 - val_loss: 0.6297 - val_acc: 0.7200
Epoch 30/80
```

```
196/196 [==============================] - 0s 46us/sample - loss: 0.6534 - acc:
0.6531 - val_loss: 0.6286 - val_acc: 0.7200
Epoch 31/80
196/196 [==============================] - 0s 47us/sample - loss: 0.6527 - acc:
0.6531 - val_loss: 0.6261 - val_acc: 0.7200
Epoch 32/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6516 - acc:
0.6531 - val_loss: 0.6245 - val_acc: 0.7200
Epoch 33/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6508 - acc:
0.6531 - val_loss: 0.6229 - val_acc: 0.7200
Epoch 34/80
196/196 [==============================] - 0s 42us/sample - loss: 0.6500 - acc:
0.6531 - val_loss: 0.6222 - val_acc: 0.7200
Epoch 35/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6496 - acc:
0.6531 - val_loss: 0.6202 - val_acc: 0.7200
Epoch 36/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6487 - acc:
0.6531 - val_loss: 0.6186 - val_acc: 0.7200
Epoch 37/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6481 - acc:
0.6531 - val_loss: 0.6175 - val_acc: 0.7200
Epoch 38/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6476 - acc:
0.6531 - val_loss: 0.6171 - val_acc: 0.7200
Epoch 39/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6472 - acc:
0.6531 - val_loss: 0.6167 - val_acc: 0.7200
Epoch 40/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6470 - acc:
0.6531 - val_loss: 0.6160 - val_acc: 0.7200
Epoch 41/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6467 - acc:
0.6531 - val_loss: 0.6152 - val_acc: 0.7200
Epoch 42/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6465 - acc:
0.6531 - val_loss: 0.6140 - val_acc: 0.7200
Epoch 43/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6461 - acc:
0.6531 - val_loss: 0.6137 - val_acc: 0.7200
Epoch 44/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6459 - acc:
0.6531 - val_loss: 0.6135 - val_acc: 0.7200
Epoch 45/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6457 - acc:
0.6531 - val_loss: 0.6124 - val_acc: 0.7200
Epoch 46/80
```

```
196/196 [==============================] - 0s 43us/sample - loss: 0.6455 - acc:
0.6531 - val_loss: 0.6123 - val_acc: 0.7200
Epoch 47/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6452 - acc:
0.6531 - val_loss: 0.6117 - val_acc: 0.7200
Epoch 48/80
196/196 [==============================] - 0s 41us/sample - loss: 0.6450 - acc:
0.6531 - val_loss: 0.6108 - val_acc: 0.7200
Epoch 49/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6447 - acc:
0.6531 - val_loss: 0.6112 - val_acc: 0.7200
Epoch 50/80
196/196 [==============================] - 0s 48us/sample - loss: 0.6447 - acc:
0.6531 - val_loss: 0.6116 - val_acc: 0.7200
Epoch 51/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6448 - acc:
0.6531 - val_loss: 0.6111 - val_acc: 0.7200
Epoch 52/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6445 - acc:
0.6531 - val_loss: 0.6111 - val_acc: 0.7200
Epoch 53/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6445 - acc:
0.6531 - val_loss: 0.6105 - val_acc: 0.7200
Epoch 54/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6443 - acc:
0.6531 - val_loss: 0.6104 - val_acc: 0.7200
Epoch 55/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6442 - acc:
0.6531 - val_loss: 0.6095 - val_acc: 0.7200
Epoch 56/80
196/196 [==============================] - 0s 41us/sample - loss: 0.6439 - acc:
0.6531 - val_loss: 0.6095 - val_acc: 0.7200
Epoch 57/80
196/196 [==============================] - 0s 44us/sample - loss: 0.6439 - acc:
0.6531 - val_loss: 0.6091 - val_acc: 0.7200
Epoch 58/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6438 - acc:
0.6531 - val_loss: 0.6086 - val_acc: 0.7200
Epoch 59/80
196/196 [==============================] - 0s 45us/sample - loss: 0.6436 - acc:
0.6531 - val_loss: 0.6082 - val_acc: 0.7200
Epoch 60/80
196/196 [==============================] - 0s 45us/sample - loss: 0.6434 - acc:
0.6531 - val_loss: 0.6077 - val_acc: 0.7200
Epoch 61/80
196/196 [==============================] - 0s 41us/sample - loss: 0.6433 - acc:
0.6531 - val_loss: 0.6077 - val_acc: 0.7200
Epoch 62/80
```

```
196/196 [==============================] - 0s 43us/sample - loss: 0.6432 - acc:
0.6531 - val_loss: 0.6073 - val_acc: 0.7200
Epoch 63/80
196/196 [==============================] - 0s 42us/sample - loss: 0.6431 - acc:
0.6531 - val_loss: 0.6065 - val_acc: 0.7200
Epoch 64/80
196/196 [==============================] - 0s 42us/sample - loss: 0.6429 - acc:
0.6531 - val_loss: 0.6061 - val_acc: 0.7200
Epoch 65/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6428 - acc:
0.6531 - val_loss: 0.6062 - val_acc: 0.7200
Epoch 66/80
196/196 [==============================] - 0s 41us/sample - loss: 0.6428 - acc:
0.6531 - val_loss: 0.6059 - val_acc: 0.7200
Epoch 67/80
196/196 [==============================] - 0s 42us/sample - loss: 0.6427 - acc:
0.6531 - val_loss: 0.6060 - val_acc: 0.7200
Epoch 68/80
196/196 [==============================] - 0s 46us/sample - loss: 0.6426 - acc:
0.6531 - val_loss: 0.6057 - val_acc: 0.7200
Epoch 69/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6426 - acc:
0.6531 - val_loss: 0.6057 - val_acc: 0.7200
Epoch 70/80
196/196 [==============================] - 0s 49us/sample - loss: 0.6424 - acc:
0.6531 - val_loss: 0.6054 - val_acc: 0.7200
Epoch 71/80
196/196 [==============================] - 0s 40us/sample - loss: 0.6423 - acc:
0.6531 - val_loss: 0.6055 - val_acc: 0.7200
Epoch 72/80
196/196 [==============================] - 0s 39us/sample - loss: 0.6423 - acc:
0.6531 - val_loss: 0.6059 - val_acc: 0.7200
Epoch 73/80
196/196 [==============================] - 0s 39us/sample - loss: 0.6422 - acc:
0.6531 - val_loss: 0.6056 - val_acc: 0.7200
Epoch 74/80
196/196 [==============================] - 0s 46us/sample - loss: 0.6421 - acc:
0.6531 - val_loss: 0.6056 - val_acc: 0.7200
Epoch 75/80
196/196 [==============================] - 0s 42us/sample - loss: 0.6422 - acc:
0.6531 - val_loss: 0.6060 - val_acc: 0.7200
Epoch 76/80
196/196 [==============================] - 0s 46us/sample - loss: 0.6421 - acc:
0.6531 - val_loss: 0.6061 - val_acc: 0.7200
Epoch 77/80
196/196 [==============================] - 0s 41us/sample - loss: 0.6419 - acc:
0.6531 - val_loss: 0.6062 - val_acc: 0.7200
Epoch 78/80
```

```
196/196 [==============================] - 0s 43us/sample - loss: 0.6419 - acc:
0.6531 - val_loss: 0.6054 - val_acc: 0.7200
Epoch 79/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6418 - acc:
0.6531 - val_loss: 0.6050 - val_acc: 0.7200
Epoch 80/80
196/196 [==============================] - 0s 43us/sample - loss: 0.6416 - acc:
0.6531 - val_loss: 0.6051 - val_acc: 0.7200
```

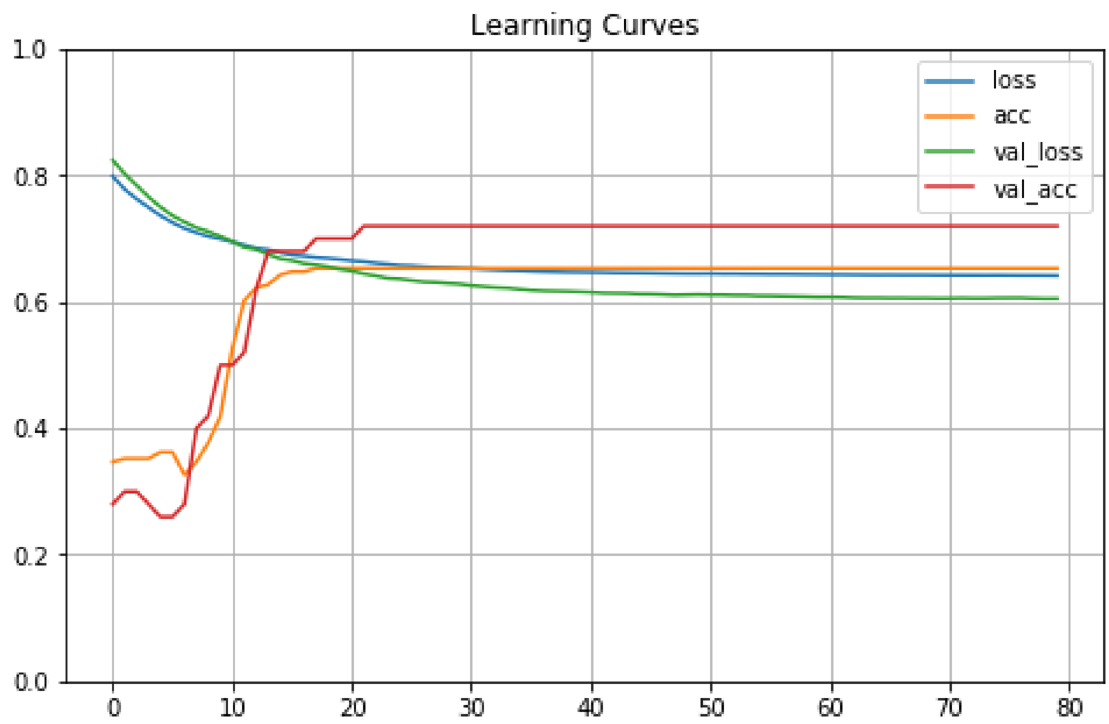
[289]:
```
y_pred_n = model.predict(X_test_n)
#Converting predictions to label
pred_n = list()
for i in range(len(y_pred_n)):
    pred_n.append(np.argmax(y_pred_n[i]))
```

[290]:
```
#Converting one hot encoded test label to label
test = list()
for i in range(len(y_test_n)):
    test.append(np.argmax(y_test_n[i]))
```

[291]:
```
from sklearn.metrics import accuracy_score
a = accuracy_score(pred_n,test)
print('Accuracy is:', a*100)
```

```
Accuracy is: 72.0
```

[292]:
```
pd.DataFrame(history.history).plot(figsize=(8,5))
plt.grid(True)
plt.gca().set_ylim(0,1) # set the vertical range to [0-1]
plt.title("Learning Curves")
plt.show()
```



Insights: We can see that the training and the test accuracy increase during the training, while the training loss and validation loss decrease. However, the model performs porer than our voting classifier and most of our other classifiers from the step above. Hence, we will neglect the neuronal network.

(6)

4.6 Model Selection Summary

Model Selection

Insights: Based on the previous steps outlined of the 'Model Selection' (i.e., selection, optimization, …) we derive the below final model, which we will use in during the further analysis.

[293]:
```
#re-asign and output final model for further analysis
finalmodel = voting_best
```

Save Model

[294]:
```
#import required libraries
import pickle
```

[295]:
```
##save finalized model
filename = 'finalmodel.sav'
```

```
pickle.dump(finalmodel, open(filename, 'wb'))
```

5 Algorithm Results

Now that we have grasped a sense of the alogorithm evaluation we will continue to discuss the results w/ looking at some evaluation approaches.

The following will be covered in this section: 1. Confusions Matrix 2. Further Model Metrics (e.g., Percision, Recall, etc.) 3. ROC Curve 4. Model Performance 5. Feature Importance Analysis

(1)

5.1 Confusion Matrix

Algorithm Results

Explanation: To get a better idea of the quality of our predictions, we can plot a confusion matrix and ROC curve. A confusion matrix is a technique for summarizing the performance of a classification algorithm that allows visualization of the performance of an algorithm. Each row of the matrix represents the instances in a predicted class while each column represents the instances in an actual class (or vice versa). The confusion matrix shows the ways in which your classification model is confused when it makes predictions. It gives you insight not only into the errors being made by your classifier but more importantly the types of errors that are being made.

[296]:
```
pip install scikit-plot
```

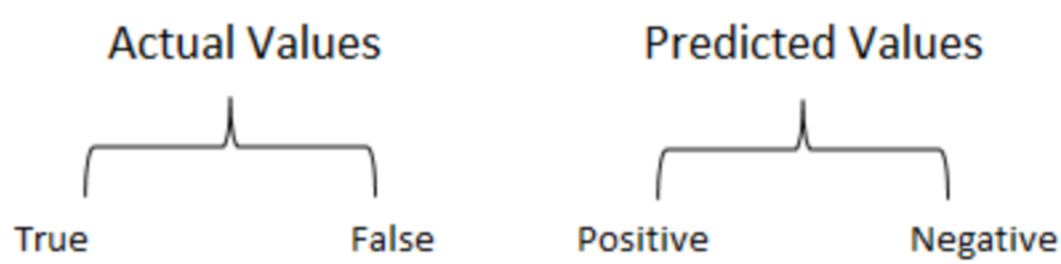
```
Requirement already satisfied: scikit-plot in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (0.3.7)
Requirement already satisfied: scikit-learn>=0.18 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from scikit-plot)
(0.22.1)
Requirement already satisfied: joblib>=0.10 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from scikit-plot)
(0.14.1)
Requirement already satisfied: matplotlib>=1.4.0 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from scikit-plot)
(3.1.3)
Requirement already satisfied: scipy>=0.9 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from scikit-plot)
(1.4.1)
Requirement already satisfied: numpy>=1.11.0 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from scikit-
learn>=0.18->scikit-plot) (1.18.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
matplotlib>=1.4.0->scikit-plot) (1.1.0)
Requirement already satisfied: cycler>=0.10 in
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
matplotlib>=1.4.0->scikit-plot) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
matplotlib>=1.4.0->scikit-plot) (2.4.6)
Requirement already satisfied: python-dateutil>=2.1 in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
matplotlib>=1.4.0->scikit-plot) (2.8.1)
Requirement already satisfied: setuptools in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
kiwisolver>=1.0.1->matplotlib>=1.4.0->scikit-plot) (46.1.3.post20200330)
Requirement already satisfied: six in
/opt/anaconda/envs/Python3/lib/python3.6/site-packages (from
cycler>=0.10->matplotlib>=1.4.0->scikit-plot) (1.14.0)
Note: you may need to restart the kernel to use updated packages.
```

[297]:
```
#import required library
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import average_precision_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import plot_precision_recall_curve
import scikitplot as skplt
```

Explanation: What actually is the confusion matrix? Well, it is a performance measurement for machine learning classification problem where output can be two or more classes. It is a table with 4 different combinations of predicted and actual values (see output structure below). Thereby, we describe predicted values as Positive and Negative and actual values as True and False. Used resources: - LINK: https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html#sphx-glr-auto-examples-model-selection-plot-confusion-matrix-py

[298]:
```
display(Image(filename='./GRAPHICS/CF_explain.png', width=400, height=40))
```

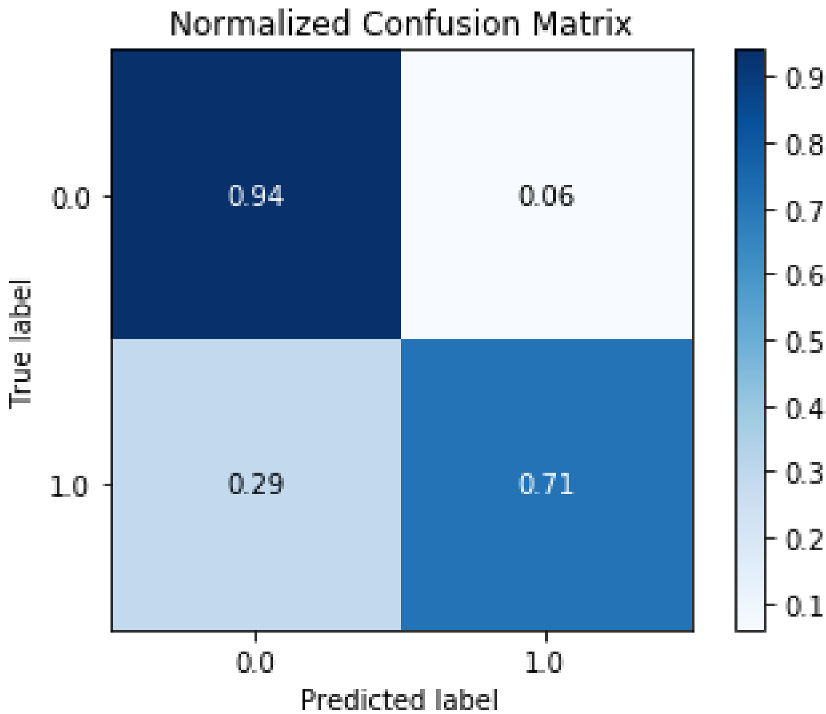


Explanation: How does one confusion matrix actually look? Based on the above defined terminology we gain the following ouput. This will be extremely useful for measuring Recall, Precision, Accuracy and most importantly ROC Curve later on.

[299]:
```
display(Image(filename='./GRAPHICS/CF_Matrix.jpeg', width=300, height=60))
```

Insights: As seen above, with real values the normalized confusion matrix indicates that we are able to predict 'no success' with a rate above 90% and success roughly 3/4 of times.

[302]:
```
#plot normalized confusion matrix
skplt.metrics.plot_confusion_matrix(y_true, y_pred, normalize=True)
plt.show()
```



(2)

5.2 Further Model Metrics (e.g., Percision, Recall, etc.)

Algorithm Results

Explanation: - Precision is defined as the number of true positives (TP) over the number of true positives (TP) plus the number of false positives (FP). - Recall is defined as the number of true positives (TP) over the number of true positives (TP) plus the number of false negatives (FN).

[303]:
```
display(Image(filename='./GRAPHICS/Formula_P_R_F1.png', width=200, height=40))
```

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

[304]:
```
#count of binary confusion matrix outcomes
TP = df_confusion_matrix.iloc[1][1]
TN = df_confusion_matrix.iloc[0][0]
FP = df_confusion_matrix.iloc[0][1]
FN = df_confusion_matrix.iloc[1][0]

#retunr values
print('True Positives:', TP), print('True Negatives:', TN),
print('False Positives:', FP), print('False Negatives:', FN)
```

```
True Positives: 12
True Negatives: 31
False Positives: 5
False Negatives: 2
```

[304]: (None, None)

[305]:
```
#calculate further model metrics

# precision tp / (tp + fp)
precision = precision_score(y_true, y_pred)

# recall: tp / (tp + fn)
recall = recall_score(y_true, y_pred)

# f1: 2 tp / (2 tp + fp + fn)
f1 = f1_score(y_true, y_pred)

#output outlined model metrics
print('MODEL METRICS'), print('-'*10)
```

```
print('Precision: %f' % precision)
print('Recall: %f' % recall)
print('F1 score: %f' % f1)
```

```
MODEL METRICS
----------
Precision: 0.857143
Recall: 0.705882
F1 score: 0.774194
```

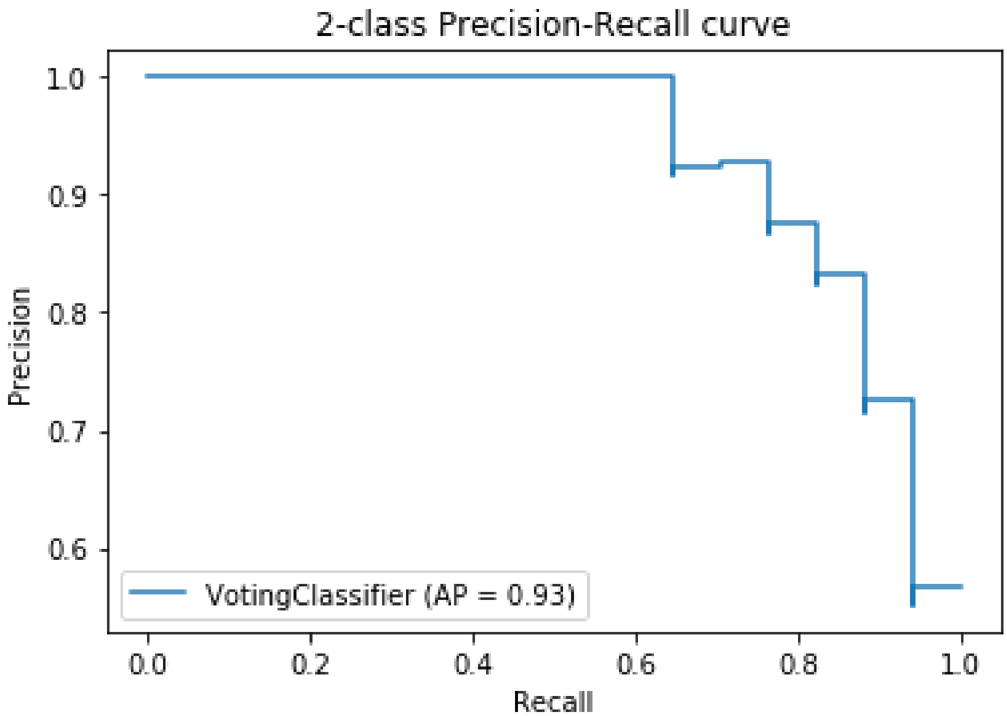
Insights: While recall expresses the ability to find all relevant instances in a dataset, precision expresses the proportion of the data points our model says was relevant actually were relevant. We continue by visualizing the relationship between percision and recall. Some resources used in the process: - LINK: https://scikit-learn.org/stable/auto_examples/model_selection/plot_precision_recall.html#sphx-glr-auto-examples-model-selection-plot-precision-recall-py - LINK: http://index-of.es/Varios-2/Hands%20on%20Machine%20Learning%20with%20Scikit%20Learn%20and%20Tensorflow.pdf

[306]:
```
#calculate average percision score
average_precision = average_precision_score(y_test, y_pred)
print('Average precision-recall score: {0:0.2f}'.format(average_precision))
```

```
Average precision-recall score: 0.71
```

[307]:
```
#plor percision score
disp = plot_precision_recall_curve(finalmodel, X_test, y_test)
disp.ax_.set_title('2-class Precision-Recall curve')
```

[307]:
```
Text(0.5, 1.0, '2-class Precision-Recall curve')
```



(3)

5.3 ROC Curve

Algorithm Results

Receiver Operating Characteristic (ROC) curves show the ability of the model to classify subjects correctly across a range of decision thresholds, i.e. it plots the True Positive Rate vs. False Positive Rate at every probability threshold.

The AUC summarizes the results of an ROC – it is the probability that a randomly chosen 'success' example has a higher probability of being a success than a randomly chosen 'failure' example. A random classification would yield an AUC of 0.5, and a perfectly accurate one would yield 1.

5.3.1 3.1. ROC Curve for Random Forrest

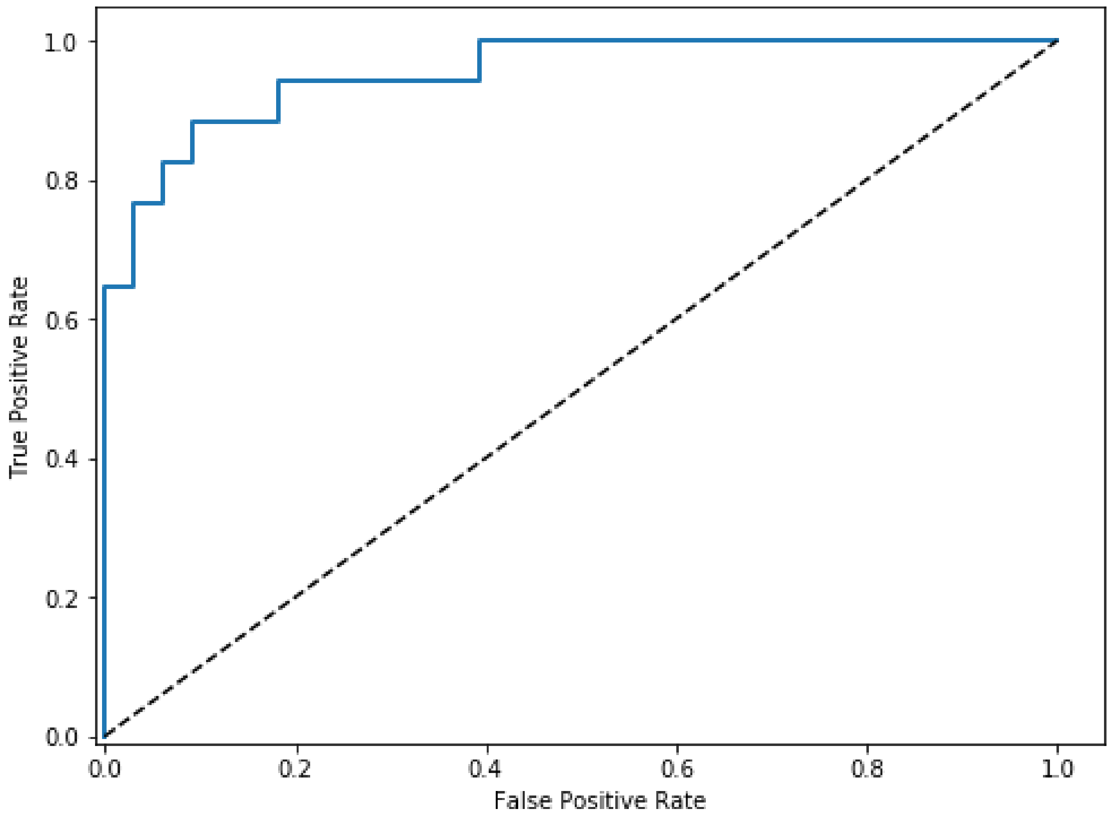
[308]:
```
#import further libraries
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import roc_auc_score
from sklearn import metrics
```

[309]:
```
#define function to plot ROC curve
def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
```

```
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([-0.01, 1.05, -0.01, 1.05])
    plt.xlabel('False Positive Rate', fontsize=10)
    plt.ylabel('True Positive Rate', fontsize=10)
```

Explanation: The ROC curve features true positive rate on the Y axis, and false positive rate on the X axis. This means that the top left corner of the plot is the "ideal" point - a false positive rate of zero, and a true positive rate of one. This is not very realistic, but it does mean that a larger area under the curve (AUC) is usually better. Before starting this part, we studied some basig online literature to get a better understanding. Some resources used: - LINK: http://index-of.es/Varios-2/Hands%20on%20Machine%20Learning%20with%20Scikit%20Learn%20and%20Tensorflow.pdf - LINK: https://machinelearningmastery.com/roc-curves-and-precision-recall-curves-for-classification-in-python/ - LINK: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3755824/

[310]:
```
#plot ROC curve

#calculate prediction probability
y_pred_proba = finalmodel.predict_proba(X_test)[::,1]
#set true and false predictions
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba)

#plot actual graph
plt.figure(figsize=(8, 6))
plot_roc_curve(fpr, tpr)
plt.show()
```



[311]:
```
#calculate auc
auc_rfc = metrics.roc_auc_score(y_test, y_pred_proba)
auc_rfc
```

[311]: 0.9536541889483066

Explanation: One notices that the ROC curve for our final model as kinks. Kinks are problems in how the data was collected and not in the ability of the model to perform. Therefore, they are not to worry about at this stage.

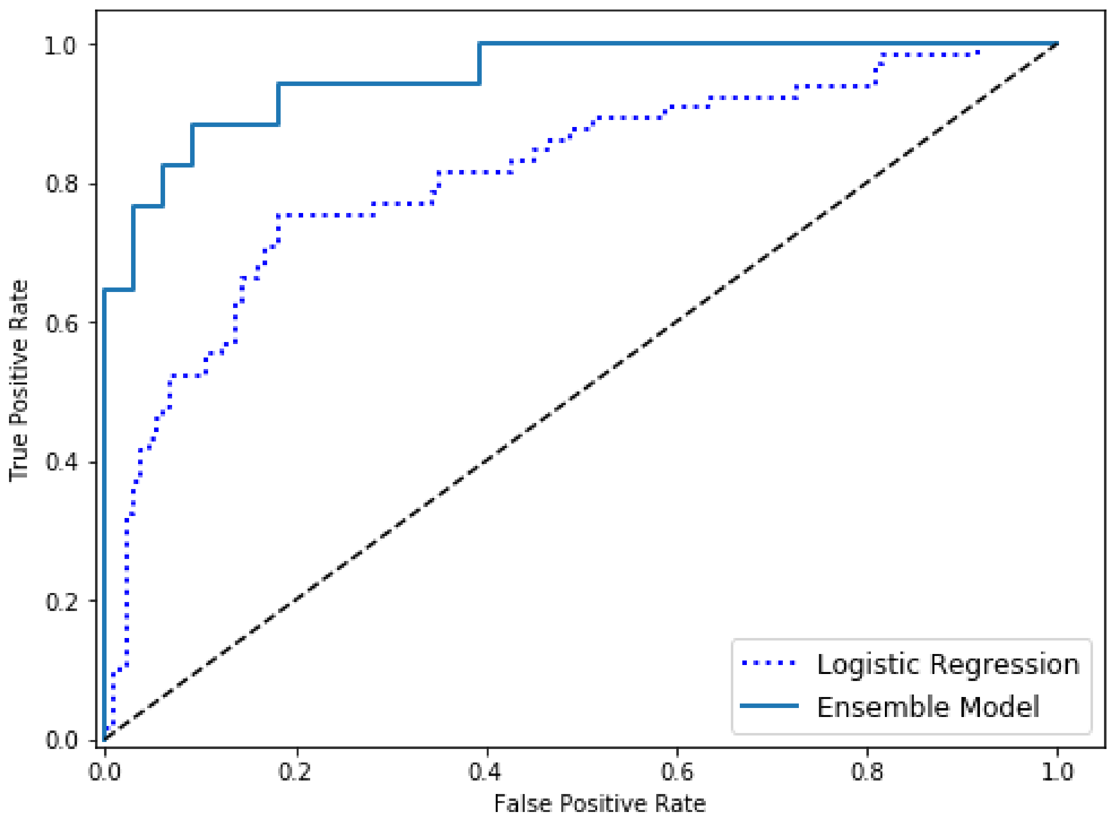
5.3.2 3.2. ROC Curve Comparison for Benchmark

[312]:
```
#prep. for comparison ROC curve (LogisticRegression as comparison)
var = LogisticRegression()
var.fit(X_train,y_train)
y_probas_logreg = cross_val_predict(var, X_train, y_train, cv=3,␣
↪method="predict_proba")
y_pred_proba_logreg = var.predict_proba(X_test)[::,1]

y_scores_logreg = y_probas_logreg[:, 1] # score = proba of positive class
```

```
fpr_logreg, tpr_logreg, thresholds_logreg = roc_curve(y_train, y_scores_logreg)
```

Insights: The ROC curve confirms the previously gained results. As expected from the accuracy calculated before, the RandomForrest performs well; especially when compared to other model (e.g., LogisticRegression - see below). The ROC curve for RFC approximately approaches the optimum (TP=1; FP=0) with a rather steep increase - the bottom line is that this model appears to perfrom well.

[313]:
```
#plot comparison ROC courve (choosen model against logistic regression)
plt.figure(figsize=(8, 6))
plt.plot(fpr_logreg, tpr_logreg, "b:", linewidth=2, label = "Logistic␣
 ↪Regression")
plot_roc_curve(fpr, tpr, "Ensemble Model")
plt.legend(loc="lower right", fontsize=12)
plt.show()
```



Explanation: Area under the curve (AUC) tells how much model is capable of distinguishing between classes. Higher the AUC, better the model is at predicting 0s as 0s and 1s as 1s. By analogy, Higher the AUC, better the model is at distinguishing between success and no success.

[314]:
```
#calculate auc for logreg
auc_logreg = metrics.roc_auc_score(y_test, y_pred_proba_logreg)

#return AUC scores
print('AREA UNDER CURVE (AUC)'), print('-'*10)
print('RFC: ', auc_rfc)
print('LogReg: ', auc_logreg)
```

```
AREA UNDER CURVE (AUC)
----------
RFC:  0.9536541889483066
LogReg:  0.8520499108734403
```

Insights: When calculating the area under the curve (AUC) for both Random Forrest and Logistic Regression, we can not only prove the better performance visualy (see ROC above), we can also quantitatvely prove the results. AUC for Random Forrest Calssifier is higher.

(4)

5.4 Model Performance

Algorithm Results

Recap: Let's shortly outline what we have done in section '5. Present Results'. First, we clarfified and defined our potential four outomes for classification. Four Outcomes of Binary Classification: - True positives (TP): data points labeled as positive that are actually positive - False positives (FP): data points labeled as positive that are actually negative - True negatives (TN): data points labeled as negative that are actually negative - False negatives (FN): data points labeled as negative that are actually positive

Recall and Precision Metrics: - Recall: ability of a classification model to identify all relevant instances - Precision: ability of a classification model to return only relevant instances - F1 score: single metric that combines recall and precision using the harmonic mean

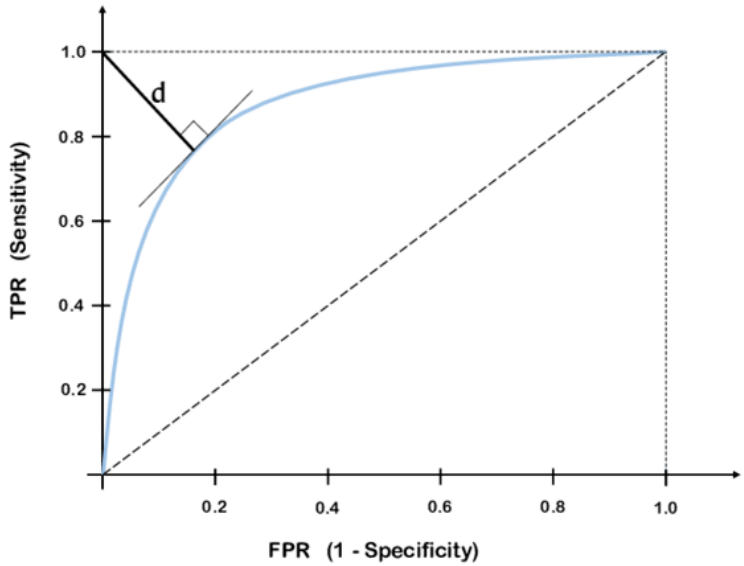
Visualizing Recall and Precision - Confusion matrix: shows the actual and predicted labels from a classification problem - Receiver operating characteristic (ROC) curve: plots the true positive rate (TPR) versus the false positive rate (FPR) as a function of the model's threshold for classifying a positive - Area under curve (AUC): metric to calculate the overall performance of a classification model based on area under the ROC curve

Confusion Matrix ***Insights:*** Our prediction for success / no success is already at a high level. However, our model in the current state often classifies False Negatives (FN) for success; however, since - as outlines - we aim to keep FPs low this tradeoff between recall and precision seems accepctable.

ROC curve ***Explanation:*** The below graph indicates a theoretical ROC curve for a given model. Focus is on 'd' the distance to TP=1 & FP = 0. This distance should be minimal in order to the model to classify with a high acuracy.

[315]:

```
display(Image(filename='./GRAPHICS/Optimal_ROC_Curve.png', width=500,␣
↪height=90))
```



Insights: While our RFC model performs comparably good when comparing with the other models tested on our dataset, it still has room for improvments. Therefore, our aim shoudl be to further reduce the distance and hence make the AUC greater.

Now that you have a validated model, we can potentially analyze the features of the model, to understand which ones have had the most impact on predicting an artist's success.

To do this, we can plot the feature importance as determined by the classifier:

(5)

5.5 Feature Importance Analysis

Algorithm Results

Explanation: Decision trees make splits that maximize the decrese in impurity. By calculating the mean decrease for each feature across all trees we can know that feature's importance.

[316]:

```
#get feature importance
feature_importances = list(rfc_best.feature_importances_)

#get attribute/feature names
attributes = df_sampled.drop('artist_success',axis=1).columns

#sort feature names according to importance
```

```
feature_importances, attributes = zip(*sorted(zip(feature_importances,␣
↪attributes), reverse=True))
```

Let's look at the feature imporatnce in detail. One can notice the following clusters of features:

- Age Groups (largest portion)
- PCA
- Gender Share
- Artist Features

Given the rather narrow scope of the project there is much more room to expand on attribute creation; which after multi-correlation check will potentially be included in the final model.

Insights: The most important feature (by far) appears to be 'artist_stream_count_general' which indicates the stream count per artist for both genders. As we will see later on, this feature is crucial for our model prediction. Additioanlly, one has to point out 'artist_success_before2016' - the importance of this feature is surprisingly low (see table below).

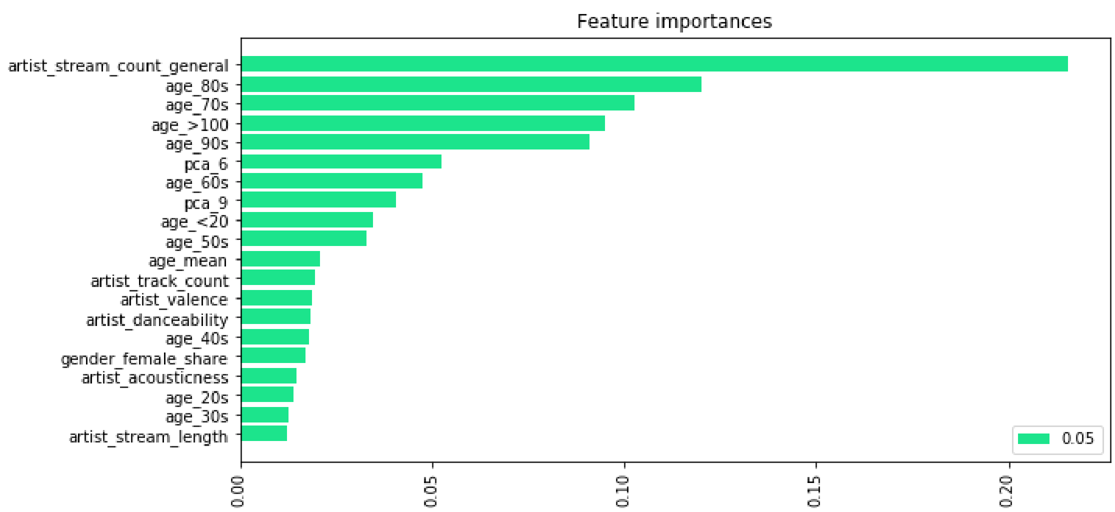
[317]:
```
#output feature and according feature importance
print('FEATURE IMPORTANCE'), print('-'*10)
for i in range(18):
    print(attributes[i], ' ', feature_importances[i])
```

```
FEATURE IMPORTANCE
----------
artist_stream_count_general   0.21567018647291497
age_80s   0.12007833748066797
age_70s   0.10267673090101369
age_>100   0.09491613956730287
age_90s   0.09100187141663212
pca_6   0.05262549178605154
age_60s   0.04777406312374869
pca_9   0.04078152022835618
age_<20   0.03450789644104383
age_50s   0.033193606092909056
age_mean   0.02095350646195437
artist_track_count   0.019767384328142009
artist_valence   0.01862275781660901
artist_danceability   0.018451444472869314
age_40s   0.017961935324029423
gender_female_share   0.017023061880280993
artist_acousticness   0.014906733341113703
age_20s   0.014075766692979106
```

[318]:
```
#calculate average feature importance
avg_feature_importances = round(np.mean(feature_importances),2)
```

Insights: It appears that age groups are very important to our model. Even more interesting is that 'higher' age groups above 70 years have a high feature importance. One reason to exlain could be that artists that reach this age groups will be successful or not (e.g., as soon as even eldery people starting listing to music it is main-stream and therefore included in the playlists).

[319]:
```
#visualize feature importance
plt.figure(figsize=[10,5])
plt.title("Feature importances")

#sort feature names according to importance
feature_importances, attributes = zip(*sorted(zip(feature_importances,␣
 ↪attributes), reverse=False))

#plot for feature importance
plt.barh(attributes,feature_importances, color='#1CE48C')
plt.xticks(rotation='vertical')
#add average importance as legend
plt.legend([avg_feature_importances])
plt.show()
```



Sensitivity: - Final dataframe is rather small (199 train; 50 test), therefore, the model in general is rather sensitive; multiple runs have shown that accurcy varies +/- 2% - This results, in the second point to mention regarding sensitivity. Splitting the dataset into Training and Validation appears to be highly sensible (especially the 'random_state value') - Model appears to be highly sensitve for artist stream count; appear logical since it is the feature with the highest importance - Sensitivity for feature exclusion commented below

5.6 —-