2012094_20127247_20127333_20127380_20127406

December 5, 2022

0.1 PROJECT TITLE: EXPLORATORY DATA ANALYSIS

ID	Name	Resposible for	% contribution
20127094	Nguyễn Minh Văn	Data Visualization and Modelling	100%
20127247	Phan Xuân Nam	Data Pre-processing	100%
20127333	Nguyễn Duy Thịnh	Data Crawling	100%
20127380	Dương Minh Tùng	Answer Questions about Dataset	100%
20127406	Thái Cẩm Phong	Data Crawling	100%

0.2 Step 1: Collecting data

[1]:
```
import requests
import requests_cache
import time
import json
import re
import pandas as pd # Dùng để đọc và hiển thị file csv/tsv
from datetime import datetime, timedelta # Dùng để xử lý dữ liệu thời gian
import csv
from selenium import webdriver
from selenium.webdriver.common.keys import Keys
from selenium.webdriver.common.by import By
from selenium.common.exceptions import TimeoutException
from selenium.webdriver.support.ui import WebDriverWait
from selenium.webdriver.support import expected_conditions as EC
```

System function

[2]:
```
def scroll_down(driver):
    time.sleep(1)
    driver.execute_script("window.scrollTo(0, document.body.scrollHeight);")

def get_elements(driver, by, name, delay=2, first=False, tries=5):
    while tries > 0:
        try:
```

```
            elem = None
            if first:
                elem = WebDriverWait(driver, delay).until(EC.
↪presence_of_element_located((by, name)))
            else:
                elem = WebDriverWait(driver, delay).until(EC.
↪presence_of_all_elements_located((by, name)))
            return elem
        except TimeoutException:
            tries-=1
```

Get data function

[3]:
```
def get_info(driver, list_users_link, users):
    driver.execute_script("window.open('');")
    driver.switch_to.window(driver.window_handles[1])
    for link, id in list_users_link.items():
        driver.get(link)
        users['id'].append(id)
        name = 'infoStats__value'
        elements = get_elements(driver, By.CLASS_NAME, name)
        try:
            users['name'].append(get_elements(driver, By.CLASS_NAME,␣
↪'profileHeaderInfo__userName', first=True).text)
        except:
            users['name'].append(None)
        attrs = ['followers', 'following', 'tracks']
        for i in range(len(attrs)):
            try:
                users[attrs[i]].append(elements[i].text)
            except:
                users[attrs[i]].append(None)

    driver.close()
    driver.switch_to.window(driver.window_handles[0])

def get_users(driver, link, tracks, tracks_id, list_users_link,␣
↪list_tracks_link):
    global user_id
    global track_id
    driver.execute_script("window.open('');")
    driver.switch_to.window(driver.window_handles[2])
    driver.get(link)
    name = 'sc-ministats-item'
    elements = get_elements(driver, By.CLASS_NAME, name)
    if link in list_tracks_link.keys():
        tracks_id.append(str(list_tracks_link[link]))
```

```
    else:
        track_id += 1
        tracks['id'].append(track_id)
        tracks_id.append(str(track_id))
        author = get_elements(driver, By.CLASS_NAME, 'sc-link-secondary',␣
 ↪first=True)
        link = author.get_attribute('href')
        if link in list_users_link.keys():
            tracks['author'].append(list_users_link[link])
        else:
            user_id += 1
            tracks['author'].append(user_id)
            list_users_link[link] = user_id
        try:
            tracks['title'].append(get_elements(driver, By.CLASS_NAME,␣
 ↪'soundTitle__title', first=True).text)
        except:
            tracks['title'].append(None)
        attrs = ['plays', 'likes', 'reposts']
        for i in range(len(attrs)):
            try:
                tracks[attrs[i]].append(elements[i].get_attribute('title').
 ↪split(' ')[0])
            except:
                tracks[attrs[i]].append('0')
        tracks['release'].append(get_elements(driver, By.CLASS_NAME,␣
 ↪'relativeTime', first=True).text)
    driver.close()
    driver.switch_to.window(driver.window_handles[1])

def get_tracks(driver, link, tracks, tracks_id, list_users_link,␣
 ↪list_tracks_link):
    driver.execute_script("window.open('');")
    driver.switch_to.window(driver.window_handles[1])
    driver.get(link)
    name = 'trackItem__trackTitle'
    elements = get_elements(driver, By.CLASS_NAME, name)
    cnt = 0
    # crawl 2 tracks of playlist
    for e in elements:
        cnt += 1
        link = e.get_attribute('href')
        get_users(driver, link, tracks, tracks_id, list_users_link,␣
 ↪list_tracks_link)
        if cnt == 2:
            break
```

```
    driver.close()
    driver.switch_to.window(driver.window_handles[0])

def get_playlists(driver, elements, playlists, tracks, list_users_link,␣
 ↪list_tracks_link):
    global playlist_id
    global user_id
    for e in elements:
        # pass unavailable and less than 5 tracks
        data = e.text.split('\n')
        link = e.find_element(By.CLASS_NAME, 'soundTitle__title').
 ↪get_attribute('href')
        user_link = e.find_element(By.CLASS_NAME, 'soundTitle__username').
 ↪get_attribute('href')
        if data[0] == 'Unavailable' or not(data[-6].startswith('View') and␣
 ↪data[-6].endswith('tracks')):
            continue
        playlist_id += 1
        tracks_id = []
        if user_link in list_users_link.keys():
            playlists['author'].append(list_users_link[user_link])
        else:
            user_id += 1
            playlists['author'].append(user_id)
            list_users_link[user_link] = user_id
        playlists['id'].append(playlist_id)
        playlists['title'].append(data[2])
        playlists['likes'].append(data[-5] if data[-5] != 'Like' else '0')
        playlists['reposts'].append(data[-4] if data[-4] != 'Repost' else '0')
        playlists['release'].append(data[4])
        get_tracks(driver, link, tracks, tracks_id, list_users_link,␣
 ↪list_tracks_link)
        playlists['tracks'].append(','.join(tracks_id))
```

Execute the crawl process

Uncomment this cell to crawl the data (It may take 1-2 days to process)

[4]:
```
# driver = webdriver.Chrome()
# cookies = False
# playlists = {'id': [], 'title': [], 'author': [], 'tracks': [], 'likes': [],␣
 ↪'reposts': [], 'release': []}
# tracks = {'id': [], 'title': [], 'author': [], 'plays': [], 'likes': [],␣
 ↪'reposts': [], 'release': []}
# users = {'id': [], 'name': [], 'followers': [], 'following': [], 'tracks': []}
# global playlist_id
# global track_id
```

```
# global user_id
# playlist_id, track_id, user_id = 0, 0, 0
# list_tracks_link, list_users_link = {}, {}
# cookies_id = 'onetrust-accept-btn-handler'
# time.sleep(1)
# for i in range(ord('o'), ord('z')+1):
#     elements = []
#     key = chr(i)
#     driver.get(f'https://soundcloud.com/search/sets?q={key}')
#     if not(cookies):
#         time.sleep(3)
#         c = get_elements(driver, By.ID, cookies_id, delay=7, first=True).click()
#         cookies = True
#     while len(elements) < 50:
#         scroll_down(driver)
#         elements = driver.find_elements(By.CLASS_NAME, 'sound__content')
#     get_playlists(driver, elements, playlists, tracks, list_users_link, list_tracks_link)
#     get_info(driver, list_users_link, users)
#     playlist_df = pd.DataFrame(playlists, columns=['id', 'title', 'author', 'tracks', 'likes', 'reposts', 'release'])
#     track_df = pd.DataFrame(tracks, columns=['id', 'title', 'author', 'plays', 'likes', 'reposts', 'release'])
#     user_df = pd.DataFrame(users, columns=['id', 'name', 'followers', 'following', 'tracks'])
#     # Export to file
#     playlist_df.to_csv('playlists.csv', index='id')
#     track_df.to_csv('tracks.csv', index='id')
#     user_df.to_csv('users.csv', index='id')
# driver.quit()
```

0.3 Step 2: Pre-processing data

0.3.1 Step 2.1: Importing important libraries

[5]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import copy
pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

0.3.2 Step 2.2: Importing datasets

There are 3 files: “playlists.csv”, “tracks.csv”, “users.csv”

[6]:
```
playlists_df = pd.read_csv("SoundcloudData/playlists.csv")
tracks_df = pd.read_csv("SoundcloudData/tracks.csv")
users_df = pd.read_csv("SoundcloudData/users.csv")
```

[7]:
```
print(playlists_df.keys())
print(tracks_df.keys())
print(users_df.keys())
```

```
Index(['Unnamed: 0', 'id', 'title', 'author', 'tracks', 'likes', 'reposts',
       'release'],
      dtype='object')
Index(['Unnamed: 0', 'id', 'title', 'author', 'plays', 'likes', 'reposts',
       'release'],
      dtype='object')
Index(['Unnamed: 0', 'id', 'name', 'followers', 'following', 'tracks'],
dtype='object')
```

Hmmmm, there is an extra column called "Unnamed: 0". Let's remove that for all 3 dataframes

[8]:
```
tracks_df.drop(columns='Unnamed: 0', inplace=True)
users_df.drop(columns='Unnamed: 0', inplace=True)
playlists_df.drop(columns='Unnamed: 0', inplace=True)
```

[9]:
```
users_df.head()
```

[9]:

	id	name	followers	following	tracks
0	1	TMN Playlisted	21.6K	116	2
1	2	nymano	69.1K	512	79
2	3	Agami	14.7K	598	1
3	4	Levi Patel	14.7K	433	19
4	5	Alice Baldwin	4,680	117	18

Seems good, let the pre-processing begin!

0.3.3 Step 2.3: Pre-processing

These are methods that we will use for data pre-processing of each dataframe: - Check for meaning of each column - Check the number of columns and rows - Check for duplicated rows - Check for missing data - Check for the min/max values, mean - Check for the data type of each column and modify values (if needed)

Let's start with the "users" dataframe. We check for the first 5 rows of it.

[10]:
```
users_df.head()
```

[10]:

	id	name	followers	following	tracks
0	1	TMN Playlisted	21.6K	116	2
1	2	nymano	69.1K	512	79
2	3	Agami	14.7K	598	1

```
3   4      Levi Patel     14.7K        433      19
4   5   Alice Baldwin     4,680        117      18
```

The meaning of each column is: + id: the id of the user (categorical) + name: the username of the user (categorical) + followers: number of followers (numeric) + following: number of people that a user follows (numeric) + tracks: the number of tracks (numeric)

The name "tracks" is quite ambiguous, let's rename it so it's clearer to understand

[11]:
```
users_df.rename(columns={"tracks": "NumTracks"}, inplace=True)
users_df.rename(columns={"id": "author_id"}, inplace=True)
users_df.set_index('author_id', inplace=True)
```

We check for any duplicated rows in the dataframe

[12]:
```
check_user_dup = users_df.duplicated().any()
if check_user_dup:
    print("There are duplicated rows")
else:
    print("There is no duplicated rows")
```

```
There are duplicated rows
```

Wow, there are duplicated rows. We have to make each row unique and remove duplicated ones

[13]:
```
users_df.drop_duplicates(inplace=True)
```

After removing duplicated values, we check for the number of rows and columns

[14]:
```
print("Number of rows: "+str(users_df.shape[0]))
print("Number of columns: "+str(users_df.shape[1]))
```

```
Number of rows: 2893
Number of columns: 4
```

We check if there are any missing data in the dataframe

[15]:
```
col_users_key = list(users_df.keys())
percent_missing = users_df[col_users_key].isnull().sum() * 100 / len(users_df)
percent_missing
```

[15]:
```
name         0.06913
followers    0.17283
following    0.20740
NumTracks    0.20740
dtype: float64
```

Since there are very small number of rows that exist "null" values, we can drop them

[16]:

```
users_df.dropna(inplace=True)
print("Number of rows: "+str(users_df.shape[0]))
print("Number of columns: "+str(users_df.shape[1]))
```

```
Number of rows: 2886
Number of columns: 4
```

Next, we see what the data type of each column

[17]:

```
users_df.dtypes
```

[17]:

```
name          object
followers     object
following     object
NumTracks     object
dtype: object
```

We find that the number of followers, following and num tracks are not in the correct type, it should be in "int" type

[18]:

```
def change_number(s):
    to_change = list(set(s))
    change = []
    for item in to_change:
        temp = item
        if ("K" in item) and ("." not in item):
            temp = item.replace("K", "000")
        elif ("K" in item) and ("." in item):
            temp = item.replace("K", "00").replace(".", "")
        elif ("M" in item) and ("." not in item):
            temp = item.replace("M", "000000")
        elif ("M" in item) and ("." in item) and (len(temp)==4):
            temp = item.replace("M", "00000").replace(".", "")
        elif ("M" in item) and ("." in item) and (len(temp)==5):
            temp = item.replace("M", "0000").replace(".", "")
        elif ("," in item):
            temp = item.replace(",", "")
        change.append(temp)
    return to_change, change
```

[19]:

```
# users_df['followers'] = users_df['followers'].str.replace(',','')
# user_to_change, user_change = change_number(users_df['followers'])
# users_df['NumTracks'] = users_df['NumTracks'].replace(['12.1K'], '12100')
# users_df['NumTracks'] = users_df['NumTracks'].str.replace(',','')
# users_df["NumTracks"] = users_df['NumTracks'].astype(int)
# users_df['followers'] = users_df['followers'].replace(user_to_change,␣
 ↪user_change)
# users_df['followers'] = users_df['followers'].astype(int)
```

```
# users_df['following'] = users_df['following'].str.replace(',','')
# users_df['following'] = users_df['following'].astype(int)
```

[20]:
```
num_track_to_change, num_track_change = change_number(users_df['NumTracks'])
users_df['NumTracks'] = users_df['NumTracks'].replace(num_track_to_change,␣
 ↪num_track_change)
follower_to_change, follower_change = change_number(users_df['followers'])
users_df['followers'] = users_df['followers'].replace(follower_to_change,␣
 ↪follower_change)
following_to_change, following_change = change_number(users_df['following'])
users_df['following'] = users_df['following'].replace(following_to_change,␣
 ↪following_change)

users_df["NumTracks"] = users_df['NumTracks'].astype(int)
users_df['followers'] = users_df['followers'].astype(int)
users_df['following'] = users_df['following'].astype(int)
```

Let's have a look at how the data distribute

[21]:
```
users_df.describe()
```

[21]:
```
          followers  following   NumTracks
count    2886.00000 2886.00000  2886.00000
mean   178472.59459  130.61296    97.39744
std    810164.81229  310.78059   444.55766
min         0.00000    0.00000     0.00000
25%       174.50000    1.00000     0.00000
50%      2549.00000   15.00000    13.00000
75%     13300.00000   94.75000    50.00000
max   9510000.00000 2027.00000 12100.00000
```

Moving on, we work with the "tracks". We look for the first 5 rows

[22]:
```
tracks_df.head()
```

[22]:
```
   id                                              title  author       plays  \
0   1                                           solitude       2  18,184,198
1   2  quand la pluie tombe (also uploaded for The Vi…       2  11,928,581
2   3                                      As she passes       4  15,385,582
3   4                                        Was am Ende       5   3,865,947
4   5  Making All Things New (Waterman/Espe) - Record…       7   5,974,821

     likes reposts                   release
0  298,037  14,517  7 years ago\n7 years ago
1  155,823   7,556  8 years ago\n8 years ago
2  228,383   7,815  7 years ago\n7 years ago
3   37,123   1,447  3 years ago\n3 years ago
4  123,856   3,261  8 years ago\n8 years ago
```

The meaning of each column is: + id: the id of the track (categorical) + title: name of the track (categorical) + author: person who makes the track (numeric) + plays: total play count of a track + likes: number of people like a track (numeric) + reposts: number of reposting (numeric) + release: total years/months/days since the track first released (categorical)

We will change the columns' name to make it easier

[23]:
```
tracks_df.rename(columns={"author": "author_id", "plays": "total_plays",␣
↪"release": "year_release", "id": "track_id"}, inplace=True)
tracks_df.set_index('track_id', inplace=True)
```

We check for duplicates in the above dataframe

[24]:
```
check_track_dup = tracks_df.duplicated().any()
if check_track_dup:
    print("There are duplicated rows")
else:
    print("There is no duplicated rows")
```

```
There are duplicated rows
```

Awesome! Now we look for the number of rows and columns

[25]:
```
print("Number of rows: "+str(tracks_df.shape[0]))
print("Number of columns: "+str(tracks_df.shape[1]))
```

```
Number of rows: 2074
Number of columns: 6
```

Okay, let's look for missing values, shall we?

[26]:
```
col_tracks_key = list(tracks_df.keys())
percent_missing = tracks_df[col_tracks_key].isnull().sum() * 100 /␣
↪len(tracks_df)
percent_missing
```

[26]:
```
title           0.04822
author_id       0.00000
total_plays     0.00000
likes           0.00000
reposts         0.00000
year_release    0.00000
dtype: float64
```

Hmmm, there are some missing titles. Since the missing ratio is too insignificant, we can dop them.

[27]:
```
tracks_df.dropna(inplace=True)
print("Number of rows: "+str(tracks_df.shape[0]))
print("Number of columns: "+str(tracks_df.shape[1]))
```

```
Number of rows: 2073
Number of columns: 6
```

Now, the important part is to check for the data type and convert them accordingly to its supposingly correct one

[28]:
```python
tracks_df.dtypes
```

[28]:
```
title           object
author_id        int64
total_plays     object
likes           object
reposts         object
year_release    object
dtype: object
```

[29]:
```python
total_play_to_change, total_play_change =
  ↪change_number(tracks_df['total_plays'])
tracks_df['total_plays'] = tracks_df['total_plays'].
  ↪replace(total_play_to_change, total_play_change)
tracks_df['total_plays'] = tracks_df['total_plays'].astype(int)
likes_to_change, likes_change = change_number(tracks_df['likes'])
tracks_df['likes'] = tracks_df['likes'].replace(likes_to_change, likes_change)
tracks_df['likes'] = tracks_df['likes'].astype(int)
reposts_to_change, reposts_change = change_number(tracks_df['reposts'])
tracks_df['reposts'] = tracks_df['reposts'].replace(reposts_to_change,
  ↪reposts_change)
tracks_df['reposts'] = tracks_df['reposts'].astype(int)

release_to_change = list(set(tracks_df['year_release']))
release_change = [x.split("\n")[1] for x in release_to_change]
tracks_df['year_release'] = tracks_df['year_release'].
  ↪replace(release_to_change, release_change)
to_year = [2022-int(x.split(" ")[0]) if "year" in x else 2022 for x in
  ↪release_change]
tracks_df['year_release'] = tracks_df['year_release'].replace(release_change,
  ↪to_year)
tracks_df.head()
```

[29]:
```
                                                            title  author_id  \
track_id
1                                                        solitude          2
2         quand la pluie tombe (also uploaded for The Vi…                 2
3                                                   As she passes          4
4                                                     Was am Ende          5
5         Making All Things New (Waterman/Espe) - Record…                 7

          total_plays  likes  reposts  year_release
```

```
track_id
1           18184198  298037    14517           2015
2           11928581  155823     7556           2014
3           15385582  228383     7815           2015
4            3865947   37123     1447           2019
5            5974821  123856     3261           2014
```

Let's have a look at how the data distribute

[30]:
```python
tracks_df.describe().drop(columns=['author_id'])
```

[30]:

	total_plays	likes	reposts	year_release
count	2073.00000	2073.00000	2073.00000	2073.00000
mean	10914330.15388	149387.32465	9689.08056	2015.63965
std	30547982.35685	359681.87191	38807.33667	3.94385
min	0.00000	0.00000	0.00000	1965.00000
25%	128689.00000	1642.00000	87.00000	2014.00000
50%	1001579.00000	15059.00000	763.00000	2015.00000
75%	6712317.00000	106360.00000	5377.00000	2018.00000
max	326472925.00000	3164571.00000	1402199.00000	2022.00000

Finally, we will work with the "playlists"

[31]:
```python
playlists_df.head()
playlists_df.set_index('id', inplace=True)
```

The meaning of each column is: + id: the ID for the playlist + title: name of the playlist + author: the ID of the author who creates the playlist + tracks: the ID of the first 2 tracks of the playlist + likes: number of likes + reposts: number of reposts + release: the years/months/days released

We should change the name of some of the columns for clarity

[32]:
```python
playlists_df.rename(columns={"author": "author_id", "tracks":␣
↪"first_2_tracks_id", \
                             "release": "year_release"}, inplace=True)
```

We check for duplicates in the above dataframe

[33]:
```python
check_playlist_dup = playlists_df.duplicated().any()
if check_playlist_dup:
    print("There are duplicated rows")
else:
    print("There is no duplicated rows")
```

```
There is no duplicated rows
```

Awesome! Now we look for the number of rows and columns

[34]:
```python
print("Number of rows: "+str(playlists_df.shape[0]))
print("Number of columns: "+str(playlists_df.shape[1]))
```

```
Number of rows: 1045
Number of columns: 6
```

Okay, let's look for missing values, shall we?

[35]:
```python
col_playlists_key = list(playlists_df.keys())
percent_missing = playlists_df[col_playlists_key].isnull().sum() * 100 / len(playlists_df)
percent_missing
```

[35]:
```
title               0.00000
author_id           0.00000
first_2_tracks_id   0.00000
likes               0.00000
reposts             0.00000
year_release        0.00000
dtype: float64
```

Awesome, we don't have to drop any rows. Now we move to check the data types and convert them if needed

[36]:
```python
playlists_df.dtypes
```

[36]:
```
title                 object
author_id              int64
first_2_tracks_id     object
likes                 object
reposts               object
year_release          object
dtype: object
```

[37]:
```python
like_to_change, like_change = change_number(playlists_df['likes'])
repost_to_change, repost_change = change_number(playlists_df['reposts'])

playlists_df['likes'] = playlists_df['likes'].replace(like_to_change, like_change)
playlists_df['likes'] = playlists_df['likes'].astype(int)
playlists_df['reposts'] = playlists_df['reposts'].replace(repost_to_change, repost_change)
playlists_df['reposts'] = playlists_df['reposts'].astype(int)

year_to_change = list(set(playlists_df['year_release']))
to_year = [2022-int(x.split(" ")[0]) if "year" in x else 2022 for x in year_to_change]
playlists_df['year_release'] = playlists_df['year_release'].replace(year_to_change, to_year)
playlists_df.head(n=5)
```

[37]:
```
                         title  author_id first_2_tracks_id   likes  reposts  \
id
1                    Acid Jazz          1               1,2  387000    35800
2                Ambient piano          3               3,4  149000     9611
3   As Beautiful As It Sounds           6               5,6   80100     4509
4                        ahmed          9               7,8       2        0
5            Artists to Watch          12              9,10   34200     2089

    year_release
id
1           2016
2           2016
3           2015
4           2020
5           2017
```

Let's have a look at how the data distribute

[38]:
```python
playlists_df.describe().drop(columns=['author_id'])
```

[38]:
```
              likes      reposts  year_release
count    1045.00000   1045.00000    1045.00000
mean    12334.79904    928.71388    2017.70335
std     37172.86578   2830.86907       2.55552
min         0.00000      0.00000    2011.00000
25%         3.00000      0.00000    2016.00000
50%        47.00000      4.00000    2017.00000
75%      6926.00000    557.00000    2020.00000
max    515000.00000  43200.00000    2022.00000
```

[39]:
```python
playlists_df.dtypes
```

[39]:
```
title                object
author_id             int64
first_2_tracks_id    object
likes                 int64
reposts               int64
year_release          int64
dtype: object
```

0.4 Step 3: Data Visualization

[40]:
```python
%%capture
!pip install pandas-profiling;
```

[41]:
```python
from pandas_profiling import ProfileReport
```

Merge 3 Dataframes to have the overview of the data

[42]:
```
# Merge 3 dataframe
new_data = playlists_df.merge(tracks_df.merge(users_df, how='inner',␣
 ↪on='author_id'), how='inner', on='author_id')
new_data.rename(columns = {'title_x':'playlist_title','likes_x':␣
 ↪'playlist_like', 'reposts_x': 'playlist_repost', 'year_release_x':␣
 ↪'playlist_year', 'title_y': 'track_title', 'likes_y': 'track_like',␣
 ↪'reposts_y':'track_repost','year_release_y': 'track_year_release', 'name':␣
 ↪'author_name'}, inplace = True)
```

[43]:
```
new_data = new_data.drop(columns=['first_2_tracks_id'])
new_data.head()
```

[43]:
```
                                playlist_title  author_id  \
0                     ADDICTED TO THE UNDERGROUND         83
1                     ADDICTED TO THE UNDERGROUND         83
2  Beach House Session #169 | Tropical & Chill (F…       99
3  Beach House Session #169 | Tropical & Chill (F…       99
4                                    BoxFest Hits        117

   playlist_like  playlist_repost  playlist_year  \
0          17700             2010           2018
1          17700             2010           2018
2         143000            10300           2016
3         143000            10300           2016
4            980              127           2022

                                     track_title  total_plays  track_like  \
0                                     POPULARITY       563398        8422
1                                      TRAVELING       339434        4285
2  Beach House Session Guest Mix Presents - Brown…     383368        4781
3  Beach House Session Guest Mix Presents - Chris…     158093        2074
4  Assembling a top-tier team: Naima Cochrane, Ta…      13139         217

   track_repost  track_year_release          author_name  followers  \
0           498                2018          DOM KENNEDY     111000
1           271                2018          DOM KENNEDY     111000
2           147                2019   Beach House Session      14800
3            96                2019   Beach House Session      14800
4            36                2020  SoundCloud Verified    2280000

   following  NumTracks
0          1         21
1          1         21
2        700          2
3        700          2
4         20        138
```

Get the pandas profiling report to see all the histogram, interation, correlation and missing value of the data

[44]:
```
all_profile = ProfileReport(new_data, title="Data Profiling Report")
```

[45]:
```
correlations = all_profile.description_set["correlations"]
correlations['auto'].style.background_gradient().format(precision=1)
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
```

```
/home/van23/.local/lib/python3.8/site-packages/multimethod/__init__.py:315:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  return func(*args, **kwargs)
```

[45]:
```
<pandas.io.formats.style.Styler at 0x7f3675ba1d90>
```

From the correlation matrix

Playlist likes and reposts have a high correlation with each others, and also have a high correlation with total plays, playlist tracks likes and reports. The play times, likes, repost of a track is also correlated with each others. So, we can consider that the playlist that contain the tracks with many streams, likes and repost also have high likes and reposts.

The followers of an author is not correlated with any number (likes, reposts, played). So, the follower of an author is not affected by their uploaded tracks.

The track year release has a high correlation with the playlist year release. So, we can consider that most of the playlist is created by the time that the tracks have been released.

The number of tracks uploaded does not correlated with the number of followers. Therefore, uploading more tracks does not help to increase your followers.

0.5 Make a question

0.5.1 Question 1:

After exploring the data, we have a better understanding of the data. Now, let's see if there are any questions that can be answered with this data.

Which song is the most popular, which is the second favorite, which is the third most favorite,...? A song is considered popular by the column "likes" and "reposts". By answering this question will partly help us orient which song is liked and reposted by the most people.

ANSWER:

First, we will group all the tracks that have the same name to calculate the total value of each track

[46]:
```
aggregation_functions = {'author_id': 'first', 'total_plays': 'sum', 'likes':␣
↪'sum', 'reposts': 'sum', 'year_release': 'first'}
```

```
tracks_df_sum = tracks_df.groupby(tracks_df['title']).
 ↪aggregate(aggregation_functions)
```

Here is the top 5 tracks by number of plays, likes and reposts

[47]:
```
tracks_df_sum.nlargest(n = 5, columns=['total_plays', 'likes' , 'reposts'])
```

[47]:
```
                                                author_id  total_plays  \
title
Lucid Dreams                                          755    977741268
XXXTENTACION - Fuck Love (feat. Trippie Redd)        1169    901944396
I don't wanna do this anymore                        1169    559188016
1.5- XO TOUR Llif3 (Produced By TM88)                  42    508994522
Lil Baby, Gunna - Drip Too Hard                       178    413577396

                                                  likes  reposts  year_release
title
Lucid Dreams                                   10985988   388303          2018
XXXTENTACION - Fuck Love (feat. Trippie Redd)   9493318   375529          2017
I don't wanna do this anymore                   6047537   346044          2016
1.5- XO TOUR Llif3 (Produced By TM88)           5217431   315497          2017
Lil Baby, Gunna - Drip Too Hard                 4241149   109244          2018
```

0.5.2 Question 2:

Which is the author that have the most played, is that author have the most followers?

ANSWER:

We merge 2 dataframe to get the name of authors

[48]:
```
aggregation_functions = {'total_plays': 'sum', 'likes': 'sum', 'reposts': 'sum'}
author_sum = tracks_df_sum.groupby(tracks_df_sum['author_id']).
 ↪aggregate(aggregation_functions)
new_author_sum = author_sum.merge(users_df, how='inner', on='author_id')
```

Top 5 authors that have largest plays, likes and reposts

[49]:
```
new_author_sum.nlargest(n = 5, columns=['total_plays', 'likes', 'reposts'])
```

[49]:
```
           total_plays     likes  reposts                   name  followers  \
author_id
1169        2303348423  26373590  1166130  XXXTENTACION Verified    5120000
755         1483450118  16473303   556054     Juice WRLD Verified    2950000
42           846724437   9077258   531416  Lil Uzi Vert Verified    2900000
839          682870794   3947068   305932            BTS Verified    4370000
427          618912337   6942549   252138        6IX9INE Verified     955000

           following  NumTracks
```

```
author_id
1169                0        182
755                72        146
42                  0        226
839                 2        140
427                 1         84
```

Top 5 authors that have largest followers

[50]:
```python
users_df.nlargest(n = 5, columns=['followers'])
```

[50]:

	name	followers	following	NumTracks
author_id				
774	Big Sean Verified	9510000	3	229
299	Def Jam Recordings Verified	8490000	58	76
2095	YMCMB-Official Verified	8460000	4	66
1249	WALE Verified	8320000	5	355
301	Pusha T Verified	8180000	1	162

We can see that the author have the most played is not the author that have the most followers.

0.5.3 Question 3:

We have seen there are many platforms to upload music nowadays such as Spotify, Youtube, Apple Music, etc. In the last few years SoundCloud always make it proof to be the best platform for musicians, is it still the king now?

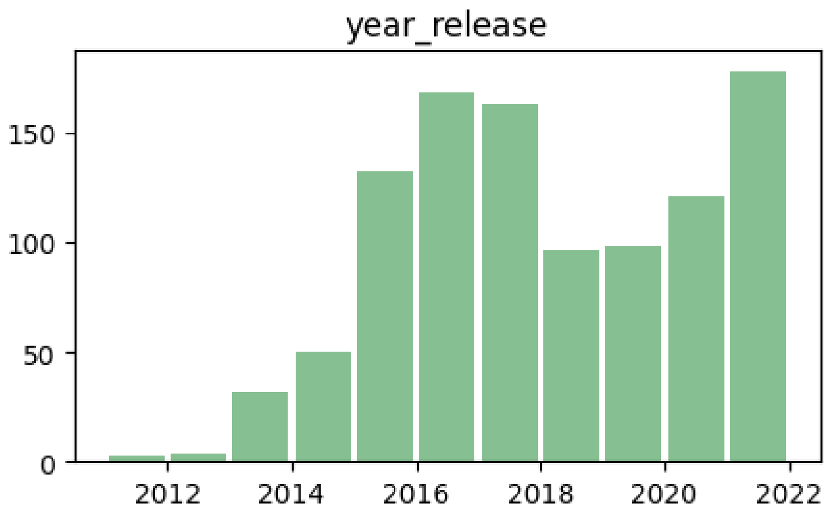
By answering this question, we will know whether SoundCloud is still the popular platform for the musicians or not.

ANSWER:

Firstly, we will plot the number of playlist created by years to see how many playlists created each year.

[51]:
```python
%matplotlib inline
playlists_df.hist(column='year_release', grid=False, figsize=(5,10),bins=11,␣
 ↪layout=(3,1), sharex=True, color='#86bf91', zorder=2, rwidth=0.9)
```

[51]:
```
array([[<AxesSubplot: title={'center': 'year_release'}>],
       [<AxesSubplot: >],
       [<AxesSubplot: >]], dtype=object)
```

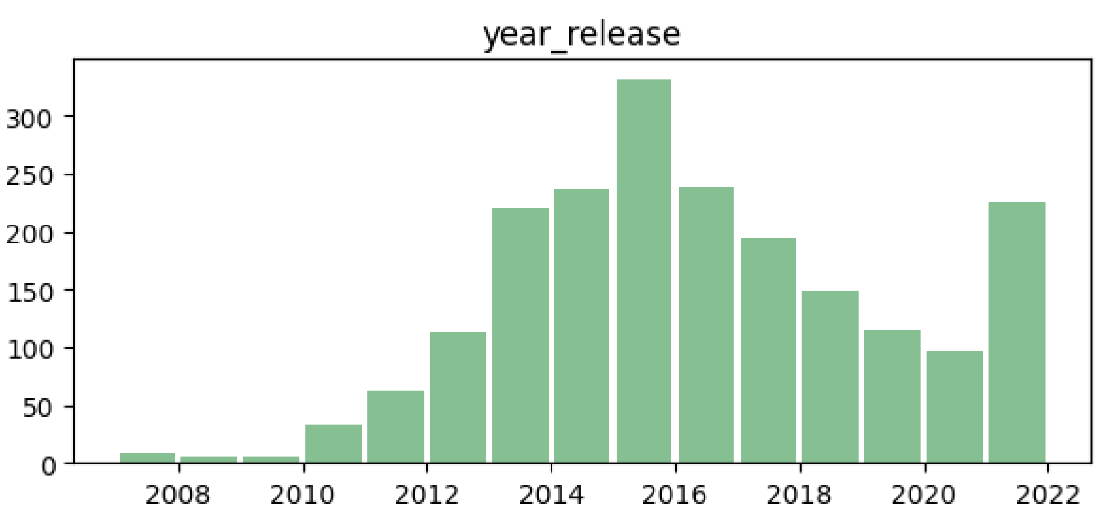


In the "year_release" graph for playlists and tracks, release rates have peaked in between 2016-2018 and 2022. This is really important in 2016, a lot of young artists gained popularity in that time, eg. Lorde, Avicii, Alan Walker (these people might not be in the data, but it is from my personal experience and opinion)

Then, we plot the release year of all tracks from 2007 to now, because the data from the year that lower than 2007 is too small to plot.

[52]:
```
%matplotlib inline
tracks_df.hist(column='year_release', range=[2007, 2022], bins=15, grid=False,␣
 ↪figsize=(16,10), layout=(3,2), sharex=True, color='#86bf91', rwidth=0.9)
```

[52]:
```
array([[<AxesSubplot: title={'center': 'year_release'}>, <AxesSubplot: >],
       [<AxesSubplot: >, <AxesSubplot: >],
       [<AxesSubplot: >, <AxesSubplot: >]], dtype=object)
```



In the graph for tracks, as the years went, the release rate seems to decrease overtime until in 2022 when many Gen-Z artists underwent a surge in popularity, mainly after the pandemic has alleviated in terms of intensity As for playlists graph, it shared a similar reduction after 2018 but slowly recovered after that.

In overall, from 2 graphs, we can conclude that Soundcloud is still popular with musicians and listeners despite a little bit drop from 2018 to 2021.

0.5.4 Question 4:

We do see the like also effect the viral of the uploaded music, we will check the effect of likes on the music play or not?

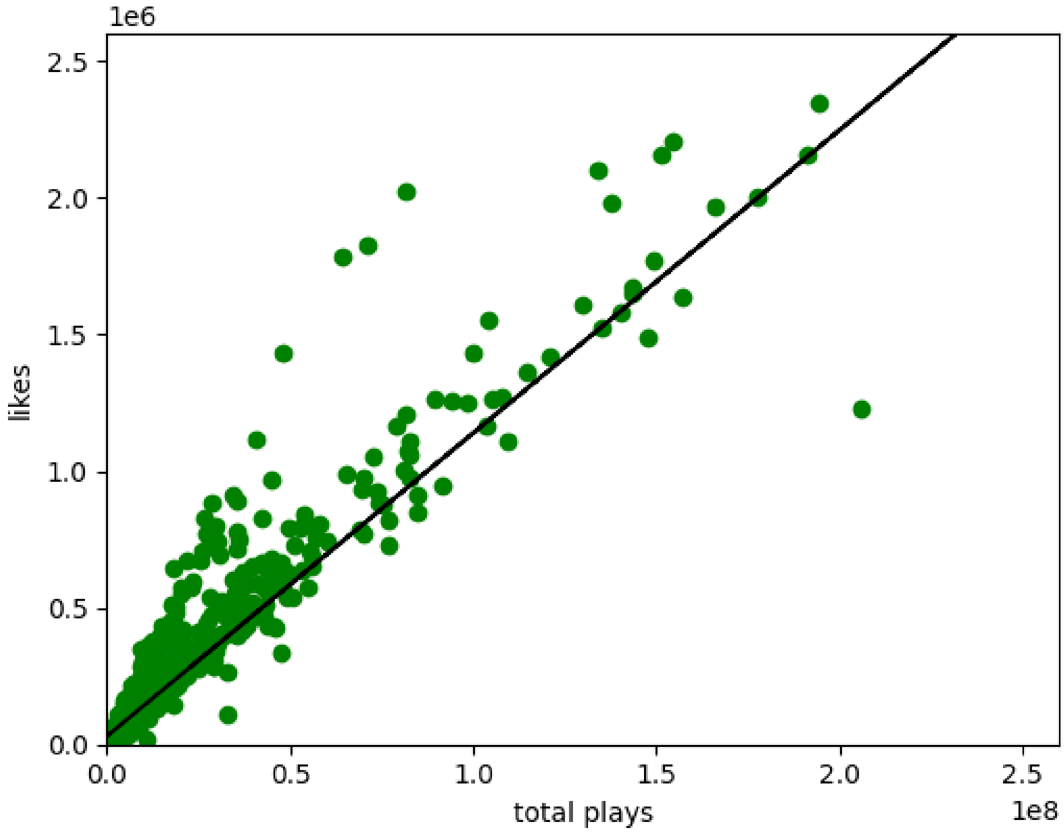
ANSWER:

We perform a linear regression model and a interative graph between number of likes and played.

[53]:
```
%%capture
!pip install sklearn;
```

[54]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test =␣
 ↪train_test_split(tracks_df_sum['total_plays'].values.reshape(-1, 1),␣
 ↪tracks_df_sum['likes'].values, test_size=0.2, random_state=10)
```

[55]:
```
%matplotlib inline
regressor = LinearRegression()
regressor.fit(X_train, y_train)

y_pred = regressor.predict(X_test)
plt.xlim([0, 260000000])
plt.ylim([0, 2600000])
plt.xlabel('total plays')
plt.ylabel('likes')
plt.scatter(X_train, y_train,color='g')
plt.plot(X_test, y_pred,color='k')

plt.show()
```



As the graph above, the number of likes and total plays has a linear combination. The more played on a track, the more likes that track will be received.

0.5.5 Question 5:

Do the songs with 10 million plays come from users with the number of followers above the mean value, which is about 178 thousand followers?

ANSWER:

We get the number of tracks with more than 10 million plays and in that tracks, filter the tracks with above 178 thousand followers.

[56]:
```
new_data_sorted = new_data[new_data['total_plays'] >= 10000000]
new_data_sorted_followers = new_data_sorted[new_data_sorted['followers'] >=␣
 ↪178000]
print("Number of tracks with more than 10 million plays: ",␣
 ↪len(new_data_sorted))
print("Number of tracks with more than 10 million plays and author have above␣
 ↪178 thousand followers: ", len(new_data_sorted_followers))
```

```
Number of tracks with more than 10 million plays:  29
```

```
Number of tracks with more than 10 million plays and author have above 178
thousand followers:  29
```

We can see that all the tracks that have more than 10 million plays come from the user with more than 178 thousand followers

0.5.6 Question 6:

So what kind of vibe music titles that the users on SoundCloud usually listen to? Positive vibe or Negative vibe?

ANSWER:

To know that which title is positive or negative, we need a machine learning model to classify the title.

Here we use the distilBERT for English text from hugging face.

[57]:
```
%%capture
!pip install transformers;
```

Run the model for all data

[58]:
```
%%capture
from transformers import pipeline

classifier = pipeline("text-classification", model =␣
 ↪"distilbert-base-uncased-finetuned-sst-2-english")
new_data['title_sentiment'] = new_data.apply(lambda row:␣
 ↪classifier(row['track_title'])[0]['label'], axis = 1);
```

```
2022-12-05 21:06:49.684468: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  AVX2 AVX_VNNI FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
2022-12-05 21:06:49.787947: I tensorflow/core/util/util.cc:169] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2022-12-05 21:06:49.809748: E tensorflow/stream_executor/cuda/cuda_blas.cc:2981]
Unable to register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
2022-12-05 21:06:50.246638: W
tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load
dynamic library 'libnvinfer.so.7'; dlerror: libnvinfer.so.7: cannot open shared
object file: No such file or directory; LD_LIBRARY_PATH:
:/home/van23/anaconda3/envs/tf/lib/:/home/van23/anaconda3/envs/min_ds-env/lib/
2022-12-05 21:06:50.246739: W
tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load
```

```
dynamic library 'libnvinfer_plugin.so.7'; dlerror: libnvinfer_plugin.so.7:
cannot open shared object file: No such file or directory; LD_LIBRARY_PATH:
:/home/van23/anaconda3/envs/tf/lib/:/home/van23/anaconda3/envs/min_ds-env/lib/
2022-12-05 21:06:50.246744: W
tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Cannot
dlopen some TensorRT libraries. If you would like to use Nvidia GPU with
TensorRT, please make sure the missing libraries mentioned above are installed
properly.
2022-12-05 21:06:51.820761: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:51.828509: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:51.828816: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:51.829202: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  AVX2 AVX_VNNI FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
2022-12-05 21:06:51.830302: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:51.830569: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:51.830852: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:52.688462: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:52.688768: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:52.688780: I
tensorflow/core/common_runtime/gpu/gpu_device.cc:1700] Could not identify NUMA
```

```
node of platform GPU id 0, defaulting to 0.  Your kernel may not have been built
with NUMA support.
2022-12-05 21:06:52.688991: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:966] could not open file to
read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2022-12-05 21:06:52.689040: I
tensorflow/core/common_runtime/gpu/gpu_device.cc:1616] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 9542 MB memory:  -> device: 0,
name: NVIDIA GeForce RTX 3060, pci bus id: 0000:01:00.0, compute capability: 8.6
2022-12-05 21:06:54.423085: I tensorflow/stream_executor/cuda/cuda_blas.cc:1614]
TensorFloat-32 will be used for the matrix multiplication. This will only be
logged once.
```

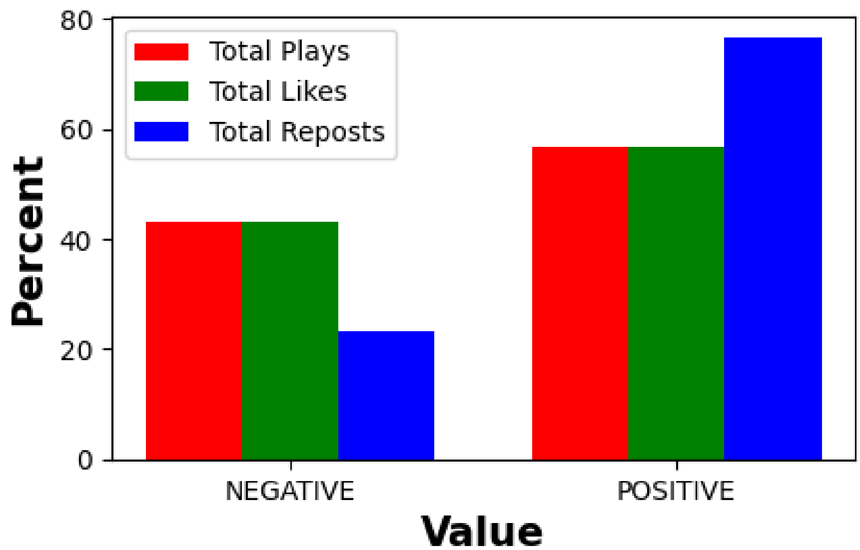
Calculate the percentage of each type (positive and negative)

[59]:
```
new_data['title_sentiment']
aggregation_functions = {'total_plays': 'sum', 'track_like': 'sum',␣
 ↪'track_repost': 'sum'}
new_data_sentiment = new_data.groupby(new_data['title_sentiment']).
 ↪aggregate(aggregation_functions)

new_data_sentiment['play_percent'] = (new_data_sentiment['total_plays'] /␣
 ↪new_data_sentiment['total_plays'].sum()) * 100
new_data_sentiment['like_percent'] = (new_data_sentiment['track_like'] /␣
 ↪new_data_sentiment['track_like'].sum()) * 100
new_data_sentiment['repost_percent'] = (new_data_sentiment['track_repost'] /␣
 ↪new_data_sentiment['track_repost'].sum()) * 100
```

Visualize

[60]:
```
%matplotlib inline
fig = plt.subplots(figsize =(5, 3))

barWidth =0.25
br1 = np.arange(len(new_data_sentiment.index))
br2 = [x + barWidth for x in br1]
br3 = [x + barWidth for x in br2]

plt.bar(br1, new_data_sentiment['play_percent'], width = barWidth, color ='r',␣
 ↪label='Total Plays')
plt.bar(br2, new_data_sentiment['like_percent'], width = barWidth, color ='g',␣
 ↪label='Total Likes')
plt.bar(br3, new_data_sentiment['repost_percent'], width = barWidth, color␣
 ↪='b', label='Total Reposts')

plt.xlabel('Value', fontweight ='bold', fontsize = 15)
plt.ylabel('Percent', fontweight ='bold', fontsize = 15)
```

```
plt.xticks([r + barWidth for r in range(len(new_data_sentiment.index))],
        list(new_data_sentiment.index))


plt.legend()
plt.show()
```



It is clear that all criterias in the "negative" are all lower than those of "positive".

The gap in "total likes" and "total plays" between "negative" and "positive" is small and similar whilst the "reposts" is a significant one. The "reposts" rate in the right side outnumbered the left side.

This could be due to the habit of SoundCloud users where they usually share/repost tracks from small and minor artists they've been following, not the big ones. Small artists tend to publish their tracks without thinking who would listen to them.