Individual Coursework

MSIN0097 Predictive Analytics

COURSEWORK: WARNER MUSIC

PREDICTING THE SUCCESS OF ARTISTS ON SPOTIFY

Please complete the sections of this Notebook with supporting code and markup analysis where appropriate. During this coursework you will:

- Understand the specific business forecast task
- Prepare a dataset, clean and impute where necessary
- Train an ensemble classifier
- Evaluate the performance and comment of success and failure modes
- Complete all necessary stages of the data science process

2000 words plus code, markup text within cells of the Notebook.

This is approximately 100 words per ACTION cell, but use the wordcount over the duration of the Notebook at your discretion.

Assessement

Assessment Deadlines

Please see the Business Analytics tab on the School of Management Student Information Centre for full details of coursework submission deadlines.

- 21/02/2019

Assessment Type:

- 60% Individual Coursework of 2000 words plus code, markup text within cells of the Notebook. Approximately 100 words per ACTION cell.

0. Business Case Understanding

INTRODUCTION

Over the last few years, the music industry has been dominated by digital streaming services, which produce vast amounts of data on listeners and their preferences.

This has required major players in the industry to adopt a data driven approach to content delivery in order to stay competitive.

Warner Music Group is looking to leverage its rich database to better understand the factors that have the most significant impact on the success of a new artist. This will allow them to optimize the allocation of resources when signing and promoting new artists.

Warner's (large) database contains several sources of data, including the streaming platforms Spotify, Amazon Live and Apple Music.

For this case study, we will be looking using the Spotify dataset to predict the success of artists. In particular, we want to understand the role of Spotify playlists on the performance of artist.

Streaming Music

When artists release music digitally, details of how their music is streamed can be closely monitored.

Some of these details include:

- How listeners found their music (a recommendation, a playlist)
- Where and when (a routine visit to the gym, a party, while working).
- On what device (mobile / PC)
- And so on…

Spotify alone *process nearly 1 billion streams every day* (Dredge, 2015) and this streaming data is documented in detail every time a user accesses the platform.

Analyzing this data potentially enables us to gain a much deeper insight into customers' listening behavior and individual tastes.

Spotify uses it to drive their recommender systems – these tailor and individualize content as well as helping the artists reach wider and more relevant audiences.

Warner Music would like to use it to better understand the factors that influence the *future success of its artists*, *identify potentially successful acts* early on in their careers and use this analysis to make resource decisions about how they market and support their artists.

What are Spotify Playlists and why are relevant today?

A playlist is a group of tracks that you can save under a name, listen to, and update at your leisure.

Figure 1. Screen shot of Spotify product show artists and playlists.

Spotify currently has more than two billion publicly available playlists, many of which are curated by Spotify's in-house team of editors.

The editors scour the web on a daily basis to remain up-to-date with the newest releases, and to create playlists geared towards different desires and needs.

Additionally, there are playlists such as Discover Weekly (https://www.spotify.com/uk/discoverweekly/) and Release Radar (https://support.spotify.com/uk/using_spotify/playlists/release-radar/) that use self-learning algorithms to study a user's listening behavior over time and recommend songs tailored to his/her tastes.

The figure below illustrates the progression of artists on Spotify Playlists:

Figure 2. Figure to illustarte selecting artists and building audience profiles over progressively larger audiences of different playlists.

The artist pool starts off very dense at the bottom, as new artists are picked up on the smaller playlists, and thins on the way to the top, as only the most promising of them make it through to more selective playlists. The playlists on the very top contain the most successful, chart-topping artists.

An important discovery that has been made is that certain playlists have more of an influence on the popularity, stream count and future success of an artist than others.

Figure 3. Figure to illustrate taking song stream data and using it to predict the trajectory, and likely success, of Warner artists.

Moreover, some playlists have been seen to be pivotal in the careers of successful artists. Artists that do make it onto one of these *key* playlists frequently go on to become highly ranked in the music charts.

It is the objective of Warner's A&R (https://en.wikipedia.org/wiki/Artists_and_repertoire) team to identify and sign artists before they achieve this level of success i.e. before they get selected for these playlists, in order to increase their ROI.

BUSINESS PROBLEM → DATA PROBLEM

Now that we have a better understanding of the business problem, we can begin to think about how we could model this problem using data.

The first thing we can do is defining a criterion for measuring artist success.

Based on our business problem, one way in which we can do this is to create a binary variable representing the success / failure of an artist and determined by whether a song ends up on a key playlist (1), or not (0). We can then generate features for that artist to determine the impact they have on the success of an artist.

Our problem thus becomes a classification task, which can be modeled as follows:

Artist Feature 1 + Artist Feature 2 .... + Artist Feature N = Probability of Success

where,

Success (1) = Artist Features on Key Playlist

The key playlists we will use for this case study are the 4 listed below, as recommended by Warner Analysts:

1. Hot Hits UK
2. Massive Dance Hits
3. The Indie List
4. New Music Friday

The coursework task is to take a look at the Spotify dataset to see how we might be able to set up this classification model.

Complete the code sections below to work through the project from start to finish.

In [1]:
```
# Python Project Template

# 1. Prepare Problem
# a) Load libraries
# b) Load dataset

# 2. Summarize Data
# a) Descriptive statistics
# b) Data visualizations

# 3. Prepare Data
# a) Data Cleaning
# b) Feature Selection
# c) Data Transforms

# 4. Evaluate Algorithms
# a) Split-out validation dataset
# b) Test options and evaluation metric
# c) Spot Check Algorithms
# d) Compare Algorithms

# 5. Improve Accuracy
# a) Algorithm Tuning
# b) Ensembles

# 6. Finalize Model
# a) Predictions on validation dataset
# b) Create standalone model on entire training dataset
# c) Save model for later use
```

Review "R6 - Predictive Modeling template" Notebook from week 6 on Moodle for further details of what each stage of the project should look like.

ACTION: Guidance

If you need to do something, instructions will appear in a box like this

1. Prepare the problem

Run your code on Sherlock. We have prepared some of the data for you already.

In addition, we have imported a custom module (spotfunc.py) containing useful functions written for this dataset.

In [2]:
```
# Preamble

#import sherlockml.filesystem as sfs
import pandas as pd
import random

#sfs.get('/input/spotfunc.py', 'spotfunc.py')
#sfs.get('/input/playlists_ids_and_titles.csv', 'playlists_ids_and_titles.csv')
#sfs.get('/input/new artists2015onwards.csv', 'newartists2015onwards.csv')

# Add more stuff here as necessary

# Import all required libraries
import pandas as pd


# Import custom functions from library, named 'spotfunc'
#import spotfunc as spotfunc_v2
```

2. Data Understanding

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 Sherlock 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'.

Note: The code for this sampling in included below, but commented out.

We can begin with reading in the datasets we will need. We will be using 2 files:

1. Primary Spotify dataset
2. Playlist Name Mapper (only playlist IDs provided in primary dataset)

In [3]:
```
# %%time
# Sampling data to read in 10%
# sfs.get('/input/all_artists_with_date_time_detail.csv', 'client-data.csv')
# # Read in data
# # The data to load
# f = 'client-data.csv'
# # Count the lines
# num_lines = sum(1 for l in open(f))
# n = 10
# # Count the lines or use an upper bound
# num_lines = sum(1 for l in open(f))
# # The row indices to skip - make sure 0 is not included to keep the header!
# skip_idx = [x for x in range(1, num_lines) if x % n != 0]
# # Read the data
# data = pd.read_csv(f, skiprows=skip_idx )
```

Read in the data

In [4]:
```
%%time
# Read in sampled data
data = pd.read_csv('cleaned_data.csv')
print('rows:',len(data))

# 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('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'])
```

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

rows: 3805499
CPU times: user 26.6 s, sys: 3.04 s, total: 29.6 s
Wall time: 28 s
```

Begin by taking a look at what the spotify data looks like:

ACTION: Inspect the data

Make sure you understand the data. Use methods like **`data.head()`** and **`data.info()`**

In [5]:
```
data.head()
```

Out[5]:

	Unnamed: 0	Unnamed: 0.1	Unnamed: 0.1.1	day	log_time	mobile	track_id	isrc	upc
0	0	9	('small_artists_2016.csv', 9)	10	20160510T12:15:00	True	8f1924eab3804f308427c31d925c1b3f	USAT21600547	7.567991e+10
1	1	19	('small_artists_2016.csv', 19)	10	20160510T12:15:00	True	8f1924eab3804f308427c31d925c1b3f	USAT21600547	7.567991e+10
2	2	29	('small_artists_2016.csv', 29)	10	20160510T14:00:00	True	8f1924eab3804f308427c31d925c1b3f	USAT21600547	7.567991e+10
3	3	39	('small_artists_2016.csv', 39)	10	20160510T10:45:00	True	8f1924eab3804f308427c31d925c1b3f	USAT21600547	7.567991e+10
4	4	49	('small_artists_2016.csv', 49)	10	20160510T10:15:00	True	8f1924eab3804f308427c31d925c1b3f	USAT21600547	7.567991e+10

5 rows × 45 columns

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3805499 entries, 0 to 3805498
Data columns (total 45 columns):
Unnamed: 0           int64
Unnamed: 0.1         int64
Unnamed: 0.1.1       object
day                  int64
log_time             object
mobile               bool
track_id             object
isrc                 object
upc                  float64
artist_name          object
track_name           object
album_name           object
customer_id          object
postal_code          object
access               object
country_code         object
gender               object
birth_year           float64
filename             object
region_code          object
referral_code        float64
partner_name         object
financial_product    object
user_product_type    object
offline_timestamp    float64
stream_length        float64
stream_cached        float64
stream_source        object
stream_source_uri    object
stream_device        object
stream_os            object
track_uri            object
track_artists        object
source               float64
DateTime             object
hour                 int64
minute               int64
week                 int64
month                int64
year                 int64
date                 object
weekday              int64
weekday_name         object
playlist_id          object
playlist_name        object
dtypes: bool(1), float64(7), int64(9), object(28)
memory usage: 1.3+ GB
```

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

The columns you should *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.

Here we create dataframe that contains the relevant columns.

```
In [7]: keep_cols=["log_time","artist_name","year","playlist_id","playlist_name","track_name","isrc","customer_id","birth_year","region_cod
        e","gender","stream_source_uri"]
        data1=data[keep_cols]
```

```
In [8]: data1.head()
```

Out[8]:

	log_time	artist_name	year	playlist_id	playlist_name	track_name	isrc	customer_id	birth_year	regic
0	20160510T12:15:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	6c022a8376c10aae37abb839eb7625fe	1968.0	(
1	20160510T12:15:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	6c022a8376c10aae37abb839eb7625fe	1968.0	(
2	20160510T14:00:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	352292382ff3ee0cfd3b73b94ea0ff8f	1995.0	
3	20160510T10:45:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	c3f2b54e76696ed491d9d8f964c97774	1992.0	
4	20160510T10:15:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	6a06a9bbe042c73e8f1a3596ec321636	1979.0	

EXPLORATORY ANALYSIS AND PLOTS

ACTION: Exploratory analysis

As demonstrated in class, explore various distribution of the data. Comment on any patterns you can see.

- Highlight on any potential uncertainties or peculiarities that you observe.
- Variables you might explore, include, but are not limited to: Age, Gender, Stream counts and playlists.
- Use figures, plots and visualization as necessary.

Now we look at the data set in more detail. At the beginning, we would like to see the age of users by using the columns 'birth_year' in the original data. From the bar chart we can see that most users were born between 1990 to 2000 which means that most users' age are between 20 to 30 years old.

```
In [9]: import matplotlib
        import matplotlib.pyplot as plt
        import seaborn as sns
        data1['birth_year'].hist()
```

```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7951882e48>
```

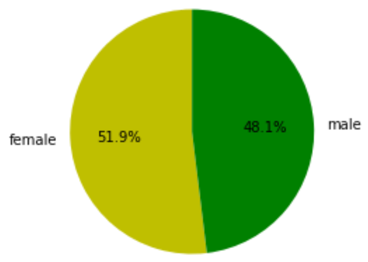
We would like to see the ratio of male and female of users then. From the pie chart below, we can see that 51.9% of all users are female and 48.1% of users are male.

```
In [10]: data1['gender'].value_counts()
```

```
Out[10]: female    1955719
         male      1809358
         Name: gender, dtype: int64
```

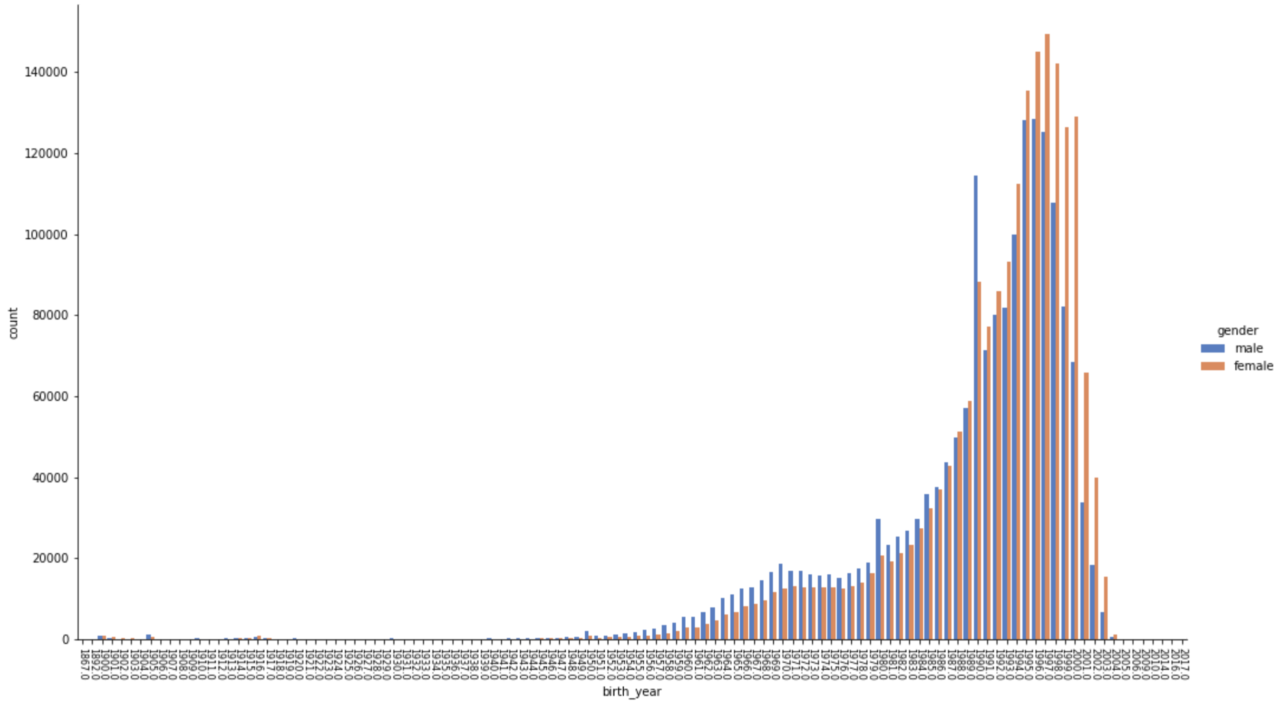
```
In  [11]: female_male=[1955719,1809358]
          activities=['female','male']
          colors=['y','g']
          plt.pie(female_male, labels=activities, colors=colors,startangle=90,autopct='%.1f%%')
          plt.show
```

```
Out[11]: <function matplotlib.pyplot.show(*args, **kw)>
```



If we look at the birth year by gender, the diagram below shows that for older generation, there are more men use spotify than women and for younger generation, there are more women use spotify. The reason might be men are more advanced in using technology or tend to like music more if people are older, and women are more advanced in using technology or tend to like music more if people are younger.

```
In  [12]: # Birth year by gender
          sns.catplot(x="birth_year", hue="gender",
                      data=data1[data1['customer_id'].isin(data1['customer_id'].unique())], kind="count",
                      height=8.27, aspect=14/8.27, palette="muted")
          plt.xticks(rotation=270, fontsize=8)
          plt.show()
```



Moreover, the ratio of premium and free users is investigated.

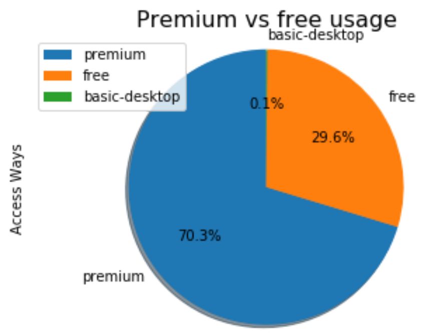
```
In  [13]: data_access = data[data.access != "deleted"]
          access = data_access["access"].value_counts()
          access
```

```
Out[13]: premium          2676048
         free             1124692
         basic-desktop       4753
         Name: access, dtype: int64
```

In [14]:
```
# Plot access pie chart
labels = ["premium", "free", "basic-desktop"] # Add labels

access_pie = data_access["access"].value_counts().plot(kind="pie", label="Access Ways",
                                                   autopct='%1.1f%%', shadow=True, startangle=90)
access_pie.legend(labels, loc="best") # Add legends
access_pie.set_title("Premium vs free usage", fontsize=16) # Add title
access_pie.axis("equal") # Equal aspect ratio ensures that pie is drawn as a circle
```

Out[14]:
```
(-1.1134317323758902,
 1.1130837153020834,
 -1.1178022984784375,
 1.1008477284989733)
```



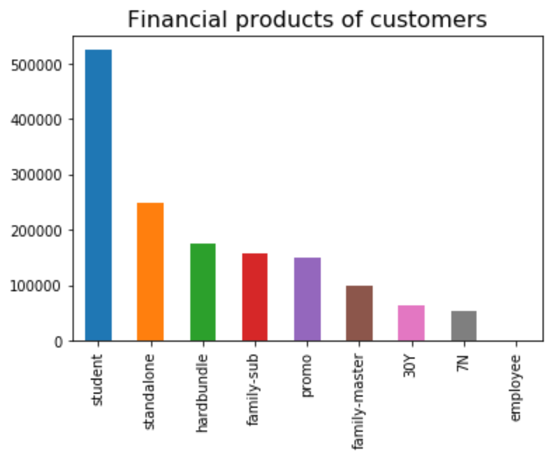
From the pie chart, we can see that 70% of customers pay for the premium service while 29.6% of them chose to use the free one. There is a very small number of people (0.1%) who use the desktop (which is also free but has the basic functions) to listen to the songs on Spotify. Therefore, there are still quite a lot potential customers that Spotify can get more revenue from.

In [15]:
```
# List the number of customers using different payment methods for premium service
data_financial = data[data.financial_product != "deleted"] # Drop the missing value (here is "deleted")
financial_product = data_financial["financial_product"].value_counts() # Number of customers with premium service paying it through
 different methods
financial_product
```

Out[15]:
```
student          525367
standalone       248559
hardbundle       176395
family-sub       156374
promo            150833
family-master     98953
30Y               64478
7N                54628
employee            807
Name: financial_product, dtype: int64
```

In [16]:
```
# Plot financial_product bar chart
financial_bar = data_financial["financial_product"].value_counts().plot(kind="bar")
financial_bar.set_title("Financial products of customers", fontsize=16) # Add title
```

Out[16]:
```
Text(0.5, 1.0, 'Financial products of customers')
```



The bar chart above shows the number of customers with premium service paying it through different payment methods. Based on that, we can observe that the top three most popular payment methods include student, stand alone, and hard bundle. Among them, the number of customers using student payment is significantly higher than other types. We assume the reason behind is because the main target market is represented by young people and most of them are students. Moreover, the special student discounts Spotify offered are relatively cheaper than other kinds of payments.

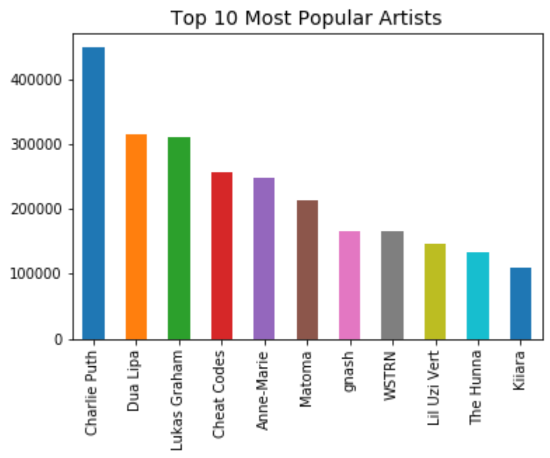
We would also like to list the top 10 most popular artists by stream counts. From the bar chart below, it can be noticed that Charlie Puth is the most popular artist who is significantly more popular than others.

In [17]:
```
#list popular artists
artists = data["artist_name"].value_counts()
artists[:11]
```

Out[17]:
```
Charlie Puth    447873
Dua Lipa        315663
Lukas Graham    311271
Cheat Codes     255820
Anne-Marie      247934
Matoma          212210
gnash           165683
WSTRN           164885
Lil Uzi Vert    146692
The Hunna       132287
Kiiara          109118
Name: artist_name, dtype: int64
```

In [18]:
```
#plot popular artists
artists_bar = artists[:11].plot(kind="bar")
artists_bar.set_title("Top 10 Most Popular Artists", fontsize=14)
```

Out[18]:
```
Text(0.5, 1.0, 'Top 10 Most Popular Artists')
```

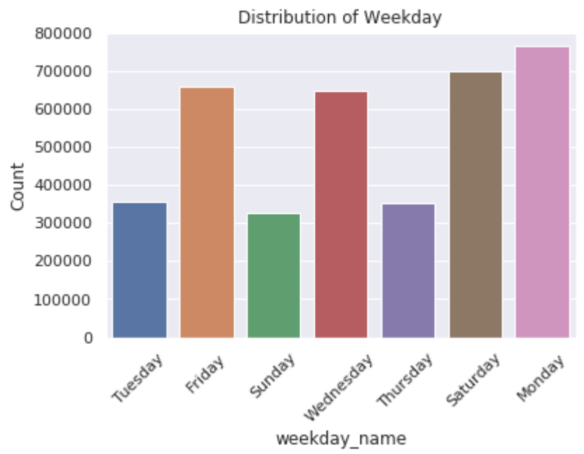


In [19]:
```
#Creating functions for drawing histogram plots

#Function for plotting of categorical variables
def categorical_plot(variable,xlabel,ylabel,title):
    sns.set(style="darkgrid")
    ax = sns.countplot(x=variable ,data=data)
    ax.set_xticklabels(ax.get_xticklabels(),rotation=45)
    #plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.title(title)
    plt.show(ax)

#Functon for plotting of interval variables
def interval_plot(variable,xlabel,ylabel,title,bins):
    a=sns.distplot(data[variable], hist=True, kde=False,
                 bins=bins, color = 'blue',
                 hist_kws={'edgecolor':'black'})
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.title(title)
    plt.show(a)
```

In [20]:
```
categorical_plot('weekday_name','Weekday','Count','Distribution of Weekday')
```



The bar chart above presents the distribution of weekday by the stream count. We can see that there are more people listening to music on Monday and Saturday.

3. Data Preperation and Feature Engineering

Since an important criteria for success is whether or not an artist has been on one of 4 key playlists. So we firstly define the 4 key playlists and then select the relevant playlists as the variable we are trying to model by using 'playlist_mapper'.

We can being by out data preperation by subsetting the 4 key playlists we are interested in and it can be noticed that there are 16 playlist id inside the 4 relevant playlists from the subset dataframe.

ACTION: Dependant variable

Set up the problem as one of classification, selecting the relevant playlists as the variable we are trying to model.

Write useful helper functions to support creating of the feature vector and target vector

In [21]:
```
# 4 key Playlists
key_playlists=["Hot Hits UK","Massive Dance Hits","The Indie List","New Music Friday"]
playlist_mapper["name"]= playlist_mapper["name"].str.upper()
playlist_mapper
```

Out[21]:

	id	name
0	607qZnoGjqhpWjOaJWakmx	80ER JAREN
1	4xP3wJiHkHfyPcGBjsZcpf	GLEE
2	1iHOfbhKGHImcrEJXhrUdg	BEST OF 1980S
3	08AR0IWSEfi0GCnB7b6AAW	KESÄHITIT/YHDEN HITIN IHMEET/SEKALAISTA
4	3DeVsW7nzA3qezOMowGkeu	MÚSICAS PARA TRANSAR
5	3ECQioqPAGUhkPp7PgP6lr	GUITAR HERO 6 - WARRIORS OF ROCK
6	57sY0t33ZSRaJAS2ALqGFY	BEFORE PRE
7	2vUYLeRET44sZhqEH8YqoE	B4.DA.$$
8	7jmQBEvJyGHPqKEl5UcEe9	TOP TRACKS IN SWEDEN
9	3mMc3888eoAg8sgnEzQN6s	#PLAYACHER
10	20fZrm4df1vgbidX2TfRZZ	DOWN THE RABBIT HOLE 2016
11	2zASQX0dx4Wo3DFgh4dfNs	100 ESSENTIALS
12	4d8UPbcSLGjChEMYPMoTYF	WATCH THE STOVE ?
13	2d7iZ08yABfObw0Ny5EGt1	CHICAGO HOUSE MUSIC
14	4fVl8YHzIpBiGhcEgxvhK6	ELECTRÓNICA 2000-2016
15	5hHLFIci647cgwwNfpykgQ	OG VEELA SONGS
16	6U01koIahEeETQT7ERVqIG	FRIDAY FRESH
17	0T2xVB3F7cFR3F5eDYtrWN	AUNKK NO ZEA KONMIGO Y MAS #RETROOZ
18	6eNJAHiYEIyL0ZDZULPVGv	TUNOG KALYE
19	2IAy5fQvooIGCE8nd9xSEB	PANCAKES
20	5JVnupHU4BdOwnJNw3POa6	BANGIN' IN SANGIN
21	37i9dQZF1DZ06evO39S5CU	THIS IS: NEK
22	0klA3IKXWnmJClwsOKjksC	DISNEY'S GREATEST CLASSICS
23	1fm7mdOoADMy0508dlNbGE	TWITCH MUSIC LIBRARY
24	5wR0ymENgJ86fGtPMnFNpx	VIERDAAGSE 2015
25	5XGo2h2IRmqGpRQNAy5spD	CALMAS
26	2CQesR9NGKYbRmflXHxEe4	POP LATINO
27	72EHB4WBxLOth162hY6fDC	TINTINMARATON
28	0dCGBp9cHWw3J44U90XUL5	MARIMBA CHIAPAS ? MARIMBAS MEXICANAS
29	2YPimJcWh0Pb3jYjqPBmXk	FIELD PRODUCTIONS IN THE HOUSE
...	...	...
194525	4UwULfx1knj6uRxkVIxowF	FELIX'S BEDTIME PLAYLIST
194526	37i9dQZF1DZ06evO0AI4xj	THIS IS: LEA MICHELE
194527	39xAcb6WQSLsh42PPSuO3w	THANKSGIVING PLAYLIST 2013
194528	37i9dQZF1DXdLRHxHMDXUP	RUN IN THE SUN
194529	4clluvLIJEbq9x4lliXz9j	THE NOTEBOOK SOUNDTRACK.
194531	6BItpfhjk0sMapPsSVsrQe	TINIE TEMPAH ? MAMACITA (FEAT. WIZKID)
194532	010UTgWTUZPygyITxlJKKA	FATHER/DAUGHTER DANCE
194533	6Bdoy8tr4wuwt0956LWcTK	SANS SONGS
194534	57wKvSf6MIlSHF9TymaLgb	NIMO ? LFR
194535	1fI1nQXIoXO2hz1uvcaMiv	EIER UND WURST
194536	5aJDR7VeBq6QcYePMZMS8N	LOS AUTÉNTICOS DECADENTES
194538	0zsas2hOjR8VwYYJQCgukr	HEAVY METAL OST (1981 FILM)
194540	3phzy9aNi06JR84CKz66aC	PERFECT HARMONY
194541	01kEU0zLLONJGplZDpM6QO	FEBRUARY ??
194542	5q3kPJ9sjhMSAgyoKlSeMG	APORED ? EVERYDAY SATUDAYL
194544	6yXc0FnLc2Uqah7TDPOSnY	STUDIO GIBLI
194545	68WUJufTgRx2OWFciHkib8	INSIDE GRAHAM PARKER'S RECORD COLLECTION
194547	5JtRcbocWdwn5hYQQ2i0Ex	YIRUMA - RIVER FLOWS IN YOU - ORIGINAL
194548	5JfH6RWAPFykM1jjcdYP19	TABATA CROSSFIT
194549	55JJhmgpJIl1jsIKfv71nl	LÉO SCHWECHLEN
194550	6H1dfMQtnFeqswIXNvmVnX	VIAJANDO CON CHESTER "EXILIADOS"

	id	name
194551	4PAeP0q39YR2wSjAJt1ojF	UK GARAGE: DEEP CUTS FROM THE EARLY YEARS
194552	427FjJ6oVgMSFGOaMccb6Z	AHORA LA DISCO LA PARTE EN DO
194553	67QfP4ladFV0WeQGYLGbkW	ROLLING HILLS
194554	60j4zQN6gN8Ryi5L7o1Ted	LOS TIGUERES DEL NORTE
194555	5U2mX7AcFOLuvXsJn2Hh0x	NINA NESBITT - THE MOMENTS I'M MISSING
194556	4JzLbL1zSJmvAFmENpu8ru	BELIEVER BY IMAGINE DRAGONS
194557	6Wkb0oG7lvoL0fOpdzE5RZ	RACK IT UP
194558	7B5a5I3vfjhEMrhypIO8oN	GHOST
194559	53j5t0O1aqd4aUz6KeAcLe	BODY SAY STREAMING

149589 rows × 2 columns

In [22]:
```
# select relevant playlists
subsetdf=playlist_mapper[playlist_mapper["name"].isin(["HOT HITS UK","MASSIVE DANCE HITS","THE INDIE LIST","NEW MUSIC FRIDAY"])]
subsetdf
```

Out[22]:

	id	name
17513	3DL9G1ApvJDIR4IhWIJ8AQ	NEW MUSIC FRIDAY
25618	6FfOZSAN3N6u7v81uS7mxZ	HOT HITS UK
27234	2mnRUIMJWqooAWlMjrlghi	NEW MUSIC FRIDAY
32459	1EnTBEgCWiTX2YHyAzkcFn	NEW MUSIC FRIDAY
35117	37i9dQZF1DWXJfnUiYjUKT	NEW MUSIC FRIDAY
72659	0dLTdpGyfO0PSyYXInvRd5	NEW MUSIC FRIDAY
83239	6wx0wiD9V6JJ2EOh4KM3Ox	NEW MUSIC FRIDAY
91903	35PofY2z4SqqbynOKXmdYV	NEW MUSIC FRIDAY
94405	37i9dQZF1DX5uokaTN4FTR	MASSIVE DANCE HITS
110448	47CSE0kHnUAZosPD3ErRwV	NEW MUSIC FRIDAY
131216	37i9dQZF1DWVTKDs2aOkxu	THE INDIE LIST
133600	4vGgUbD6tW2xMTABaVzCXo	NEW MUSIC FRIDAY
137620	7lc3WCkMnfPyFbgTdVgSSh	HOT HITS UK
140255	37i9dQZF1DX4JAvHpjipBk	NEW MUSIC FRIDAY
151213	37i9dQZF1DWY4lFlS4Pnso	HOT HITS UK
170678	37i9dQZF1DWT2SPAYawYcO	NEW MUSIC FRIDAY

Then we can create our dependent variable "success". If the value of success is 0, it means that the stream can not be predicted as successful since it is not in the key playlist. If the value of success is 1, it means that the stream can be predicted as successful.

In [23]:
```python
# Define Dependent Variable
successid=subsetdf["id"].unique().tolist()
successid
data1["success"]=0
data1.loc[data1["playlist_id"].isin(successid),"success"]=1
data1.head()
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/pandas/core/indexing.py:543: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
  self.obj[item] = s
```

Out[23]:

	log_time	artist_name	year	playlist_id	playlist_name	track_name	isrc	customer_id	birth_year	regio
0	20160510T12:15:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	6c022a8376c10aae37abb839eb7625fe	1968.0	(
1	20160510T12:15:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	6c022a8376c10aae37abb839eb7625fe	1968.0	(
2	20160510T14:00:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	352292382ff3ee0cfd3b73b94ea0ff8f	1995.0	
3	20160510T10:45:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	c3f2b54e76696ed491d9d8f964c97774	1992.0	
4	20160510T10:15:00	Sturgill Simpson	2016	NaN	NaN	Call To Arms	USAT21600547	6a06a9bbe042c73e8f1a3596ec321636	1979.0	

After create the dependent variable, we would like to see that how many artists can be seem as successful. We group the original dataframe by the variable 'artist name' and apply the function into 'get_successful_artists'. A particular artist is successful if there is at least one stream turns to 1, otherwise, it turns to 0.

In [24]:
```
def get_successful_artists(data):
    df1=data['playlist_id'].unique().tolist()
    return bool(set(df1).intersection(set(successid)))

successful_artists=data1.groupby("artist_name").apply(get_successful_artists)
successful_artists=pd.DataFrame(successful_artists)
successful_artists=successful_artists.astype(int)
successful_artists.rename(columns={0:"success"},inplace=True)
successful_artists
```

Out[24]:

	success
artist_name	
#90s Update	0
17 Memphis	0
2D	0
3JS	0
99 Percent	0
A Boogie Wit Da Hoodie	0
A Boogie Wit da Hoodie	1
A R I Z O N A	1
AGWA	0
ALMA	0
ALP	0
AV AV AV	0
AVVAH	0
AXSHN	1
Absofacto	1
Adam Sample	0
Adan Carmona	0
Adia Victoria	0
Alcatraz	0
Alessio Bernabei	0
Alex Hoyer	0
Alex Roy	0
Alexander Brown	0
Alexander Cardinale	0
Alexander Charles	0
Alice	0
Aliose	0
All Tvvins	1
Alma	0
Amaro Ferreiro	0
...	...
Wild Youth	1
Wildling	0
Will Joseph Cook	1
Willy William	0
Witek Muzyk Ulicy	0
Wudstik	0
Xavier Cugat y su orquesta	0
Xavier Dunn	1
YFN Lucci	0
YONAKA	0
Yasutaka Nakata	0
Yellow Claw	1
Ylric Illians	0
Young F	0
Young Spray	0
YoungBoy Never Broke Again	0
Youngboy Never Broke Again	0
Yvng Swag	0
Zac Brown	0
Zak & Diego	0

	success
artist_name	
Zak Abel	1
Zakopower	0
Zarcort	0
Zbigniew Kurtycz	0
Zion & Lennox	1
birthday	0
dvsn	1
flor	1
gnash	1
livetune+	0

661 rows × 1 columns

```
In [25]: sum(successful_artists['success'])
```

```
Out[25]: 83
```

From the dataframe above, there are total 661 artists in spotify. 83 of them can be predicted as successful.

Then we would like to analyze how many artists are successful before the year 2017 using the same method.

In [26]:
```
# def get_successful_before_2017(data):
df_before2017=data1.loc[data1['year']<2017]
df_before2017=df_before2017.groupby("artist_name").apply(get_successful_artists)
df_before2017=pd.DataFrame(df_before2017)
df_before2017=df_before2017.astype(int)
df_before2017.rename(columns={0:"success"},inplace=True)
df_before2017
```

Out[26]:

	success
artist_name	
3JS	0
99 Percent	0
A Boogie Wit Da Hoodie	0
A R I Z O N A	0
AGWA	0
ALMA	0
AV AV AV	0
AVVAH	0
Adan Carmona	0
Adia Victoria	0
Alessio Bernabei	0
Alex Hoyer	0
Alex Roy	0
Alexander Brown	0
Alexander Cardinale	0
Alice	0
Aliose	0
All Tvvins	1
Alma	0
Amaro Ferreiro	0
Amir	1
Andy Bros	0
Angel	0
Angelica Garcia	0
Anna Puu	0
Annabel Jones	0
Anne-Marie	1
Anteros	0
Arco	0
Arsen	0
...	...
Ugly God	0
Urbano Prodigy	0
Usher	0
Utha Likumahuwa	0
VAN HOLZEN	0
VANT	0
VIMIC	0
Venus II	0
Vice	1
Vinyl on HBO	1
Virgul	0
WEDNESDAY CAMPANELLA	0
WSTRN	1
Waylon	0
We Are Messengers	0
Whethan	0
Will Joseph Cook	1
Willy William	0
Witek Muzyk Ulicy	0
Wudstik	0

	success
artist_name	
Xavier Dunn	1
Yellow Claw	0
Young Spray	0
Zac Brown	0
Zak & Diego	0
Zak Abel	0
Zion & Lennox	1
dvsn	0
gnash	1
livetune+	0

366 rows × 1 columns

```
In [27]: sum(df_before2017['success'])
```

```
Out[27]: 28
```

It can be noticed that 28 of 366 artists were successful before the year 2017.

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.

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-base features

Artist features

- Stream count
- Total Number of users
- Passion Score

The metric passion score is a metric suggested to us by Warner business analysts.

It is defined as the number of stream divided by the total number of users.

Warner analysts believe that repeated listens by a user is a far more indicative future success that simply total number of listens or total unique users. By including this in your model, we can evaluate whether this metric in fact might be of any significance.

ACTION: Artist features

Write useful functions to create these new features.

Firstly we calculate the stream count per artist for all the 661 artists into a dataframe 'stream_count'.

In [28]:
```
# Stream count per artist

stream_count=data1.groupby("artist_name")['artist_name'].count()
stream_count=pd.DataFrame(stream_count)
stream_count.rename(columns={"artist_name":"count"},inplace=True)
stream_count
#data1=pd.merge(data1,stream_count, on="artist_name")
#data1.head()
```

Out[28]:

	count
artist_name	
#90s Update	16
17 Memphis	12
2D	1
3JS	5
99 Percent	1291
A Boogie Wit Da Hoodie	9904
A Boogie Wit da Hoodie	13264
A R I Z O N A	68830
AGWA	3
ALMA	8
ALP	4
AV AV AV	57
AVVAH	20
AXSHN	112
Absofacto	138
Adam Sample	42
Adan Carmona	14
Adia Victoria	671
Alcatraz	7
Alessio Bernabei	191
Alex Hoyer	27
Alex Roy	3
Alexander Brown	147
Alexander Cardinale	584
Alexander Charles	53
Alice	45
Aliose	21
All Tvvins	10446
Alma	994
Amaro Ferreiro	8
...	...
Wild Youth	284
Wildling	17
Will Joseph Cook	15322
Willy William	1916
Witek Muzyk Ulicy	17
Wudstik	23
Xavier Cugat y su orquesta	1
Xavier Dunn	5824
YFN Lucci	1487
YONAKA	340
Yasutaka Nakata	90
Yellow Claw	6734
Ylric Illians	3
Young F	1
Young Spray	667
YoungBoy Never Broke Again	783
Youngboy Never Broke Again	104
Yvng Swag	238
Zac Brown	59
Zak & Diego	12

	count
artist_name	
Zak Abel	26966
Zakopower	1
Zarcort	25
Zbigniew Kurtycz	2
Zion & Lennox	10721
birthday	20
dvsn	25168
flor	109
gnash	165683
livetune+	7

661 rows × 1 columns

Then we calculate the number of users per artist using 'customer_id' into a dataframe 'num_users'.

In [29]:
```
# Number of users per artist
num_users=data1.groupby("artist_name")['customer_id'].nunique()
num_users=pd.DataFrame(num_users)

#data1=pd.merge(data1,num_users,on="artist_name")
#data1.head()
num_users
```

Out[29]:

	customer_id
artist_name	
#90s Update	15
17 Memphis	12
2D	1
3JS	4
99 Percent	1189
A Boogie Wit Da Hoodie	7713
A Boogie Wit da Hoodie	11154
A R I Z O N A	58987
AGWA	3
ALMA	8
ALP	4
AV AV AV	54
AVVAH	20
AXSHN	109
Absofacto	136
Adam Sample	42
Adan Carmona	12
Adia Victoria	607
Alcatraz	7
Alessio Bernabei	156
Alex Hoyer	27
Alex Roy	3
Alexander Brown	141
Alexander Cardinale	552
Alexander Charles	51
Alice	39
Aliose	18
All Tvvins	9156
Alma	832
Amaro Ferreiro	4
...	...
Wild Youth	284
Wildling	17
Will Joseph Cook	12585
Willy William	1607
Witek Muzyk Ulicy	11
Wudstik	23
Xavier Cugat y su orquesta	1
Xavier Dunn	5406
YFN Lucci	1395
YONAKA	336
Yasutaka Nakata	77
Yellow Claw	5948
Ylric Illians	1
Young F	1
Young Spray	634
YoungBoy Never Broke Again	621
Youngboy Never Broke Again	75
Yvng Swag	226
Zac Brown	59
Zak & Diego	10

	customer_id
artist_name	
Zak Abel	23417
Zakopower	1
Zarcort	18
Zbigniew Kurtycz	2
Zion & Lennox	9303
birthday	20
dvsn	18712
flor	108
gnash	146108
livetune+	6

661 rows × 1 columns

And we calculate the passion score for each artist into a dataframe 'passionscore'. The number of stream is divided by the total number of users by using 'count' and 'customer_id' in the last two dataframe.

In [30]:
```
# Passion Score
passionscore=stream_count['count']/num_users['customer_id']
passionscore=pd.DataFrame(passionscore)
passionscore
passionscore.rename(columns={0:'passionscore'},inplace=True)
passionscore
#data1['passion_score']=data1['count']/data1['customer_id_y']
#data1.head()
```

Out[30]:

	passionscore
artist_name	
#90s Update	1.066667
17 Memphis	1.000000
2D	1.000000
3JS	1.250000
99 Percent	1.085786
A Boogie Wit Da Hoodie	1.284066
A Boogie Wit da Hoodie	1.189170
A R I Z O N A	1.166867
AGWA	1.000000
ALMA	1.000000
ALP	1.000000
AV AV AV	1.055556
AVVAH	1.000000
AXSHN	1.027523
Absofacto	1.014706
Adam Sample	1.000000
Adan Carmona	1.166667
Adia Victoria	1.105437
Alcatraz	1.000000
Alessio Bernabei	1.224359
Alex Hoyer	1.000000
Alex Roy	1.000000
Alexander Brown	1.042553
Alexander Cardinale	1.057971
Alexander Charles	1.039216
Alice	1.153846
Aliose	1.166667
All Tvvins	1.140891
Alma	1.194712
Amaro Ferreiro	2.000000
...	...
Wild Youth	1.000000
Wildling	1.000000
Will Joseph Cook	1.217481
Willy William	1.192284
Witek Muzyk Ulicy	1.545455
Wudstik	1.000000
Xavier Cugat y su orquesta	1.000000
Xavier Dunn	1.077321
YFN Lucci	1.065950
YONAKA	1.011905
Yasutaka Nakata	1.168831
Yellow Claw	1.132145
Ylric Illians	3.000000
Young F	1.000000
Young Spray	1.052050
YoungBoy Never Broke Again	1.260870
Youngboy Never Broke Again	1.386667
Yvng Swag	1.053097
Zac Brown	1.000000
Zak & Diego	1.200000

	passionscore
artist_name	
Zak Abel	1.151557
Zakopower	1.000000
Zarcort	1.388889
Zbigniew Kurtycz	1.000000
Zion & Lennox	1.152424
birthday	1.000000
dvsn	1.345019
flor	1.009259
gnash	1.133976
livetune+	1.166667

661 rows × 1 columns

At last, we create a new dataframe contains 'success' and the three variables regarding to artist features for all artists which will be used later

In [31]:
```
# Artist Features DataFrame

df_artist_features=successful_artists
df_artist_features['count']=stream_count['count']
df_artist_features['number_users']=num_users['customer_id']
df_artist_features['passion_score']=passionscore['passionscore']

df_artist_features
```

Out[31]:

	success	count	number_users	passion_score
artist_name				
#90s Update	0	16	15	1.066667
17 Memphis	0	12	12	1.000000
2D	0	1	1	1.000000
3JS	0	5	4	1.250000
99 Percent	0	1291	1189	1.085786
A Boogie Wit Da Hoodie	0	9904	7713	1.284066
A Boogie Wit da Hoodie	1	13264	11154	1.189170
A R I Z O N A	1	68830	58987	1.166867
AGWA	0	3	3	1.000000
ALMA	0	8	8	1.000000
ALP	0	4	4	1.000000
AV AV AV	0	57	54	1.055556
AVVAH	0	20	20	1.000000
AXSHN	1	112	109	1.027523
Absofacto	1	138	136	1.014706
Adam Sample	0	42	42	1.000000
Adan Carmona	0	14	12	1.166667
Adia Victoria	0	671	607	1.105437
Alcatraz	0	7	7	1.000000
Alessio Bernabei	0	191	156	1.224359
Alex Hoyer	0	27	27	1.000000
Alex Roy	0	3	3	1.000000
Alexander Brown	0	147	141	1.042553
Alexander Cardinale	0	584	552	1.057971
Alexander Charles	0	53	51	1.039216
Alice	0	45	39	1.153846
Aliose	0	21	18	1.166667
All Tvvins	1	10446	9156	1.140891
Alma	0	994	832	1.194712
Amaro Ferreiro	0	8	4	2.000000
...	...	...	...	...
Wild Youth	1	284	284	1.000000
Wildling	0	17	17	1.000000
Will Joseph Cook	1	15322	12585	1.217481
Willy William	0	1916	1607	1.192284
Witek Muzyk Ulicy	0	17	11	1.545455
Wudstik	0	23	23	1.000000
Xavier Cugat y su orquesta	0	1	1	1.000000
Xavier Dunn	1	5824	5406	1.077321
YFN Lucci	0	1487	1395	1.065950
YONAKA	0	340	336	1.011905
Yasutaka Nakata	0	90	77	1.168831
Yellow Claw	1	6734	5948	1.132145
Ylric Illians	0	3	1	3.000000
Young F	0	1	1	1.000000
Young Spray	0	667	634	1.052050
YoungBoy Never Broke Again	0	783	621	1.260870
Youngboy Never Broke Again	0	104	75	1.386667
Yvng Swag	0	238	226	1.053097
Zac Brown	0	59	59	1.000000
Zak & Diego	0	12	10	1.200000

	success	count	number_users	passion_score
artist_name				
Zak Abel	1	26966	23417	1.151557
Zakopower	0	1	1	1.000000
Zarcort	0	25	18	1.388889
Zbigniew Kurtycz	0	2	2	1.000000
Zion & Lennox	1	10721	9303	1.152424
birthday	0	20	20	1.000000
dvsn	1	25168	18712	1.345019
flor	1	109	108	1.009259
gnash	1	165683	146108	1.133976
livetune+	0	7	6	1.166667

661 rows × 4 columns

```
In  [32]: df_artist_features.success.sum()
Out[32]: 83
```

Playlist Features

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.

In turn, this could help us identify the most influential playlists and the reasons for their influence.

One way to model the effect of playlists on an artist's performance has been to include them as categorical features in our model, to note if there are any particular playlists or combinations of playlists that are responsible for propelling an artist to future success:

Artist Feature 1 + Artist Feature 2 …. + Artist Feature N = Probability of Success

Success (1) = Artist Features on Key Playlist Failure (0) = Artist Not Featured on Key Playlist

Where,

⇒Artist Feature N = Prior Playlist 1 + Prior Playlist 2 +…Prior Playlist N

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. One way to do this would be to consider the top 20 playlists each artist has featured on.

Even better would be to come up with one metric that captures the net effect of all top 20 prior playlists, for each artist, rather including using all 20 playlists for each artists as binary variables. The intuition here is that if this metric as a whole has an influence on the performance of an artist, it would suggest that rather than the individual playlists themselves, it is a combination of their generalized features that affects the future performance of an artist.

Accordingly, different combinations of playlists could equate to having the same impact on an artist, thereby allowing us to identify undervalued playlists.

Some of the features such a metric could use is the number of unique users or 'reach', number of stream counts, and the passion score of each playlist

- Prior Playlist Stream Counts
- Prior Playlist Unique Users (Reach)
- Prior Playlist Passion Score

There are several other such features that you could generate to better capture the general characteristics of playlists, such as the average lift in stream counts and users they generate for artists that have featured on them.

The code to calculate these metrics is provided below:

ACTION: Playlist features

Write useful functions to create new playlist features, like those listed in the cell above.

Are there other sensible ones you could suggest, work in your group to think about what other features might be useful and whether you can calculate them with the data you have

We decide to create a dataframe contains streamcount, number of users and the passion score of each playlist and then calculate the weighted average of top 20 playlists' passion score for each artist. Thus, we work out the streamcount of each playlist and create the dataframe 'df_playlist' firstly.

In [33]:
```
# you could divide up the work in the group by getting different people to calculate different features

#def playlist_avg_stream_counts(data):

playlist_count=data1.groupby("playlist_name")['playlist_name'].count()
playlist_count=pd.DataFrame(playlist_count)
df_playlist=playlist_count
df_playlist.rename(columns={"playlist_name":"playlist_streamcount"},inplace=True)

df_playlist
```

Out[33]:

	playlist_streamcount
playlist_name	
SEPTEMBER 2016 TOP HITS	24
2015 Hits	2
2016 Rap ?	5
?Space ?	1
Avicii - Tiësto - Calvin Harris - Alesso - Swedish house mafia - Zedd - Nause - David Guetta - Har	1
Fall 2015 Hip Hop / R&B playlist	5
Hollister Vibe 2016	8
I took a pill in biza	1
Me & My Girls	2
Music Hits 2016 - Best Songs Playlist	2
Now 97 (Nick's Pediction)	17
PRESIDENT DAVO- I DONT WANNA BE A PLAYA	1
Perreos - Reggeaton - Pachangeo 2015/ Daddy Yankee Ft Omega El Fuerte - Estrellita de Madrugada	1
Throw back	1
iSpy	2
now96	2
top hit songs 2016	1
#1 Most Wanted Hits	10
#AbdiTVBdayMix	2
#AlDub: Happily Ever After	3
#BESTE INDIE	5
#Beste Urban	10
#CantoPop Hong Kong ?? ??? ????	2
#Covers	11
#Dance	14
#FlashbackFriday	1
#GIRLPOWER	3
#HDYNATION RADIO	1
#HairFlipPlaylist	1
#Hideout2017 First Artists Playlist	2
...	...
you are beautiful??????	1
yup	4
zion y lenox motivan2	1
{ SEX SONGS }	1
{musica pra dançar pelado}	1
|Solo Dance - Martin Jensen|Setting Fire - The Chainsmokers|Castle on the Hill - Ed Sheeran|Shape of	1
~* 2016 Favs *~	2
~*cool finds*~	1
¡ADRENALINA!	2
¡Baila Sin Parar!	1
¡Hola 2016!	70
¡Por Fin Vacaciones!	1
¡Por Fin Viernes!	4
© Inrocks - Top 2016	1
® Summerfeeling 2017 [Kygo]	2
Årets bidrag & artister	20
ÉXITOS 2017 ABRIL - APRIL HITS - Shakira Me Enamoré Shakira - DNCE Kissing Strangers DNCE Europa F	116
Éxitos Argentina	7
Éxitos Chile	1
Éxitos Colombia	17

	playlist_streamcount
playlist_name	
Éxitos España	46
Éxitos MX	5
Éxitos México	13
Éxitos Party 2016	1
Éxitos Pop (los remixes)	2
Éxitos de Hoy - Chile	25
Éxitos en acústico	1
Ö3-Hörerplaylist	1
Örnis Playlist	1
écouter	2

7102 rows × 1 columns

We can see that there are 7102 playlists in total. Then we work out the number of users of each playlist and add it to the dataframe 'df_playlist'.

In [34]:
```
#def playlist_avg_number_of_users(data):

playlist_users=data1.groupby("playlist_name")['customer_id'].nunique()
playlist_users=pd.DataFrame(playlist_users)
playlist_users.rename(columns={"customer_id":"playlist_users"},inplace=True)
playlist_users
df_playlist['playlist_users']=playlist_users['playlist_users']
df_playlist
```

Out[34]:

	playlist_streamcount	playlist_users
playlist_name		
SEPTEMBER 2016 TOP HITS	24	14
2015 Hits	2	2
2016 Rap ?	5	5
?Space ?	1	1
Avicii - Tiësto - Calvin Harris - Alesso - Swedish house mafia - Zedd - Nause - David Guetta - Har	1	1
Fall 2015 Hip Hop / R&B playlist	5	4
Hollister Vibe 2016	8	8
I took a pill in biza	1	1
Me & My Girls	2	2
Music Hits 2016 - Best Songs Playlist	2	2
Now 97 (Nick's Pediction)	17	17
PRESIDENT DAVO- I DONT WANNA BE A PLAYA	1	1
Perreos - Reggeaton - Pachangeo 2015/ Daddy Yankee Ft Omega El Fuerte - Estrellita de Madrugada	1	1
Throw back	1	1
iSpy	2	2
now96	2	2
top hit songs 2016	1	1
#1 Most Wanted Hits	10	10
#AbdiTVBdayMix	2	2
#AlDub: Happily Ever After	3	3
#BESTE INDIE	5	3
#Beste Urban	10	9
#CantoPop Hong Kong ?? ??? ????	2	2
#Covers	11	11
#Dance	14	13
#FlashbackFriday	1	1
#GIRLPOWER	3	3
#HDYNATION RADIO	1	1
#HairFlipPlaylist	1	1
#Hideout2017 First Artists Playlist	2	2
...	...	...
you are beautiful??????	1	1
yup	4	2
zion y lenox motivan2	1	1
{ SEX SONGS }	1	1
{musica pra dançar pelado}	1	1
|Solo Dance - Martin Jensen|Setting Fire - The Chainsmokers|Castle on the Hill - Ed Sheeran|Shape of	1	1
~* 2016 Favs *~	2	2
~*cool finds*~	1	1
¡ADRENALINA!	2	2
¡Baila Sin Parar!	1	1
¡Hola 2016!	70	68
¡Por Fin Vacaciones!	1	1
¡Por Fin Viernes!	4	4
© Inrocks - Top 2016	1	1
® Summerfeeling 2017 [Kygo]	2	2
Årets bidrag & artister	20	15
ÉXITOS 2017 ABRIL - APRIL HITS - Shakira Me Enamoré Shakira - DNCE Kissing Strangers DNCE Europa F	116	109
Éxitos Argentina	7	6
Éxitos Chile	1	1
Éxitos Colombia	17	14

	playlist_streamcount	playlist_users
playlist_name		
Éxitos España	46	43
Éxitos MX	5	5
Éxitos México	13	13
Éxitos Party 2016	1	1
Éxitos Pop (los remixes)	2	2
Éxitos de Hoy - Chile	25	14
Éxitos en acústico	1	1
Ö3-Hörerplaylist	1	1
Örnis Playlist	1	1
écouter	2	2

7102 rows × 2 columns

Similarly, we calculate the passion score of each playlist by dividing streamcount by number of users and add it to the dataframe 'df_playlist'.

In [35]:
```
#def playlist_avg_passion_score(data):
playlist_ps=playlist_count['playlist_streamcount']/playlist_users['playlist_users']
playlist_ps=pd.DataFrame(playlist_ps)
playlist_ps.rename(columns={0:'playlist_ps'},inplace=True)

df_playlist['playlist_ps']=playlist_ps['playlist_ps']
df_playlist
```

Out[35]:

	playlist_streamcount	playlist_users	playlist_ps
playlist_name			
SEPTEMBER 2016 TOP HITS	24	14	1.714286
2015 Hits	2	2	1.000000
2016 Rap ?	5	5	1.000000
?Space ?	1	1	1.000000
Avicii - Tiësto - Calvin Harris - Alesso - Swedish house mafia - Zedd - Nause - David Guetta - Har	1	1	1.000000
Fall 2015 Hip Hop / R&B playlist	5	4	1.250000
Hollister Vibe 2016	8	8	1.000000
I took a pill in biza	1	1	1.000000
Me & My Girls	2	2	1.000000
Music Hits 2016 - Best Songs Playlist	2	2	1.000000
Now 97 (Nick's Pediction)	17	17	1.000000
PRESIDENT DAVO- I DONT WANNA BE A PLAYA	1	1	1.000000
Perreos - Reggeaton - Pachangeo 2015/ Daddy Yankee Ft Omega El Fuerte - Estrellita de Madrugada	1	1	1.000000
Throw back	1	1	1.000000
iSpy	2	2	1.000000
now96	2	2	1.000000
top hit songs 2016	1	1	1.000000
#1 Most Wanted Hits	10	10	1.000000
#AbdiTVBdayMix	2	2	1.000000
#AlDub: Happily Ever After	3	3	1.000000
#BESTE INDIE	5	3	1.666667
#Beste Urban	10	9	1.111111
#CantoPop Hong Kong ?? ??? ????	2	2	1.000000
#Covers	11	11	1.000000
#Dance	14	13	1.076923
#FlashbackFriday	1	1	1.000000
#GIRLPOWER	3	3	1.000000
#HDYNATION RADIO	1	1	1.000000
#HairFlipPlaylist	1	1	1.000000
#Hideout2017 First Artists Playlist	2	2	1.000000
...	...	...	...
you are beautiful??????	1	1	1.000000
yup	4	2	2.000000
zion y lenox motivan2	1	1	1.000000
{ SEX SONGS }	1	1	1.000000
{musica pra dançar pelado}	1	1	1.000000
|Solo Dance - Martin Jensen|Setting Fire - The Chainsmokers|Castle on the Hill - Ed Sheeran|Shape of	1	1	1.000000
~* 2016 Favs *~	2	2	1.000000
~*cool finds*~	1	1	1.000000
¡ADRENALINA!	2	2	1.000000
¡Baila Sin Parar!	1	1	1.000000
¡Hola 2016!	70	68	1.029412
¡Por Fin Vacaciones!	1	1	1.000000
¡Por Fin Viernes!	4	4	1.000000
© Inrocks - Top 2016	1	1	1.000000
® Summerfeeling 2017 [Kygo]	2	2	1.000000
Årets bidrag & artister	20	15	1.333333
ÉXITOS 2017 ABRIL - APRIL HITS - Shakira Me Enamoré Shakira - DNCE Kissing Strangers DNCE Europa F	116	109	1.064220
Éxitos Argentina	7	6	1.166667
Éxitos Chile	1	1	1.000000

playlist_name	playlist_streamcount	playlist_users	playlist_ps
Éxitos Colombia	17	14	1.214286
Éxitos España	46	43	1.069767
Éxitos MX	5	5	1.000000
Éxitos México	13	13	1.000000
Éxitos Party 2016	1	1	1.000000
Éxitos Pop (los remixes)	2	2	1.000000
Éxitos de Hoy - Chile	25	14	1.785714
Éxitos en acústico	1	1	1.000000
Ö3-Hörerplaylist	1	1	1.000000
Örnis Playlist	1	1	1.000000
écouter	2	2	1.000000

7102 rows × 3 columns

For calculating the weighted average of top 20 playlists' passion scores for each artist, we need to find the top 20 stream count of playlists for each artists firstly.

In [36]:
```
playlist_count=data1.groupby(['artist_name','playlist_name']).size()
playlist_count=playlist_count.groupby(level=0,group_keys=False).nlargest(20)
df_ap1=pd.DataFrame(playlist_count).reset_index()
df_ap1.rename(columns={0:'count'},inplace=True)
df_ap1
```

Out[36]:

	artist_name	playlist_name	count
0	#90s Update	After Work House	3
1	#90s Update	ENERGY - HIT MUSIC ONLY!	1
2	17 Memphis	Wild Country	6
3	99 Percent	Musical.ly songs	8
4	99 Percent	Party Bangers!	8
5	99 Percent	jacob sartorius' musical.ly's.	5
6	99 Percent	Topsify US Top 40	5
7	99 Percent	Tomorrow's Hits	4
8	99 Percent	ROAD TRIP	3
9	99 Percent	Top Songs of the Month - Sworkit Workout Playl...	3
10	99 Percent	CLEAN MUSIC ONLY	2
11	99 Percent	99 Percent ? iTwerk (She Twerk)i	1
12	99 Percent	iTunes UK TOP 40 - Continously updated	1
13	99 Percent	Topsify US Dance Top 50	1
14	99 Percent	Tastemaker	1
15	99 Percent	The Weeknd - Starboy	1
16	99 Percent	BassBoosted???	1
17	99 Percent	NEW LOVE	1
18	99 Percent	Music.ly songs	1
19	99 Percent	Hits 2000-2016	1
20	99 Percent	slutty pre game	1
21	A Boogie Wit Da Hoodie	Rap Caviar	1982
22	A Boogie Wit Da Hoodie	Hip Hop Party	213
23	A Boogie Wit Da Hoodie	Most DefiLitly	145
24	A Boogie Wit Da Hoodie	RapCaviar	143
25	A Boogie Wit Da Hoodie	Hip Hop Club Bangers: 'LUDACRIS SPECIAL' Week	74
26	A Boogie Wit Da Hoodie	The 411	25
27	A Boogie Wit Da Hoodie	Roots Picnic NYC	22
28	A Boogie Wit Da Hoodie	HipHop Hot 50	18
29	A Boogie Wit Da Hoodie	Highbridge The Label	12
...	...	...	...
4175	flor	Chill Vibes	3
4176	flor	Study Break	2
4177	flor	Electro Rock Top Tracks	1
4178	flor	Indie Rock Top Tracks	1
4179	flor	It's ALT Good!	1
4180	flor	License To Chill	1
4181	flor	New Music Tuesday	1
4182	flor	SAINTE - Winter Rotation	1
4183	flor	Tomorrow's Hits	1
4184	gnash	Hot Hits UK	8947
4185	gnash	Today's Top Hits	8481
4186	gnash	Heartbreaker	2515
4187	gnash	Topsify UK Top 40	2426
4188	gnash	Revision Ballads	2391
4189	gnash	Mellow Pop	1979
4190	gnash	Top Tracks in The United Kingdom	1845
4191	gnash	Chilled Pop Hits	1144
4192	gnash	The Pop List	1038
4193	gnash	New Music Monday UK	989
4194	gnash	NEW CHILLOUT	850
4195	gnash	Top 100 tracks currently on Spotify	684

	artist_name	playlist_name	count
4196	gnash	Easy	678
4197	gnash	Chill Hits	674
4198	gnash	Official UK Top 40 Charts | 7th June 2015 | Up...	528
4199	gnash	Top Tracks of 2016 UK	417
4200	gnash	Acoustic & Chill	388
4201	gnash	Broken Heart	369
4202	gnash	Pop Right Now!	369
4203	gnash	UK Top 40 2016	367
4204	livetune+	J-Track Makunouchi	1

4205 rows × 3 columns

Then we merge it with the relevant playlist passion score.

In [37]:
```
df_apmerge=df_ap1.merge(df_playlist,on='playlist_name',how='inner')
df_apmerge=df_apmerge.sort_values(by=['artist_name','count'],ascending=[1,0])

df_apmerge.drop(columns=['playlist_streamcount','playlist_users'],inplace=True)
df_apmerge
```

Out[37]:

	artist_name	playlist_name	count	playlist_ps
0	#90s Update	After Work House	3	1.116279
4	#90s Update	ENERGY - HIT MUSIC ONLY!	1	1.387097
12	17 Memphis	Wild Country	6	1.062500
18	99 Percent	Musical.ly songs	8	1.000000
20	99 Percent	Party Bangers!	8	1.410072
33	99 Percent	jacob sartorius' musical.ly's.	5	1.000000
34	99 Percent	Topsify US Top 40	5	1.498516
45	99 Percent	Tomorrow's Hits	4	1.662338
76	99 Percent	ROAD TRIP	3	1.166667
77	99 Percent	Top Songs of the Month - Sworkit Workout Playl...	3	1.055556
78	99 Percent	CLEAN MUSIC ONLY	2	1.500000
79	99 Percent	99 Percent ? iTwerk (She Twerk)i	1	1.000000
80	99 Percent	iTunes UK TOP 40 - Continously updated	1	1.416667
81	99 Percent	Topsify US Dance Top 50	1	1.730769
86	99 Percent	Tastemaker	1	2.000000
87	99 Percent	The Weeknd - Starboy	1	1.105263
88	99 Percent	BassBoosted???	1	1.000000
89	99 Percent	NEW LOVE	1	2.000000
90	99 Percent	Music.ly songs	1	1.000000
92	99 Percent	Hits 2000-2016	1	1.000000
93	99 Percent	slutty pre game	1	1.000000
94	A Boogie Wit Da Hoodie	Rap Caviar	1982	1.229883
103	A Boogie Wit Da Hoodie	Hip Hop Party	213	1.147480
111	A Boogie Wit Da Hoodie	Most DefiLitly	145	1.190289
126	A Boogie Wit Da Hoodie	RapCaviar	143	1.252530
136	A Boogie Wit Da Hoodie	Hip Hop Club Bangers: 'LUDACRIS SPECIAL' Week	74	1.070755
146	A Boogie Wit Da Hoodie	The 411	25	1.455760
167	A Boogie Wit Da Hoodie	Roots Picnic NYC	22	1.353698
177	A Boogie Wit Da Hoodie	HipHop Hot 50	18	1.054054
180	A Boogie Wit Da Hoodie	Highbridge The Label	12	1.833333
...	...	...	...	...
1645	flor	Chill Vibes	3	1.149606
2875	flor	Study Break	2	1.204545
75	flor	Tomorrow's Hits	1	1.662338
1236	flor	New Music Tuesday	1	1.171184
1991	flor	License To Chill	1	1.000000
2002	flor	Indie Rock Top Tracks	1	1.000000
4201	flor	Electro Rock Top Tracks	1	1.000000
4202	flor	It's ALT Good!	1	1.333333
4203	flor	SAINTE - Winter Rotation	1	1.000000
1313	gnash	Hot Hits UK	8947	1.273152
366	gnash	Today's Top Hits	8481	1.292694
2517	gnash	Heartbreaker	2515	1.061522
470	gnash	Topsify UK Top 40	2426	1.744574
2675	gnash	Revision Ballads	2391	1.076402
379	gnash	Mellow Pop	1979	1.193107
1353	gnash	Top Tracks in The United Kingdom	1845	1.331047
2558	gnash	Chilled Pop Hits	1144	1.170234
563	gnash	The Pop List	1038	1.188460
540	gnash	New Music Monday UK	989	1.184445
1427	gnash	NEW CHILLOUT	850	1.124306
312	gnash	Top 100 tracks currently on Spotify	684	1.288153

	artist_name	playlist_name	count	playlist_ps
1730	gnash	Easy	678	1.147103
391	gnash	Chill Hits	674	1.322059
1400	gnash	Official UK Top 40 Charts | 7th June 2015 | Up...	528	1.289677
3449	gnash	Top Tracks of 2016 UK	417	1.086371
1241	gnash	Acoustic & Chill	388	1.066171
480	gnash	Pop Right Now!	369	1.221854
4204	gnash	Broken Heart	369	1.049929
2202	gnash	UK Top 40 2016	367	1.204271
4131	livetune+	J-Track Makunouchi	1	1.000000

4205 rows × 4 columns

And calculate the sum of the different playlist's stream count for each artist.

In [38]:
```
artist_20_sum=df_apmerge.groupby(['artist_name']).agg({'count':sum})
df_apmerge=df_apmerge.merge(artist_20_sum,on='artist_name',how='inner',suffixes=('','_sum'))
df_apmerge
#ap_mg['wavg_passion']=ap_mg['count']*ap_mg['playlist_ps']/ap_mg['count_sum']
```

Out[38]:

	artist_name	playlist_name	count	playlist_ps	count_sum
0	#90s Update	After Work House	3	1.116279	4
1	#90s Update	ENERGY - HIT MUSIC ONLY!	1	1.387097	4
2	17 Memphis	Wild Country	6	1.062500	6
3	99 Percent	Musical.ly songs	8	1.000000	48
4	99 Percent	Party Bangers!	8	1.410072	48
5	99 Percent	jacob sartorius' musical.ly's.	5	1.000000	48
6	99 Percent	Topsify US Top 40	5	1.498516	48
7	99 Percent	Tomorrow's Hits	4	1.662338	48
8	99 Percent	ROAD TRIP	3	1.166667	48
9	99 Percent	Top Songs of the Month - Sworkit Workout Playl...	3	1.055556	48
10	99 Percent	CLEAN MUSIC ONLY	2	1.500000	48
11	99 Percent	99 Percent ? iTwerk (She Twerk)i	1	1.000000	48
12	99 Percent	iTunes UK TOP 40 - Continously updated	1	1.416667	48
13	99 Percent	Topsify US Dance Top 50	1	1.730769	48
14	99 Percent	Tastemaker	1	2.000000	48
15	99 Percent	The Weeknd - Starboy	1	1.105263	48
16	99 Percent	BassBoosted???	1	1.000000	48
17	99 Percent	NEW LOVE	1	2.000000	48
18	99 Percent	Music.ly songs	1	1.000000	48
19	99 Percent	Hits 2000-2016	1	1.000000	48
20	99 Percent	slutty pre game	1	1.000000	48
21	A Boogie Wit Da Hoodie	Rap Caviar	1982	1.229883	2697
22	A Boogie Wit Da Hoodie	Hip Hop Party	213	1.147480	2697
23	A Boogie Wit Da Hoodie	Most DefiLitly	145	1.190289	2697
24	A Boogie Wit Da Hoodie	RapCaviar	143	1.252530	2697
25	A Boogie Wit Da Hoodie	Hip Hop Club Bangers: 'LUDACRIS SPECIAL' Week	74	1.070755	2697
26	A Boogie Wit Da Hoodie	The 411	25	1.455760	2697
27	A Boogie Wit Da Hoodie	Roots Picnic NYC	22	1.353698	2697
28	A Boogie Wit Da Hoodie	HipHop Hot 50	18	1.054054	2697
29	A Boogie Wit Da Hoodie	Highbridge The Label	12	1.833333	2697
...	...	...	...	...	...
4175	flor	Chill Vibes	3	1.149606	37
4176	flor	Study Break	2	1.204545	37
4177	flor	Tomorrow's Hits	1	1.662338	37
4178	flor	New Music Tuesday	1	1.171184	37
4179	flor	License To Chill	1	1.000000	37
4180	flor	Indie Rock Top Tracks	1	1.000000	37
4181	flor	Electro Rock Top Tracks	1	1.000000	37
4182	flor	It's ALT Good!	1	1.333333	37
4183	flor	SAINTE - Winter Rotation	1	1.000000	37
4184	gnash	Hot Hits UK	8947	1.273152	37079
4185	gnash	Today's Top Hits	8481	1.292694	37079
4186	gnash	Heartbreaker	2515	1.061522	37079
4187	gnash	Topsify UK Top 40	2426	1.744574	37079
4188	gnash	Revision Ballads	2391	1.076402	37079
4189	gnash	Mellow Pop	1979	1.193107	37079
4190	gnash	Top Tracks in The United Kingdom	1845	1.331047	37079
4191	gnash	Chilled Pop Hits	1144	1.170234	37079
4192	gnash	The Pop List	1038	1.188460	37079
4193	gnash	New Music Monday UK	989	1.184445	37079
4194	gnash	NEW CHILLOUT	850	1.124306	37079
4195	gnash	Top 100 tracks currently on Spotify	684	1.288153	37079

	artist_name	playlist_name	count	playlist_ps	count_sum
4196	gnash	Easy	678	1.147103	37079
4197	gnash	Chill Hits	674	1.322059	37079
4198	gnash	Official UK Top 40 Charts | 7th June 2015 | Up...	528	1.289677	37079
4199	gnash	Top Tracks of 2016 UK	417	1.086371	37079
4200	gnash	Acoustic & Chill	388	1.066171	37079
4201	gnash	Pop Right Now!	369	1.221854	37079
4202	gnash	Broken Heart	369	1.049929	37079
4203	gnash	UK Top 40 2016	367	1.204271	37079
4204	livetune+	J-Track Makunouchi	1	1.000000	1

4205 rows × 5 columns

Here we calculate the weighted average for each playlist of each artist. For example, each artist might be included in many playlists, the stream count and the passion score of this artist in each playlist is different. We sum the total stream count for each artists in all their playlists and then use the weighted average method with multiplying the passion score to see the score of one artist in a particular playlist. The formula is: Stream count * playlist passion score / the sum of the stream count of one artist in different playlists.

In [39]:
```
df_apmerge
fly=df_apmerge['count']
fly
fly1=df_apmerge['playlist_ps']
fly1
fly2=df_apmerge['count_sum']
fly2
fly3=fly*fly1/fly2
fly3
```

Out[39]:
```
0       0.837209
1       0.346774
2       1.062500
3       0.166667
4       0.235012
5       0.104167
6       0.156095
7       0.138528
8       0.072917
9       0.065972
10      0.062500
11      0.020833
12      0.029514
13      0.036058
14      0.041667
15      0.023026
16      0.020833
17      0.041667
18      0.020833
19      0.020833
20      0.020833
21      0.903829
22      0.090624
23      0.063994
24      0.066411
25      0.029379
26      0.013494
27      0.011042
28      0.007035
29      0.008157
          ...
4175    0.093211
4176    0.065111
4177    0.044928
4178    0.031654
4179    0.027027
4180    0.027027
4181    0.027027
4182    0.036036
4183    0.027027
4184    0.307206
4185    0.295675
4186    0.072001
4187    0.114144
4188    0.069411
4189    0.063679
4190    0.066231
4191    0.036105
4192    0.033270
4193    0.031592
4194    0.025774
4195    0.023763
4196    0.020975
4197    0.024032
4198    0.018365
4199    0.012218
4200    0.011157
4201    0.012160
4202    0.010449
4203    0.011920
4204    1.000000
Length: 4205, dtype: float64
```

Here we add the weighted average score into the dataframe. 'wavg_x' is the score of each playlist and 'wavg_y' is the total weighted score of all the playlists of one artist.

In [40]:
```
df_apmerge['wavg']=fly3
playlistavg=df_apmerge.groupby('artist_name').agg({'wavg':sum})
playlistavg
df_apmerge=df_apmerge.merge(playlistavg,on='artist_name',how='inner')
df_apmerge
```

Out[40]:

	artist_name	playlist_name	count	playlist_ps	count_sum	wavg_x	wavg_y
0	#90s Update	After Work House	3	1.116279	4	0.837209	1.183983
1	#90s Update	ENERGY - HIT MUSIC ONLY!	1	1.387097	4	0.346774	1.183983
2	17 Memphis	Wild Country	6	1.062500	6	1.062500	1.062500
3	99 Percent	Musical.ly songs	8	1.000000	48	0.166667	1.277956
4	99 Percent	Party Bangers!	8	1.410072	48	0.235012	1.277956
5	99 Percent	jacob sartorius' musical.ly's.	5	1.000000	48	0.104167	1.277956
6	99 Percent	Topsify US Top 40	5	1.498516	48	0.156095	1.277956
7	99 Percent	Tomorrow's Hits	4	1.662338	48	0.138528	1.277956
8	99 Percent	ROAD TRIP	3	1.166667	48	0.072917	1.277956
9	99 Percent	Top Songs of the Month - Sworkit Workout Playl...	3	1.055556	48	0.065972	1.277956
10	99 Percent	CLEAN MUSIC ONLY	2	1.500000	48	0.062500	1.277956
11	99 Percent	99 Percent ? iTwerk (She Twerk)i	1	1.000000	48	0.020833	1.277956
12	99 Percent	iTunes UK TOP 40 - Continously updated	1	1.416667	48	0.029514	1.277956
13	99 Percent	Topsify US Dance Top 50	1	1.730769	48	0.036058	1.277956
14	99 Percent	Tastemaker	1	2.000000	48	0.041667	1.277956
15	99 Percent	The Weeknd - Starboy	1	1.105263	48	0.023026	1.277956
16	99 Percent	BassBoosted???	1	1.000000	48	0.020833	1.277956
17	99 Percent	NEW LOVE	1	2.000000	48	0.041667	1.277956
18	99 Percent	Music.ly songs	1	1.000000	48	0.020833	1.277956
19	99 Percent	Hits 2000-2016	1	1.000000	48	0.020833	1.277956
20	99 Percent	slutty pre game	1	1.000000	48	0.020833	1.277956
21	A Boogie Wit Da Hoodie	Rap Caviar	1982	1.229883	2697	0.903829	1.224615
22	A Boogie Wit Da Hoodie	Hip Hop Party	213	1.147480	2697	0.090624	1.224615
23	A Boogie Wit Da Hoodie	Most DefiLitly	145	1.190289	2697	0.063994	1.224615
24	A Boogie Wit Da Hoodie	RapCaviar	143	1.252530	2697	0.066411	1.224615
25	A Boogie Wit Da Hoodie	Hip Hop Club Bangers: 'LUDACRIS SPECIAL' Week	74	1.070755	2697	0.029379	1.224615
26	A Boogie Wit Da Hoodie	The 411	25	1.455760	2697	0.013494	1.224615
27	A Boogie Wit Da Hoodie	Roots Picnic NYC	22	1.353698	2697	0.011042	1.224615
28	A Boogie Wit Da Hoodie	HipHop Hot 50	18	1.054054	2697	0.007035	1.224615
29	A Boogie Wit Da Hoodie	Highbridge The Label	12	1.833333	2697	0.008157	1.224615
...	...	...	...	...	...	...	...
4175	flor	Chill Vibes	3	1.149606	37	0.093211	1.160215
4176	flor	Study Break	2	1.204545	37	0.065111	1.160215
4177	flor	Tomorrow's Hits	1	1.662338	37	0.044928	1.160215
4178	flor	New Music Tuesday	1	1.171184	37	0.031654	1.160215
4179	flor	License To Chill	1	1.000000	37	0.027027	1.160215
4180	flor	Indie Rock Top Tracks	1	1.000000	37	0.027027	1.160215
4181	flor	Electro Rock Top Tracks	1	1.000000	37	0.027027	1.160215
4182	flor	It's ALT Good!	1	1.333333	37	0.036036	1.160215
4183	flor	SAINTE - Winter Rotation	1	1.000000	37	0.027027	1.160215
4184	gnash	Hot Hits UK	8947	1.273152	37079	0.307206	1.260124
4185	gnash	Today's Top Hits	8481	1.292694	37079	0.295675	1.260124
4186	gnash	Heartbreaker	2515	1.061522	37079	0.072001	1.260124
4187	gnash	Topsify UK Top 40	2426	1.744574	37079	0.114144	1.260124
4188	gnash	Revision Ballads	2391	1.076402	37079	0.069411	1.260124
4189	gnash	Mellow Pop	1979	1.193107	37079	0.063679	1.260124
4190	gnash	Top Tracks in The United Kingdom	1845	1.331047	37079	0.066231	1.260124
4191	gnash	Chilled Pop Hits	1144	1.170234	37079	0.036105	1.260124
4192	gnash	The Pop List	1038	1.188460	37079	0.033270	1.260124
4193	gnash	New Music Monday UK	989	1.184445	37079	0.031592	1.260124
4194	gnash	NEW CHILLOUT	850	1.124306	37079	0.025774	1.260124
4195	gnash	Top 100 tracks currently on Spotify	684	1.288153	37079	0.023763	1.260124

	artist_name	playlist_name	count	playlist_ps	count_sum	wavg_x	wavg_y
4196	gnash	Easy	678	1.147103	37079	0.020975	1.260124
4197	gnash	Chill Hits	674	1.322059	37079	0.024032	1.260124
4198	gnash	Official UK Top 40 Charts | 7th June 2015 | Up...	528	1.289677	37079	0.018365	1.260124
4199	gnash	Top Tracks of 2016 UK	417	1.086371	37079	0.012218	1.260124
4200	gnash	Acoustic & Chill	388	1.066171	37079	0.011157	1.260124
4201	gnash	Pop Right Now!	369	1.221854	37079	0.012160	1.260124
4202	gnash	Broken Heart	369	1.049929	37079	0.010449	1.260124
4203	gnash	UK Top 40 2016	367	1.204271	37079	0.011920	1.260124
4204	livetune+	J-Track Makunouchi	1	1.000000	1	1.000000	1.000000

4205 rows × 7 columns

After that, we create a dataframe regarding to the total weighted score of each artist and merge this to the dataframe 'df_artist_features' which contains all the useful features variables.

In [41]:
```
df_apmerge
df_apmerge.rename(columns={'wavg_x':'playlistavg'},inplace=True)
df_apmerge.rename(columns={'wavg_y':'weightedscore'},inplace=True)
df_apmerge
df_wght=df_apmerge[['artist_name','weightedscore']]
df_wght=df_wght.drop_duplicates()
df_wght=df_wght.set_index('artist_name')
df_wght
```

Out[41]:

	weightedscore
artist_name	
#90s Update	1.183983
17 Memphis	1.062500
99 Percent	1.277956
A Boogie Wit Da Hoodie	1.224615
A Boogie Wit da Hoodie	1.272593
A R I Z O N A	1.245686
AGWA	2.000000
ALP	1.000000
AVVAH	1.092715
AXSHN	1.323853
Absofacto	1.143588
Adam Sample	1.545097
Adan Carmona	2.767196
Adia Victoria	1.050996
Alessio Bernabei	1.114286
Alex Hoyer	1.153571
Alex Roy	2.767196
Alexander Brown	1.084948
Alexander Cardinale	1.100414
Alexander Charles	1.261209
Alice	1.210582
Aliose	1.333333
All Tvvins	1.115551
Alma	1.110234
Amir	1.099209
Andrew von Oeyen	1.000000
Andy Bros	1.038462
Angela Torres	1.000000
Angeles	1.312195
Angelica Garcia	1.075000
...	...
Viktor Frisk	1.500000
Vince Pope	1.000000
Vinyl on HBO	1.190875
Virgul	1.272572
WEDNESDAY CAMPANELLA	1.833333
WSTRN	1.299935
Waylon	2.000000
We Are Messengers	1.051429
Whethan	1.429354
Wild Youth	1.122784
Will Joseph Cook	1.343154
Willy William	1.209903
Xavier Dunn	1.054221
YFN Lucci	1.200079
YONAKA	1.068039
Yasutaka Nakata	1.114286
Yellow Claw	1.173007
Young Spray	1.028498
YoungBoy Never Broke Again	1.378724
Youngboy Never Broke Again	1.335477

	weightedscore
artist_name	
Yvng Swag	1.497963
Zac Brown	1.229198
Zak Abel	1.222618
Zarcort	1.875000
Zion & Lennox	1.265757
birthday	1.000000
dvsn	1.128136
flor	1.160215
gnash	1.260124
livetune+	1.000000

471 rows × 1 columns

```
In [42]: df_artist_features['weightedscore']=df_wght['weightedscore']
         df_artist_features
```

Out[42]:

	success	count	number_users	passion_score	weightedscore
artist_name					
#90s Update	0	16	15	1.066667	1.183983
17 Memphis	0	12	12	1.000000	1.062500
2D	0	1	1	1.000000	NaN
3JS	0	5	4	1.250000	NaN
99 Percent	0	1291	1189	1.085786	1.277956
A Boogie Wit Da Hoodie	0	9904	7713	1.284066	1.224615
A Boogie Wit da Hoodie	1	13264	11154	1.189170	1.272593
A R I Z O N A	1	68830	58987	1.166867	1.245686
AGWA	0	3	3	1.000000	2.000000
ALMA	0	8	8	1.000000	NaN
ALP	0	4	4	1.000000	1.000000
AV AV AV	0	57	54	1.055556	NaN
AVVAH	0	20	20	1.000000	1.092715
AXSHN	1	112	109	1.027523	1.323853
Absofacto	1	138	136	1.014706	1.143588
Adam Sample	0	42	42	1.000000	1.545097
Adan Carmona	0	14	12	1.166667	2.767196
Adia Victoria	0	671	607	1.105437	1.050996
Alcatraz	0	7	7	1.000000	NaN
Alessio Bernabei	0	191	156	1.224359	1.114286
Alex Hoyer	0	27	27	1.000000	1.153571
Alex Roy	0	3	3	1.000000	2.767196
Alexander Brown	0	147	141	1.042553	1.084948
Alexander Cardinale	0	584	552	1.057971	1.100414
Alexander Charles	0	53	51	1.039216	1.261209
Alice	0	45	39	1.153846	1.210582
Aliose	0	21	18	1.166667	1.333333
All Tvvins	1	10446	9156	1.140891	1.115551
Alma	0	994	832	1.194712	1.110234
Amaro Ferreiro	0	8	4	2.000000	NaN
...	...	...	...	...	...
Wild Youth	1	284	284	1.000000	1.122784
Wildling	0	17	17	1.000000	NaN
Will Joseph Cook	1	15322	12585	1.217481	1.343154
Willy William	0	1916	1607	1.192284	1.209903
Witek Muzyk Ulicy	0	17	11	1.545455	NaN
Wudstik	0	23	23	1.000000	NaN
Xavier Cugat y su orquesta	0	1	1	1.000000	NaN
Xavier Dunn	1	5824	5406	1.077321	1.054221
YFN Lucci	0	1487	1395	1.065950	1.200079
YONAKA	0	340	336	1.011905	1.068039
Yasutaka Nakata	0	90	77	1.168831	1.114286
Yellow Claw	1	6734	5948	1.132145	1.173007
Ylric Illians	0	3	1	3.000000	NaN
Young F	0	1	1	1.000000	NaN
Young Spray	0	667	634	1.052050	1.028498
YoungBoy Never Broke Again	0	783	621	1.260870	1.378724
Youngboy Never Broke Again	0	104	75	1.386667	1.335477
Yvng Swag	0	238	226	1.053097	1.497963
Zac Brown	0	59	59	1.000000	1.229198
Zak & Diego	0	12	10	1.200000	NaN

artist_name	success	count	number_users	passion_score	weightedscore
Zak Abel	1	26966	23417	1.151557	1.222618
Zakopower	0	1	1	1.000000	NaN
Zarcort	0	25	18	1.388889	1.875000
Zbigniew Kurtycz	0	2	2	1.000000	NaN
Zion & Lennox	1	10721	9303	1.152424	1.265757
birthday	0	20	20	1.000000	1.000000
dvsn	1	25168	18712	1.345019	1.128136
flor	1	109	108	1.009259	1.160215
gnash	1	165683	146108	1.133976	1.260124
livetune+	0	7	6	1.166667	1.000000

661 rows × 5 columns

In [43]:
```
artist_wavg=df_apmerge.groupby('artist_name').agg({'weightedscore':sum})
```

User-base features

In this part, we will identify the user-base features by using the age and gender columns to create an audience profile per artist which includes gender percentage breakdown and age vector quantization.

ACTION: User features

Write useful functions to create new user features, like those listed in the cell above.

Are there other sensible ones you could suggest? Work in your group to think about what other features might be useful and whether you can calculate them with the data you have. Justify your reasoning.

In [44]:
```
# Gender breakdown

df_gen=data1.copy()

def gender_percentage(df_gen):
    if (len(df_gen)!=0):
        df_gen=df_gen.drop_duplicates(subset=['customer_id'])
        perc=len(df_gen[df_gen.gender=='male'])/len(df_gen)
        return perc
    else:
        return 0

gender_per=df_gen.groupby('artist_name').apply(gender_percentage)
gender_per=pd.DataFrame(gender_per)
gender_per.rename(columns={0:'malepercentage'},inplace=True)
gender_per
df_artist_features['malepercentage']=gender_per['malepercentage']
df_artist_features
```

Out[44]:

	success	count	number_users	passion_score	weightedscore	malepercentage
artist_name						
#90s Update	0	16	15	1.066667	1.183983	0.600000
17 Memphis	0	12	12	1.000000	1.062500	0.333333
2D	0	1	1	1.000000	NaN	1.000000
3JS	0	5	4	1.250000	NaN	0.750000
99 Percent	0	1291	1189	1.085786	1.277956	0.315391
A Boogie Wit Da Hoodie	0	9904	7713	1.284066	1.224615	0.712952
A Boogie Wit da Hoodie	1	13264	11154	1.189170	1.272593	0.670522
A R I Z O N A	1	68830	58987	1.166867	1.245686	0.473392
AGWA	0	3	3	1.000000	2.000000	1.000000
ALMA	0	8	8	1.000000	NaN	0.500000
ALP	0	4	4	1.000000	1.000000	0.250000
AV AV AV	0	57	54	1.055556	NaN	0.796296
AVVAH	0	20	20	1.000000	1.092715	0.350000
AXSHN	1	112	109	1.027523	1.323853	0.449541
Absofacto	1	138	136	1.014706	1.143588	0.588235
Adam Sample	0	42	42	1.000000	1.545097	0.404762
Adan Carmona	0	14	12	1.166667	2.767196	0.416667
Adia Victoria	0	671	607	1.105437	1.050996	0.635914
Alcatraz	0	7	7	1.000000	NaN	0.571429
Alessio Bernabei	0	191	156	1.224359	1.114286	0.506410
Alex Hoyer	0	27	27	1.000000	1.153571	0.407407
Alex Roy	0	3	3	1.000000	2.767196	0.000000
Alexander Brown	0	147	141	1.042553	1.084948	0.631206
Alexander Cardinale	0	584	552	1.057971	1.100414	0.394928
Alexander Charles	0	53	51	1.039216	1.261209	0.823529
Alice	0	45	39	1.153846	1.210582	0.692308
Aliose	0	21	18	1.166667	1.333333	0.500000
All Tvvins	1	10446	9156	1.140891	1.115551	0.666776
Alma	0	994	832	1.194712	1.110234	0.643029
Amaro Ferreiro	0	8	4	2.000000	NaN	0.750000
...	...	...	...	...	...	...
Wild Youth	1	284	284	1.000000	1.122784	0.485915
Wildling	0	17	17	1.000000	NaN	0.764706
Will Joseph Cook	1	15322	12585	1.217481	1.343154	0.469130
Willy William	0	1916	1607	1.192284	1.209903	0.500311
Witek Muzyk Ulicy	0	17	11	1.545455	NaN	0.909091
Wudstik	0	23	23	1.000000	NaN	0.565217
Xavier Cugat y su orquesta	0	1	1	1.000000	NaN	0.000000
Xavier Dunn	1	5824	5406	1.077321	1.054221	0.497595
YFN Lucci	0	1487	1395	1.065950	1.200079	0.774194
YONAKA	0	340	336	1.011905	1.068039	0.642857
Yasutaka Nakata	0	90	77	1.168831	1.114286	0.688312
Yellow Claw	1	6734	5948	1.132145	1.173007	0.690484
Ylric Illians	0	3	1	3.000000	NaN	1.000000
Young F	0	1	1	1.000000	NaN	1.000000
Young Spray	0	667	634	1.052050	1.028498	0.799685
YoungBoy Never Broke Again	0	783	621	1.260870	1.378724	0.805153
Youngboy Never Broke Again	0	104	75	1.386667	1.335477	0.826667
Yvng Swag	0	238	226	1.053097	1.497963	0.539823
Zac Brown	0	59	59	1.000000	1.229198	0.559322
Zak & Diego	0	12	10	1.200000	NaN	0.500000

	success	count	number_users	passion_score	weightedscore	malepercentage
artist_name						
Zak Abel	1	26966	23417	1.151557	1.222618	0.465559
Zakopower	0	1	1	1.000000	NaN	1.000000
Zarcort	0	25	18	1.388889	1.875000	0.777778
Zbigniew Kurtycz	0	2	2	1.000000	NaN	1.000000
Zion & Lennox	1	10721	9303	1.152424	1.265757	0.450715
birthday	0	20	20	1.000000	1.000000	0.400000
dvsn	1	25168	18712	1.345019	1.128136	0.452170
flor	1	109	108	1.009259	1.160215	0.527778
gnash	1	165683	146108	1.133976	1.260124	0.400450
livetune+	0	7	6	1.166667	1.000000	0.500000

661 rows × 6 columns

We add the percentage of male users of each artist into the dataframe firstly. For the age breakdown, we use the birth year of users in original dataset to calculate the age of users. We divided users into 4 groups where age between 0-18 belongs to Dependent, age between 18-25 belongs to youngadult, age between 25-50 belongs to adult and age between 50-100 belongs to senior. To avoid any collinearity, we drop the variable 'adult' later. And finally we add these user-base features into dataframe 'df_artist_features'.

In [45]:
```
# Age breakdown
import numpy as np
def age_percentages(df_age):
    df_age=df_age.dropna(subset=['birth_year'])

    df_age.birth_year=np.float64(df_age.birth_year)
    if 'DataTime' not in df_age.columns:
        df_age['DataTime']=pd.to_datetime(df_age.log_time)
    df_age['age']=df_age.year - df_age.birth_year
    df_age=df_age.drop_duplicates(subset=['customer_id'])
    bins=[0,18,25,50,100]
    group_names=['Dependent','YoungAdult','Adult','Senior']
    categories=pd.cut(df_age['age'],bins,labels=group_names)
    return pd.DataFrame([{y:x/categories.value_counts().sum() for x,y in zip(categories.value_counts(),categories.value_counts().key
s())}])
age_per=df_gen.groupby('artist_name').apply(age_percentages)
age_per=pd.DataFrame(age_per)
age_per=age_per.reset_index()
age_per=age_per.drop(columns=['level_1'])
#to avoid any collinearity
age_per=age_per.drop(columns=['Adult'])

age_per=age_per.set_index('artist_name')
age_per
df_artist_features[['Dependent','Senior','YoungAdult']]=age_per[['Dependent','Senior','YoungAdult']]
df_artist_features
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:14: RuntimeWarning: invalid value encountered in long
_scalars
```

Out[45]:

artist_name	success	count	number_users	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult
#90s Update	0	16	15	1.066667	1.183983	0.600000	0.066667	0.000000	0.200000
17 Memphis	0	12	12	1.000000	1.062500	0.333333	0.166667	0.083333	0.416667
2D	0	1	1	1.000000	NaN	1.000000	1.000000	0.000000	0.000000
3JS	0	5	4	1.250000	NaN	0.750000	0.000000	0.000000	0.250000
99 Percent	0	1291	1189	1.085786	1.277956	0.315391	0.379661	0.027966	0.347458
A Boogie Wit Da Hoodie	0	9904	7713	1.284066	1.224615	0.712952	0.222888	0.020725	0.498175
A Boogie Wit da Hoodie	1	13264	11154	1.189170	1.272593	0.670522	0.269546	0.025340	0.438182
A R I Z O N A	1	68830	58987	1.166867	1.245686	0.473392	0.140033	0.034987	0.406650
AGWA	0	3	3	1.000000	2.000000	1.000000	0.000000	0.666667	0.000000
ALMA	0	8	8	1.000000	NaN	0.500000	0.000000	0.125000	0.375000
ALP	0	4	4	1.000000	1.000000	0.250000	0.500000	0.000000	0.250000
AV AV AV	0	57	54	1.055556	NaN	0.796296	0.000000	0.000000	0.277778
AVVAH	0	20	20	1.000000	1.092715	0.350000	0.100000	0.000000	0.550000
AXSHN	1	112	109	1.027523	1.323853	0.449541	0.214953	0.046729	0.317757
Absofacto	1	138	136	1.014706	1.143588	0.588235	0.117647	0.022059	0.411765
Adam Sample	0	42	42	1.000000	1.545097	0.404762	0.119048	0.023810	0.642857
Adan Carmona	0	14	12	1.166667	2.767196	0.416667	0.000000	0.000000	0.272727
Adia Victoria	0	671	607	1.105437	1.050996	0.635914	0.044702	0.082781	0.241722
Alcatraz	0	7	7	1.000000	NaN	0.571429	0.000000	0.142857	0.142857
Alessio Bernabei	0	191	156	1.224359	1.114286	0.506410	0.089744	0.025641	0.384615
Alex Hoyer	0	27	27	1.000000	1.153571	0.407407	0.148148	0.037037	0.296296
Alex Roy	0	3	3	1.000000	2.767196	0.000000	0.000000	0.000000	0.666667
Alexander Brown	0	147	141	1.042553	1.084948	0.631206	0.028369	0.042553	0.290780
Alexander Cardinale	0	584	552	1.057971	1.100414	0.394928	0.105647	0.060109	0.355191
Alexander Charles	0	53	51	1.039216	1.261209	0.823529	0.137255	0.000000	0.529412
Alice	0	45	39	1.153846	1.210582	0.692308	0.102564	0.076923	0.307692
Aliose	0	21	18	1.166667	1.333333	0.500000	0.000000	0.055556	0.277778
All Tvvins	1	10446	9156	1.140891	1.115551	0.666776	0.115156	0.030136	0.396942
Alma	0	994	832	1.194712	1.110234	0.643029	0.153012	0.038554	0.346988
Amaro Ferreiro	0	8	4	2.000000	NaN	0.750000	0.000000	0.000000	0.333333
...	...	...	...	...	...	...	...	...	...
Wild Youth	1	284	284	1.000000	1.122784	0.485915	0.031690	0.140845	0.211268
Wildling	0	17	17	1.000000	NaN	0.764706	0.058824	0.117647	0.352941
Will Joseph Cook	1	15322	12585	1.217481	1.343154	0.469130	0.148583	0.035848	0.432974
Willy William	0	1916	1607	1.192284	1.209903	0.500311	0.130707	0.028143	0.472170
Witek Muzyk Ulicy	0	17	11	1.545455	NaN	0.909091	0.000000	0.000000	0.181818
Wudstik	0	23	23	1.000000	NaN	0.565217	0.000000	0.043478	0.434783
Xavier Cugat y su orquesta	0	1	1	1.000000	NaN	0.000000	0.000000	0.000000	0.000000
Xavier Dunn	1	5824	5406	1.077321	1.054221	0.497595	0.070619	0.048318	0.366475
YFN Lucci	0	1487	1395	1.065950	1.200079	0.774194	0.205904	0.017279	0.493880
YONAKA	0	340	336	1.011905	1.068039	0.642857	0.089552	0.026866	0.367164
Yasutaka Nakata	0	90	77	1.168831	1.114286	0.688312	0.092105	0.013158	0.592105
Yellow Claw	1	6734	5948	1.132145	1.173007	0.690484	0.113360	0.023279	0.469130
Ylric Illians	0	3	1	3.000000	NaN	1.000000	0.000000	0.000000	0.000000
Young F	0	1	1	1.000000	NaN	1.000000	0.000000	0.000000	1.000000
Young Spray	0	667	634	1.052050	1.028498	0.799685	0.141046	0.020602	0.522979
YoungBoy Never Broke Again	0	783	621	1.260870	1.378724	0.805153	0.197411	0.019417	0.487055
Youngboy Never Broke Again	0	104	75	1.386667	1.335477	0.826667	0.246575	0.013699	0.493151
Yvng Swag	0	238	226	1.053097	1.497963	0.539823	0.351351	0.009009	0.427928
Zac Brown	0	59	59	1.000000	1.229198	0.559322	0.050847	0.084746	0.305085
Zak & Diego	0	12	10	1.200000	NaN	0.500000	0.000000	0.000000	0.222222

	success	count	number_users	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult
artist_name									
Zak Abel	1	26966	23417	1.151557	1.222618	0.465559	0.099047	0.039911	0.429319
Zakopower	0	1	1	1.000000	NaN	1.000000	0.000000	0.000000	0.000000
Zarcort	0	25	18	1.388889	1.875000	0.777778	0.166667	0.055556	0.388889
Zbigniew Kurtycz	0	2	2	1.000000	NaN	1.000000	0.000000	0.000000	0.000000
Zion & Lennox	1	10721	9303	1.152424	1.265757	0.450715	0.074226	0.024814	0.417413
birthday	0	20	20	1.000000	1.000000	0.400000	0.250000	0.000000	0.400000
dvsn	1	25168	18712	1.345019	1.128136	0.452170	0.137550	0.023677	0.493021
flor	1	109	108	1.009259	1.160215	0.527778	0.157407	0.037037	0.370370
gnash	1	165683	146108	1.133976	1.260124	0.400450	0.231351	0.029931	0.389555
livetune+	0	7	6	1.166667	1.000000	0.500000	0.333333	0.000000	0.166667

661 rows × 9 columns

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.

Please refer to "L7 - Dimensionality Reduction" in Week 7 as necessary.

ACTION: PCA features

Write useful functions to create new user feature based on regions data.

Are there other sensible features you could suggest? Work in your group to think about what other features might be useful and whether you can calculate them with the data you have. Justify your reasoning.

WARNING: PCA features

If you struggle to complete this section successfully **please email me** and we will provide code to compute the new features. This will help with performance of the classifier in the next stage.

Firstly, we construct the streams region code breakdown for artist dataset by grouping data 1 by artist name and region code, and counting the nuber of region code rows of a particular region code. Name the data as artist_region_stream.

```
In [46]: artist_region_stream=data1.groupby(['artist_name','region_code']).agg({'region_code':'count'})
```

We pivot the region code level of the index labels, return a DataFrame artist_region_stream_unstack having a new level of column labels whose inner-most level consists of the pivoted index labels and fill missing values by 0. And then nomralizing the artist_region_stream_unstack dataframe using standard Scaler.

```
In [47]: artist_region_stream_unstack=artist_region_stream.unstack().fillna(0)
In  [48]: from sklearn.preprocessing import StandardScaler

          scaler=StandardScaler()

          artist_region_scaled=scaler.fit_transform(artist_region_stream_unstack)
```

The linear dimensionality needed to be reduced, so we use the decomposition tool to reduce it. In our model, we will use 10 components of PCA and use Singular Value Decomposition of the data to project it to a lower dimensional space.Visualize region_pca dataframe.

```
In  [49]: # Region Code PCA

          from sklearn import decomposition

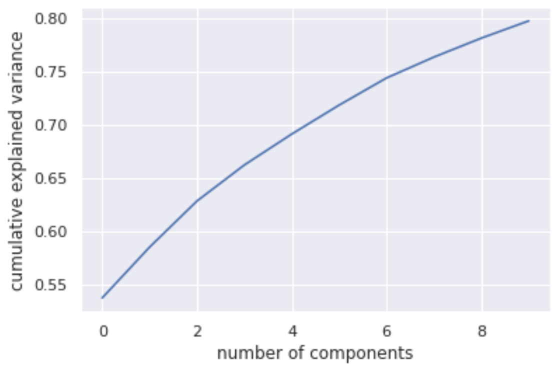
          pca = decomposition.PCA(n_components=10)
          region_pca=pca.fit_transform(artist_region_scaled)
```

ACTION: PCA plot

Use a figure to show which components of PCA explain the majority of variation in the data. Accordingly, use only those components in your further analysis.

The pca.explained_variance*ratio* parameter returns a vector of the variance explained by each dimension. Therefore the output will be the explained variance ratio by each dimension from the 10 dimensions.

```
In  [50]: plt.plot(np.cumsum(pca.explained_variance_ratio_))
          plt.xlabel('number of components')
          plt.ylabel('cumulative explained variance')
          plt.show()
```



Here the shape of region_pca dataframe is investigated.

```
In  [51]: pca.explained_variance_ratio_

Out[51]: array([0.53696704, 0.04771371, 0.04332677, 0.03385378, 0.02905212,
                0.02722307, 0.02546508, 0.01961776, 0.01781458, 0.01618459])

In  [52]: region_pca.shape

Out[52]: (650, 10)
```

Here we generate a name list for the principle components and create a Dataframe for the region_pca and use the name list created above. Get the artist name in the region_stream_unstack dataframe and Concatenate artist_pca and region_pca dataframe along the columns.

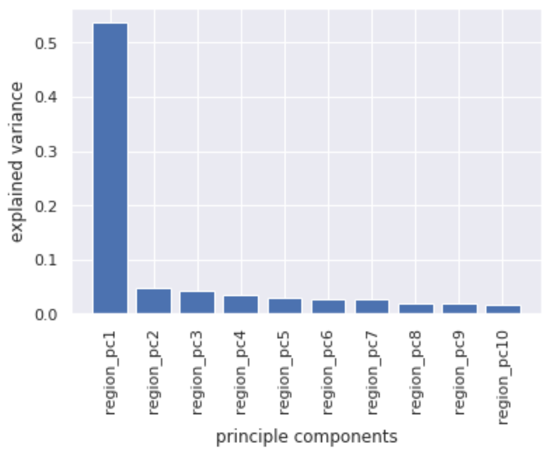
```
In  [53]: pc_name=[]
          for i in range(1,11):
              pc_name.append('region_pc'+str(i))

In  [54]: region_pcaDF=pd.DataFrame(data=region_pca,columns=pc_name)

In  [55]: artist_pca=pd.Series(artist_region_stream_unstack.index.values,name='artist_name')
In  [56]: region_pcaDF=pd.concat([artist_pca,region_pcaDF],axis=1)
```

At last, we can plot the cumunative pca explained variance ratio according to number of components.

```
In  [57]: plt.bar(pc_name,pca.explained_variance_ratio_)
          plt.xticks(rotation=90)
          plt.xlabel('principle components')
          plt.ylabel('explained variance')
          plt.show()
```



When we add up the explianed variance ratio of the 10 components, we can know that the total expleined variance ratio will be greater than 90% only when we include all of the 10 components. So we will keep all of the 10 pca components in our further analysis.

```
In  [58]: df_artist_features=pd.merge(df_artist_features,region_pcaDF, on="artist_name",how="outer")
          df_artist_features.describe()
```

Out[58]:

	success	count	number_users	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult	region_pc
count	661.000000	661.000000	661.000000	661.000000	471.000000	661.000000	660.000000	660.000000	660.000000	6.500000e+0
mean	0.125567	5757.184569	4797.928896	1.160953	1.238894	0.582713	0.089986	0.061952	0.357977	-2.035978e-1
std	0.331612	32638.464044	27057.108261	0.826511	0.268372	0.231221	0.121536	0.137552	0.210957	1.662607e+0
min	0.000000	1.000000	1.000000	1.000000	1.000000	0.000000	0.000000	0.000000	0.000000	-3.009433e+0
25%	0.000000	7.000000	6.000000	1.000000	1.088645	0.454545	0.000000	0.000000	0.247930	-2.999401e+0
50%	0.000000	44.000000	39.000000	1.042735	1.185329	0.558764	0.065214	0.024550	0.386817	-2.972168e+0
75%	0.000000	499.000000	468.000000	1.140891	1.290773	0.719298	0.138223	0.047982	0.479066	-2.630680e+0
max	1.000000	447873.000000	367023.000000	19.000000	3.750000	1.000000	1.000000	1.000000	1.000000	2.206560e+0

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.

ACTION: Feature transformation

Comment on whether transforming particular features (influence, gender breakdown, age breakdown) is useful. Calculate the transformation where necessary.

We have already combined all of our features that we generated above into the dataframe 'df_artist_features' that can be processed by a machine learning algorithm. Here we create a copy of it called 'df_af' and we drop the missing values of total weighted score to 0 here.

In [59]:
```
df_af=df_artist_features.copy()
df_af = df_af.reset_index()
df_af['weightedscore'].fillna(0,inplace=True)
df_af.head()
```

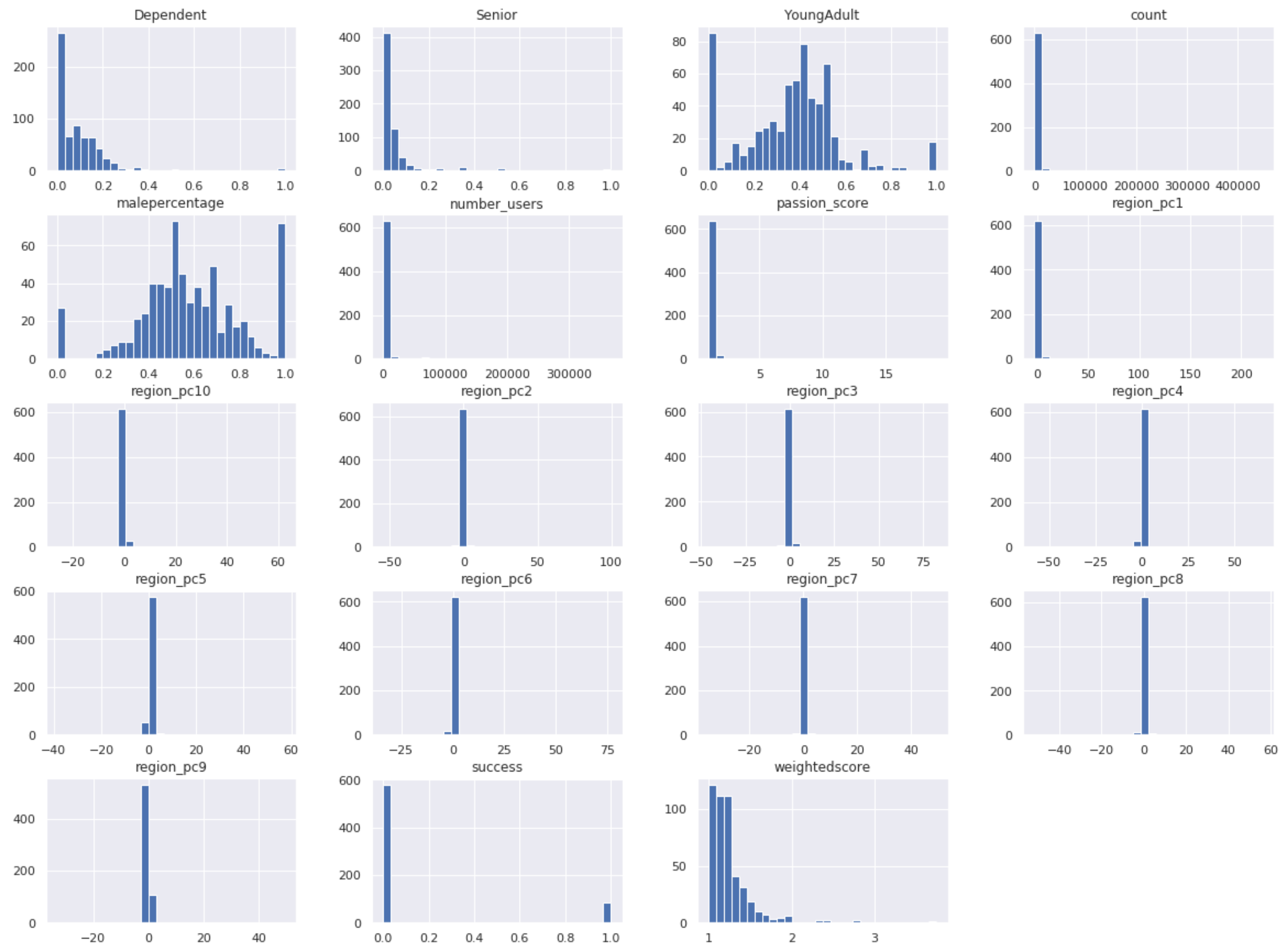
Out[59]:

	index	artist_name	success	count	number_users	passion_score	weightedscore	malepercentage	Dependent	Senior	...	region_pc1	region
0	0	#90s Update	0	16	15	1.066667	1.183983	0.600000	0.066667	0.000000	...	-2.996537	0.13
1	1	17 Memphis	0	12	12	1.000000	1.062500	0.333333	0.166667	0.083333	...	-2.995259	0.13
2	2	2D	0	1	1	1.000000	0.000000	1.000000	1.000000	0.000000	...	-3.001679	0.13
3	3	3JS	0	5	4	1.250000	0.000000	0.750000	0.000000	0.000000	...	-2.999616	0.13
4	4	99 Percent	0	1291	1189	1.085786	1.277956	0.315391	0.379661	0.027966	...	-2.421869	0.06

5 rows × 21 columns

We plot the bar chart of all the features here.

In [60]:
```
%matplotlib inline
import matplotlib.pyplot as plt
df_artist_features.hist(bins=30,figsize=(20,15))
plt.show()
```



By looking at the histogram of all variables, we decide to normalize "stream count", "total number of users" and all the pca region features. We create x and x1, where x is the "stream_count" column's values, x1 is the "total_number_of_users" column's values and x2-x10 are the values of pca 1 to pca 9 columns. We normalize them and create dataframes containing the value after normalized.

In [61]:
```
import numpy as np
from sklearn import preprocessing

x = df_af[["count"]].values
x_scaled=preprocessing.scale(x)
df_nor=pd.DataFrame(x_scaled)
df_nor
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/utils/validation.py:595: DataConversionWarning: Data with input dty
pe int64 was converted to float64 by the scale function.
  warnings.warn(msg, DataConversionWarning)
```

Out[61]:

	0
0	-0.176036
1	-0.176158
2	-0.176496
3	-0.176373
4	-0.136942
5	0.127149
6	0.230173
7	1.933932
8	-0.176434
9	-0.176281
10	-0.176404
11	-0.174778
12	-0.175913
13	-0.173092
14	-0.172295
15	-0.175238
16	-0.176097
17	-0.155952
18	-0.176312
19	-0.170670
20	-0.175698
21	-0.176434
22	-0.172019
23	-0.158620
24	-0.174901
25	-0.175146
26	-0.175882
27	0.143768
28	-0.146048
29	-0.176281
...	...
631	-0.167818
632	-0.176005
633	0.293275
634	-0.117778
635	-0.176005
636	-0.175821
637	-0.176496
638	0.002049
639	-0.130932
640	-0.166101
641	-0.173767
642	0.029951
643	-0.176434
644	-0.176496
645	-0.156075
646	-0.152518
647	-0.173337
648	-0.169229
649	-0.174717
650	-0.176158
651	0.650303

	0
652	-0.176496
653	-0.175760
654	-0.176465
655	0.152200
656	-0.175913
657	0.595172
658	-0.173184
659	4.903629
660	-0.176312

661 rows × 1 columns

In [62]:
```
x1 = df_af[["number_users"]].values
x1_scaled=preprocessing.scale(x1)
df_nor0=pd.DataFrame(x1_scaled)
df_nor0
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/utils/validation.py:595: DataConversionWarning: Data with input dty
pe int64 was converted to float64 by the scale function.
  warnings.warn(msg, DataConversionWarning)
```

Out[62]:

```
            0
  0 -0.176905
  1 -0.177016
  2 -0.177423
  3 -0.177312
  4 -0.133483
  5  0.107819
  6  0.235091
  7  2.004283
  8 -0.177349
  9 -0.177164
 10 -0.177312
 11 -0.175463
 12 -0.176721
 13 -0.173429
 14 -0.172430
 15 -0.175907
 16 -0.177016
 17 -0.155009
 18 -0.177201
 19 -0.171690
 20 -0.176462
 21 -0.177349
 22 -0.172245
 23 -0.157044
 24 -0.175574
 25 -0.176018
 26 -0.176795
 27  0.161191
 28 -0.146687
 29 -0.177312
...       ...
631 -0.166956
632 -0.176832
633  0.288019
634 -0.118022
635 -0.177053
636 -0.176610
637 -0.177423
638  0.022491
639 -0.125864
640 -0.165033
641 -0.174612
642  0.042538
643 -0.177423
644 -0.177423
645 -0.154011
646 -0.154491
647 -0.174686
648 -0.169101
649 -0.175278
650 -0.177090
651  0.688661
```

```
            0
652 -0.177423
653 -0.176795
654 -0.177386
655  0.166628
656 -0.176721
657  0.514638
658 -0.173466
659  5.226615
660 -0.177238

661 rows × 1 columns
```

Before normalize the region pca variables, we decide to fill the missing values 'NA' by the mean of the variables.

In [63]:
```
pc=df_af[['region_pc1', 'region_pc2', 'region_pc3', 'region_pc4', 'region_pc5',
       'region_pc6', 'region_pc7', 'region_pc8', 'region_pc9', 'region_pc10']]
pc=pc.apply(lambda x: x.fillna(x.mean()),axis=0)
```

In [64]:
```
x2=pc[['region_pc1']].values
x3=pc[['region_pc2']].values
x4=pc[['region_pc3']].values
x5=pc[['region_pc4']].values
x6=pc[['region_pc5']].values
x7=pc[['region_pc6']].values
x8=pc[['region_pc7']].values
x9=pc[['region_pc8']].values
x10=pc[['region_pc9']].values
x11=pc[['region_pc10']].values

x2_scaled=preprocessing.scale(x2)
x3_scaled=preprocessing.scale(x3)
x4_scaled=preprocessing.scale(x4)
x5_scaled=preprocessing.scale(x5)
x6_scaled=preprocessing.scale(x6)
x7_scaled=preprocessing.scale(x7)
x8_scaled=preprocessing.scale(x8)
x9_scaled=preprocessing.scale(x9)
x10_scaled=preprocessing.scale(x10)
x11_scaled=preprocessing.scale(x11)

df_nor2=pd.DataFrame(x2_scaled)
df_nor3=pd.DataFrame(x3_scaled)
df_nor4=pd.DataFrame(x4_scaled)
df_nor5=pd.DataFrame(x5_scaled)
df_nor6=pd.DataFrame(x6_scaled)
df_nor7=pd.DataFrame(x7_scaled)
df_nor8=pd.DataFrame(x8_scaled)
df_nor9=pd.DataFrame(x9_scaled)
df_nor10=pd.DataFrame(x10_scaled)
df_nor11=pd.DataFrame(x11_scaled)
```

In [65]:
```
df_af['count']=df_nor
df_af['number_users']=df_nor0
df_af['region_pc1']=df_nor2
df_af['region_pc2']=df_nor3
df_af['region_pc3']=df_nor4
df_af['region_pc4']=df_nor5
df_af['region_pc5']=df_nor6
df_af['region_pc6']=df_nor7
df_af['region_pc7']=df_nor8
df_af['region_pc8']=df_nor9
df_af['region_pc9']=df_nor10
df_af['region_pc10']=df_nor11
df_af
```

Out[65]:

	index	artist_name	success	count	number_users	passion_score	weightedscore	malepercentage	Dependent	Senior	...	region_pc1
0	0	#90s Update	0	-0.176036	-0.176905	1.066667	1.183983	0.600000	0.066667	0.000000	...	-0.181890
1	1	17 Memphis	0	-0.176158	-0.177016	1.000000	1.062500	0.333333	0.166667	0.083333	...	-0.181812
2	2	2D	0	-0.176496	-0.177423	1.000000	0.000000	1.000000	1.000000	0.000000	...	-0.182202
3	3	3JS	0	-0.176373	-0.177312	1.250000	0.000000	0.750000	0.000000	0.000000	...	-0.182077
4	4	99 Percent	0	-0.136942	-0.133483	1.085786	1.277956	0.315391	0.379661	0.027966	...	-0.147007
5	5	A Boogie Wit Da Hoodie	0	0.127149	0.107819	1.284066	1.224615	0.712952	0.222888	0.020725	...	0.019168
6	6	A Boogie Wit da Hoodie	1	0.230173	0.235091	1.189170	1.272593	0.670522	0.269546	0.025340	...	0.394901
7	7	A R I Z O N A	1	1.933932	2.004283	1.166867	1.245686	0.473392	0.140033	0.034987	...	2.879146
8	8	AGWA	0	-0.176434	-0.177349	1.000000	2.000000	1.000000	0.000000	0.666667	...	-0.182138
9	9	ALMA	0	-0.176281	-0.177164	1.000000	0.000000	0.500000	0.000000	0.125000	...	-0.181863
10	10	ALP	0	-0.176404	-0.177312	1.000000	1.000000	0.250000	0.500000	0.000000	...	-0.182207
11	11	AV AV AV	0	-0.174778	-0.175463	1.055556	0.000000	0.796296	0.000000	0.000000	...	-0.181647
12	12	AVVAH	0	-0.175913	-0.176721	1.000000	1.092715	0.350000	0.100000	0.000000	...	-0.181954
13	13	AXSHN	1	-0.173092	-0.173429	1.027523	1.323853	0.449541	0.214953	0.046729	...	-0.179053
14	14	Absofacto	1	-0.172295	-0.172430	1.014706	1.143588	0.588235	0.117647	0.022059	...	-0.176228
15	15	Adam Sample	0	-0.175238	-0.175907	1.000000	1.545097	0.404762	0.119048	0.023810	...	-0.175237
16	16	Adan Carmona	0	-0.176097	-0.177016	1.166667	2.767196	0.416667	0.000000	0.000000	...	-0.182151
17	17	Adia Victoria	0	-0.155952	-0.155009	1.105437	1.050996	0.635914	0.044702	0.082781	...	-0.168537
18	18	Alcatraz	0	-0.176312	-0.177201	1.000000	0.000000	0.571429	0.000000	0.142857	...	-0.181977
19	19	Alessio Bernabei	0	-0.170670	-0.171690	1.224359	1.114286	0.506410	0.089744	0.025641	...	-0.172524
20	20	Alex Hoyer	0	-0.175698	-0.176462	1.000000	1.153571	0.407407	0.148148	0.037037	...	-0.181371
21	21	Alex Roy	0	-0.176434	-0.177349	1.000000	2.767196	0.000000	0.000000	0.000000	...	-0.182184
22	22	Alexander Brown	0	-0.172019	-0.172245	1.042553	1.084948	0.631206	0.028369	0.042553	...	-0.180284
23	23	Alexander Cardinale	0	-0.158620	-0.157044	1.057971	1.100414	0.394928	0.105647	0.060109	...	-0.167502
24	24	Alexander Charles	0	-0.174901	-0.175574	1.039216	1.261209	0.823529	0.137255	0.000000	...	-0.181089
25	25	Alice	0	-0.175146	-0.176018	1.153846	1.210582	0.692308	0.102564	0.076923	...	-0.181159
26	26	Aliose	0	-0.175882	-0.176795	1.166667	1.333333	0.500000	0.000000	0.055556	...	-0.181810
27	27	All Tvvins	1	0.143768	0.161191	1.140891	1.115551	0.666776	0.115156	0.030136	...	0.052643
28	28	Alma	0	-0.146048	-0.146687	1.194712	1.110234	0.643029	0.153012	0.038554	...	-0.079220
29	29	Amaro Ferreiro	0	-0.176281	-0.177312	2.000000	0.000000	0.750000	0.000000	0.000000	...	-0.182217
...	...	...	...	...	...	...	...	...	...	...	...	...
631	631	Wild Youth	1	-0.167818	-0.166956	1.000000	1.122784	0.485915	0.031690	0.140845	...	-0.156552
632	632	Wildling	0	-0.176005	-0.176832	1.000000	0.000000	0.764706	0.058824	0.117647	...	-0.182000
633	633	Will Joseph Cook	1	0.293275	0.288019	1.217481	1.343154	0.469130	0.148583	0.035848	...	0.269432
634	634	Willy William	0	-0.117778	-0.118022	1.192284	1.209903	0.500311	0.130707	0.028143	...	-0.098638
635	635	Witek Muzyk Ulicy	0	-0.176005	-0.177053	1.545455	0.000000	0.909091	0.000000	0.000000	...	-0.181888
636	636	Wudstik	0	-0.175821	-0.176610	1.000000	0.000000	0.565217	0.000000	0.043478	...	-0.181758
637	637	Xavier Cugat y su orquesta	0	-0.176496	-0.177423	1.000000	0.000000	0.000000	0.000000	0.000000	...	-0.182219
638	638	Xavier Dunn	1	0.002049	0.022491	1.077321	1.054221	0.497595	0.070619	0.048318	...	-0.047847
639	639	YFN Lucci	0	-0.130932	-0.125864	1.065950	1.200079	0.774194	0.205904	0.017279	...	-0.132275
640	640	YONAKA	0	-0.166101	-0.165033	1.011905	1.068039	0.642857	0.089552	0.026866	...	-0.163413
641	641	Yasutaka Nakata	0	-0.173767	-0.174612	1.168831	1.114286	0.688312	0.092105	0.013158	...	-0.180006

	index	artist_name	success	count	number_users	passion_score	weightedscore	malepercentage	Dependent	Senior	...	region_pc1
642	642	Yellow Claw	1	0.029951	0.042538	1.132145	1.173007	0.690484	0.113360	0.023279	...	0.151826
643	643	Ylric Illians	0	-0.176434	-0.177423	3.000000	0.000000	1.000000	0.000000	0.000000	...	-0.182150
644	644	Young F	0	-0.176496	-0.177423	1.000000	0.000000	1.000000	0.000000	0.000000	...	-0.182200
645	645	Young Spray	0	-0.156075	-0.154011	1.052050	1.028498	0.799685	0.141046	0.020602	...	-0.168229
646	646	YoungBoy Never Broke Again	0	-0.152518	-0.154491	1.260870	1.378724	0.805153	0.197411	0.019417	...	-0.158712
647	647	Youngboy Never Broke Again	0	-0.173337	-0.174686	1.386667	1.335477	0.826667	0.246575	0.013699	...	-0.178787
648	648	Yvng Swag	0	-0.169229	-0.169101	1.053097	1.497963	0.539823	0.351351	0.009009	...	-0.172383
649	649	Zac Brown	0	-0.174717	-0.175278	1.000000	1.229198	0.559322	0.050847	0.084746	...	-0.180501
650	650	Zak & Diego	0	-0.176158	-0.177090	1.200000	0.000000	0.500000	0.000000	0.000000	...	-0.182115
651	651	Zak Abel	1	0.650303	0.688661	1.151557	1.222618	0.465559	0.099047	0.039911	...	0.550193
652	652	Zakopower	0	-0.176496	-0.177423	1.000000	0.000000	1.000000	0.000000	0.000000	...	-0.182219
653	653	Zarcort	0	-0.175760	-0.176795	1.388889	1.875000	0.777778	0.166667	0.055556	...	-0.173227
654	654	Zbigniew Kurtycz	0	-0.176465	-0.177386	1.000000	0.000000	1.000000	0.000000	0.000000	...	-0.182187
655	655	Zion & Lennox	1	0.152200	0.166628	1.152424	1.265757	0.450715	0.074226	0.024814	...	0.578635
656	656	birthday	0	-0.175913	-0.176721	1.000000	1.000000	0.400000	0.250000	0.000000	...	-0.181827
657	657	dvsn	1	0.595172	0.514638	1.345019	1.128136	0.452170	0.137550	0.023677	...	0.469397
658	658	flor	1	-0.173184	-0.173466	1.009259	1.160215	0.527778	0.157407	0.037037	...	-0.179915
659	659	gnash	1	4.903629	5.226615	1.133976	1.260124	0.400450	0.231351	0.029931	...	4.020854
660	660	livetune+	0	-0.176312	-0.177238	1.166667	1.000000	0.500000	0.333333	0.000000	...	-0.182148

661 rows × 21 columns

As the dataframe above presented, the values after normalized of stream count, number of users and all the pca variables have been merged into it.

In terms to improve accuracy of the model, we still decide to normalize all the other variables except the dependent variable 'success'.The new values will be added into the final dataframe 'df_af'.

In [66]:
```
df_af=df_af.dropna(subset=['Dependent','Senior','YoungAdult'])
df_af
xp=df_af[['passion_score']].values
xw=df_af[['weightedscore']].values
xm=df_af[['malepercentage']].values
xd=df_af[['Dependent']].values
xs=df_af[['Senior']].values
xy=df_af[['YoungAdult']].values

xp_scaled=preprocessing.scale(xp)
xw_scaled=preprocessing.scale(xw)
xm_scaled=preprocessing.scale(xm)
xd_scaled=preprocessing.scale(xd)
xs_scaled=preprocessing.scale(xs)
xy_scaled=preprocessing.scale(xy)
```

In [67]:
```
dfnormalp=pd.DataFrame(xp_scaled)
dfnormalw=pd.DataFrame(xw_scaled)
dfnormalm=pd.DataFrame(xm_scaled)
dfnormald=pd.DataFrame(xd_scaled)
dfnormals=pd.DataFrame(xs_scaled)
dfnormaly=pd.DataFrame(xy_scaled)

df_af['passion_score']=dfnormalp
df_af['weightedscore']=dfnormalw
df_af['malepercentage']=dfnormalm
df_af['Dependent']=dfnormald
df_af['Senior']=dfnormals
df_af['YoungAdult']=dfnormaly
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
/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.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/ipykernel/__main__.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

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

In [68]:
```
df_af.head()
```

Out[68]:

	index	artist_name	success	count	number_users	passion_score	weightedscore	malepercentage	Dependent	Senior	...	region_pc1	re
0	0	#90s Update	0	-0.176036	-0.176905	-0.114376	0.496370	0.077692	-0.192020	-0.450729	...	-0.181890	
1	1	17 Memphis	0	-0.176158	-0.177016	-0.195039	0.295276	-1.078466	0.631405	0.155563	...	-0.181812	
2	2	2D	0	-0.176496	-0.177423	-0.195039	-1.463501	1.811929	7.493283	-0.450729	...	-0.182202	
3	3	3JS	0	-0.176373	-0.177312	0.107446	-1.463501	0.728031	-0.740970	-0.450729	...	-0.182077	
4	4	99 Percent	0	-0.136942	-0.133483	-0.091243	0.651924	-1.156256	2.385255	-0.247261	...	-0.147007	

5 rows × 21 columns

Preprocessing

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.

We have already fill the missing values of PCA variables by their mean. Here we just drop the rest missing values of other variables.

In [69]:
```
final_df = df_af
final_df=final_df.dropna()
final_df.describe()
```

Out[69]:

	index	success	count	number_users	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult	reg
count	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	65
mean	329.757208	0.125948	0.000535	0.000538	-0.001999	0.002221	0.000540	0.001124	-0.002076	-0.001022	(
std	190.700083	0.332043	1.002230	1.002229	1.000199	0.999890	1.001422	1.001101	1.000095	1.001174	'
min	0.000000	0.000000	-0.176496	-0.177423	-0.195039	-1.463501	-2.523663	-0.740970	-0.450729	-1.698210	-(
25%	165.500000	0.000000	-0.176312	-0.177238	-0.195039	-1.463501	-0.552939	-0.740970	-0.450729	-0.531870	-(
50%	330.000000	0.000000	-0.175146	-0.176018	-0.143332	0.379213	-0.101091	-0.201019	-0.272408	0.135481	-(
75%	494.500000	0.000000	-0.161226	-0.160095	-0.024730	0.588245	0.594175	0.398058	-0.103065	0.572346	-(
max	659.000000	1.000000	13.556110	13.397566	21.583878	4.743947	1.811929	7.493283	6.824777	3.045692	1:

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.

ACTION: Multi-collinearity

Check and deal with multi-collinearity in your feature set.

We check for multicollinearity by using the corr() function and sort the value from highest to lowest. From the correlation,it can be noticed that there are high collinearity between stream count and number of users and region_pca1 since the values are higher than 90%.

In [70]:
```
# Check for multicollinearity
# Check for highly correlated variables (>90%)
features=['count',"number_users","passion_score","malepercentage","weightedscore","Dependent","Senior","YoungAdult",'region_pc1', 'r
egion_pc2', 'region_pc3', 'region_pc4', 'region_pc5','region_pc6', 'region_pc7', 'region_pc8', 'region_pc9', 'region_pc10']
c = final_df[features].corr().abs()
s = c.unstack()
corr = sorted(s.items(),key = lambda x: x[1],  reverse=True)
corr = [corr[x] for x in range(len(corr)) if corr[x][1]!=1]
corr
```

```
Out[70]: [(('count', 'number_users'), 0.996105303736572),
          (('number_users', 'count'), 0.996105303736572),
          (('count', 'region_pc1'), 0.9898737867659627),
          (('region_pc1', 'count'), 0.9898737867659627),
          (('number_users', 'region_pc1'), 0.9873308518917375),
          (('region_pc1', 'number_users'), 0.9873308518917375),
          (('Senior', 'YoungAdult'), 0.2900948562835749),
          (('YoungAdult', 'Senior'), 0.2900948562835749),
          (('malepercentage', 'weightedscore'), 0.26453641954549817),
          (('weightedscore', 'malepercentage'), 0.26453641954549817),
          (('weightedscore', 'YoungAdult'), 0.245518881382504l6),
          (('YoungAdult', 'weightedscore'), 0.245518881382504l6),
          (('malepercentage', 'Dependent'), 0.1940672876063316),
          (('Dependent', 'malepercentage'), 0.1940672876063316),
          (('malepercentage', 'Senior'), 0.19224178410800338),
          (('Senior', 'malepercentage'), 0.19224178410800338),
          (('Dependent', 'Senior'), 0.18306656522873146),
          (('Senior', 'Dependent'), 0.18306656522873146),
          (('weightedscore', 'Senior'), 0.17368201581352172),
          (('Senior', 'weightedscore'), 0.17368201581352172),
          (('weightedscore', 'Dependent'), 0.15621261849548154),
          (('Dependent', 'weightedscore'), 0.15621261849548154),
          (('number_users', 'Dependent'), 0.11213086543677231),
          (('Dependent', 'number_users'), 0.11213086543677231),
          (('malepercentage', 'YoungAdult'), 0.1114751232025845),
          (('YoungAdult', 'malepercentage'), 0.1114751232025845),
          (('number_users', 'region_pc3'), 0.10957352045088477),
          (('region_pc3', 'number_users'), 0.10957352045088477),
          (('count', 'region_pc3'), 0.10902012311526688),
          (('region_pc3', 'count'), 0.10902012311526688),
          (('count', 'Dependent'), 0.10895342847840789),
          (('Dependent', 'count'), 0.10895342847840789),
          (('passion_score', 'malepercentage'), 0.10360014603062476),
          (('malepercentage', 'passion_score'), 0.10360014603062476),
          (('Dependent', 'region_pc1'), 0.10028118899657193),
          (('region_pc1', 'Dependent'), 0.10028118899657193),
          (('passion_score', 'weightedscore'), 0.0975993741394282),
          (('weightedscore', 'passion_score'), 0.0975993741394282),
          (('passion_score', 'YoungAdult'), 0.09690902730132399),
          (('YoungAdult', 'passion_score'), 0.09690902730132399),
          (('weightedscore', 'region_pc10'), 0.0687990323717114),
          (('region_pc10', 'weightedscore'), 0.0687990323717114),
          (('malepercentage', 'region_pc1'), 0.06455253149903238),
          (('region_pc1', 'malepercentage'), 0.06455253149903238),
          (('Dependent', 'region_pc3'), 0.06408214210887761),
          (('region_pc3', 'Dependent'), 0.06408214210887761),
          (('number_users', 'malepercentage'), 0.0636047636563406),
          (('malepercentage', 'number_users'), 0.0636047636563406),
          (('count', 'malepercentage'), 0.060545756616547),
          (('malepercentage', 'count'), 0.060545756616547),
          (('number_users', 'weightedscore'), 0.06033980308806775),
          (('weightedscore', 'number_users'), 0.06033980308806775),
          (('malepercentage', 'region_pc7'), 0.05774476674353545),
          (('region_pc7', 'malepercentage'), 0.05774476674353545),
          (('count', 'weightedscore'), 0.056937283818603544),
          (('weightedscore', 'count'), 0.056937283818603544),
          (('weightedscore', 'region_pc1'), 0.056445049551071505),
          (('region_pc1', 'weightedscore'), 0.056445049551071505),
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          (('region_pc5', 'count'), 0.04880734305689876),
          (('passion_score', 'Dependent'), 0.045957677884510974),
          (('Dependent', 'passion_score'), 0.045957677884510974),
          (('YoungAdult', 'region_pc10'), 0.044651042285670905),
          (('region_pc10', 'YoungAdult'), 0.044651042285670905),
          (('YoungAdult', 'region_pc8'), 0.038532889700918935),
          (('region_pc8', 'YoungAdult'), 0.038532889700918935),
          (('malepercentage', 'region_pc8'), 0.038409406275909504),
          (('region_pc8', 'malepercentage'), 0.038409406275909504),
          (('Dependent', 'region_pc4'), 0.038174282112028994),
          (('region_pc4', 'Dependent'), 0.038174282112028994),
          (('Dependent', 'region_pc8'), 0.03329161019137374),
          (('region_pc8', 'Dependent'), 0.03329161019137374),
          (('count', 'region_pc7'), 0.03134405782914076),
          (('region_pc7', 'count'), 0.03134405782914076),
          (('number_users', 'region_pc4'), 0.03071636858597516),
          (('region_pc4', 'number_users'), 0.03071636858597516),
          (('Dependent', 'region_pc9'), 0.029701234307331917),
          (('region_pc9', 'Dependent'), 0.029701234307331917),
          (('malepercentage', 'region_pc4'), 0.02951811129583706),
          (('region_pc4', 'malepercentage'), 0.02951811129583706),
          (('number_users', 'region_pc10'), 0.02868690893762176),
          (('region_pc10', 'number_users'), 0.02868690893762176),
          (('malepercentage', 'region_pc10'), 0.028305190598450932),
          (('region_pc10', 'malepercentage'), 0.028305190598450932),
          (('number_users', 'region_pc5'), 0.02814543419312314),
          (('region_pc5', 'number_users'), 0.02814543419312314),
          (('Dependent', 'YoungAdult'), 0.027891528463898602),
          (('YoungAdult', 'Dependent'), 0.027891528463898602),
          (('malepercentage', 'region_pc5'), 0.02747630067346027),
          (('region_pc5', 'malepercentage'), 0.02747630067346027),
          (('weightedscore', 'region_pc8'), 0.02521810640738936),
          (('region_pc8', 'weightedscore'), 0.02521810640738936),
          (('weightedscore', 'region_pc6'), 0.024558204965050092),
          (('region_pc6', 'weightedscore'), 0.024558204965050092),
          (('YoungAdult', 'region_pc7'), 0.02381356791507353),
          (('region_pc7', 'YoungAdult'), 0.02381356791507353),
          (('YoungAdult', 'region_pc9'), 0.02274344833197705),
          (('region_pc9', 'YoungAdult'), 0.02274344833197705),
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```

We need to remove one of the highly correlated varibles. Firstly we remove the variable 'number of userscount'and check the collinearity again.

In [71]:
```
final_df=final_df.drop(columns=['index'])
final_df=final_df.drop(columns=['number_users'])
final_df
```

Out[71]:

	artist_name	success	count	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult	region_pc1	region_pc2
0	#90s Update	0	-0.176036	-0.114376	0.496370	0.077692	-0.192020	-0.450729	-0.749429	-0.181890	0.027127
1	17 Memphis	0	-0.176158	-0.195039	0.295276	-1.078466	0.631405	0.155563	0.278416	-0.181812	0.027157
2	2D	0	-0.176496	-0.195039	-1.463501	1.811929	7.493283	-0.450729	-1.698210	-0.182202	0.027240
3	3JS	0	-0.176373	0.107446	-1.463501	0.728031	-0.740970	-0.450729	-0.512234	-0.182077	0.027143
4	99 Percent	0	-0.136942	-0.091243	0.651924	-1.156256	2.385255	-0.247261	-0.049905	-0.147007	0.014216
5	A Boogie Wit Da Hoodie	0	0.127149	0.148664	0.563629	0.567407	1.094350	-0.299946	0.665084	0.019168	-0.023976
6	A Boogie Wit da Hoodie	1	0.230173	0.033845	0.643047	0.383446	1.478543	-0.266364	0.380483	0.394901	0.341414
7	A R I Z O N A	1	1.933932	0.006860	0.598507	-0.471227	0.412100	-0.196180	0.230898	2.879146	-0.022420
8	AGWA	0	-0.176434	-0.195039	1.847138	1.811929	-0.740970	4.399609	-1.698210	-0.182138	0.027221
9	ALMA	0	-0.176281	-0.195039	-1.463501	-0.355867	-0.740970	0.458709	0.080753	-0.181863	0.027089
10	ALP	0	-0.176404	-0.195039	0.191819	-1.439765	3.376156	-0.450729	-0.512234	-0.182207	0.027249
11	AV AV AV	0	-0.174778	-0.127820	-1.463501	0.928753	-0.740970	-0.450729	-0.380459	-0.181647	0.027098
12	AVVAH	0	-0.175913	-0.195039	0.345292	-1.006206	0.082455	-0.450729	0.910936	-0.181954	0.027176
13	AXSHN	1	-0.173092	-0.161738	0.727898	-0.574635	1.029010	-0.110752	-0.190802	-0.179053	0.026326
14	Absofacto	1	-0.172295	-0.177246	0.429502	0.026685	0.227766	-0.290240	0.255162	-0.176228	0.025227
15	Adam Sample	0	-0.175238	-0.195039	1.094128	-0.768781	0.239298	-0.277503	1.351442	-0.175237	0.031843
16	Adan Carmona	0	-0.176097	0.006618	3.117092	-0.717166	-0.740970	-0.450729	-0.404418	-0.182151	0.027261
17	Adia Victoria	0	-0.155952	-0.067467	0.276233	0.233402	-0.372883	0.151548	-0.551505	-0.168537	0.022534
18	Alcatraz	0	-0.176312	-0.195039	-1.463501	-0.046182	-0.740970	0.588629	-1.020510	-0.181977	0.027176
19	Alessio Bernabei	0	-0.170670	0.076422	0.380998	-0.328075	-0.001999	-0.264177	0.126368	-0.172524	0.020383
20	Alex Hoyer	0	-0.175698	-0.195039	0.446028	-0.757311	0.478919	-0.181266	-0.292609	-0.181371	0.027117
21	Alex Roy	0	-0.176434	-0.195039	3.117092	-2.523663	-0.740970	-0.450729	1.464392	-0.182184	0.027229
22	Alexander Brown	0	-0.172019	-0.143552	0.332434	0.212987	-0.507374	-0.141133	-0.318777	-0.180284	0.026580
23	Alexander Cardinale	0	-0.158620	-0.124898	0.358036	-0.811418	0.128951	-0.013403	-0.013217	-0.167502	0.020393
24	Alexander Charles	0	-0.174901	-0.147590	0.624202	1.046825	0.389222	-0.450729	0.813268	-0.181089	0.026740
25	Alice	0	-0.175146	-0.008894	0.540400	0.477901	0.103569	0.108925	-0.238548	-0.181159	0.026626
26	Aliose	0	-0.175882	0.006618	0.743592	-0.355867	-0.740970	-0.046534	-0.380459	-0.181810	0.027139
27	All Tvvins	1	0.143768	-0.024569	0.383093	0.367205	0.207255	-0.231471	0.184846	0.052643	-0.060070
28	Alma	0	-0.146048	0.040550	0.374291	0.264248	0.518970	-0.170227	-0.052133	-0.079220	-0.188054
29	Amaro Ferreiro	0	-0.176281	1.014901	-1.463501	0.728031	-0.740970	-0.450729	-0.116909	-0.182217	0.027250
...	...	...	...	...	...	...	...	...	...	...	...
630	Whethan	0	-0.041675	-0.195039	0.395066	-0.416932	-0.480025	0.573990	-0.695977	-0.038634	0.023829
631	Wild Youth	1	-0.167818	-0.195039	-1.463501	0.791790	-0.256602	0.405213	-0.023891	-0.156552	0.077764
632	Wildling	0	-0.176005	0.068100	0.759848	-0.489707	0.482499	-0.189914	0.355777	-0.182000	0.027202
633	Will Joseph Cook	1	0.293275	0.037613	0.539275	-0.354518	0.335302	-0.245977	0.541719	0.269432	-0.252760
634	Willy William	0	-0.117778	0.464928	-1.463501	1.417784	-0.740970	-0.450729	-0.835682	-0.098638	-0.156896
635	Witek Muzyk Ulicy	0	-0.176005	-0.195039	-1.463501	-0.073111	-0.740970	-0.134403	0.364356	-0.181888	0.027241
636	Wudstik	0	-0.175821	-0.195039	-1.463501	-2.523663	-0.740970	-0.450729	-1.698210	-0.181758	0.027013
637	Xavier Cugat y su orquesta	0	-0.176496	-0.101485	0.281572	-0.366293	-0.159477	-0.099190	0.040310	-0.182219	0.027251
638	Xavier Dunn	1	0.002049	-0.115244	0.523013	0.832924	0.954492	-0.325018	0.644711	-0.047847	-0.024444
639	YFN Lucci	0	-0.130932	-0.180635	0.304444	0.263503	-0.003574	-0.255268	0.043581	-0.132275	0.020076
640	YONAKA	0	-0.166101	0.009237	0.380998	0.460576	0.017448	-0.354999	1.110680	-0.163413	-0.083496

	artist_name	success	count	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult	region_pc1	region_pc2
641	Yasutaka Nakata	0	-0.173767	-0.035151	0.478201	0.469995	0.192468	-0.281360	0.527295	-0.180006	0.026421
642	Yellow Claw	1	0.029951	2.224841	-1.463501	1.811929	-0.740970	-0.450729	-1.698210	0.151826	-0.265502
643	Ylric Illians	0	-0.176434	-0.195039	-1.463501	1.811929	-0.740970	-0.450729	3.045692	-0.182150	0.027246
644	Young F	0	-0.176496	-0.132061	0.238992	0.943443	0.420438	-0.300837	0.782753	-0.182200	0.027241
645	Young Spray	0	-0.156075	0.120597	0.818727	0.967152	0.884562	-0.309457	0.612332	-0.168229	0.023239
646	YoungBoy Never Broke Again	0	-0.152518	0.272804	0.747140	1.060427	1.289394	-0.351064	0.641249	-0.158712	0.024421
647	Youngboy Never Broke Again	0	-0.173337	-0.130794	1.016106	-0.183211	2.152146	-0.385184	0.331838	-0.178787	0.026837
648	Yvng Swag	0	-0.169229	-0.195039	0.571214	-0.098671	-0.322279	0.165839	-0.250918	-0.172383	0.025746
649	Zac Brown	0	-0.174717	0.046949	-1.463501	-0.355867	-0.740970	-0.450729	-0.644009	-0.180501	0.026656
650	Zak & Diego	0	-0.176158	-0.011665	0.560322	-0.505188	0.074610	-0.160358	0.338439	-0.182115	0.027224
651	Zak Abel	1	0.650303	-0.195039	-1.463501	1.811929	-0.740970	-0.450729	-1.698210	0.550193	0.001384
652	Zakopower	0	-0.176496	0.275493	1.640223	0.848464	0.631405	-0.046534	0.146641	-0.182219	0.027251
653	Zarcort	0	-0.175760	-0.195039	-1.463501	1.811929	-0.740970	-0.450729	-1.698210	-0.173227	-0.014794
654	Zbigniew Kurtycz	0	-0.176465	-0.010615	0.631732	-0.569547	-0.129775	-0.270195	0.281956	-0.182187	0.027241
655	Zion & Lennox	1	0.152200	-0.195039	0.191819	-0.789426	1.317593	-0.450729	0.199351	0.578635	0.750254
656	birthday	0	-0.175913	0.222413	0.403924	-0.563240	0.391649	-0.278470	0.640631	-0.181827	0.027139
657	dvsn	1	0.595172	-0.183836	0.457025	-0.235434	0.555162	-0.181266	0.058791	0.469397	-0.294230
658	flor	1	-0.173184	-0.032936	0.622407	-0.787474	1.164031	-0.232967	0.149800	-0.179915	0.026429
659	gnash	1	4.903629	0.006618	0.191819	-0.355867	2.003781	-0.450729	-0.907560	4.020854	-1.664809

659 rows × 19 columns

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c = final_df[features].corr().abs()
s = c.unstack()
corr = sorted(s.items(),key = lambda x: x[1],  reverse=True)
corr = [corr[x] for x in range(len(corr)) if corr[x][1]!=1]
corr
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          (('region_pc1', 'region_pc4'), 1.873900781895363e-08),
          (('region_pc4', 'region_pc1'), 1.873900781895363e-08),
          (('region_pc8', 'region_pc10'), 7.266197752399767e-09),
          (('region_pc10', 'region_pc8'), 7.266197752399767e-09),
          (('region_pc4', 'region_pc7'), 5.942120958912061e-09),
          (('region_pc7', 'region_pc4'), 5.942120958912061e-09),
          (('region_pc3', 'region_pc4'), 4.8522421476040205e-09),
          (('region_pc4', 'region_pc3'), 4.8522421476040205e-09),
          (('region_pc4', 'region_pc5'), 3.6392944584245098e-09),
          (('region_pc5', 'region_pc4'), 3.6392944584245098e-09),
          (('region_pc2', 'region_pc4'), 2.801228203917875e-09),
          (('region_pc4', 'region_pc2'), 2.801228203917875e-09),
          (('region_pc4', 'region_pc6'), 2.0556818239044856e-09),
          (('region_pc6', 'region_pc4'), 2.0556818239044856e-09),
          (('region_pc4', 'region_pc9'), 7.517937617539371e-10),
          (('region_pc9', 'region_pc4'), 7.517937617539371e-10),
          (('region_pc4', 'region_pc10'), 2.187676956468748e-10),
          (('region_pc10', 'region_pc4'), 2.187676956468748e-10),
          (('region_pc4', 'region_pc8'), 1.1519515839384683e-10),
          (('region_pc8', 'region_pc4'), 1.1519515839384683e-10)]
```

Then we remove the stream count.

In [73]:
```
final_df=final_df.drop(columns=['count'])
final_df
```

Out[73]:

	artist_name	success	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult	region_pc1	region_pc2	region_pc3
0	#90s Update	0	-0.114376	0.496370	0.077692	-0.192020	-0.450729	-0.749429	-0.181890	0.027127	-0.047444
1	17 Memphis	0	-0.195039	0.295276	-1.078466	0.631405	0.155563	0.278416	-0.181812	0.027157	-0.047693
2	2D	0	-0.195039	-1.463501	1.811929	7.493283	-0.450729	-1.698210	-0.182202	0.027240	-0.047163
3	3JS	0	0.107446	-1.463501	0.728031	-0.740970	-0.450729	-0.512234	-0.182077	0.027143	-0.047344
4	99 Percent	0	-0.091243	0.651924	-1.156256	2.385255	-0.247261	-0.049905	-0.147007	0.014216	-0.096025
5	A Boogie Wit Da Hoodie	0	0.148664	0.563629	0.567407	1.094350	-0.299946	0.665084	0.019168	-0.023976	-0.157641
6	A Boogie Wit da Hoodie	1	0.033845	0.643047	0.383446	1.478543	-0.266364	0.380483	0.394901	0.341414	2.427304
7	A R I Z O N A	1	0.006860	0.598507	-0.471227	0.412100	-0.196180	0.230898	2.879146	-0.022420	6.251410
8	AGWA	0	-0.195039	1.847138	1.811929	-0.740970	4.399609	-1.698210	-0.182138	0.027221	-0.047156
9	ALMA	0	-0.195039	-1.463501	-0.355867	-0.740970	0.458709	0.080753	-0.181863	0.027089	-0.047690
10	ALP	0	-0.195039	0.191819	-1.439765	3.376156	-0.450729	-0.512234	-0.182207	0.027249	-0.047151
11	AV AV AV	0	-0.127820	-1.463501	0.928753	-0.740970	-0.450729	-0.380459	-0.181647	0.027098	-0.047443
12	AVVAH	0	-0.195039	0.345292	-1.006206	0.082455	-0.450729	0.910936	-0.181954	0.027176	-0.046786
13	AXSHN	1	-0.161738	0.727898	-0.574635	1.029010	-0.110752	-0.190802	-0.179053	0.026326	-0.047692
14	Absofacto	1	-0.177246	0.429502	0.026685	0.227766	-0.290240	0.255162	-0.176228	0.025227	-0.029911
15	Adam Sample	0	-0.195039	1.094128	-0.768781	0.239298	-0.277503	1.351442	-0.175237	0.031843	-0.025801
16	Adan Carmona	0	0.006618	3.117092	-0.717166	-0.740970	-0.450729	-0.404418	-0.182151	0.027261	-0.047170
17	Adia Victoria	0	-0.067467	0.276233	0.233402	-0.372883	0.151548	-0.551505	-0.168537	0.022534	-0.059181
18	Alcatraz	0	-0.195039	-1.463501	-0.046182	-0.740970	0.588629	-1.020510	-0.181977	0.027176	-0.047120
19	Alessio Bernabei	0	0.076422	0.380998	-0.328075	-0.001999	-0.264177	0.126368	-0.172524	0.020383	0.026792
20	Alex Hoyer	0	-0.195039	0.446028	-0.757311	0.478919	-0.181266	-0.292609	-0.181371	0.027117	-0.046930
21	Alex Roy	0	-0.195039	3.117092	-2.523663	-0.740970	-0.450729	1.464392	-0.182184	0.027229	-0.047196
22	Alexander Brown	0	-0.143552	0.332434	0.212987	-0.507374	-0.141133	-0.318777	-0.180284	0.026580	-0.049804
23	Alexander Cardinale	0	-0.124898	0.358036	-0.811418	0.128951	-0.013403	-0.013217	-0.167502	0.020393	-0.065333
24	Alexander Charles	0	-0.147590	0.624202	1.046825	0.389222	-0.450729	0.813268	-0.181089	0.026740	-0.048547
25	Alice	0	-0.008894	0.540400	0.477901	0.103569	0.108925	-0.238548	-0.181159	0.026626	-0.048573
26	Aliose	0	0.006618	0.743592	-0.355867	-0.740970	-0.046534	-0.380459	-0.181810	0.027139	-0.046714
27	All Tvvins	1	-0.024569	0.383093	0.367205	0.207255	-0.231471	0.184846	0.052643	-0.060070	-0.256201
28	Alma	0	0.040550	0.374291	0.264248	0.518970	-0.170227	-0.052133	-0.079220	-0.188054	0.176932
29	Amaro Ferreiro	0	1.014901	-1.463501	0.728031	-0.740970	-0.450729	-0.116909	-0.182217	0.027250	-0.047136
...	...	...	...	...	...	...	...	...	...	...	...
630	Whethan	0	-0.195039	0.395066	-0.416932	-0.480025	0.573990	-0.695977	-0.038634	0.023829	-0.086762
631	Wild Youth	1	-0.195039	-1.463501	0.791790	-0.256602	0.405213	-0.023891	-0.156552	0.077764	0.002793
632	Wildling	0	0.068100	0.759848	-0.489707	0.482499	-0.189914	0.355777	-0.182000	0.027202	-0.047004
633	Will Joseph Cook	1	0.037613	0.539275	-0.354518	0.335302	-0.245977	0.541719	0.269432	-0.252760	-0.049741
634	Willy William	0	0.464928	-1.463501	1.417784	-0.740970	-0.450729	-0.835682	-0.098638	-0.156896	-0.010792
635	Witek Muzyk Ulicy	0	-0.195039	-1.463501	-0.073111	-0.740970	-0.134403	0.364356	-0.181888	0.027241	-0.046777
636	Wudstik	0	-0.195039	-1.463501	-2.523663	-0.740970	-0.450729	-1.698210	-0.181758	0.027013	-0.047703
637	Xavier Cugat y su orquesta	0	-0.101485	0.281572	-0.366293	-0.159477	-0.099190	0.040310	-0.182219	0.027251	-0.047132
638	Xavier Dunn	1	-0.115244	0.523013	0.832924	0.954492	-0.325018	0.644711	-0.047847	-0.024444	-0.123017
639	YFN Lucci	0	-0.180635	0.304444	0.263503	-0.003574	-0.255268	0.043581	-0.132275	0.020076	0.278806
640	YONAKA	0	0.009237	0.380998	0.460576	0.017448	-0.354999	1.110680	-0.163413	-0.083496	-0.000707

	artist_name	success	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult	region_pc1	region_pc2	region_pc3
641	Yasutaka Nakata	0	-0.035151	0.478201	0.469995	0.192468	-0.281360	0.527295	-0.180006	0.026421	-0.047073
642	Yellow Claw	1	2.224841	-1.463501	1.811929	-0.740970	-0.450729	-1.698210	0.151826	-0.265502	0.364808
643	Ylric Illians	0	-0.195039	-1.463501	1.811929	-0.740970	-0.450729	3.045692	-0.182150	0.027246	-0.047180
644	Young F	0	-0.132061	0.238992	0.943443	0.420438	-0.300837	0.782753	-0.182200	0.027241	-0.047171
645	Young Spray	0	0.120597	0.818727	0.967152	0.884562	-0.309457	0.612332	-0.168229	0.023239	-0.060957
646	YoungBoy Never Broke Again	0	0.272804	0.747140	1.060427	1.289394	-0.351064	0.641249	-0.158712	0.024421	-0.035003
647	Youngboy Never Broke Again	0	-0.130794	1.016106	-0.183211	2.152146	-0.385184	0.331838	-0.178787	0.026837	-0.048167
648	Yvng Swag	0	-0.195039	0.571214	-0.098671	-0.322279	0.165839	-0.250918	-0.172383	0.025746	-0.025219
649	Zac Brown	0	0.046949	-1.463501	-0.355867	-0.740970	-0.450729	-0.644009	-0.180501	0.026656	-0.048918
650	Zak & Diego	0	-0.011665	0.560322	-0.505188	0.074610	-0.160358	0.338439	-0.182115	0.027224	-0.047210
651	Zak Abel	1	-0.195039	-1.463501	1.811929	-0.740970	-0.450729	-1.698210	0.550193	0.001384	0.417429
652	Zakopower	0	0.275493	1.640223	0.848464	0.631405	-0.046534	0.146641	-0.182219	0.027251	-0.047132
653	Zarcort	0	-0.195039	-1.463501	1.811929	-0.740970	-0.450729	-1.698210	-0.173227	-0.014794	-0.027215
654	Zbigniew Kurtycz	0	-0.010615	0.631732	-0.569547	-0.129775	-0.270195	0.281956	-0.182187	0.027241	-0.047041
655	Zion & Lennox	1	-0.195039	0.191819	-0.789426	1.317593	-0.450729	0.199351	0.578635	0.750254	2.771638
656	birthday	0	0.222413	0.403924	-0.563240	0.391649	-0.278470	0.640631	-0.181827	0.027139	-0.046582
657	dvsn	1	-0.183836	0.457025	-0.235434	0.555162	-0.181266	0.058791	0.469397	-0.294230	0.637802
658	flor	1	-0.032936	0.622407	-0.787474	1.164031	-0.232967	0.149800	-0.179915	0.026429	-0.049804
659	gnash	1	0.006618	0.191819	-0.355867	2.003781	-0.450729	-0.907560	4.020854	-1.664809	-4.657319

659 rows × 18 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:

ACTION: Class balance

Calculate and comment on class balance.

We will calculate and comment on class balance in the next part.

In [74]:
```
final_df.describe()
```

Out[74]:

	success	passion_score	weightedscore	malepercentage	Dependent	Senior	YoungAdult	region_pc1	region_pc2	region_pc3	reg
count	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	659.000000	6.590
mean	0.125948	-0.001999	0.002221	0.000540	0.001124	-0.002076	-0.001022	0.000553	-0.000083	0.000143	1.02
std	0.332043	1.000199	0.999890	1.001422	1.001101	1.000095	1.001174	1.002227	1.002276	1.002274	1.002
min	0.000000	-0.195039	-1.463501	-2.523663	-0.740970	-0.450729	-1.698210	-0.182673	-11.115732	-9.772089	-1.404
25%	0.000000	-0.195039	-1.463501	-0.552939	-0.740970	-0.450729	-0.531870	-0.182056	0.024155	-0.047922	-6.79
50%	0.000000	-0.143332	0.379213	-0.101091	-0.201019	-0.272408	0.135481	-0.180331	0.027143	-0.047149	-7.64
75%	0.000000	-0.024730	0.588245	0.594175	0.398058	-0.103065	0.572346	-0.156454	0.027247	-0.039213	3.31
max	1.000000	21.583878	4.743947	1.811929	7.493283	6.824777	3.045692	13.393821	20.287415	17.666122	1.577

4. Evaluate algorithms

Model Selection

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.
- Test the model on hold-out set

Make reference to "P6 - Pipelines and parameter tuning" from week 6 as necessary.

ACTION: Spot-check algorithms

Try a mixture of algorithm representations (e.g. instances and trees).

Try a mixture of learning algorithms (e.g. different algorithms for learning the same type of representation).

Try a mixture of modeling types (e.g. linear and nonlinear functions or parametric and nonparametric).

Divide this work up among the different members of your team and then compare and comment on the performance of various approaches.

In this part, we firstly split the data into train and validation set, using test size ratio equals to 0.2 and keep random state equals to 42.

In [75]:
```
from sklearn.model_selection import train_test_split
features2=['passion_score','malepercentage','weightedscore','Dependent','Senior','YoungAdult','region_pc1', 'region_pc2', 'region_pc
3', 'region_pc4', 'region_pc5','region_pc6', 'region_pc7', 'region_pc8', 'region_pc9', 'region_pc10']
X=final_df[features2]
Y=final_df['success']

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

In [76]:
```
print(len(x_train))
```

```
527
```

Then we create a dataframe named train_set which contains x train and y train.

In [77]:
```
train_set=x_train.copy()
train_set["success"]=y_train
train_set
```

Out[77]:

	passion_score	malepercentage	weightedscore	Dependent	Senior	YoungAdult	region_pc1	region_pc2	region_pc3	region_pc4	
18	-0.195039	-0.046182	-1.463501	-0.740970	0.588629	-1.020510	-1.819767e-01	2.717605e-02	-4.712030e-02	-5.833343e-05	3
363	-0.145987	-0.678107	0.807414	0.547382	-0.302249	0.076720	-1.821755e-01	2.723835e-02	-4.721750e-02	-9.376095e-05	3
389	0.118649	-0.917888	0.310056	-0.740970	0.088197	0.410191	-1.821835e-01	2.724189e-02	-4.719324e-02	-8.943787e-05	3
452	-0.195039	-0.355867	-1.463501	-0.740970	-0.450729	0.673741	-1.822058e-01	2.724584e-02	-4.714971e-02	-7.956949e-05	3
61	-0.195039	0.366732	0.832587	0.288312	-0.450729	1.266729	-1.765837e-01	3.148539e-02	-3.706627e-02	-4.156105e-03	3
265	-0.195039	1.811929	0.595555	-0.740970	1.974440	-0.116909	-1.809136e-01	2.678007e-02	-4.770876e-02	3.928689e-05	3
418	-0.195039	1.811929	-1.463501	-0.740970	-0.450729	-1.698210	-1.819862e-01	2.719817e-02	-4.711783e-02	3.684685e-05	3
29	1.014901	0.728031	-1.463501	-0.740970	-0.450729	-0.116909	-1.822170e-01	2.724997e-02	-4.713639e-02	-7.020079e-05	3
158	-0.195039	-0.789426	-1.463501	-0.740970	-0.450729	-0.749429	-1.821515e-01	2.723987e-02	-4.719322e-02	-6.479092e-05	3
287	0.400834	0.100511	0.473121	-0.431412	0.151005	-0.645991	-1.821051e-01	2.725181e-02	-4.671435e-02	2.052338e-04	3
211	-0.195039	-0.552939	0.191819	0.007598	-0.450729	-0.404418	-1.820883e-01	2.714923e-02	-4.727706e-02	-1.513760e-04	3
303	-0.195039	1.811929	-1.463501	-0.740970	-0.450729	3.045692	-1.808722e-01	2.685999e-02	-4.883770e-02	-5.523059e-04	3
394	-0.180970	-0.759178	0.507679	-0.549476	0.141463	-0.594977	-1.764518e-01	2.549962e-02	-3.099126e-02	1.308614e-02	4
183	-0.168447	-0.117648	0.753021	0.578330	-0.169356	0.346124	-1.791806e-01	2.667086e-02	-4.902779e-02	-5.256255e-04	3
383	-0.195039	-2.523663	-1.463501	-0.740970	-0.450729	-1.698210	-1.770931e-01	2.544677e-02	-5.135797e-02	-1.233894e-03	3
590	-0.195039	0.077692	0.555989	-0.740970	-0.450729	-0.749429	-1.818181e-01	2.728438e-02	-4.789282e-02	-4.838841e-04	3
336	-0.195039	1.811929	-1.463501	-0.740970	3.187024	0.673741	-1.822140e-01	2.724862e-02	-4.713878e-02	-7.161555e-05	3
333	-0.195039	1.811929	-1.463501	-0.740970	-0.450729	-1.698210	-1.822036e-01	2.724284e-02	-4.717100e-02	-7.312064e-05	3
182	-0.186973	0.829195	0.454428	0.796091	-0.353722	0.357481	-1.766622e-01	2.915473e-02	5.044172e-02	-5.369756e-02	
205	-0.149163	-0.028852	0.480750	-0.088470	-0.207669	0.234527	-1.378678e-01	1.740332e-02	-6.528351e-02	2.060853e-03	
619	-0.195039	-0.789426	1.019478	-0.740970	-0.450729	0.199351	-1.818933e-01	2.713172e-02	-4.740327e-02	-9.680981e-05	3
624	-0.195039	0.366732	-1.463501	2.003781	-0.450729	-0.116909	-1.801225e-01	2.924881e-02	-4.254675e-02	2.002322e-03	3
453	-0.195039	1.811929	-1.463501	-0.740970	-0.450729	-1.698210	-1.822117e-01	2.724841e-02	-4.713931e-02	-7.214275e-05	3
353	-0.195039	-1.078466	2.398911	-0.740970	-0.450729	1.464392	-1.821565e-01	2.725226e-02	-4.718472e-02	-7.436708e-05	3
257	-0.195039	1.811929	-1.463501	-0.740970	6.824777	-1.698210	-1.788919e-01	2.652303e-02	-4.671080e-02	3.648985e-04	3
516	-0.195039	1.811929	-1.463501	-0.740970	6.824777	-1.698210	-1.822067e-01	2.724622e-02	-4.714949e-02	-7.543941e-05	3
104	0.194679	-1.357762	0.445337	2.191863	-0.302808	0.334381	-1.194811e-01	3.660933e-02	-6.730388e-02	-2.166522e-02	3
114	-0.168671	-0.157984	0.505425	0.266683	-0.213908	0.315065	-5.963937e-02	3.107895e-02	1.532542e-01	1.868665e-01	3
165	-0.013548	-0.355867	0.926033	1.111737	-0.450729	0.673741	-1.819640e-01	2.707665e-02	-4.756597e-02	-9.169617e-05	3
339	-0.195039	-2.523663	-1.463501	-0.740970	-0.450729	-1.698210	-1.773345e-01	4.086087e-02	9.380572e-02	1.051013e-01	
...	...	...	...	...	...	...	...	...	...	...	
475	-0.030979	0.121783	0.414700	0.096412	-0.327415	0.311918	-1.747560e-01	3.196033e-02	-2.130046e-05	-1.698441e-02	2
561	0.409931	-0.139087	1.295365	-0.535114	-0.268841	-1.105222	-1.820628e-01	2.721775e-02	-4.659597e-02	2.174508e-04	3
253	-0.137423	0.779645	0.494353	0.992557	-0.450729	0.548902	-1.822053e-01	2.724647e-02	-4.714741e-02	-7.124630e-05	3

	passion_score	malepercentage	weightedscore	Dependent	Senior	YoungAdult	region_pc1	region_pc2	region_pc3	region_pc4	
21	-0.195039	-2.523663	3.117092	-0.740970	-0.450729	1.464392	-1.821841e-01	2.722863e-02	-4.719617e-02	-8.276441e-05	3
314	-0.091060	0.321569	0.258197	0.030991	-0.337049	0.525494	-1.820912e-01	2.722448e-02	-4.720843e-02	-7.393355e-05	3
460	-0.110498	-0.679978	0.554435	0.190507	-0.236743	0.401843	-1.818261e-01	2.707615e-02	-4.699044e-02	1.354145e-04	3
161	0.059613	-0.786138	0.610521	0.592496	-0.199339	0.147812	8.521464e-18	3.769045e-18	-1.281014e-17	4.936926e-19	6
277	-0.195039	-1.439765	-1.463501	-0.740970	-0.450729	-0.512234	-1.821436e-01	2.723244e-02	-4.688446e-02	4.385339e-05	3
192	0.168083	-0.297926	0.347863	-0.414030	0.121590	-0.290847	-1.818001e-01	2.711326e-02	-4.676865e-02	2.209048e-04	3
386	0.024950	-0.651476	0.469291	1.879020	-0.120024	-0.296602	-1.821917e-01	2.723551e-02	-4.717437e-02	-8.658890e-05	3
414	-0.195039	-2.523663	-1.463501	7.493283	-0.450729	-1.698210	-1.789456e-01	3.191332e-02	-2.218329e-02	-8.362956e-03	4
492	-0.115366	-0.584487	0.638061	0.828242	-0.239463	0.430397	-4.624907e-02	2.241126e-01	3.155800e-01	3.459787e-02	
344	-0.195039	-0.572647	-1.463501	0.559175	-0.450729	1.048260	-1.815693e-01	2.682776e-02	-4.804028e-02	-3.702010e-04	3
309	-0.098244	0.858099	0.695300	0.411825	-0.450729	1.148131	-1.822140e-01	2.724862e-02	-4.713878e-02	-7.161555e-05	3
130	-0.144988	0.345938	0.455478	1.447077	-0.201003	0.444298	4.684330e-02	-1.266712e-01	1.494517e-01	1.338378e-01	
99	-0.170931	-0.312675	0.527389	-0.513849	0.127692	-0.453866	-1.289844e-01	2.583232e-02	1.044968e-02	1.462316e-02	1
373	0.002157	-0.338202	0.464116	0.502846	-0.144033	0.190463	-1.806601e-01	2.667409e-02	-4.896062e-02	-6.655521e-04	3
87	-0.104066	-0.046182	0.841685	-0.431412	-0.122511	-0.235804	-1.740907e-01	3.949288e-02	-3.329101e-02	-1.987233e-03	2
459	-0.195039	0.077692	0.191819	-0.740970	-0.086954	-0.986625	3.331612e-01	-1.436613e-01	-6.254941e-01	-2.049828e-01	
331	11.904359	1.811929	-1.463501	-0.740970	-0.450729	-1.698210	-1.822187e-01	2.725086e-02	-4.713206e-02	-6.983581e-05	3
215	-0.085045	1.417784	-1.463501	0.007598	-0.450729	1.751901	-1.743961e-01	2.843560e-02	2.582719e-01	-2.061555e-01	
467	-0.088941	-0.675039	0.731198	0.197370	-0.218249	0.153693	-1.822155e-01	2.725042e-02	-4.713176e-02	-7.047764e-05	3
121	-0.195039	-0.355867	-1.463501	-0.740970	3.187024	-1.698210	-1.821731e-01	2.723985e-02	-4.722449e-02	-1.183901e-04	3
615	-0.195039	-1.078466	-1.463501	0.631405	-0.450729	-0.380459	-1.690151e-01	2.251880e-02	-6.226047e-02	-5.074609e-03	2
20	-0.195039	-0.757311	0.446028	0.478919	-0.181266	-0.292609	-1.813707e-01	2.711700e-02	-4.692955e-02	-1.905033e-05	3
71	-0.195039	1.811929	-1.463501	-0.740970	-0.450729	-1.698210	-1.822187e-01	2.725086e-02	-4.713206e-02	-6.983581e-05	3
106	-0.155369	1.101176	0.386562	0.338932	-0.450729	0.868163	-1.806680e-01	2.703206e-02	-4.715721e-02	2.170092e-06	3
271	0.036923	0.311210	0.351285	0.707187	-0.277372	0.675535	-7.232600e-02	-7.368285e-02	2.670108e-01	2.415764e-01	1
436	0.025343	0.882874	0.251696	0.144434	-0.424652	0.614230	-1.755706e-01	2.559214e-02	-4.714047e-02	9.512779e-04	2
102	0.071494	-0.729089	0.701651	0.954735	-0.163196	0.088704	1.339382e+01	2.028742e+01	-1.442709e+00	6.766193e-01	6.

527 rows × 17 columns

Class Balance

In our analysis before, we know that most value of the dependent variable 'success' is 0, so there will be a strong bias toward predicting to artist failure. Here we use resample method to increase the size of 'success' and generate a new dataframe containing the increased training set which is called x_train_final. After the calculation, we set the value of n_samples as 450 and we can see that the ratio between success and failure is close to 1 after checking for the success value count.

In [78]:
```
from sklearn.utils import resample


train_set_fail = train_set[train_set.success==0]
train_set_success = train_set[train_set.success==1]

df_rs = resample(train_set_success, replace=True, n_samples=450, random_state=42)
x_train_final = pd.concat([train_set, df_rs])
x_train_final
x_train_final.success.value_counts()
```

Out[78]:
```
1    516
0    461
Name: success, dtype: int64
```

Here we split the x_train_final dataset into dependent variable and independent variables named x_final and y_final.

In [79]:
```
x_final=x_train_final[features2]
y_final=x_train_final['success']
```

We need to calculate the cross validation scores of different models, including decision tree, SGD, random forest, KNN and SVR. Comparing the scores of each model, we can see that the score of random forest is the highest. Thus, we select random forest to improve our result.

In [80]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVR
from sklearn.neighbors import KNeighborsClassifier
```

In [81]:
```
from sklearn.model_selection import cross_val_score
X =x_final.values
y = y_final.values

tree_clf = DecisionTreeClassifier()
FOLDS = 5
s_secision_tree = cross_val_score(tree_clf, X, y, cv=FOLDS, verbose=0)
print("tree_clf: " + str(s_secision_tree.mean()))

#bag_clf = BaggingClassifier()
#FOLDS = 5
#s_secision_tree = cross_val_score(estimator_decision_tree, X, y, cv=FOLDS, verbose=0)
#print("bag_clf: " + str(s_secision_tree.mean()))

SGD_clf=SGDClassifier()
FOLDS = 5
s_SGD = cross_val_score(SGD_clf, X, y, cv=FOLDS, verbose=0)
print("SGD_clf: " + str(s_SGD.mean()))

forest = RandomForestClassifier()
FOLDS = 5
s_forest = cross_val_score(forest, X, y, cv=FOLDS, verbose=0)
print("forest: " + str(s_forest.mean()))

KNN_classifier = KNeighborsClassifier()
FOLDS = 5
s_KNN = cross_val_score(KNN_classifier, X, y, cv=FOLDS, verbose=0)
print("KNN_classifier: " + str(s_KNN.mean()))

svm_reg_clf=LinearSVR()
FOLDS = 5
s_SVR = cross_val_score(svm_reg_clf, X, y, cv=FOLDS, verbose=0)
print("svm_reg_clf: " + str(s_SVR.mean()))
```

```
tree_clf: 0.9610985292203565
SGD_clf: 0.8157178185604581
forest: 0.9785031888585187
KNN_classifier: 0.9263100351425224
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:166: FutureWarning: max_iter an
d tol parameters have been added in SGDClassifier in 0.19. If both are left unset, they default to max_iter=5 and tol=None. If tol
is not None, max_iter defaults to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:166: FutureWarning: max_iter an
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is not None, max_iter defaults to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:166: FutureWarning: max_iter an
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  FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:166: FutureWarning: max_iter an
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is not None, max_iter defaults to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:166: FutureWarning: max_iter an
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is not None, max_iter defaults to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The default value of n_estim
ators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The default value of n_estim
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  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The default value of n_estim
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  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The default value of n_estim
ators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The default value of n_estim
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  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/svm/base.py:922: ConvergenceWarning: Liblinear failed to converge,
increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/svm/base.py:922: ConvergenceWarning: Liblinear failed to converge,
increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/svm/base.py:922: ConvergenceWarning: Liblinear failed to converge,
increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/svm/base.py:922: ConvergenceWarning: Liblinear failed to converge,
increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

```
svm_reg_clf: -1.9128310111905324
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/svm/base.py:922: ConvergenceWarning: Liblinear failed to converge,
increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

5. Improve Results

Hyper Parameter Tuning

It should be clear from your analysis above that you have selected a particular class of classifier as it gives the best result.

We can now tune the classifier (Hyper Parameter Tuning using Grid Search) to determine the optimal parameters.

ACTION: Hyper Parameter Tuning

Perform hyperparameter turing and demonstrate improved performance. Comment on any specific behaviour of your chosen classifier and set out the final structure and parameter settings.

We use grid search to find the best parameters of the random forest classifier here. From the output, we can see that the best parameters to get the best score include the max features 'log2' and when number of estimators equals to 200.

In [82]:
```
# SELECTED MODEL:
# Random forest

# GRIDSEARCH
model = RandomForestClassifier(n_jobs=-1,max_features= 'sqrt' ,n_estimators=50, oob_score = True)
from sklearn.model_selection import GridSearchCV, cross_val_score
param_grid = {
        'n_estimators': [100,125,150,200,250],
        'max_features': ['auto', 'sqrt', 'log2']
    }

CV_rfc = GridSearchCV(estimator=model, param_grid=param_grid, cv= 5)
CV_rfc.fit(x_final, y_final)

print('GRIDSEARCH')
print('-'*10)
print('Best Parameters: ',CV_rfc.best_params_)
print('Best Score: ',CV_rfc.best_score_)
```

```
GRIDSEARCH
----------
Best Parameters:  {'max_features': 'sqrt', 'n_estimators': 100}
Best Score:  0.9856704196519959
```

Finally, we can use the final model(random forest) to predict the test set and it can be noticed that the accuracy score of the predction is 87.12%.

In [83]:
```
# PRINT FINAL MODEL RESULT
finalmodel = RandomForestClassifier(n_jobs=-1,max_features= CV_rfc.best_params_['max_features'] ,n_estimators=CV_rfc.best_params_['n
_estimators'], oob_score = True)
finalmodel.fit(x_final, y_final)
```

Out[83]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='sqrt', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=-1,
            oob_score=True, random_state=None, verbose=0, warm_start=False)
```

In [84]:
```
# VALIDATION SET SCORE
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix

y_pred = finalmodel.predict(x_test)
train_score = finalmodel.score(x_final, y_final)
validation_score = accuracy_score(y_test, y_pred)
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)

print(validation_score)
```

```
[[106   9]
 [  8   9]]
0.8712121212121212
```

Ensemble model

Now that we have a good classifier working, explore building an ensemble model.

This might include Boostrapping, Bagging, Boosting and Stacking.

Refer to "L6 - Trees and Forests, Ensemble Learning 1" from Week 6 as necessary.

ACTION: Ensemble modeling

Build an ensemble model and demonstrate improved performance. Comment on any specific behaviour of your chosen classifier and set out the final structure and parameter settings.

Divide this work up among the different members of your team and then compare and comment on the performance of various approaches.

In the part of ensemble modeling, gradient boosting classifier, bagging classifier, adaboosting classifier, and voting classifier are applied. Fitting them with X_final and Y_final and printing out the accuracy score of each model. We can see that accuracy score of each models have been improved and voting classifier is the highest now.

In [85]:
```
# Ensemble models

#Bagging Classifier
from sklearn.ensemble import BaggingClassifier
bagging_clf = BaggingClassifier(DecisionTreeClassifier(random_state=42), n_estimators=500,
                                              max_samples=100, bootstrap=True, n_jobs=-1, random_state=42)
bagging_clf.fit(x_final, y_final)
y_pred_bagging = bagging_clf.predict(x_test)
print(accuracy_score(y_test, y_pred_bagging))
```

```
0.8560606060606061
```

In [86]:
```
from sklearn.ensemble import AdaBoostClassifier
ada_clf = AdaBoostClassifier(
    DecisionTreeClassifier(max_depth=2,random_state=42), n_estimators=200,
    algorithm="SAMME.R", learning_rate=0.5, random_state=42)
ada_clf.fit(x_final, y_final)
y_pred_ada=ada_clf.predict(x_test)
print(accuracy_score(y_test, y_pred_ada))
```

```
0.8939393939393939
```

In [87]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier


log_clf = LogisticRegression()
rnd_clf = RandomForestClassifier(n_jobs=-1,max_features= CV_rfc.best_params_['max_features'] ,n_estimators=CV_rfc.best_params_['n_es
timators'], oob_score = True)

svm_clf = SVC()
KNN_clf = KNeighborsClassifier(n_neighbors=5)
SGD_clf=SGDClassifier(random_state=42)
#
tree_clf=DecisionTreeClassifier(max_depth=2, random_state=42)
#

voting_clf = VotingClassifier(estimators=[('lr', log_clf), ('rf', rnd_clf), ('svc', svm_clf),('knn',KNN_clf),('sgd',SGD_clf),('tf',t
ree_clf)],
voting='hard')
voting_clf.fit(x_final, y_final)

from sklearn.metrics import accuracy_score
log_clf.fit(x_final, y_final)
y_predlog=log_clf.predict(x_test)
print('logisticregression', accuracy_score(y_test, y_predlog))

rnd_clf .fit(x_final, y_final)
y_predrnd=rnd_clf.predict(x_test)
print('randomforest', accuracy_score(y_test, y_predrnd))

svm_clf.fit(x_final, y_final)
y_predsvm=svm_clf.predict(x_test)
print('SVM', accuracy_score(y_test, y_predsvm))

KNN_clf.fit(x_final, y_final)
y_predknn=KNN_clf.predict(x_test)
print('KNN', accuracy_score(y_test, y_predknn))

SGD_clf.fit(x_final, y_final)
y_predsgd=SGD_clf.predict(x_test)
print('SGD', accuracy_score(y_test, y_predsgd))

tree_clf.fit(x_final, y_final)
y_predtree=tree_clf.predict(x_test)
print('Tree', accuracy_score(y_test, y_predtree))

voting_clf.fit(x_final, y_final)
y_predvoting=voting_clf.predict(x_test)
print('Voting', accuracy_score(y_test, y_predvoting))
```

```
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be
changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarning: The default value of gamma will cha
nge from 'auto' to 'scale' in version 0.22 to account better for unscaled features. Set gamma explicitly to 'auto' or 'scale' to a
void this warning.
  "avoid this warning.", FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:166: FutureWarning: max_iter an
d tol parameters have been added in SGDClassifier in 0.19. If both are left unset, they default to max_iter=5 and tol=None. If tol
is not None, max_iter defaults to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be
changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)

logisticregression 0.8409090909090909
randomforest 0.8863636363636364
SVM 0.7651515151515151
KNN 0.75
SGD 0.7575757575757576
Tree 0.7803030303030303

/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarning: The default value of gamma will cha
nge from 'auto' to 'scale' in version 0.22 to account better for unscaled features. Set gamma explicitly to 'auto' or 'scale' to a
void this warning.
  "avoid this warning.", FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:166: FutureWarning: max_iter an
d tol parameters have been added in SGDClassifier in 0.19. If both are left unset, they default to max_iter=5 and tol=None. If tol
is not None, max_iter defaults to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be
changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)

Voting 0.8939393939393939

/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarning: The default value of gamma will cha
nge from 'auto' to 'scale' in version 0.22 to account better for unscaled features. Set gamma explicitly to 'auto' or 'scale' to a
void this warning.
  "avoid this warning.", FutureWarning)
/opt/anaconda/envs/Python3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:166: FutureWarning: max_iter an
d tol parameters have been added in SGDClassifier in 0.19. If both are left unset, they default to max_iter=5 and tol=None. If tol
is not None, max_iter defaults to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  FutureWarning)
```

6. Present Results

Confusion Matrix

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.

ACTION: Confusion matrix

Comment on the performance of your final algorithm. Repeat analysis from earlier in the Notebook if necessary.

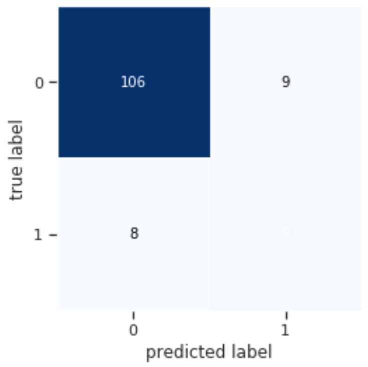
Explain confusion matrix results, calculate accuracy and precision etc.

In [88]:
```
# Confusion Matrix
# install the plot package
!pip install mlxtend
```

```
Collecting mlxtend
  Using cached https://files.pythonhosted.org/packages/16/e6/30e50ed9c053a1530c83149090e1f5fd9fccc8503dca2ecce1bb52f34de0/mlxtend-
0.15.0.0-py2.py3-none-any.whl
Requirement already satisfied: pandas>=0.17.1 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from mlxtend) (0.23.4)
Requirement already satisfied: scipy>=0.17 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from mlxtend) (1.1.0)
Requirement already satisfied: numpy>=1.10.4 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from mlxtend) (1.15.4)
Requirement already satisfied: scikit-learn>=0.18 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from mlxtend) (0.20.
1)
Requirement already satisfied: matplotlib>=1.5.1 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from mlxtend) (3.0.2)
Requirement already satisfied: setuptools in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from mlxtend) (40.6.3)
Requirement already satisfied: python-dateutil>=2.5.0 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from pandas>=0.1
7.1->mlxtend) (2.7.5)
Requirement already satisfied: pytz>=2011k in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from pandas>=0.17.1->mlxten
d) (2018.7)
Requirement already satisfied: cycler>=0.10 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from matplotlib>=1.5.1->mlx
tend) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from matplotlib>=1.5.1
->mlxtend) (1.0.1)
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>=1.5.1->mlxtend) (2.3.0)
Requirement already satisfied: six>=1.5 in /opt/anaconda/envs/Python3/lib/python3.6/site-packages (from python-dateutil>=2.5.0->pa
ndas>=0.17.1->mlxtend) (1.12.0)
Installing collected packages: mlxtend
Successfully installed mlxtend-0.15.0.0
```

In [89]:
```
# Plot Confusion Matrix
from mlxtend.plotting import plot_confusion_matrix

fig, ax = plot_confusion_matrix(conf_mat=confusion_matrix)
plt.show()
```



ROC Curve

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.

ACTION: ROC Curve

Comment on the performance of your final algorithm. Repeat analysis from earlier in the Notebook if necessary.

Explain any observations about the ROC results.

Here we plot the ROC curve.

In [90]:
```
# ROC curve

from sklearn.metrics import roc_curve, auc

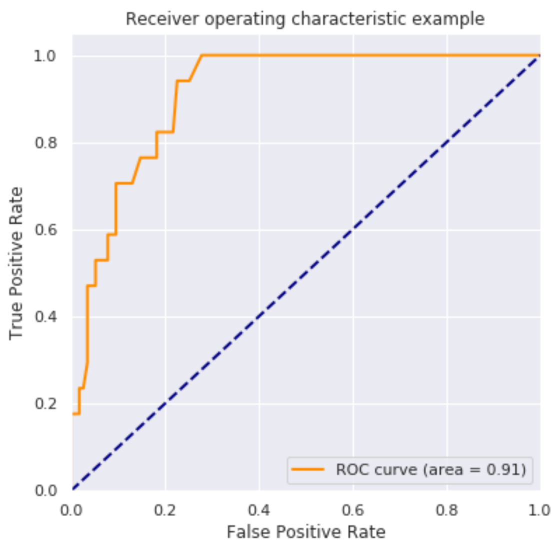
# Compute predicted probabilities: y_pred_prob
y_pred_rf_prob = finalmodel.predict_proba(x_test)[:,1]

# Generate ROC curve values: fpr, tpr, thresholds
fpr, tpr, threholds = roc_curve(y_test, y_pred_rf_prob)

roc_auc = auc(fpr,tpr)

plt.figure()
lw = 2
plt.figure(figsize=(6,6))
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
# Plot classifier ROC
```

```
<Figure size 432x288 with 0 Axes>
```



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:

ACTION: Feature importance

Where possible, comment on the feature selection and performance of your final algorithm. Repeat analysis from earlier in the Notebook if necessary. Explain any observations about the sensitivity of your final analysis.

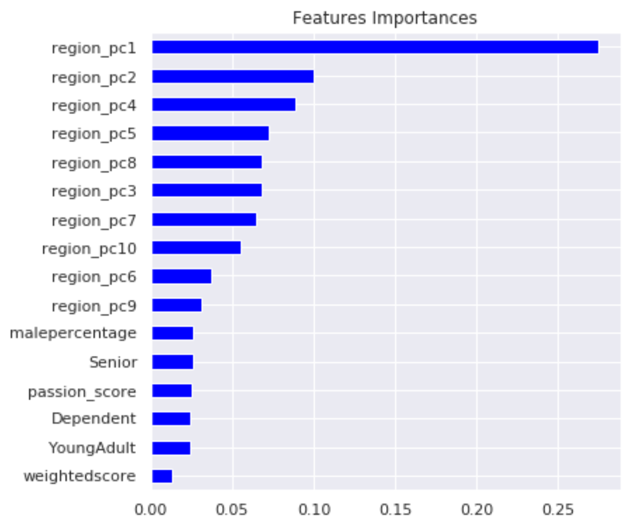
At last, we analyze the feature importance and create a pd.Series of features importances. Plotting the features importance and sort the importance level from highest to lowest. We can see that region_pca 1 is significantly higher than others and the total weighted score is the lowest one.

In [91]:
```
# Feature importance analysis
import seaborn as sns

# Create a pd.Series of features importances
importances = pd.Series(data=finalmodel.feature_importances_,
                        index=x_final.columns)

# Sort importances
importances_sorted = importances.sort_values()

# Draw a horizontal barplot of importances_sorted
plt.figure(figsize = (6,6))
sns.set(font_scale=1.0)
importances_sorted.plot(kind='barh', color='blue')
plt.title('Features Importances')
plt.show()
```



Summary

In this analysis, we firstly create dependent variable which is the success or not for each artist. Then we did the feature engineering part which includes Artist Features, Playlist Features and User-base features. Principle Component Analysis (PCA) is did after that. We combined all of our features that we generated into a new dataframe that can be processed by a machine learning algorithm. We work with the missing values of variables by filling them to the average or 0 and normalize every independent variables. The multicollinearity has been checked and the highly correlated independent variables has been dropped. Before building the final model, we split the data into train and validation set and resample in class balance part. After calculating the cross validation scores of different models, we select random forest with the highest score to improve the result. We use grid search to find the best parameters of the random forest classifier. Then, the performance of model has been improved by ensemble modeling. Finally, to get a better idea of the quality of our predictions, we plot a confusion matrix and ROC curve and also analyze the feature importances.

Tips completing the coursework

- **Sherlock** - You are free to run the code on your local machine, but if training timings and memory become an issue then use Sherlock to complete the coursework. Technical support for using Sherlock will be provided as necessary. https://sherlockml.com (https://sherlockml.com)
- **Kanban** - Assess the different potential work packages and break the overall objectitves into a set of tasks and queue them up in the backlog column of the Kanban board. Create new tasks as and when necessary during the course of your analysis.
- **Fast First Pass**. Make a first-pass through the project steps as fast as possible. This will give you confidence that you have all the parts that you need and a baseline from which to improve.
- **Cycles**. The process in not linear but cyclic. You will loop between steps, and probably spend most of your time in tight loops between steps 3-4 or 3-4-5 until you achieve a level of accuracy that is sufficient or you run out of time. The write up in the final submitted Notebook in more linear - you do not need to include all of your work, ie. including all dead-ends, and it should be consise and consistent.
- **Attempt Every Step**. It is easy to skip steps, especially if you are not confident or familiar with the tasks of that step. Try and do something at each step in the process, even if it does not improve accuracy. You can always build upon it later. Don't skip steps, just reduce their contribution.
- **Ratchet Accuracy**. The goal of the project is to achieve good model performance (which ever metric you use to measure this). Every step contributes towards this goal. Treat changes that you make as experiments that increase accuracy as the golden path in the process and reorganize other steps around them. Performance is a ratchet that can only move in one direction (better, not worse).
- **Adapt As Needed**. Modify the steps as you need on a project, especially as you become more experienced with the template. Blur the edges of tasks, such as steps 4-5 to best serve model accuracy. The final submitted Notebook does not need to preserve the current sections and structure if you think something else is more apporpirate.

```
In [ ]:
```