GROUP COURSEWORK

MSIN0097
Predictive Analytics

Group Name: Group 25

Emails: uceikjo@ucl.ac.uk, Uceida1@ucl.ac.uk, uceiaid@ucl.ac.uk, uceicos@ucl.ac.uk, UCEICJN@ucl.ac.uk

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

There should be around 100 words per ACTION cell, but use the wordcount over the duration of the Notebook at your discretion.

- **Please use the below green cell, when writing your comments in markup.**
- **Please feel free to add extra code cells in the notebook if needed.**

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

# WEEK 7

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

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

# WEEK 8

# 3. Prepare Data
# a) Data Cleaning
# b) Feature Selection
# c) Data Transforms (PCA, missing values, multi-collinearity, normalizing, class balan
ce)

# WEEK 9-10

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

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

ACTION: Guidance

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

1. Prepare the problem

Run your code on Faculty. 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 [182]:

```
# Preamble

# To support both python 2 and python 3
from __future__ import division, print_function, unicode_literals

# Import all required libraries
import pandas as pd
import numpy as np
from numpy import mean
from numpy import std
import os
import seaborn as sns
import matplotlib.pyplot as plt
from pprint import pprint

from sklearn.svm import SVC
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
import xgboost as xgb
from sklearn.ensemble import VotingClassifier

from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
from sklearn.model_selection import StratifiedKFold

from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve


# To make notebook output stable across runs
np.random.seed(42)

# to plot pretty figures
sns.set_style("darkgrid")
sns.set(rc={'figure.figsize':(10,5)})

# Ignore useless warnings (see SciPy issue #5998)
import warnings
warnings.filterwarnings(action="ignore", message="^internal gelsd")
```

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 Faculty server is about 16GB, containing data from 2015 - 2017. Given the limits on RAM and cores, we will be taking a further sample of this data for purposes of this case study: a 10% random sample of the total dataset, saved as 'cleaned_data.csv'.

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]:

```
# Fetching the dataset
spotify = pd.read_csv("/project/data n sources/cleaned_data.csv", low_memory = False)

# To display all columns
pd.set_option('display.max_columns', None)
```

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

In [5]:

```
# Preview dataset
spotify.head()
```

Out[5]:

	Unnamed: 0	Unnamed: 0.1	Unnamed: 0.1.1	day	log_time	mobile	
0	0	9	('small_artists_2016.csv', 9)	10	20160510T12:15:00	True	8f1924eab3
1	1	19	('small_artists_2016.csv', 19)	10	20160510T12:15:00	True	8f1924eab3
2	2	29	('small_artists_2016.csv', 29)	10	20160510T14:00:00	True	8f1924eab3
3	3	39	('small_artists_2016.csv', 39)	10	20160510T10:45:00	True	8f1924eab3
4	4	49	('small_artists_2016.csv', 49)	10	20160510T10:15:00	True	8f1924eab3

ACTION: Inspect the data Make sure you understand the data. Use methods like **data.head()**, **data.info()**, etc.

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.

In [6]:

```
spotify.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3805499 entries, 0 to 3805498
Data columns (total 45 columns):
 #   Column             Dtype  
---  ------             -----  
 0   Unnamed: 0         int64  
 1   Unnamed: 0.1       int64  
 2   Unnamed: 0.1.1     object 
 3   day                int64  
 4   log_time           object 
 5   mobile             bool   
 6   track_id           object 
 7   isrc               object 
 8   upc                float64
 9   artist_name        object 
 10  track_name         object 
 11  album_name         object 
 12  customer_id        object 
 13  postal_code        object 
 14  access             object 
 15  country_code       object 
 16  gender             object 
 17  birth_year         float64
 18  filename           object 
 19  region_code        object 
 20  referral_code      float64
 21  partner_name       object 
 22  financial_product  object 
 23  user_product_type  object 
 24  offline_timestamp  float64
 25  stream_length      float64
 26  stream_cached      float64
 27  stream_source      object 
 28  stream_source_uri  object 
 29  stream_device      object 
 30  stream_os          object 
 31  track_uri          object 
 32  track_artists      object 
 33  source             float64
 34  DateTime           object 
 35  hour               int64  
 36  minute             int64  
 37  week               int64  
 38  month              int64  
 39  year               int64  
 40  date               object 
 41  weekday            int64  
 42  weekday_name       object 
 43  playlist_id        object 
 44  playlist_name      object 
dtypes: bool(1), float64(7), int64(9), object(28)
memory usage: 1.3+ GB
```

In [7]:

```
spotify.count(0)/spotify.shape[0] * 100
```

Out[7]:

```
Unnamed: 0             100.000000
Unnamed: 0.1           100.000000
Unnamed: 0.1.1         100.000000
day                    100.000000
log_time               100.000000
mobile                 100.000000
track_id               100.000000
isrc                    99.999895
upc                    100.000000
artist_name            100.000000
track_name             100.000000
album_name             100.000000
customer_id            100.000000
postal_code             64.467708
access                 100.000000
country_code           100.000000
gender                  98.937800
birth_year              99.736671
filename               100.000000
region_code             93.116382
referral_code            0.000000
partner_name            11.216742
financial_product       38.796489
user_product_type       99.395822
offline_timestamp        0.000000
stream_length          100.000000
stream_cached            0.000000
stream_source          100.000000
stream_source_uri       27.430595
stream_device          100.000000
stream_os              100.000000
track_uri              100.000000
track_artists          100.000000
source                   0.000000
DateTime               100.000000
hour                   100.000000
minute                 100.000000
week                   100.000000
month                  100.000000
year                   100.000000
date                   100.000000
weekday                100.000000
weekday_name           100.000000
playlist_id             27.430595
playlist_name           25.728820
dtype: float64
```

EXPLORATORY ANALYSIS AND PLOTS

Now look at the data set in more detail.

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.

In [8]:

```
# summary statistics of the dataset
summary_stats = {"Total Number of Rows": len(spotify),
                "Total Number of Columns": len(spotify.columns),
                "Total Number of Unique Artists":spotify.artist_name.nunique(),
                "Total Number of Unique Users":spotify.customer_id.nunique(),
                "Total Number of Unique Playlists":spotify.playlist_name.nunique(),
                "Total Number of Unique Regions":spotify.region_code.nunique(),}
summary_stats
```

Out[8]:

```
{'Total Number of Rows': 3805499,
 'Total Number of Columns': 45,
 'Total Number of Unique Artists': 661,
 'Total Number of Unique Users': 2091144,
 'Total Number of Unique Playlists': 7102,
 'Total Number of Unique Regions': 514}
```

In [9]:

```
# datetime
date = pd.to_datetime(spotify['date'], format = '%Y-%m-%d')
date_range = str(date.dt.date.min()) + ' to ' +str(date.dt.date.max())
date_range
```

Out[9]:

```
'2014-06-10 to 2017-07-10'
```

In [10]:

```
# most popular playlists by stream count
popular_playlists = spotify.groupby(["playlist_name"])["customer_id"].count().reset_ind
ex()
popular_playlists = popular_playlists.sort_values(by="customer_id", ascending = False)
popular_playlists.reset_index(drop = True, inplace = True)
popular_playlists.rename(columns={'customer_id': 'Count'}, inplace=True)
popular_playlists = popular_playlists.head(10)
popular_playlists
```

Out[10]:

	playlist_name	Count
0	Hot Hits UK	193654
1	Today's Top Hits	105383
2	Topsify UK Top 40	54982
3	Freshness: Hot House Music	32961
4	The Pop List	28630
5	New Music Monday UK	27793
6	Happy Hits!	18767
7	Summer Hits	16822
8	Top Tracks in The United Kingdom	15524
9	You've Got Male - R&B: The Men	14777

In [11]:

```
# most popular artists by stream count
# Creating Dataframe of Top 10 Artists
data = spotify.copy()
top_ten = data[["artist_name", "stream_length"]]
top_ten = top_ten.groupby("artist_name").sum()
top_ten = top_ten.sort_values(by="stream_length", ascending = False)
top_ten = top_ten.reset_index()
top_ten = top_ten.iloc[0:10]
top_ten
```

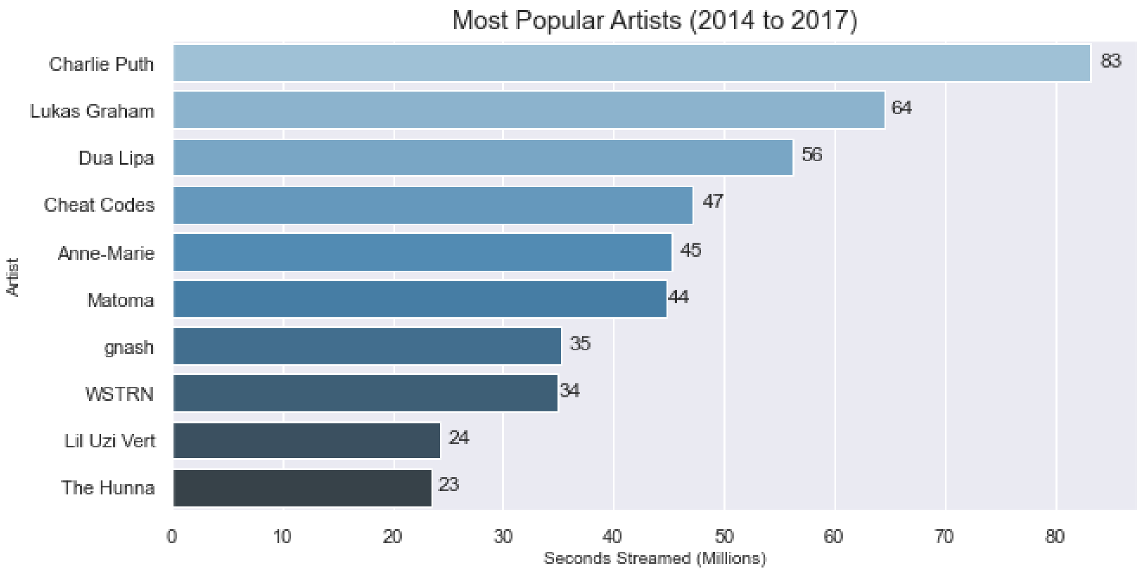
Out[11]:

	artist_name	stream_length
0	Charlie Puth	83200389.0
1	Lukas Graham	64529983.0
2	Dua Lipa	56221544.0
3	Cheat Codes	47190001.0
4	Anne-Marie	45243135.0
5	Matoma	44838664.0
6	gnash	35278062.0
7	WSTRN	34932583.0
8	Lil Uzi Vert	24300599.0
9	The Hunna	23578647.0

In [12]:

```
# Setting data for chart
ax = sns.barplot(x="stream_length", y="artist_name", data=top_ten, palette="Blues_d")

# Renaming and setting font size of X, Y Axis Labels and Title
ax.set_xlabel("Seconds Streamed (Millions)",fontsize=10)
ax.set_ylabel("Artist",fontsize=10)
ax.set_title("Most Popular Artists (2014 to 2017)", fontsize=15)

# Renumbering X Axis
xlabels = [int(x) for x in ax.get_xticks()/1000000]
ax.set_xticklabels(xlabels)

# Creating annotations for the chart
annotations = top_ten["stream_length"]/1000000
annotations = annotations.astype(int)

# Adding annotations to the chart
for index, value in enumerate(annotations):
    plt.text((value*1000000)+10**6, index+0.075, str(value), fontsize=12)

plt.savefig('Most Popular Artists 2014 to 2017.png')
```

```
<ipython-input-12-32d6c059436c>:11: UserWarning: FixedFormatter should onl
y be used together with FixedLocator
  ax.set_xticklabels(xlabels)
```



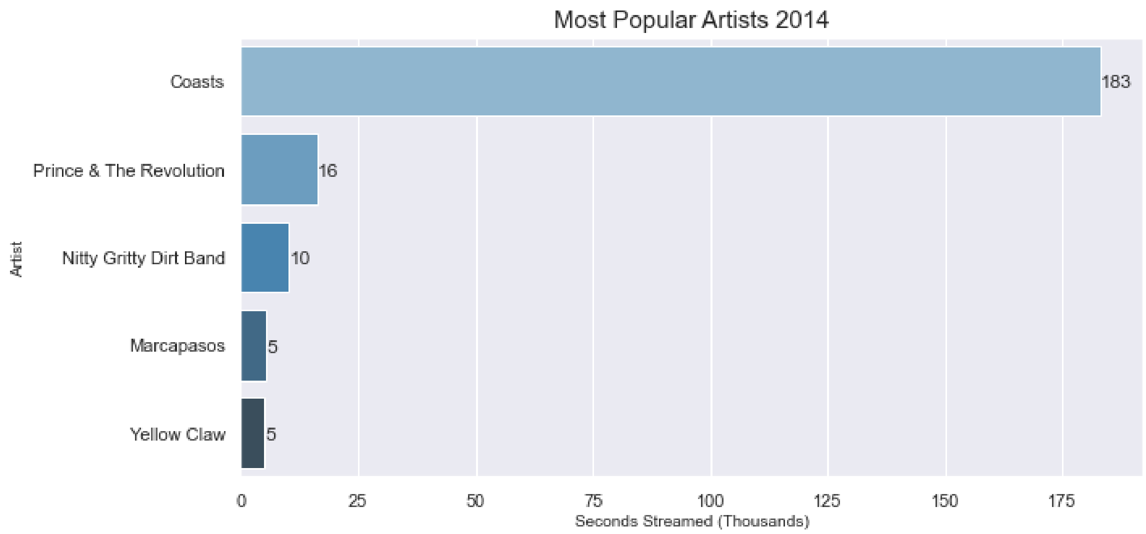
In [13]:

```
# Creating Dataframe of Top 10 Artists by Year
top_five_yearly = data[["artist_name", "stream_length", "year"]]
top_five_yearly = top_five_yearly.groupby(["year", "artist_name"]).sum()
top_five_yearly = top_five_yearly.sort_values(by=["year","stream_length"], ascending =
False)
top_five_yearly = top_five_yearly.reset_index(level=["artist_name", "year"])
top_five_yearly = top_five_yearly.groupby("year").head().sort_values(by=["year","stream
_length"], ascending = False)

# Dataframe for top 5 artists in 2014, 2015, 2016, 2017
top_five_2014 = top_five_yearly[top_five_yearly["year"]==2014]
top_five_2015 = top_five_yearly[top_five_yearly["year"]==2015]
top_five_2016 = top_five_yearly[top_five_yearly["year"]==2016]
top_five_2017 = top_five_yearly[top_five_yearly["year"]==2017]
```

In [14]:

```
# 2014
# Plotting 2014 data for chart
ax14 = sns.barplot(x="stream_length", y="artist_name", data=top_five_2014, palette="Blu
es_d")

# Renaming and setting font size of X, Y Axis Labels and Title
ax14.set_xlabel("Seconds Streamed (Thousands)",fontsize=10)
ax14.set_ylabel("Artist",fontsize=10)
ax14.set_title("Most Popular Artists 2014", fontsize=15)

# Renumbering X Axis
xlabels = [int(x) for x in ax14.get_xticks()/1000]
ax14.set_xticklabels(xlabels)

# Creating annotations for the chart
annotations14 = top_five_2014["stream_length"]
annotations14 = annotations14.astype(int)

# Adding annotations to the chart
for index, value in enumerate(annotations14):
    plt.text(value, index+0.075, int(value/1000), fontsize=12)

plt.savefig('Most Popular Artists 2014.png')
plt.show()
```

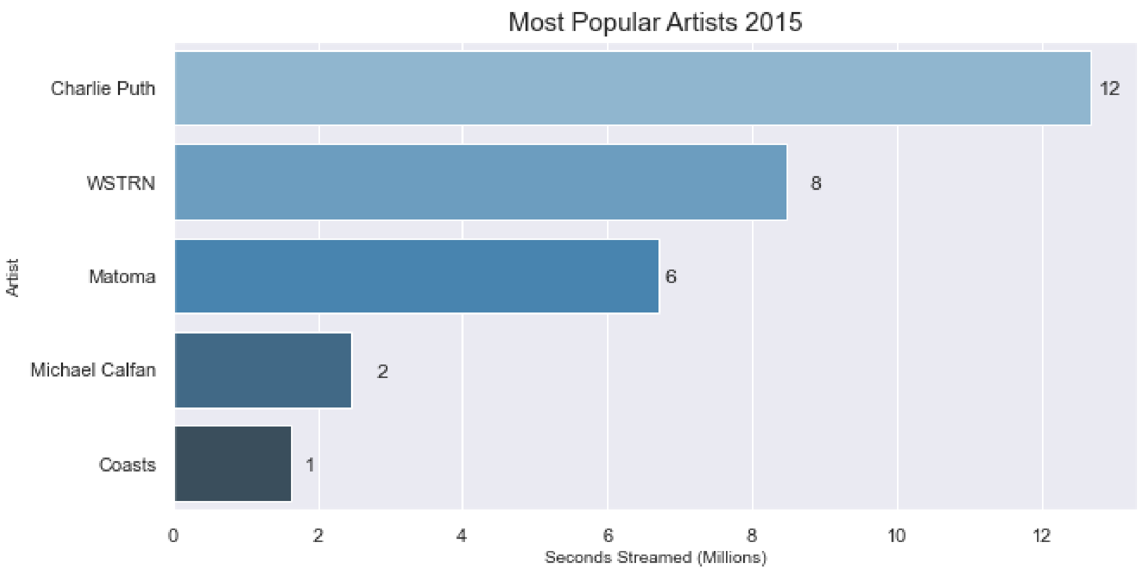
```
<ipython-input-14-7de77de71170>:12: UserWarning: FixedFormatter should onl
y be used together with FixedLocator
  ax14.set_xticklabels(xlabels)
```



In [15]:

```
# 2015
# Plotting 2015 data for chart
ax15 = sns.barplot(x="stream_length", y="artist_name", data=top_five_2015, palette="Blu
es_d")

# Renaming and setting font size of X, Y Axis Labels and Title
ax15.set_xlabel("Seconds Streamed (Millions)",fontsize=10)
ax15.set_ylabel("Artist",fontsize=10)
ax15.set_title("Most Popular Artists 2015", fontsize=15)

# Renumbering X Axis
xlabels = [int(x) for x in ax15.get_xticks()/1000000]
ax15.set_xticklabels(xlabels)

# Creating annotations for the chart
annotations15 = top_five_2015["stream_length"]/1000000
annotations15 = annotations15.astype(int)

# Adding annotations to the chart
for index, value in enumerate(annotations15):
    plt.text((value*1000000)+8*10**5, index+0.075, str(value), fontsize=12)

plt.savefig('Most Popular Artists 2015.png')
plt.show()
```

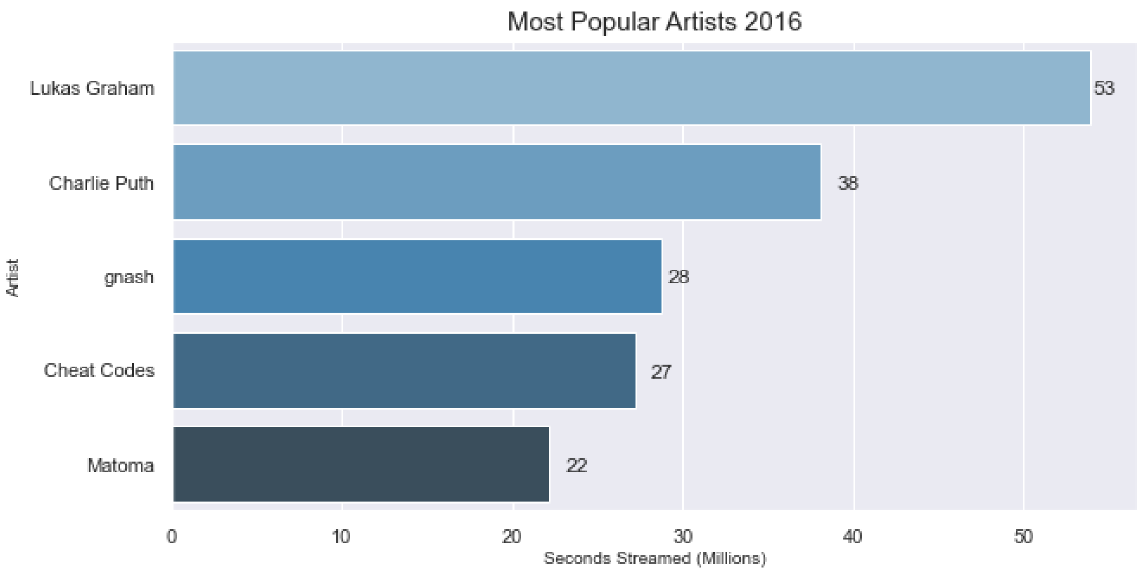
```
<ipython-input-15-b72b7d8fd756>:12: UserWarning: FixedFormatter should onl
y be used together with FixedLocator
  ax15.set_xticklabels(xlabels)
```



In [16]:

```
# 2016
# Plotting 2016 data for chart
ax16 = sns.barplot(x="stream_length", y="artist_name", data=top_five_2016, palette="Blu
es_d")

# Renaming and setting font size of X, Y Axis Labels and Title
ax16.set_xlabel("Seconds Streamed (Millions)",fontsize=10)
ax16.set_ylabel("Artist",fontsize=10)
ax16.set_title("Most Popular Artists 2016", fontsize=15)

# Renumbering X Axis
xlabels = [int(x) for x in ax16.get_xticks()/1000000]
ax16.set_xticklabels(xlabels)

# Creating annotations for the chart
annotations16 = top_five_2016["stream_length"]/1000000
annotations16 = annotations16.astype(int)

# Adding annotations to the chart
for index, value in enumerate(annotations16):
    plt.text((value*1000000)+11*10**5, index+0.075, str(value), fontsize=12)

plt.savefig('Most Popular Artists 2016.png')
plt.show()
```

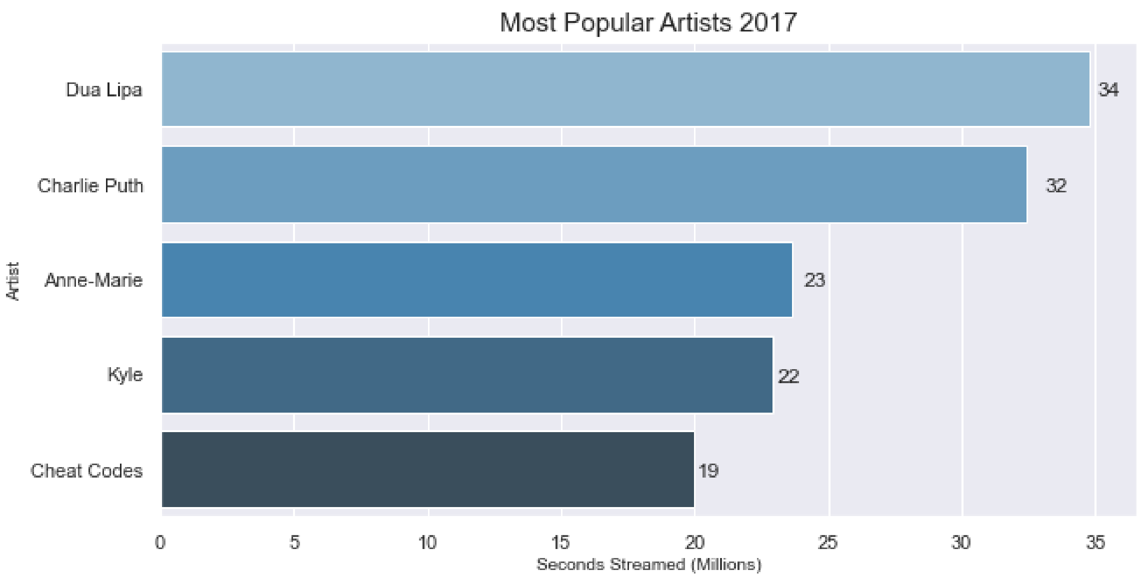
```
<ipython-input-16-8225fd8fbd1d>:12: UserWarning: FixedFormatter should onl
y be used together with FixedLocator
  ax16.set_xticklabels(xlabels)
```



In [17]:

```
# 2017
# Plotting 2017 data for chart
ax17 = sns.barplot(x="stream_length", y="artist_name", data=top_five_2017, palette="Blues_d")

# Renaming and setting font size of X, Y Axis Labels and Title
ax17.set_xlabel("Seconds Streamed (Millions)",fontsize=10)
ax17.set_ylabel("Artist",fontsize=10)
ax17.set_title("Most Popular Artists 2017", fontsize=15)

# Renumbering X Axis
xlabels = [int(x) for x in ax17.get_xticks()/1000000]
ax17.set_xticklabels(xlabels)

# Creating annotations for the chart
annotations17 = top_five_2017["stream_length"]/1000000
annotations17 = annotations17.astype(int)

# Adding annotations to the chart
for index, value in enumerate(annotations17):
    plt.text((value*1000000)+11*10**5, index+0.075, str(value), fontsize=12)

plt.savefig('Most Popular Artists 2017.png')
plt.show()
```

```
<ipython-input-17-932dcd6c6809>:12: UserWarning: FixedFormatter should onl
y be used together with FixedLocator
  ax17.set_xticklabels(xlabels)
```

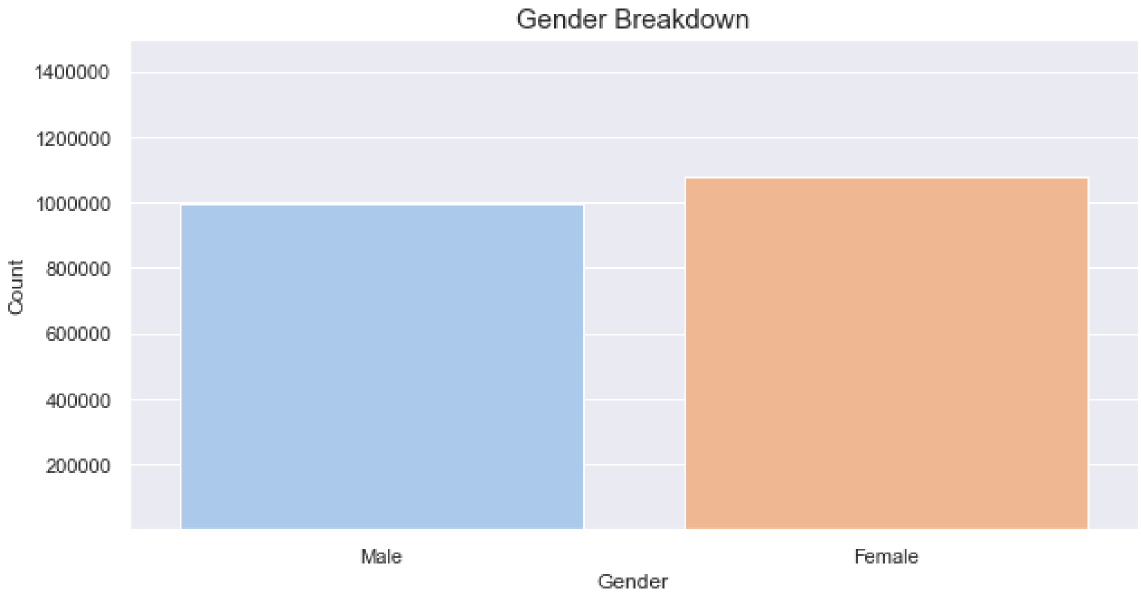


In [18]:

```
# visualizing customer membership access
access_types = spotify[spotify["access"]!="deleted"]
access_types = access_types[access_types["access"]!="basic-desktop"]

access_types.rename(columns={'year': 'Year'}, inplace=True)

access_from_2014 = access_types[access_types["Year"]>2014]

# set color palette
sns.set_palette(sns.color_palette(["#6AACD6", "#F7A480"]))

# plot customer membership access across gender
g = sns.catplot(x="access", hue="gender", col="Year", data=access_from_2014, kind="coun
t")

plt.ticklabel_format(style='plain', axis='y');

g.despine(left=True)
g.set_xlabels("Access")
g.set_ylabels("Count")
g.set(xticklabels=["Free", "Premium"])

# g.fig.suptitle("Customer Membership Access from 2015-2017", fontsize=10)

g.fig.subplots_adjust(top=0.8) # adjust the Figure in rp
g.fig.suptitle("Customer Membership Access from 2015-2017", fontsize=15)

# title
new_title = 'Gender'
g._legend.set_title(new_title)
# replace labels
new_labels = ['Male', 'Female']
for t, l in zip(g._legend.texts, new_labels): t.set_text(l)

plt.gcf().subplots_adjust(bottom=0.15)

plt.savefig('Customer Membership Access from 2015-2017.png')
plt.show();
```

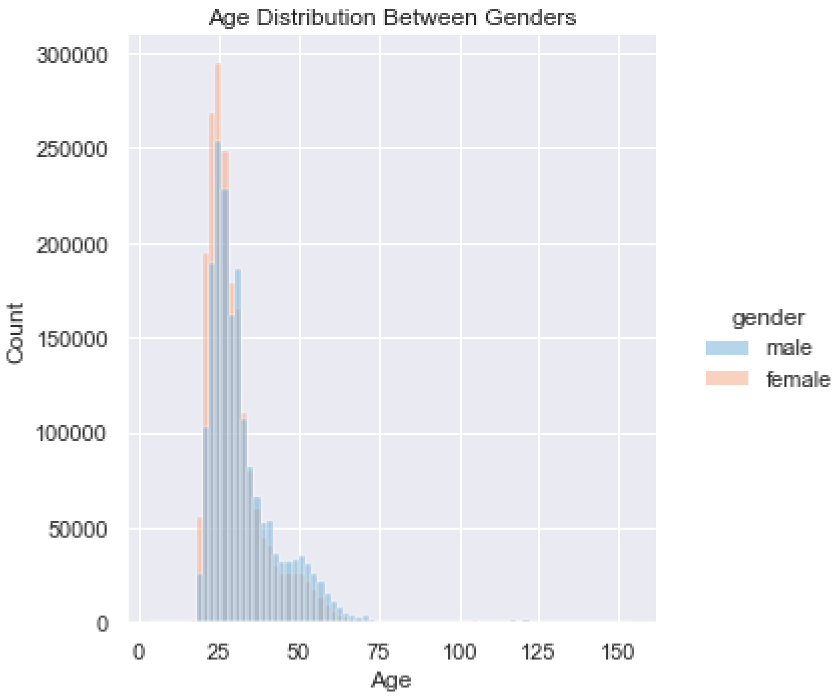
In [19]:

```
# plot gender
spot_gender = spotify.copy()
spot_gender["gender"] = spot_gender["gender"].replace(["male"],"Male")
spot_gender["gender"] = spot_gender["gender"].replace(["female"],"Female")
spot_gender = spot_gender.drop_duplicates(["customer_id"])

g1 = sns.countplot(x="gender", data=spot_gender, palette="pastel").set_title("Gender Br
eakdown", fontsize = 15)

# axes labels
plt.xlabel("Gender")
plt.ylabel("Count")

plt.ticklabel_format(style='plain', axis='y');
plt.ylim(100, 1500000);
plt.savefig('Gender Breakdown.png')
plt.show();
```



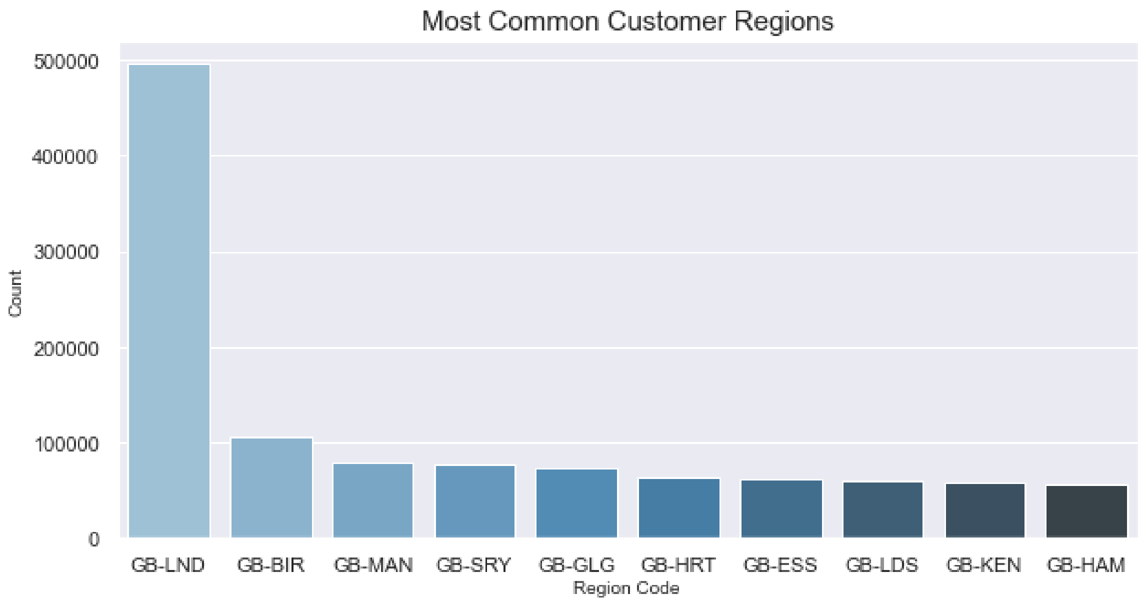
In [20]:

```
# calculate age
spotify["age"] = 2021 - spotify["birth_year"]

# set color palette
sns.set_palette(sns.color_palette(["#6AACD6", "#F7A480"]))

# plot gender across age groups
sns.displot(spotify, x="age", hue="gender", stat="count", bins = 75)

# title
plt.title("Age Distribution Between Genders")

# axes label axes
plt.xlabel("Age")
plt.ylabel("Count")

plt.gcf().subplots_adjust(bottom=0.15)

# y-axis scale
plt.savefig('Age Distribution Between Gender.png')
plt.show()
```



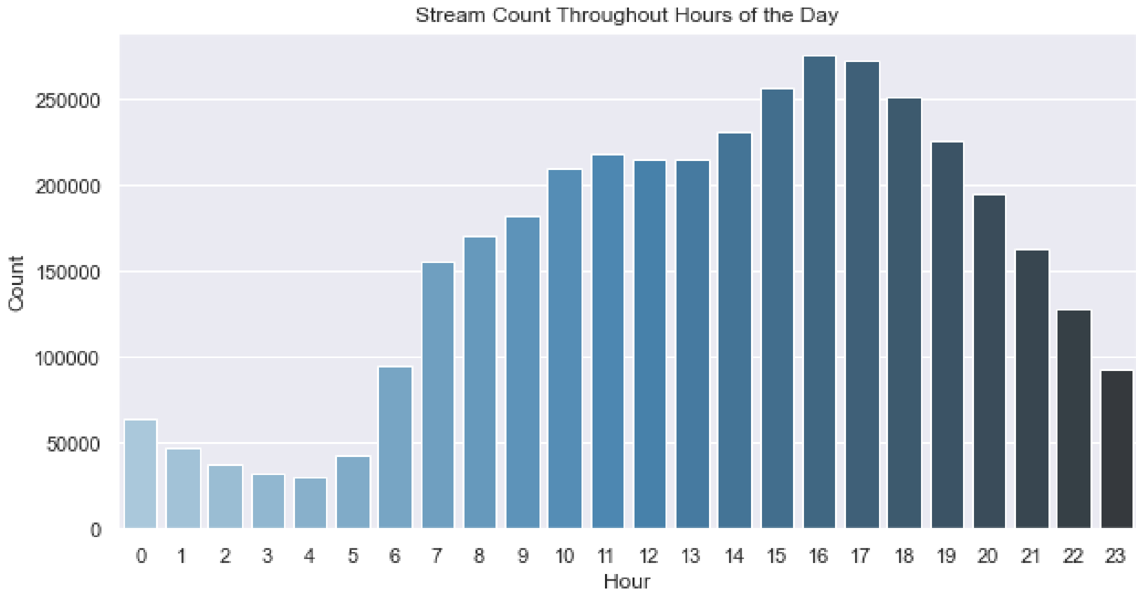
In [21]:

```
# visualizing customer regions

common_regions = spotify.groupby(["region_code"])["customer_id"].count().reset_index()

common_regions = common_regions.sort_values(by="customer_id", ascending = False)
common_regions.reset_index(drop = True, inplace = True)
common_regions.rename(columns={'customer_id': 'Count'}, inplace=True)
common_regions = common_regions.head(10)

ax = sns.barplot(x="region_code", y="Count", data=common_regions, palette="Blues_d")
ax.set_title('Most Common Customer Regions', fontsize=15)
plt.xlabel('Region Code', axes=ax, fontsize = 10)
plt.ylabel('Count', axes=ax, fontsize = 10)

plt.savefig('Most Common Customer Regions.png')
plt.show();
```



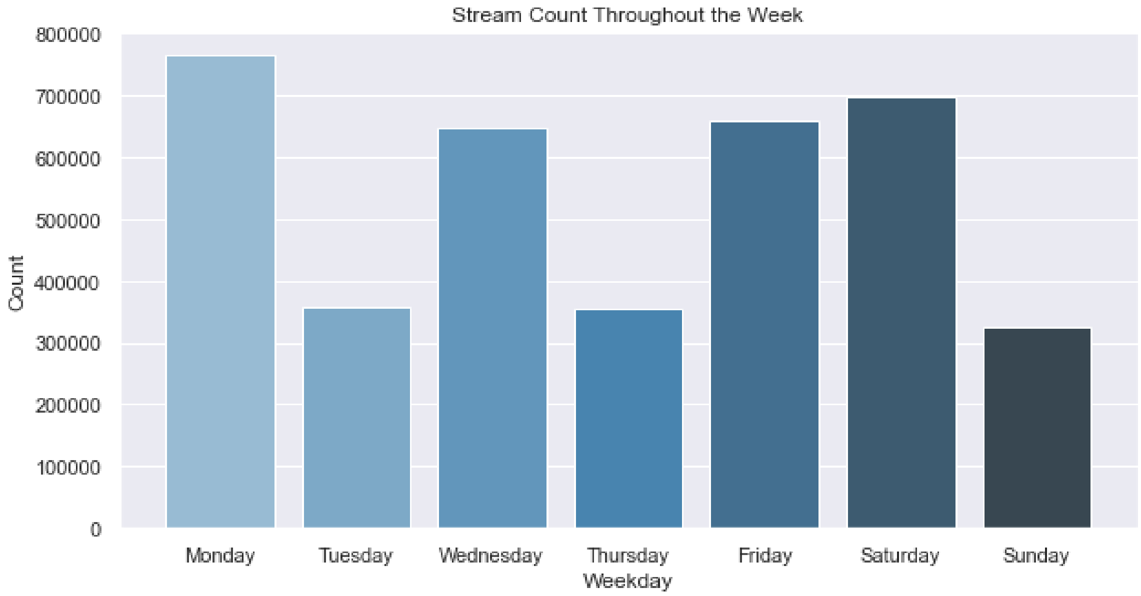
In [22]:

```
# Plot of Streams vs hour
sns.countplot(x="hour", data=spotify, palette="Blues_d").set_title("Stream Count Throug
hout Hours of the Day")
plt.xlabel('Hour')
plt.ylabel('Count')
plt.savefig('Stream count vs Hours of the day.png')
plt.show();
```



In [23]:

```
#Plot of Streams vs day
ax = sns.countplot(x="weekday_name", order=["Monday", "Tuesday", "Wednesday", "Thursda
y", "Friday",
                                      "Saturday", "Sunday"], data=data, palette="Blues_
d").set_title("Stream Count Throughout the Week")
plt.xlabel('Weekday')
plt.ylabel('Count')
plt.savefig('Stream Count Throughout the Week.png')
plt.plot();
```



3. Data Preperation and Feature Engineering

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

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

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

Create Dependent Variable

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 [24]:

```
# define key playlists indicating success
success_playlists = ['Hot Hits UK', 'Massive Dance Hits', 'The Indie List', 'New Music
 Friday']

# create appearance column, where 0 = no appearance and 1 = one apperance (in success p
laylists)
spotify['playlist_appearances'] = np.where(spotify.playlist_name.isin(success_playlists
), 1, 0)

# group artist appearance in playlists
success_artists = pd.DataFrame(spotify.groupby('artist_name').playlist_appearances.sum
())

# top 10 artist
success_artists.sort_values(['playlist_appearances'], ascending=False).head(10)
```

Out[24]:

artist_name	playlist_appearances
Dua Lipa	37003
Anne-Marie	29165
Charlie Puth	21733
Cheat Codes	17165
Maggie Lindemann	14813
Lukas Graham	14598
WSTRN	13209
Sage The Gemini	11371
Matoma	10793
gnash	8961

In [25]:

```
# Define Dependent Variable
# create binary column where 0 = no success and 1 = success (at least one appearance in success playlists)
success_artists ["success_binary"] = np.where(success_artists['playlist_appearances'] > 0, 1, 0)
success_artists
```

Out[25]:

	playlist_appearances	success_binary
artist_name		
#90s Update	0	0
17 Memphis	0	0
2D	0	0
3JS	0	0
99 Percent	0	0
...	...	...
birthday	0	0
dvsn	11	1
flor	9	1
gnash	8961	1
livetune+	0	0

661 rows × 2 columns

In [26]:

```
# create dependant variable (success_binary) into a dataframe
dependant_variable = pd.DataFrame(success_artists["success_binary"])
dependant_variable
```

Out[26]:

	success_binary
artist_name	
#90s Update	0
17 Memphis	0
2D	0
3JS	0
99 Percent	0
...	...
birthday	0
dvsn	1
flor	1
gnash	1
livetune+	0

661 rows × 1 columns

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.

In [27]:

```
# Stream count per artist

# stream count function
def stream_count(df):

    # Creating Copy of dataframe
    new_df = df

    # Adding new column with one as the value
    new_df["Stream Count"] = 1

    #Grouping new dataframe by artist name
    new_df = new_df.groupby("artist_name").sum()
    new_df.reset_index(inplace = True)

    # Selecting Artists and Stream Count for dataframe
    new_df = new_df[["artist_name", "Stream Count"]]

    # Setting order of dataframe in alphabetical order
    new_df = new_df.sort_values(by = "artist_name")
    return new_df
```

In [28]:

```
# Number of users per artist

# number of users per artist function
def number_of_users(df):

    # Creating Copy of dataframe
    new_df = df

    # Adding new column with one as the value
    new_df["Number of Users"] = 1

    # Dropping duplicates based on artist name and customer id
    new_df = new_df.drop_duplicates(["artist_name", "customer_id"])

    # Secting only artist name, customer id and number of users columns
    new_df = new_df[["artist_name", "customer_id", "Number of Users"]]

    #Grouping new dataframe by artist name
    new_df = new_df.groupby(["artist_name"]).sum()
    new_df.reset_index(inplace = True)

    # Setting order of dataframe in alphabetical order
    new_df = new_df.sort_values(by = "artist_name")
    return new_df
```

In [29]:

```
# Passion Score

# Passion Score function
def passion_score(df):

    # Applying number of users function to dataframe
    users_df = number_of_users(df)

    # Applying number of streams function to dataframe
    streams_df = stream_count(df)

    # Concatenating dataframes as they have the same order (alphabetical)
    new_df = pd.concat([streams_df, users_df["Number of Users"]], axis=1)

    # Creating Passion Score Column
    new_df["Passion Score"] = new_df["Stream Count"] / new_df["Number of Users"]

    # Selecting relevant columns for final dataframe
    new_df = new_df[["artist_name", "Passion Score"]]
    return new_df
```

In [30]:

```
artist_streams = stream_count(spotify)
artist_num_users = number_of_users(spotify)
artist_passion = passion_score(spotify)
```

In [31]:

```
len(spotify.artist_name.unique()) # 661 unique artists
```

Out[31]:

661

In [32]:

```
artist_features = pd.merge(artist_streams, artist_num_users, on = "artist_name")
artist_features = pd.merge(artist_features, artist_passion, on = "artist_name")
artist_features
```

Out[32]:

	artist_name	Stream Count	Number of Users	Passion Score
0	#90s Update	16	15	1.066667
1	17 Memphis	12	12	1.000000
2	2D	1	1	1.000000
3	3JS	5	4	1.250000
4	99 Percent	1291	1189	1.085786
...	...	...	...	...
656	birthday	20	20	1.000000
657	dvsn	25168	18712	1.345019
658	flor	109	108	1.009259
659	gnash	165683	146108	1.133976
660	livetune+	7	6	1.166667

661 rows × 4 columns

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

In [33]:

```
keep_col = ["artist_name", "playlist_name", "customer_id"]
df = spotify[keep_col]
df_notna = df[df['playlist_name'].notna()] # filter to songs in playlists
df_na = df[df['playlist_name'].isna()] # filter to songs not in playlists
```

In [34]:

```
# playlist stream count

stream1 = df_notna.groupby(["artist_name","playlist_name"])["customer_id"].count().rese
t_index(name = "count")

# average playlist streams per artist (for artists in playlists)
avg_stream = stream1.groupby(['artist_name']).agg({"count":"mean"}).reset_index()
avg_stream1 = avg_stream.rename(columns={"count": "playlist_avg_stream"})

# average playlist streams per artist -- na values --> 0 (for artists not in playlists)
stream2 = df_na.drop_duplicates(subset=['artist_name'])

stream2 = stream2.drop(["playlist_name","customer_id"], axis = 1)

stream2["playlist_avg_stream"] = 0

avg = pd.concat([avg_stream1, stream2], ignore_index=True)
avg = avg.drop_duplicates(subset=['artist_name'])
```

In [35]:

```
# playlist unique users

user2 = df_na.drop_duplicates(subset=['artist_name'])
user2 = user2.drop(["playlist_name","customer_id"], axis = 1)
user2["playlist_avg_user"] = 0
user2 # artists not in playlists

user1 = df_notna.groupby(["artist_name", "playlist_name"]).customer_id.nunique().reset_
index()
user1 # initial count of customers (of artists in playlists)

user1 = user1.rename(columns={"customer_id": "playlist_avg_user"})
user1 = user1.groupby(['artist_name']).agg({"playlist_avg_user":"mean"}).reset_index()

avg_unique_user = pd.concat([user1, user2], ignore_index=True)
avg_unique_user = avg_unique_user.drop_duplicates(subset=['artist_name'])
```

In [36]:

```
# playlist passion score and final playlist features df
unique_user_avg = avg_unique_user
stream_avg = avg

playlist_features = pd.merge(unique_user_avg, stream_avg, on = "artist_name")

playlist_features["passion_score"]= playlist_features["playlist_avg_stream"]/playlist_f
eatures["playlist_avg_user"]
playlist_features
```

Out[36]:

	artist_name	playlist_avg_user	playlist_avg_stream	passion_score
0	#90s Update	2.000000	2.000000	1.000000
1	17 Memphis	6.000000	6.000000	1.000000
2	99 Percent	2.666667	2.666667	1.000000
3	A Boogie Wit Da Hoodie	39.090909	41.666667	1.065891
4	A Boogie Wit da Hoodie	15.527778	16.138889	1.039356
...	...	...	...	...
656	Captain Beefheart	0.000000	0.000000	NaN
657	Painters and Dockers	0.000000	0.000000	NaN
658	ALMA	0.000000	0.000000	NaN
659	Angel	0.000000	0.000000	NaN
660	Hundred Waters	0.000000	0.000000	NaN

661 rows × 4 columns

Extra Playlist Feature

In [37]:

```
# Best of the Rest Playlists (Other Top 10)

# Creating List of all the playlists
playlists_list = list(spotify["playlist_name"].drop_duplicates())

# Creating lsit of success playlists
success_playlists = ['Hot Hits UK', 'Massive Dance Hits', 'The Indie List', 'New Music
 Friday']

# Creating list of playlists that are not defined as success playlists
non_success_playlists = [playlist for playlist in playlists_list if playlist not in suc
cess_playlists]

# Checking if 4 big playlists have been dropped from non success playlists
print(len(playlists_list))
print(len(non_success_playlists))
```

```
7103
7099
```

In [38]:

```
#Making copy of Spotify
sub_spotify = spotify.copy()

# Creating a streams column with values of 1
sub_spotify["streams"] = 1

# Removing rows associated with Success Playlists
sub_spotify = sub_spotify[sub_spotify["playlist_name"].isin(non_success_playlists)]

# Grouping dataframe by Playlist name calculating streams per playlist
sub_spotify = sub_spotify.groupby("playlist_name").agg({"streams":"count"})

# Extracting the (other) top 10 streamed playlists
other_top_10 = sub_spotify.sort_values(by = "streams", ascending = False).iloc[:9]

# Putting Other 10 top 10 playlists in a list
other_top_10 = list(other_top_10.index.values)
other_top_10
```

Out[38]:

```
["Today's Top Hits",
 'Topsify UK Top 40',
 'Freshness: Hot House Music',
 'The Pop List',
 'New Music Monday UK',
 'Happy Hits!',
 'Summer Hits',
 'Top Tracks in The United Kingdom',
 "You've Got Male - R&B: The Men"]
```

In [39]:

```
# create appearance column, where 0 = no appearance and 1 = one apperance (in other top 10)
spotify['top_10_appearances'] = np.where(spotify.playlist_name.isin(other_top_10), 1, 0
)

# group artist appearance in playlists
other_top_10_df = pd.DataFrame(spotify.groupby('artist_name').top_10_appearances.sum())
other_top_10_df
```

Out[39]:

	top_10_appearances
artist_name	
#90s Update	0
17 Memphis	0
2D	0
3JS	0
99 Percent	0
...	...
birthday	0
dvsn	2
flor	0
gnash	14788
livetune+	0

661 rows × 1 columns

User-base features

We can use the age and gender columns to create an audience profile per artist.

- Gender Percentage Breakdown
- 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 [40]:

```
# Gender breakdown

# Creating dummy variable column for gender (1 if male)
spotify.loc[spotify.gender=="male","gender_num"] = 1
spotify.loc[spotify.gender=="female","gender_num"] = 0

# Generating the mean gender numerical values (Percentage of Audience: Male) for each a
rtist
gender_breakdown = spotify.groupby(["artist_name"]).gender_num.mean()
gender_breakdown

# Merging new Percentage of Audience: Male column onto main dataframe and dropping irre
lavant column
gender_split = pd.merge(spotify, gender_breakdown, on = "artist_name")
gender_split.drop(["gender_num_x"], axis = 1, inplace = True)

# Renaming Percentage of Audience column: Male
gender_split = gender_split.rename(columns = {"gender_num_y":"male_audience"})
gender_split = gender_split[["artist_name","male_audience"]]
gender_split = gender_split.drop_duplicates(subset = ['artist_name'])
gender_split
```

Out[40]:

	artist_name	male_audience
0	Sturgill Simpson	0.660596
4898	Delafe	0.250000
4930	Willy William	0.526149
6846	Benjamin Beilman	0.635135
6920	Topic	0.563101
...	...	...
3350052	Will Joseph Cook	0.462090
3365374	WSTRN	0.474242
3530259	YONAKA	0.648968
3530599	Zak Abel	0.469928
3557565	Anne-Marie	0.397090

661 rows × 2 columns

In [41]:

```
# Age breakdown

#Create age attribute (However this would be made above !!)
spotify['birth_year'] = 2021 - spotify['birth_year']
spotify.rename(columns = {'birth_year':'Age'}, inplace = True)
```

In [42]:

```
# check null values
spotify['Age'].isna().sum()
#Fill missing values with mean age
spotify['Age'].fillna(spotify['Age'].mean())
```

Out[42]:

```
0          53.0
1          53.0
2          26.0
3          29.0
4          42.0
           ...
3805494    31.0
3805495    40.0
3805496    22.0
3805497    34.0
3805498    29.0
Name: Age, Length: 3805499, dtype: float64
```

In [43]:

```
# Age breakdown/ Age vector quantisation
spotify['Age_profile'] = None
age_profile_artist = spotify[["artist_name", "customer_id", "Age"]]
age_profile_artist = age_profile_artist.drop_duplicates(subset = ['customer_id','artist
_name'])

#Define thresold for each age category
age_group_values=[0,18,30,45,100]
age_groups = ['Minor', 'YoungAdult', 'Adult', 'Senior']

#Categorise each age into the age group

categories = pd.cut(x=age_profile_artist['Age'], bins=age_group_values, labels=age_grou
ps)
age_profile_artist["Age profile"]= categories
age_profile_artist = age_profile_artist.set_index('artist_name')

#reshape
age_profile_artist['Customer count']= age_profile_artist.groupby(['artist_name','Age pr
ofile']).customer_id.transform('count')
age_profile_artist = age_profile_artist.reset_index()
age_profile_artist = age_profile_artist.drop_duplicates(subset = ['Age profile','artist
_name'])
age_profile_artist = age_profile_artist[["artist_name", "Age profile", "Customer count"
]]
age_profile_artist
```

Out[43]:

	artist_name	Age profile	Customer count
0	Sturgill Simpson	Senior	1135.0
1	Sturgill Simpson	YoungAdult	999.0
3	Sturgill Simpson	Adult	2003.0
36	Delafe	YoungAdult	7.0
37	Willy William	YoungAdult	980.0
...	...	...	...
2951018	Anne-Marie	NaN	NaN
2951019	Anne-Marie	Adult	60519.0
2951021	Anne-Marie	YoungAdult	133721.0
2951034	Anne-Marie	Senior	22992.0
2953247	Anne-Marie	Minor	2122.0

2168 rows × 3 columns

In [44]:

```
age_profile_artist_sum = age_profile_artist.pivot(index='artist_name', columns='Age pro
file', values='Customer count')
age_profile_artist_sum = age_profile_artist_sum.fillna(0)
age_profile_artist_sum = age_profile_artist_sum[['Minor', 'YoungAdult', 'Adult', 'Senio
r']]
age_profile_artist_sum
```

Out[44]:

Age profile	Minor	YoungAdult	Adult	Senior
artist_name				
#90s Update	0.0	5.0	9.0	1.0
17 Memphis	0.0	9.0	2.0	1.0
2D	1.0	0.0	0.0	0.0
3JS	0.0	1.0	1.0	2.0
99 Percent	16.0	846.0	188.0	129.0
...	...	...	...	...
birthday	1.0	13.0	6.0	0.0
dvsn	25.0	12145.0	5304.0	1137.0
flor	0.0	58.0	40.0	10.0
gnash	1008.0	90173.0	39105.0	15157.0
livetune+	0.0	3.0	3.0	0.0

661 rows × 4 columns

In [45]:

```
# Merging individual dataframes
final_df = pd.merge(artist_features, playlist_features, on = "artist_name")
final_df = pd.merge(final_df, age_profile_artist_sum, on = "artist_name")
final_df = pd.merge(final_df, gender_split, on = "artist_name")
final_df = pd.merge(final_df, other_top_10_df, on = "artist_name")
final_df = pd.merge(final_df, dependant_variable, on = "artist_name")
#final_df = pd.merge(final_df, positivity_score, on = "artist_name")
```

In [46]:

```
# Renaming columns for consistency in formatting
final_df = final_df.rename(columns={"Stream Count": "artist_stream_count", "Number of U
sers": "artist_num_users",
                                    "Passion Score": "artist_passion_score", "passion_sc
ore": "playlist_passion_score"})
```

In [47]:

```
# Reviewing final dataframe
final_df
```

Out[47]:

	artist_name	artist_stream_count	artist_num_users	artist_passion_score	playlist_avg_us
0	#90s Update	16	15	1.066667	2.0000(
1	17 Memphis	12	12	1.000000	6.0000(
2	2D	1	1	1.000000	0.0000(
3	3JS	5	4	1.250000	0.0000(
4	99 Percent	1291	1189	1.085786	2.6666(
...	...	...	...	...	
656	birthday	20	20	1.000000	1.0000(
657	dvsn	25168	18712	1.345019	24.8368
658	flor	109	108	1.009259	3.0833
659	gnash	165683	146108	1.133976	57.2170
660	livetune+	7	6	1.166667	1.0000(

661 rows × 14 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.

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.

In [48]:

```
# Taking Relevant Columns to create Regions Dataset
regions = spotify.copy()
regions["streams"] = 1
regions = regions[["artist_name","region_code","streams"]]
regions
```

Out[48]:

	artist_name	region_code	streams
0	Sturgill Simpson	GB-DUR	1
1	Sturgill Simpson	GB-DUR	1
2	Sturgill Simpson	GB-ESS	1
3	Sturgill Simpson	GB-HRT	1
4	Sturgill Simpson	GB-LND	1
...	...	...	...
3805494	Anne-Marie	GB-ESX	1
3805495	Anne-Marie	GB-STE	1
3805496	Anne-Marie	GB-BNE	1
3805497	Anne-Marie	GB-RDG	1
3805498	Anne-Marie	NaN	1

3805499 rows × 3 columns

In [49]:

```
# Finding the most common region for filling NA values (GB-LND)
most_common = regions.groupby(["region_code"])["streams"].count().reset_index()
most_common = most_common.sort_values(by="streams", ascending = False)
most_common.reset_index(drop = True, inplace = True)
common_region = most_common.iloc[0, 0]
common_region
```

Out[49]:

```
'GB-LND'
```

In [50]:

```
# Filling NAs with the most common region and grouping regions table
regions["region_code"].fillna(value = common_region, inplace = True)
regions = regions.groupby(by = ["artist_name", "region_code"]).sum()
regions.reset_index(inplace = True)
regions.head()
```

Out[50]:

	artist_name	region_code	streams
0	#90s Update	GB-BRY	1
1	#90s Update	GB-COV	1
2	#90s Update	GB-GLG	1
3	#90s Update	GB-HAV	2
4	#90s Update	GB-HLD	1

In [51]:

```
# Unpivotting region_code colum for structure needed to conduct PCA
regions = regions.pivot(index = "artist_name", columns = "region_code", values = "strea
ms")
regions = regions.fillna(0)
regions = regions.astype(int)
regions
```

Out[51]:

region_code	0	500	501	502	504	505	506	508	510	511	512	513	514	517	518	5
artist_name																
#90s Update	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
17 Memphis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
3JS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
99 Percent	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
birthday	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
dvsn	0	0	1	0	2	0	1	0	0	0	0	0	0	1	0	
flor	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
gnash	0	0	3	0	0	0	1	0	0	2	0	0	0	0	0	
livetune+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

661 rows × 514 columns

In [52]:

```
# Merging final dataset and region dataset
final_incl_regions_df = pd.merge(final_df, regions, on = "artist_name")
final_incl_regions_df
```

Out[52]:

	artist_name	artist_stream_count	artist_num_users	artist_passion_score	playlist_avg_us
0	#90s Update	16	15	1.066667	2.0000(
1	17 Memphis	12	12	1.000000	6.0000(
2	2D	1	1	1.000000	0.0000(
3	3JS	5	4	1.250000	0.0000(
4	99 Percent	1291	1189	1.085786	2.6666(
...	...	...	...	...	
656	birthday	20	20	1.000000	1.0000(
657	dvsn	25168	18712	1.345019	24.8368
658	flor	109	108	1.009259	3.0833;
659	gnash	165683	146108	1.133976	57.2170!
660	livetune+	7	6	1.166667	1.0000(

661 rows × 528 columns

In [53]:

```
# Dividing the final regions into predictor and labels
X = final_incl_regions_df.drop(['success_binary'], axis=1)
y = final_incl_regions_df['success_binary']
```

In [54]:

```
from sklearn.model_selection import train_test_split

# Splitting the dataframe into test and train sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state
= 0, stratify =y)
```

In [55]:

```
# Assessing shape of train predictors
X_train.shape
```

Out[55]:

```
(462, 527)
```

In [56]:

```
# Assessing shape of test predictors
X_test.shape
```

Out[56]:

```
(199, 527)
```

In [57]:

```
# Splitting regions from other variable columns in Train Set
X_train_regions = X_train.iloc[:, 13:]
X_train_no_regions = X_train.iloc[:, :13]
X_train_no_regions
```

Out[57]:

	artist_name	artist_stream_count	artist_num_users	artist_passion_score	playlist_avg_us
133	Daniella Mason	115	110	1.045455	1.00000
126	Crying Day Care Choir	25	25	1.000000	3.75000
639	YFN Lucci	1487	1395	1.065950	12.96000
490	SWEAT	2265	1998	1.133634	81.50000
206	HEDIA	5119	4932	1.037916	137.8076
...	...	...	...	...	
461	RIVRS	1424	1331	1.069872	11.65000
76	Bl!ndman	2	2	1.000000	0.00000
362	Maria Peszek	40	38	1.052632	2.00000
365	Marie Bothmer	6	6	1.000000	2.00000
218	Hundred Waters	19	19	1.000000	0.00000

462 rows × 13 columns

In [58]:

```
# Splitting regions from other variable columns in Test Set
X_test_regions = X_test.iloc[:, 13:]
X_test_no_regions = X_test.iloc[:, :13]
```

In [59]:

```
# Region Code PCA

# Importing Relevant Packages
from sklearn.decomposition import PCA

# Indicating the initial desired level of variance to be kept
pca = PCA(0.99)
```

In [60]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_regions = scaler.fit_transform(X_train_regions)
```

In [61]:

```
# Fitting PCA to X Train Regions
pca.fit(X_train_regions)
```

Out[61]:

```
PCA(n_components=0.99)
```

In [62]:

```
# Number of Principal Compontents
pca.n_components_
```

Out[62]:

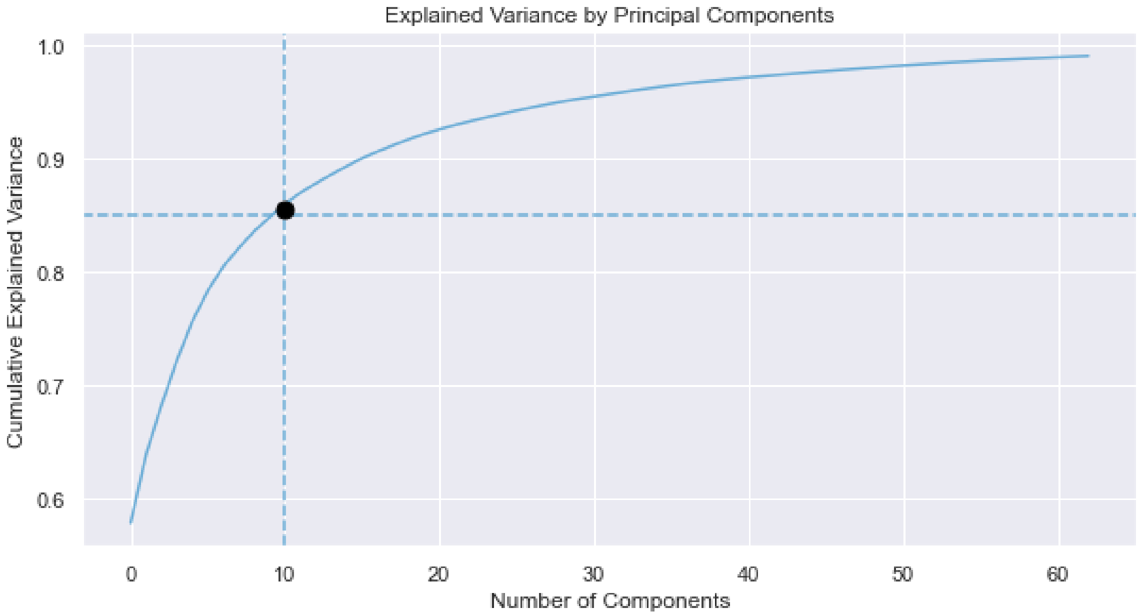
```
63
```

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.

In [63]:

```
# PCA Visualisation Assessing the Variance Explained by Components

plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.title('Explained Variance by Principal Components')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')

plt.axhline(y=0.85, xmin=0, xmax=63,  linestyle='--')
plt.axvline(x=10, ymin=0, ymax=1, linestyle='--')

plt.plot(9.9, 0.855, marker='o', markersize=9, color="black")

plt.show()
```



In [64]:

```
# Setting new level of variance based on the graphs elbow point
pca = PCA(n_components = 10)

# Fitting PCA to X Train Regions
pca.fit(X_train_regions)

# Number of Principal Components
pca.n_components_
```

Out[64]:

10

In [65]:

```
# Explained Variance for each of the 10 Components
pca.explained_variance_ratio_
```

Out[65]:

```
array([0.57804112, 0.06032819, 0.04362859, 0.03962056, 0.03446092,
       0.02699665, 0.02129331, 0.01625789, 0.01487334, 0.01225947])
```

In [66]:

```
# Transforming the X_train regions through PCA
X_train_pca = pca.transform(X_train_regions)
```

In [67]:

```
# Transforming the X_test regions through PCA
X_test_pca = pca.transform(X_test_regions)
```

In [68]:

```
# Explaining the effect of PCA on the training regions data
old_dimensions = str(X_train_regions.shape[1])
new_dimensions = str(X_train_pca.shape[1])
variance_explained = str(round(sum(pca.explained_variance_ratio_), 3)*100)

print("PCA reduced the regions dataframe dimensions from " + old_dimensions + " to " +
new_dimensions + ". These new PCA compenents explain " + variance_explained + "% of the
variance within the prior variables.")
```

```
PCA reduced the regions dataframe dimensions from 514 to 10. These new PCA
compenents explain 84.8% of the variance within the prior variables.
```

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

In [69]:

```
# Converting PCA component array into a Dataframe for merging
pca_columns = ["pca_component_1", "pca_component_2", "pca_component_3", "pca_component_
4", "pca_component_5", "pca_component_6", "pca_component_7", "pca_component_8", "pca_co
mponent_9", "pca_component_10"]
X_train_pca = pd.DataFrame(data = X_train_pca, columns = pca_columns)
X_train_pca
```

Out[69]:

	pca_component_1	pca_component_2	pca_component_3	pca_component_4	pca_compor
0	-2.992491	0.145448	-0.102796	-0.075100	-0.2
1	-3.004898	0.144743	-0.105028	-0.075653	-0.2
2	-2.369132	0.135369	0.036813	0.101779	-0.0
3	-2.263916	0.416266	-0.195282	-0.216819	0.0
4	0.721657	-1.210932	-0.800722	1.889089	-1.2
...	...	...	...	...	
457	-2.359498	0.047680	-0.177895	-0.185154	0.1
458	-3.019408	0.147580	-0.101181	-0.072484	-0.2
459	-3.012279	0.146968	-0.101727	-0.074116	-0.2
460	-3.018585	0.147597	-0.101214	-0.072495	-0.2
461	-3.014807	0.147332	-0.100100	-0.072575	-0.2

462 rows × 10 columns

In [70]:

```
# Merging PCA components to the remaining x train data
# By setting the PCA components indexes to the remaining x train data's indexes
X_train_merged = pd.concat([X_train_no_regions, X_train_pca.set_index(X_train_no_region
s.index)], axis=1)
X_train_merged
```

Out[70]:

	artist_name	artist_stream_count	artist_num_users	artist_passion_score	playlist_avg_us
133	Daniella Mason	115	110	1.045455	1.00000
126	Crying Day Care Choir	25	25	1.000000	3.75000
639	YFN Lucci	1487	1395	1.065950	12.96000
490	SWEAT	2265	1998	1.133634	81.50000
206	HEDIA	5119	4932	1.037916	137.8076
...	...	...	...	...	
461	RIVRS	1424	1331	1.069872	11.65000
76	Bl!ndman	2	2	1.000000	0.00000
362	Maria Peszek	40	38	1.052632	2.00000
365	Marie Bothmer	6	6	1.000000	2.00000
218	Hundred Waters	19	19	1.000000	0.00000

462 rows × 23 columns

In [71]:

```
# Converting PCA component array into a Dataframe for merging
X_test_pca = pd.DataFrame(data = X_test_pca, columns = pca_columns)

# Merging PCA components to the remaining x test data
X_test_merged = pd.concat([X_test_no_regions, X_test_pca.set_index(X_test_no_regions.in
dex)], axis=1)
```

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.

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.

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

In [72]:

```
# data transformation - standardizing data
from sklearn import preprocessing
# from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

ACTION: Feature transformation

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

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.

ACTION: Missing values

Use the **Imputer** class to alter your final Dataframe that contains your feature vector.

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.

In [73]:

```
# transformation and pre-processing of training set
```

In [74]:

```
x_train = X_train_merged.copy()
```

In [75]:

```
# pca columns
pca = ["pca_component_1", "pca_component_2", "pca_component_3", "pca_component_4",
       "pca_component_5", "pca_component_6", "pca_component_7", "pca_component_8",
       "pca_component_9", "pca_component_10"]
x_train_pca = x_train[pca]
```

In [76]:

```
# artist column
x_train_artist = x_train["artist_name"]
```

In [77]:

```
x_train_features = x_train.drop(["artist_name", "pca_component_1", "pca_component_2",
                                "pca_component_3", "pca_component_4", "pca_component_5",
                                "pca_component_6", "pca_component_7", "pca_component_8",
                                "pca_component_9", "pca_component_10"], axis = 1) # sele
ct variables to standardize
```

In [78]:

```
# scale remaining features
scaler = preprocessing.StandardScaler().fit(x_train_features)
x_train_features_scaled = scaler.transform(x_train_features)
```

In [79]:

```
x_train_scaled = pd.DataFrame(x_train_features_scaled, index=x_train_features.index, co
lumns=x_train_features.columns)
x_train_scaled
```

Out[79]:

	artist_stream_count	artist_num_users	artist_passion_score	playlist_avg_user	playlist_a
133	-0.175496	-0.174864	-0.173275	-0.462083	
126	-0.177899	-0.177613	-0.262308	-0.334123	
639	-0.138866	-0.133305	-0.133130	0.094423	
490	-0.118095	-0.113803	-0.000557	3.283631	
206	-0.041898	-0.018912	-0.188042	5.903662	
...	...	...	...	...	
461	-0.140548	-0.135375	-0.125447	0.033468	
76	-0.178513	-0.178357	-0.262308	-0.508613	
362	-0.177499	-0.177192	-0.159217	-0.415552	
365	-0.178407	-0.178227	-0.262308	-0.415552	
218	-0.178060	-0.177807	-0.262308	-0.508613	

462 rows × 12 columns

In [80]:

```
x_train_scaled = pd.concat([x_train_artist, x_train_scaled.set_index(x_train_artist.ind
ex)], axis=1)
x_train_scaled = pd.concat([x_train_scaled, x_train_pca.set_index(x_train_scaled.index
)], axis=1)
x_train_scaled
```

Out[80]:

	artist_name	artist_stream_count	artist_num_users	artist_passion_score	playlist_avg_us
133	Daniella Mason	-0.175496	-0.174864	-0.173275	-0.4620
126	Crying Day Care Choir	-0.177899	-0.177613	-0.262308	-0.3341
639	YFN Lucci	-0.138866	-0.133305	-0.133130	0.0944
490	SWEAT	-0.118095	-0.113803	-0.000557	3.2836
206	HEDIA	-0.041898	-0.018912	-0.188042	5.9036
...	...	...	...	...	
461	RIVRS	-0.140548	-0.135375	-0.125447	0.0334
76	Bl!ndman	-0.178513	-0.178357	-0.262308	-0.5086
362	Maria Peszek	-0.177499	-0.177192	-0.159217	-0.4155
365	Marie Bothmer	-0.178407	-0.178227	-0.262308	-0.4155
218	Hundred Waters	-0.178060	-0.177807	-0.262308	-0.5086

462 rows × 23 columns

In [81]:

```
# Check for missing values
x_train_scaled.count(0)/x_train_scaled.shape[0] * 100
```

Out[81]:

```
artist_name              100.000000
artist_stream_count      100.000000
artist_num_users         100.000000
artist_passion_score     100.000000
playlist_avg_user        100.000000
playlist_avg_stream      100.000000
playlist_passion_score    73.376623
Minor                    100.000000
YoungAdult               100.000000
Adult                    100.000000
Senior                   100.000000
male_audience             99.783550
top_10_appearances       100.000000
pca_component_1          100.000000
pca_component_2          100.000000
pca_component_3          100.000000
pca_component_4          100.000000
pca_component_5          100.000000
pca_component_6          100.000000
pca_component_7          100.000000
pca_component_8          100.000000
pca_component_9          100.000000
pca_component_10         100.000000
dtype: float64
```

Missing values observed in columns "playlist_passion_score" and "male_audience"

In [82]:

```
# Handle missing values

# Fill playlist passion score NA = 0
x_train_scaled["playlist_passion_score"].fillna(0, inplace=True)

# Fill male audience NA = mean
x_train_scaled["male_audience"].fillna(x_train_scaled["male_audience"].mean(), inplace
= True)
```

To check for linear dependencies between variables, the Variance Inflation Factor (VIF) of each variable is calculated. VIF values greater than 10 are regarded as indicating multicollinearity.

In [83]:

```
# Multicollinearity

# import library
from statsmodels.stats.outliers_influence import variance_inflation_factor

# only keep numerical columns
VIF_test = x_train_scaled.drop(columns=["artist_name"])

# create VIF dataframe
vif_data = pd.DataFrame()
vif_data["Variable"] = VIF_test.columns

# calculating VIF for each variable
vif_data["VIF"] = [variance_inflation_factor(VIF_test.values, i)
                          for i in range(len(VIF_test.columns))]

vif_data
```

Out[83]:

	Variable	VIF
0	artist_stream_count	4.651136e+03
1	artist_num_users	4.659123e+07
2	artist_passion_score	1.018119e+00
3	playlist_avg_user	7.964755e+02
4	playlist_avg_stream	8.002060e+02
5	playlist_passion_score	1.158220e+00
6	Minor	2.714515e+03
7	YoungAdult	1.676724e+07
8	Adult	3.667414e+06
9	Senior	6.394686e+05
10	male_audience	1.025928e+00
11	top_10_appearances	3.350739e+01
12	pca_component_1	3.046989e+03
13	pca_component_2	2.113375e+01
14	pca_component_3	9.902943e+00
15	pca_component_4	1.156406e+01
16	pca_component_5	1.130344e+01
17	pca_component_6	1.681654e+01
18	pca_component_7	1.737154e+01
19	pca_component_8	2.203714e+00
20	pca_component_9	2.105520e+00
21	pca_component_10	2.914438e+00

In [84]:

```
# dropping the largest VIF variable, recalculating VIF with each drop.
VIF_test = VIF_test.drop(columns=["artist_stream_count"]) # artist_stream_count is the
 greatest source of multicollinearity
VIF_test = VIF_test.drop(columns=["playlist_avg_stream"]) # followed by playlist_avg_st
ream
VIF_test = VIF_test.drop(columns=["artist_num_users"]) # followed by artist_num_users
VIF_test = VIF_test.drop(columns=["top_10_appearances"]) # followed by top_10_appearanc
es

# re-creating VIF dataframe
vif_data = pd.DataFrame()
vif_data["Variable"] = VIF_test.columns

# re-calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(VIF_test.values, i)
                          for i in range(len(VIF_test.columns))]

vif_data
```

Out[84]:

	Variable	VIF
0	artist_passion_score	1.017316
1	playlist_avg_user	1.421450
2	playlist_passion_score	1.026881
3	Minor	137.652194
4	YoungAdult	597.239206
5	Adult	2146.097290
6	Senior	1930.805035
7	male_audience	1.020410
8	pca_component_1	257.575954
9	pca_component_2	7.660739
10	pca_component_3	5.545694
11	pca_component_4	3.031501
12	pca_component_5	2.142919
13	pca_component_6	13.002207
14	pca_component_7	10.895438
15	pca_component_8	1.913011
16	pca_component_9	1.357953
17	pca_component_10	1.142789

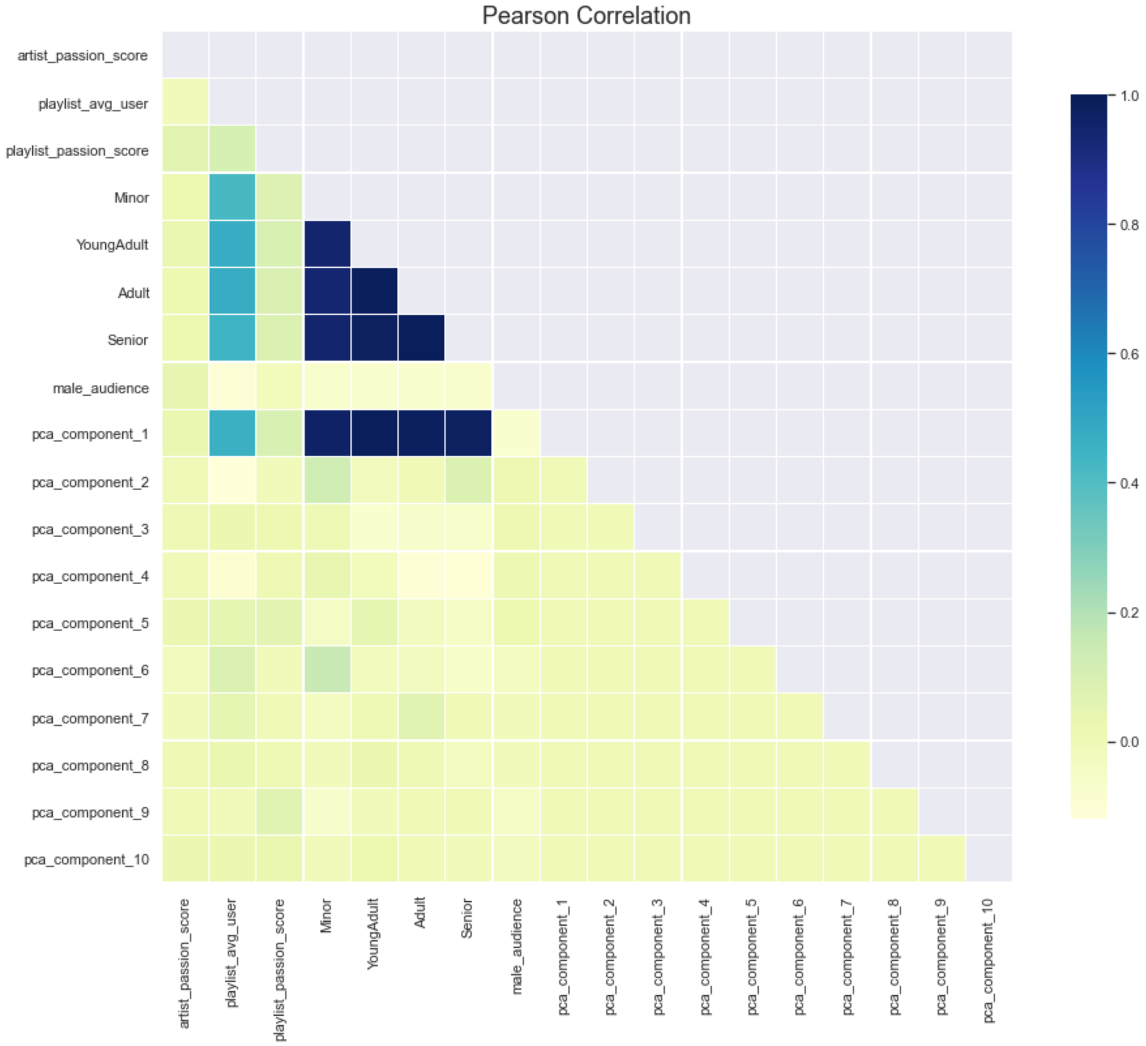
In [85]:

```
# drop variables indicating multicollinearity
x_train_final = x_train_scaled.drop(["artist_stream_count",
                                     "playlist_avg_stream",
                                     "artist_num_users",
                                     "top_10_appearances"], axis = 1)
```

In [86]:

```
# Pearson Correlation, without multicollinearity
mask = np.zeros_like(x_train_final.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(16, 12))
plt.title('Pearson Correlation',fontsize=18)

cmap = "YlGnBu"

sns.heatmap(x_train_final.corr(),linewidths=0.30,vmax=1.00,square=True,linecolor='w',cm
ap = cmap,
            mask=mask,cbar_kws={"shrink": 0.85})
plt.show();
```

```
<ipython-input-86-fb91101167e8>:2: DeprecationWarning: `np.bool` is a depr
ecated alias for the builtin `bool`. To silence this warning, use `bool` b
y itself. Doing this will not modify any behavior and is safe. If you spec
ifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.or
g/devdocs/release/1.20.0-notes.html#deprecations
  mask = np.zeros_like(x_train_final.corr(), dtype=np.bool)
```


Pearson Correlation
artist_passion_score
playlist_avg_user
playlist_passion_score
Minor
YoungAdult
Adult
Senior
male_audience
pca_component_1
pca_component_2
pca_component_3
pca_component_4
pca_component_5
pca_component_6
pca_component_7
pca_component_8
pca_component_9
pca_component_10
1.0
0.8
0.6
0.4
0.2
0.0

In [87]:

```
# transformation and pre-processing of test set
```

In [88]:

```
x_test = X_test_merged.copy()
```

In [89]:

```
# pca columns
pca = ["pca_component_1", "pca_component_2", "pca_component_3", "pca_component_4",
       "pca_component_5", "pca_component_6", "pca_component_7", "pca_component_8",
       "pca_component_9", "pca_component_10"]
x_test_pca = x_test[pca]
```

In [90]:

```
# artist column
x_test_artist = x_test["artist_name"]
```

In [91]:

```
x_test_features = x_test.drop(["artist_name", "pca_component_1", "pca_component_2",
                               "pca_component_3", "pca_component_4", "pca_component_5",
                               "pca_component_6", "pca_component_7", "pca_component_8",
                               "pca_component_9", "pca_component_10"], axis = 1) # sele
ct variables to standardize
```

In [92]:

```
# scale remaining features
scaler = preprocessing.StandardScaler().fit(x_test_features)
x_test_features_scaled = scaler.transform(x_test_features)
```

In [93]:

```
x_test_scaled = pd.DataFrame(x_test_features_scaled, index=x_test_features.index, colum
ns=x_test_features.columns)
x_test_scaled
```

Out[93]:

	artist_stream_count	artist_num_users	artist_passion_score	playlist_avg_user	playlist_a\
56	-0.218290	-0.217904	-0.173909	-0.455539	
106	-0.215244	-0.214548	-0.148422	0.488827	
154	-0.155895	-0.168254	0.163696	-0.414480	
641	-0.213599	-0.213429	-0.042668	-0.398056	
643	-0.218900	-0.218744	1.380797	-0.455539	
...	...	...	...	...	
448	-0.202326	-0.199863	-0.162435	0.276686	
81	-0.164547	-0.174478	0.146105	-0.150527	
100	-0.218900	-0.218604	-0.173909	-0.455539	
59	-0.151264	-0.159653	0.071426	-0.193786	
601	-0.218290	-0.217904	-0.173909	-0.168124	

199 rows × 12 columns

In [94]:

```
x_test_scaled = pd.concat([x_test_artist, x_test_scaled.set_index(x_test_artist.index
)], axis=1)
x_test_scaled = pd.concat([x_test_scaled, x_test_pca.set_index(x_test_scaled.index)], a
xis=1)
x_test_scaled
```

Out[94]:

	artist_name	artist_stream_count	artist_num_users	artist_passion_score	playlist_avg_us
56	BSSMNT	-0.218290	-0.217904	-0.173909	-0.4555
106	Chevy Woods	-0.215244	-0.214548	-0.148422	0.4888
154	Dexys	-0.155895	-0.168254	0.163696	-0.4144
641	Yasutaka Nakata	-0.213599	-0.213429	-0.042668	-0.3980
643	Ylric Illians	-0.218900	-0.218744	1.380797	-0.4555
...	...	...	...	...	
448	Pink Slip	-0.202326	-0.199863	-0.162435	0.2766
81	Boef	-0.164547	-0.174478	0.146105	-0.1505
100	Chad	-0.218900	-0.218604	-0.173909	-0.4555
59	Banks & Steelz	-0.151264	-0.159653	0.071426	-0.1937
601	Truls Mork	-0.218290	-0.217904	-0.173909	-0.1681

199 rows × 23 columns

In [95]:

```
# Check for missing values
x_test_scaled.count(0)/x_test_scaled.shape[0] * 100
```

Out[95]:

```
artist_name               100.000000
artist_stream_count       100.000000
artist_num_users          100.000000
artist_passion_score      100.000000
playlist_avg_user         100.000000
playlist_avg_stream       100.000000
playlist_passion_score     66.331658
Minor                     100.000000
YoungAdult                100.000000
Adult                     100.000000
Senior                    100.000000
male_audience             100.000000
top_10_appearances        100.000000
pca_component_1           100.000000
pca_component_2           100.000000
pca_component_3           100.000000
pca_component_4           100.000000
pca_component_5           100.000000
pca_component_6           100.000000
pca_component_7           100.000000
pca_component_8           100.000000
pca_component_9           100.000000
pca_component_10          100.000000
dtype: float64
```

Missing values observed in columns "playlist_passion_score"

In [96]:

```
# Handle missing values

# Fill playlist passion score NA = 0
x_test_scaled["playlist_passion_score"] = x_test_scaled["playlist_passion_score"].filln
a(0)
```

In [97]:

```
# drop variables indicating multicollinearity
x_test_final = x_test_scaled.drop(["artist_stream_count",
                                    "playlist_avg_stream",
                                    "artist_num_users",
                                    "top_10_appearances"], axis = 1)
```

In [98]:

```
# final train set
train_set = pd.concat([x_train_final, y_train], axis = 1)
train_set
```

Out[98]:

	artist_name	artist_passion_score	playlist_avg_user	playlist_passion_score	Minor
133	Daniella Mason	-0.173275	-0.462083	-0.368571	-0.151011
126	Crying Day Care Choir	-0.262308	-0.334123	-0.368571	-0.151011
639	YFN Lucci	-0.133130	0.094423	-0.154737	-0.073473
490	SWEAT	-0.000557	3.283631	1.629140	-0.151011
206	HEDIA	-0.188042	5.903662	-0.107530	-0.095011
...	...	...	...	...	...
461	RIVRS	-0.125447	0.033468	-0.219896	-0.133780
76	Bl!ndman	-0.262308	-0.508613	0.000000	-0.151011
362	Maria Peszek	-0.159217	-0.415552	-0.368571	-0.151011
365	Marie Bothmer	-0.262308	-0.415552	-0.368571	-0.151011
218	Hundred Waters	-0.262308	-0.508613	0.000000	-0.151011

462 rows × 20 columns

In [99]:

```
# final test set
test_set = pd.concat([x_test_final, y_test], axis = 1)
test_set
```

Out[99]:

	artist_name	artist_passion_score	playlist_avg_user	playlist_passion_score	Minor
56	BSSMNT	-0.173909	-0.455539	0.000000	-0.151457
106	Chevy Woods	-0.148422	0.488827	-0.349166	-0.151457
154	Dexys	0.163696	-0.414480	-0.349166	-0.151457
641	Yasutaka Nakata	-0.042668	-0.398056	-0.349166	-0.151457
643	Ylric Illians	1.380797	-0.455539	0.000000	-0.151457
...	...	...	...	...	...
448	Pink Slip	-0.162435	0.276686	-0.231975	-0.138959
81	Boef	0.146105	-0.150527	0.936935	-0.101464
100	Chad	-0.173909	-0.455539	0.000000	-0.151457
59	Banks & Steelz	0.071426	-0.193786	-0.349166	-0.145208
601	Truls Mork	-0.173909	-0.168124	-0.349166	-0.151457

199 rows × 20 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.

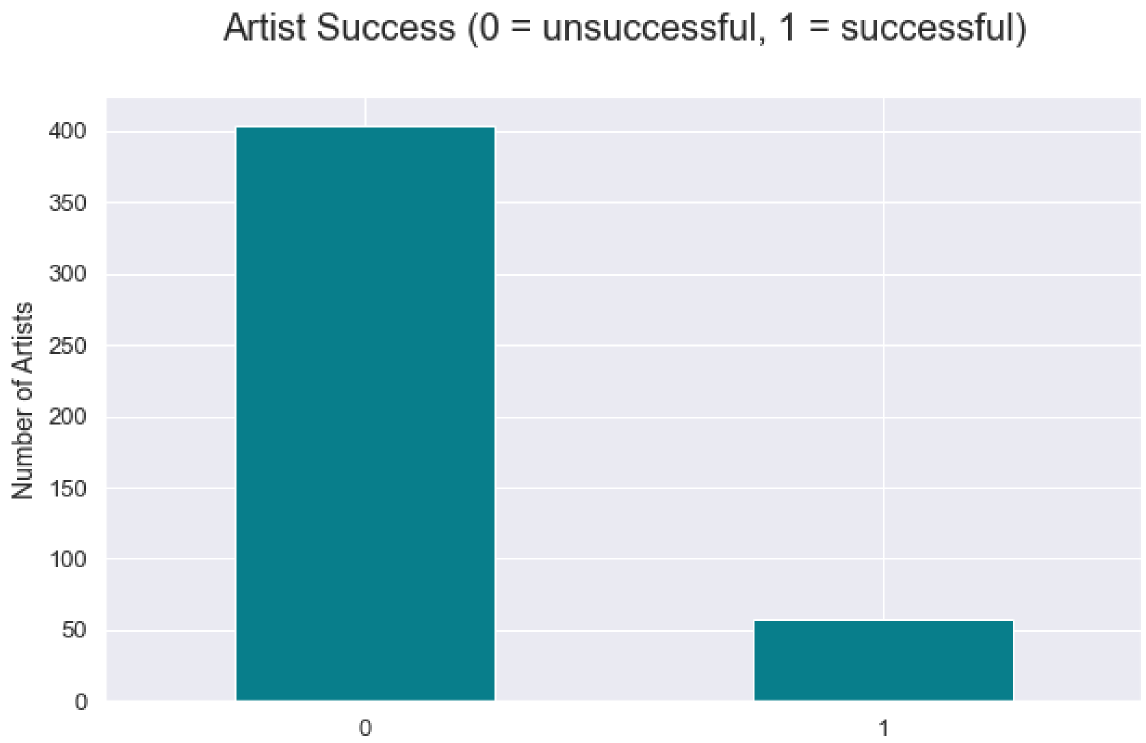
There is another way to determine the accuracy of our predictions using a confusion matrix and ROC curve, but more on that later. For now, we will go ahead with sampling the bigger class:

ACTION: Class balance

Calculate and comment on class balance.

In [100]:

```
# Class balance
ax = train_set['success_binary'].value_counts().plot(kind='bar', figsize=(10, 6), fonts
ize=13, color='#087E8B')
ax.set_title('Artist Success (0 = unsuccessful, 1 = successful)', size=20, pad=30)
ax.set_ylabel('Number of Artists', fontsize=14)

plt.xticks(rotation=0)
plt.show();
```



In [101]:

```
# utilize SMOTE to give a more even class balance
!pip install imbalanced-learn
!pip install imblearn -U;
from imblearn import under_sampling, over_sampling
from imblearn.over_sampling import SMOTE
!pip install delayed; # restart kernel after installing
# !conda install -c conda-forge imbalanced-learn
# !conda install nb_conda
```

```
Requirement already satisfied: imbalanced-learn in c:\users\jnlew\anaconda
3\envs\predictive analytics\lib\site-packages (0.8.0)
Requirement already satisfied: scikit-learn>=0.24 in c:\users\jnlew\anacon
da3\envs\predictive analytics\lib\site-packages (from imbalanced-learn)
(0.24.1)
Requirement already satisfied: scipy>=0.19.1 in c:\users\jnlew\anaconda3\e
nvs\predictive analytics\lib\site-packages (from imbalanced-learn) (1.6.1)
Requirement already satisfied: joblib>=0.11 in c:\users\jnlew\anaconda3\en
vs\predictive analytics\lib\site-packages (from imbalanced-learn) (1.0.1)
Requirement already satisfied: numpy>=1.13.3 in c:\users\jnlew\anaconda3\e
nvs\predictive analytics\lib\site-packages (from imbalanced-learn) (1.20.
1)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\jnlew\anac
onda3\envs\predictive analytics\lib\site-packages (from scikit-learn>=0.24
->imbalanced-learn) (2.1.0)

Usage:
  pip install [options] <requirement specifier> [package-index-options]
...
  pip install [options] -r <requirements file> [package-index-options] ...
  pip install [options] [-e] <vcs project url> ...
  pip install [options] [-e] <local project path> ...
  pip install [options] <archive url/path> ...

no such option: -;
ERROR: Invalid requirement: '#'
```

In [102]:

```
# describes info about train and test set
print("Number X_train dataset: ", x_train_final.shape)
print("Number  y_train dataset: ", y_train.shape)
```

```
Number X_train dataset:  (462, 19)
Number  y_train dataset:  (462,)
```

In [103]:

```
#Hightlight Oversampling bias of uncessful artists
print("Before OverSampling, counts of label '1': {}".format(sum(train_set['success_bina
ry'] == 1)))
print("Before OverSampling, counts of label '0': {} \n".format(sum(train_set['success_b
inary'] == 0)))
```

```
Before OverSampling, counts of label '1': 58
Before OverSampling, counts of label '0': 404
```

In [104]:

```
X = train_set.drop(['success_binary','artist_name'], axis=1)
y = train_set['success_binary']

#implement SMOTE
sm = SMOTE(random_state = 2)
X_sm, y_sm = sm.fit_resample(X, y)

y_sm.head()

print("After OverSampling, counts of label '1': {}".format(sum(y_sm == 1)))
print("After OverSampling, counts of label '0': {}".format(sum(y_sm == 0)))
```

```
After OverSampling, counts of label '1': 404
After OverSampling, counts of label '0': 404
```

For reference - our training data is now equal in successful and unsucessful artists. Train set is under variables X_sm and y_sm

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

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 [105]:

```
# Removing artist name from set as this is not relevant to predicting success
val_test_set = test_set.drop(['artist_name'], axis=1)

# Removing success binary as this labels should not be in x values
X_val_test = val_test_set.drop(['success_binary'], axis=1)

# Renaming Y val test to avoid clashing with previously named variables
y_val_test = y_test
```

In [106]:

```
# Splitting validation and test sets based of the original test set
# The SMOTE datasets (X_sm and y_sm) will be used to train the models
X_val, X_test, y_val, y_test_final = train_test_split(X_val_test, y_val_test,
                                                test_size=0.5, random_state=42)
```

Support Vector Machine

Baseline Model

In [107]:

```
# Setting up Base Support Vector Machine Classifier Model
SVM = SVC(gamma='auto', random_state=42)

# Fitting Support Vector Machine Classifier Model
SVM = SVM.fit(X_sm, y_sm)
```

In [108]:

```
# Predicting Values with the validation set
y_pred_SVM_val = SVM.predict(X_val)

# Accuracy score for Base SVC
SVM_base_accuracy = accuracy_score(y_val, y_pred_SVM_val)
print('The Base SVM classifier has an accuracy score of {:0.2f}%.'.format(100*SVM_base_
accuracy))

# F1 score for Base SVC
SVM_base_f1_score = f1_score(y_val,y_pred_SVM_val,average='macro')
print('The Base SVM classifier has an f1-score of {:0.2f}%.'.format(100*SVM_base_f1_sco
re))
```

```
The Base SVM classifier has an accuracy score of 12.12%.
The Base SVM classifier has an f1-score of 10.81%.
```

Tuned Model with Grid Search

In [109]:

```
#Define parameter grid
param_grid_SVM = {'C':[0.1,1,10,100],
                  'gamma':[1,0.1,0.01,0.001],
                  'kernel':['rbf','poly','sigmoid']}

# Setting the Grid Search with 3 fold cross Validation
grid_search_SVM = GridSearchCV(estimator = SVM,
                               param_grid = param_grid_SVM,
                               n_jobs = 4,
                               cv=3,
                               refit = True)

# Fitting Grid Search
grid_search_SVM.fit(X_sm, y_sm)

# Viewing the Best Parameters of the Grid Search
grid_search_SVM.best_params_
```

Out[109]:

```
{'C': 10, 'gamma': 1, 'kernel': 'poly'}
```

In [110]:

```
#Fitting tuned SVM Classifier
SVM2 = grid_search_SVM.best_estimator_.fit(X_sm, y_sm)

# Predicting Values with the validation set
y_pred_SVM_val_2 = SVM2.predict(X_val)

# Accuracy score for the Tuned SVC
SVM_grid_accuracy= accuracy_score(y_val, y_pred_SVM_val_2)
print('The tuned SVM classifier has an accuracy score of {:0.2f}%.'.format(100*SVM_grid
_accuracy))
print('The hypertuning has induced an improvement of {:0.2f}% in the model accuracy sco
re.'.format( 100 * (SVM_grid_accuracy - SVM_base_accuracy) / SVM_base_accuracy))

# F! score for the Tuned SVC
SVM_grid_f1_score = f1_score(y_val, y_pred_SVM_val_2, average='macro')
print('The tuned SVM classifier has an f1 score of {:0.2f}%.'.format(100*SVM_grid_f1_sc
ore))
print('The hypertuning has induced an improvement of {:0.2f}% in the model f1 score'.fo
rmat( 100 * (SVM_grid_f1_score - SVM_base_f1_score) / SVM_base_f1_score))
```

```
The tuned SVM classifier has an accuracy score of 15.15%.
The hypertuning has induced an improvement of 25.00% in the model accuracy
score.
The tuned SVM classifier has an f1 score of 14.44%.
The hypertuning has induced an improvement of 33.61% in the model f1 score
```

Linear Discriminant Analysis

Baseline Model

In [111]:

```
# Setting up Base Linear Discriminant Analysis Classifier Model
lda = LinearDiscriminantAnalysis()

# Fitting Linear Discriminant Analysis Classifier Model
lda = lda.fit(X_sm, y_sm)

# Predicting Values with the validation set
y_pred_lda = lda.predict(X_val)

# Assigning observations to groups
print(np.unique(y_pred_lda, return_counts=True))
```

```
(array([0, 1]), array([54, 45], dtype=int64))
```

Model assigned 54 observations to unsuccessful group and 45 observations to the successful group.

In [112]:

```
# Printing Confusion Matrix
print(confusion_matrix(y_pred_lda, y_val))
```

```
[[54  0]
 [33 12]]
```

In [113]:

```
# Printing Classification Report
print(classification_report(y_val, y_pred_lda, digits=3))
```

```
              precision    recall  f1-score   support

           0      1.000     0.621     0.766        87
           1      0.267     1.000     0.421        12

    accuracy                          0.667        99
   macro avg      0.633     0.810     0.594        99
weighted avg      0.911     0.667     0.724        99
```

Tuned Model with Grid Search

In [114]:

```
# parameter tuning
lda1 = LinearDiscriminantAnalysis(shrinkage='auto')

# Search grid for optimal parameters
parameters_1 = {
    'solver': ('lsqr','eigen'),  #note svd does not run with shrinkage and models using
it will be tuned separately
    'n_components': (1,5,1),
                   }

# Setting the Grid Search with 3 fold cross Validation
gs_lda = GridSearchCV(estimator = lda1,
                      param_grid = parameters_1,
                      scoring = 'accuracy',
                      n_jobs = -1,
                      cv = 3)

# Fitting Grid Search
gs_lda.fit(X_sm, y_sm)
```

```
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\sklea
rn\model_selection\_search.py:918: UserWarning: One or more of the test sc
ores are non-finite: [0.78342283 0.78342283        nan        nan 0.783422
83 0.78342283]
  warnings.warn(
```

Out[114]:

```
GridSearchCV(cv=3, estimator=LinearDiscriminantAnalysis(shrinkage='auto'),
             n_jobs=-1,
             param_grid={'n_components': (1, 5, 1),
                         'solver': ('lsqr', 'eigen')},
             scoring='accuracy')
```

In [115]:

```
# Printing best parameters and score based on Grid Search
print(gs_lda.best_params_)
print(gs_lda.best_score_)
```

```
{'n_components': 1, 'solver': 'lsqr'}
0.7834228280324934
```

In [116]:

```
#Fitting tuned LDA Classifier Model
lda2 = gs_lda.best_estimator_.fit(X_sm, y_sm)

# Predicting Values with the validation set
y_pred_lda2 = lda2.predict(X_val)

# Printing Classification Report
print(classification_report(y_val, y_pred_lda2, digits=3))
```

```
              precision    recall  f1-score   support

           0      0.986     0.816     0.893        87
           1      0.407     0.917     0.564        12

    accuracy                          0.828        99
   macro avg      0.697     0.866     0.729        99
weighted avg      0.916     0.828     0.853        99
```

Decision Tree

Baseline Model

In [117]:

```
# Setting up Base Decision Tree Classifier
dt_clf = DecisionTreeClassifier(random_state=42)

# Fitting Decision Tree Classifier Model
dt_clf = dt_clf.fit(X_sm, y_sm)
```

In [118]:

```
# Predicting Values with the validation set
y_pred_dt_val = dt_clf.predict(X_val)

# Accuracy score for Base Decision Tree Classifier
dt_base_accuracy = accuracy_score(y_val, y_pred_dt_val)
print('The Base Decision Tree classifier has an accuracy score of {:0.2f}%.'.format(100
*dt_base_accuracy))

# F1 score for Base Decision Tree Classifier
dt_base_f1_score = f1_score(y_val,y_pred_dt_val,average='macro')
print('The Base Decision Tree classifier has an f1-score of {:0.2f}%.'.format(100*dt_ba
se_f1_score))
```

```
The Base Decision Tree classifier has an accuracy score of 60.61%.
The Base Decision Tree classifier has an f1-score of 45.60%.
```

Tuned Model with Grid Search

In [119]:

```
# Inputting range for each parameter based on best parameters of random search
param_grid = {
    "criterion": ["gini", "entropy"],
    "max_features": ["auto", "sqrt"],
    "max_depth": [10, 12, 14, 16, 18, 20, 22, 24],
    "min_samples_leaf": [2, 4, 6, 8, 10, 12, 14, 16],
    "min_samples_split": [5, 10, 15, 20, 25, 30, 35, 40],
}

# Starting the grid search models
grid_dt = GridSearchCV(estimator = dt_clf, param_grid = param_grid,
                       cv = 3, n_jobs = -1, verbose = 2)

# Fitting the grid search models
grid_dt.fit(X_sm, y_sm)

# Viewing the Best Parameters
pprint(grid_dt.best_params_)
```

```
Fitting 3 folds for each of 2048 candidates, totalling 6144 fits
{'criterion': 'gini',
 'max_depth': 12,
 'max_features': 'auto',
 'min_samples_leaf': 4,
 'min_samples_split': 15}
```

In [120]:

```
#Fitting tuned SVM Classifier
dt_clf2 = grid_dt.best_estimator_.fit(X_sm, y_sm)

# Predicting Values with the validation set
y_pred_dt_val_2 = dt_clf2.predict(X_val)

# Accuracy score for the Tuned SVC
dt_grid_accuracy = accuracy_score(y_val, y_pred_dt_val_2)
print('The tuned Decision Tree classifier has an accuracy score of {:0.2f}%.'.format(10
0*dt_grid_accuracy))
print('The hypertuning has induced an improvement of {:0.2f}% in the model accuracy sco
re.'.format( 100 * (dt_grid_accuracy - dt_base_accuracy) / dt_base_accuracy))

# F! score for the Tuned SVC
dt_grid_f1_score = f1_score(y_val, y_pred_dt_val_2, average='macro')
print('The tuned Decision Tree classifier has an f1 score of {:0.2f}%.'.format(100*dt_g
rid_f1_score))
print('The hypertuning has induced an improvement of {:0.2f}% in the model f1 score.'.f
ormat( 100 * (dt_grid_f1_score - dt_base_f1_score) / dt_base_f1_score))
```

```
The tuned Decision Tree classifier has an accuracy score of 64.65%.
The hypertuning has induced an improvement of 6.67% in the model accuracy
score.
The tuned Decision Tree classifier has an f1 score of 56.89%.
The hypertuning has induced an improvement of 24.76% in the model f1 scor
e.
```

Random Forest

Baseline Model

In [121]:

```
# Setting up Base Random Forest Classifier
rf_clf = RandomForestClassifier(random_state=42)

# Fitting Random Forest Classifier Model
rf_clf = rf_clf.fit(X_sm, y_sm)
```

In [122]:

```
# Predicting Values with the validation set
y_pred_rf_val = rf_clf.predict(X_val)

# Accuracy score for Base Random Forest Classifier
rf_base_accuracy = accuracy_score(y_val, y_pred_rf_val)
print('The Base Random Forest classifier has an accuracy score of {:0.2f}%.'.format(100
*rf_base_accuracy))

# F1 score for Base Random Forest Classifier
rf_base_f1_score = f1_score(y_val,y_pred_rf_val, average='macro')
print('The Base Random Forest classifier has an f1-score of {:0.2f}%.'.format(100*rf_ba
se_f1_score))
```

```
The Base Random Forest classifier has an accuracy score of 90.91%.
The Base Random Forest classifier has an f1-score of 79.40%.
```

Tuned Model with Grid Search

In [123]:

```
#Define parameter grid
param_grid_rf = {'bootstrap': [True],
                 'criterion': ['gini', "entropy"],
                 'max_depth': [None, 10, 15, 20],
                 'max_features': ['auto', "sqrt"],
                 'min_samples_leaf': [1, 2, 4, 8, 12],
                 'min_samples_split': [2, 5, 10, 15],
                 'n_estimators': [100, 120, 150]}

# Setting the Grid Search with 3 fold cross Validation
grid_search_rf = GridSearchCV(estimator = rf_clf,
                              param_grid = param_grid_rf,
                              n_jobs = 4,
                              cv=3,
                              refit = True)

# Fitting Grid Search
grid_search_rf.fit(X_sm, y_sm)

# Viewing the Best Parameters of the Grid Search
grid_search_rf.best_params_
```

Out[123]:

```
{'bootstrap': True,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'auto',
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 120}
```

In [124]:

```
#Fitting tuned SVM Classifier
rf_clf2 = grid_search_rf.best_estimator_.fit(X_sm, y_sm)

# Predicting Values with the validation set
y_pred_rf_val_2 = rf_clf2.predict(X_val)

# Accuracy score for the Tuned SVC
rf_grid_accuracy= accuracy_score(y_val, y_pred_rf_val_2)
print('The tuned Random Forest classifier has an accuracy score of {:0.2f}%.'.format(10
0*rf_grid_accuracy))
print('The hypertuning has induced an improvement of {:0.2f}% in the model accuracy sco
re.'.format( 100 * (rf_grid_accuracy - rf_base_accuracy) / rf_base_accuracy))

# F! score for the Tuned SVC
rf_grid_f1_score = f1_score(y_val, y_pred_rf_val_2, average='macro')
print('The tuned Random Forest classifier has an f1 score of {:0.2f}%.'.format(100*rf_g
rid_f1_score))
print('The hypertuning has induced an improvement of {:0.2f}% in the model f1 score'.fo
rmat( 100 * (rf_grid_f1_score - rf_base_f1_score) / rf_base_f1_score))
```

```
The tuned Random Forest classifier has an accuracy score of 91.92%.
The hypertuning has induced an improvement of 1.11% in the model accuracy
score.
The tuned Random Forest classifier has an f1 score of 82.29%.
The hypertuning has induced an improvement of 3.64% in the model f1 score
```

Gradient Boosting

Baseline Model

In [125]:

```
# Setting up Base Gradient Boosting Classifier
gb_clf = GradientBoostingClassifier(random_state = 42)

# Fitting Base Gradient Boosting Classifier Model
gb_clf = gb_clf.fit(X_sm, y_sm)
```

In [126]:

```
# Predicting Values with the validation set
y_pred_gb_val = gb_clf.predict(X_val)

# Accuracy score for Base Gradient Boosting Classifier
gb_base_accuracy = accuracy_score(y_val, y_pred_gb_val)
print('The Base Gradient Boosting classifier has an accuracy score of {:0.2f}%.'.format
(100*gb_base_accuracy))

# F1 score for Base Gradient Boosting Classifier
gb_base_f1_score = f1_score(y_val, y_pred_gb_val, average='macro')
print('The Base Gradient Boosting classifier has an f1-score of {:0.2f}%.'.format(100*g
b_base_f1_score))
```

```
The Base Gradient Boosting classifier has an accuracy score of 81.82%.
The Base Gradient Boosting classifier has an f1-score of 70.69%.
```

Randomised Search for Grid Search Parameters

In [127]:

```
# Setting the loss function to be optimised
loss = ["deviance", "exponential"]

# Seting the learning rate to be used
learning_rate = [0.001, 0.01, 0.1, 0.2, 0.3]

# Setting the number of boosting stages
n_estimators = [int(i) for i in np.linspace(start = 100, stop = 500, num = 5)]

# Setting the number of features to consider when searching for the best split
max_features = ['auto', 'sqrt']

# Setting the maximum number of levels of regression estimators
max_depth = [5, 10, 15, 20]

# Setting the minimum number of samples required to split an internal node
min_samples_split = [2, 5, 10]

# Setting the minimum number of samples required to be a leaf node
min_samples_leaf = [1, 2, 4]

# Inputting range for each parameter into the random grid search
rand_grid = {'loss': loss,
             'learning_rate': learning_rate,
             'n_estimators': n_estimators,
             'max_features': max_features,
             'max_depth': max_depth,
             'min_samples_split': min_samples_split,
             'min_samples_leaf': min_samples_leaf}

# Viewing random grid search parameters
pprint(rand_grid)
```

```
{'learning_rate': [0.001, 0.01, 0.1, 0.2, 0.3],
 'loss': ['deviance', 'exponential'],
 'max_depth': [5, 10, 15, 20],
 'max_features': ['auto', 'sqrt'],
 'min_samples_leaf': [1, 2, 4],
 'min_samples_split': [2, 5, 10],
 'n_estimators': [100, 200, 300, 400, 500]}
```

In [128]:

```
# Randomly searching parameters, with 3-fold cross validation, across 1000 combinations
rand_gb = RandomizedSearchCV(estimator = gb_clf, param_distributions = rand_grid, n_ite
r = 1000,
                             cv = 3, verbose=2, random_state = 42, n_jobs = -1)

# Fitting the random search models
rand_gb.fit(X_sm, y_sm)

# Vieweing the Best Parameters
pprint(rand_gb.best_params_)
```

```
Fitting 3 folds for each of 1000 candidates, totalling 3000 fits
{'learning_rate': 0.3,
 'loss': 'deviance',
 'max_depth': 5,
 'max_features': 'sqrt',
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 400}
```

Tuned Model with Grid Search

In [129]:

```
#Define parameter grid
param_grid_gb = {"learning_rate": [0.25, 0.3, 0.3],
              "loss" : ["deviance"],
              "max_depth": [3, 5, 10],
              "max_features": ["sqrt"],
              "min_samples_leaf": [1, 2],
              "min_samples_split": [2, 3],
              "n_estimators": [200, 400, 600]}


# Setting the Grid Search with 3 fold cross Validation
grid_search_gb = GridSearchCV(estimator = gb_clf, param_grid = param_grid_gb,
                              cv = 3, n_jobs = -1, verbose = 2)

# Fitting Grid Search
grid_search_gb.fit(X_sm, y_sm)

# Viewing the Best Parameters of the Grid Search
grid_search_gb.best_params_
```

```
Fitting 3 folds for each of 108 candidates, totalling 324 fits
```

Out[129]:

```
{'learning_rate': 0.3,
 'loss': 'deviance',
 'max_depth': 5,
 'max_features': 'sqrt',
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 400}
```

In [130]:

```
#Fitting tuned Gradient Boosting Classifier
gb_clf2 = grid_search_gb.best_estimator_.fit(X_sm, y_sm)

# Predicting Values with the validation set
y_pred_gb_val_2 = gb_clf2.predict(X_val)

# Accuracy score for the Tuned Gradient Boosting
gb_grid_accuracy= accuracy_score(y_val, y_pred_gb_val_2)
print('The tuned Gradient Boosting classifier has an accuracy score of {:0.2f}%.'.forma
t(100*gb_grid_accuracy))
print('The hypertuning has induced an improvement of {:0.2f}% in the model accuracy sco
re.'.format( 100 * (gb_grid_accuracy - gb_base_accuracy) / gb_base_accuracy))

# F! score for the Tuned Gradient Boosting
gb_grid_f1_score = f1_score(y_val, y_pred_rf_val_2, average='macro')
print('The tuned Gradient Boosting classifier has an f1 score of {:0.2f}%.'.format(100*
gb_grid_f1_score))
print('The hypertuning has induced an improvement of {:0.2f}% in the model f1 score'.fo
rmat( 100 * (gb_grid_f1_score - gb_base_f1_score) / gb_base_f1_score))
```

```
The tuned Gradient Boosting classifier has an accuracy score of 90.91%.
The hypertuning has induced an improvement of 11.11% in the model accuracy
score.
The tuned Gradient Boosting classifier has an f1 score of 82.29%.
The hypertuning has induced an improvement of 16.41% in the model f1 score
```

XGBoost

Baseline Model

In [131]:

```
# Setting up Base XGBoost Classifier
xgb_clf = xgb.XGBClassifier(random_state = 42)

# Fitting Base XGBoost Model
xgb_clf = xgb_clf.fit(X_sm, y_sm)
```

```
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:07:13] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

In [132]:

```
# Predicting Values with the validation set
y_pred_xgb_val = xgb_clf.predict(X_val)

# Accuracy score for Base Random Forest Classifier
xgb_base_accuracy = accuracy_score(y_val, y_pred_xgb_val)
print('The Base XGBoost classifier has an accuracy score of {:0.2f}%.'.format(100*xgb_b
ase_accuracy))

# F1 score for Base Random Forest Classifier
xgb_base_f1_score = f1_score(y_val, y_pred_xgb_val, average='macro')
print('The Base XGBoost classifier has an f1-score of {:0.2f}%.'.format(100*xgb_base_f1
_score))
```

```
The Base XGBoost classifier has an accuracy score of 79.80%.
The Base XGBoost classifier has an f1-score of 70.78%.
```

Randomised Search for Grid Search Parameters

In [133]:

```
# Setting the maximum number of levels of regression estimators
max_depth = [5, 10, 20, 25]

# Setting the loweset number of weigths of observations needed in a child
min_child_weight = [1, 2, 5]

# Seting the learning rate (eta) to be used
learning_rate = [0.01, 0.1, 0.2]

# Setting the fraction of random samples per tree
subsample = [0.5, 0.75, 1]

# Setting the ratio of columns to sample from with each tree
colsample_bytree = [0.25, 0.5, 1]

# Setting the minimum decrease in loss for a node to split
gamma = [0.5, 1, 2]

# Setting the number of boosting stages
n_estimators = [int(i) for i in np.linspace(start = 100, stop = 500, num = 5)]

# Inputting range for each parameter into the random grid search
rand_grid = {'max_depth': max_depth,
             'min_child_weight': min_child_weight,
             'learning_rate': learning_rate,
             'subsample': subsample,
             'colsample_bytree': colsample_bytree,
             'gamma': gamma,
             'n_estimators': n_estimators
}

# Viewing random grid search parameters
pprint(rand_grid)
```

```
{'colsample_bytree': [0.25, 0.5, 1],
 'gamma': [0.5, 1, 2],
 'learning_rate': [0.01, 0.1, 0.2],
 'max_depth': [5, 10, 20, 25],
 'min_child_weight': [1, 2, 5],
 'n_estimators': [100, 200, 300, 400, 500],
 'subsample': [0.5, 0.75, 1]}
```

In [134]:

```
# Randomly searching parameters, with 3-fold cross validation, across 1000 combinations
rand_xgb = RandomizedSearchCV(estimator = xgb_clf, param_distributions = rand_grid, n_i
ter = 1000,
                              cv = 3, verbose=2, random_state = 42, n_jobs = -1)

# Fitting the random search models
rand_xgb.fit(X_sm, y_sm)

# Vieweing the Best Parameters
pprint(rand_xgb.best_params_)
```

```
Fitting 3 folds for each of 1000 candidates, totalling 3000 fits
```

```
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

```
[23:13:07] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
{'colsample_bytree': 0.5,
 'gamma': 1,
 'learning_rate': 0.1,
 'max_depth': 20,
 'min_child_weight': 1,
 'n_estimators': 400,
 'subsample': 1}
```

Tuned Model with Grid Search

In [135]:

```
#Define parameter grid
param_grid_xgb = {'max_depth': [10, 15, 20],
                  'min_child_weight': [1, 2],
                  'learning_rate': [0.01, 0.1, 0.2],
                  'subsample': [0.5, 0.75, 1],
                  'colsample_bytree': [0.25, 0.5, 0.75],
                  'gamma': [0.5, 1],
                  'n_estimators': [200, 400, 800]}


# Setting the Grid Search with 3 fold cross Validation
grid_search_xgb = GridSearchCV(estimator = xgb_clf, param_grid = param_grid_xgb,
                               cv = 3, n_jobs = -1, verbose = 2)

# Fitting Grid Search
grid_search_xgb.fit(X_sm, y_sm)

# Viewing the Best Parameters of the Grid Search
grid_search_xgb.best_params_
```

```
Fitting 3 folds for each of 972 candidates, totalling 2916 fits

C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:22:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

Out[135]:

```
{'colsample_bytree': 0.25,
 'gamma': 0.5,
 'learning_rate': 0.01,
 'max_depth': 10,
 'min_child_weight': 1,
 'n_estimators': 400,
 'subsample': 1}
```

In [136]:

```
#Fitting tuned Gradient Boosting Classifier
xgb_clf2 = grid_search_xgb.best_estimator_.fit(X_sm, y_sm)

# Predicting Values with the validation set
y_pred_xgb_val_2 = xgb_clf2.predict(X_val)

# Accuracy score for the Tuned Gradient Boosting
xgb_grid_accuracy= accuracy_score(y_val, y_pred_xgb_val_2)
print('The tuned XGBoost classifier has an accuracy score of {:0.2f}%.'.format(100*xgb_
grid_accuracy))
print('The hypertuning has induced an improvement of {:0.2f}% in the model accuracy sco
re.'.format( 100 * (xgb_grid_accuracy - xgb_base_accuracy) / xgb_base_accuracy))

# F! score for the Tuned Gradient Boosting
xgb_grid_f1_score = f1_score(y_val, y_pred_rf_val_2, average='macro')
print('The tuned XGBoost classifier has an f1 score of {:0.2f}%.'.format(100*xgb_grid_f
1_score))
print('The hypertuning has induced an improvement of {:0.2f}% in the model f1 score'.fo
rmat( 100 * (xgb_grid_f1_score - xgb_base_f1_score) / xgb_base_f1_score))
```

```
[23:22:35] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
The tuned XGBoost classifier has an accuracy score of 87.88%.
The hypertuning has induced an improvement of 10.13% in the model accuracy
score.
The tuned XGBoost classifier has an f1 score of 82.29%.
The hypertuning has induced an improvement of 16.26% in the model f1 score
```

Evaluate Classifiers

In [137]:

```
# List of Base classifiers
base_classifiers = [SVM, lda, dt_clf, rf_clf, gb_clf, xgb_clf]
```

In [140]:

```
# Empty list for models accuracy and f1 scores
clf_base_accuracy = []
clf_base_f1_score = []

# Importing relevant packages
from sklearn.base import clone

# Setting number of cross validation folds to 3
skfolds = StratifiedKFold(n_splits=3, random_state=42, shuffle = True)

# For loop which appends cross validation (accuracy and f1) scores of base models to em
pty lists
for clf in base_classifiers:

    for (train_index, val_index), (train_index2, val_index2) in zip((skfolds.split(X_sm
, y_sm)), (skfolds.split(X_val, y_val))):
        clone_clf = clone(clf)
        X_train_folds = X_sm.iloc[train_index]
        y_train_folds = (y_sm.iloc[train_index])
        X_val_fold = X_val.iloc[val_index2]
        y_val_fold = (y_val.iloc[val_index2])

        clone_clf.fit(X_train_folds, y_train_folds)
        y_pred = clone_clf.predict(X_val_fold)

        accuracy = accuracy_score(y_val_fold, y_pred)*100
        clf_base_accuracy.append(accuracy)

        f1 = f1_score(y_val_fold, y_pred, average='macro')*100
        clf_base_f1_score.append(f1)
```

```
[23:26:32] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[23:26:32] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[23:26:32] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.

C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

In [141]:

```python
# Reshaping scores array based on number of models and cross validation folds
clf_base_accuracy = np.reshape(clf_base_accuracy, (6, 3))
clf_base_f1_score = np.reshape(clf_base_f1_score, (6, 3))

# Calculating mean values for each model across their 3 folds
clf_base_mean_accuracy = clf_base_accuracy.mean(axis=1)
clf_base_mean_f1_score = clf_base_f1_score.mean(axis=1)
```

In [142]:

```python
# Assigning each fine tuned model estimator to a variable
dt_clf2 = grid_dt.best_estimator_
rf_clf2 = grid_search_rf.best_estimator_
gb_clf2 = grid_search_gb.best_estimator_
xgb_clf2 = grid_search_xgb.best_estimator_

# List of Tuned classifiers
tuned_classifiers = [SVM2, lda2, dt_clf2, rf_clf2, gb_clf2, xgb_clf2]
```

In [143]:

```
# Empty list for models accuracy and f1 scores
clf_tuned_accuracy = []
clf_tuned_f1_score = []

# Setting number of cross validation folds to 3
skfolds = StratifiedKFold(n_splits=3, random_state=42, shuffle = True)

# For loop which appends cross validation (accuracy and f1) scores of tuned models to e
mpty lists
for clf in tuned_classifiers:

    for (train_index, val_index), (train_index2, val_index2) in zip((skfolds.split(X_sm
, y_sm)), (skfolds.split(X_val, y_val))):
        clone_clf = clone(clf)
        X_train_folds = X_sm.iloc[train_index]
        y_train_folds = (y_sm.iloc[train_index])
        X_val_fold = X_val.iloc[val_index2]
        y_val_fold = (y_val.iloc[val_index2])

        clone_clf.fit(X_train_folds, y_train_folds)
        y_pred = clone_clf.predict(X_val_fold)

        accuracy = accuracy_score(y_val_fold, y_pred)*100
        clf_tuned_accuracy.append(accuracy)

        f1 = f1_score(y_val_fold, y_pred, average='macro')*100
        clf_tuned_f1_score.append(f1)
```

```
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:26:35] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.

C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:26:35] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
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or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.

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ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)


[23:26:35] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

In [144]:

```
# Reshaping scores array based on number of models and cross validation folds
clf_tuned_accuracy = np.reshape(clf_tuned_accuracy, (6, 3))
clf_tuned_f1_score = np.reshape(clf_tuned_f1_score, (6, 3))

# Calculating mean values for each model across their 3 folds
clf_tuned_mean_accuracy = clf_tuned_accuracy.mean(axis=1)
clf_tuned_mean_f1_score = clf_tuned_f1_score.mean(axis=1)
```

In [145]:

```
# List of the column and row names of model evaluation table
column_names = ["base_accuracy", "tuned_accuracy", "base_f1_score", "tuned_f1_score"]
row_names = ["SVC", "LDA", "Descision Tree", "Random Forest", "Gradient Boosting", "XGB
oost"]

# Concatenating, reshaping and transposing data for model evaluation table
eval_table_data = np.concatenate((clf_base_mean_accuracy, clf_tuned_mean_accuracy, clf_
base_mean_f1_score, clf_tuned_mean_f1_score))
eval_table_data = np.reshape(eval_table_data, (4, 6))
eval_table_data = np.transpose(eval_table_data)

# Creating model evaluation table
eval_table = pd.DataFrame(data = eval_table_data,
                          index = row_names,
                          columns = column_names)

eval_table
```

Out[145]:

	base_accuracy	tuned_accuracy	base_f1_score	tuned_f1_score
SVC	12.121212	15.151515	10.810811	14.253776
LDA	64.646465	83.838384	57.989851	74.474959
Descision Tree	73.737374	83.838384	60.707368	76.612364
Random Forest	89.898990	90.909091	78.990205	80.869408
Gradient Boosting	80.808081	91.919192	70.776440	84.836270
XGBoost	82.828283	88.888889	72.959332	80.190396

Voting ensemble

In [149]:

```
# Empty List for accuracy and f1 score
vote_accuracy = []
vote_f1_score = []

# 3 fold cross validation being set up
skfolds = StratifiedKFold(n_splits=3, random_state=42, shuffle = True)


# Setting up voting classifier with equal weights
vote_clf = VotingClassifier(estimators=[('rf', rf_clf2),
                                        ('xgb', xgb_clf2),
                                        ('gb', gb_clf2)],
                            weights = None,
                            voting = "soft")

# For loop which appends cross validation (accuracy and f1) scores of tuned models to e
mpty lists
for (train_index, val_index), (train_index2, val_index2) in zip((skfolds.split(X_sm, y_
sm)), (skfolds.split(X_val, y_val))):
    clone_clf = clone(vote_clf)
    X_train_folds = X_sm.iloc[train_index]
    y_train_folds = (y_sm.iloc[train_index])
    X_val_fold = X_val.iloc[val_index2]
    y_val_fold = (y_val.iloc[val_index2])

    clone_clf.fit(X_train_folds, y_train_folds)
    y_pred = clone_clf.predict(X_val_fold)

    accuracy = accuracy_score(y_val_fold, y_pred)*100
    vote_accuracy.append(accuracy)

    f1 = f1_score(y_val_fold, y_pred, average='macro')*100
    vote_f1_score.append(f1)
```

```
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:27:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.

C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
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ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:27:24] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.

C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:27:25] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

In [150]:

```
# Reshaping scores array based on number of models and cross validation folds
vote_accuracy = np.reshape(vote_accuracy, (1, 3))
vote_f1_score = np.reshape(vote_f1_score, (1, 3))

# Calculating mean values for each model across their 3 folds
vote_accuracy_mean = vote_accuracy.mean(axis=1)
vote_f1_score_mean = vote_f1_score.mean(axis=1)
```

In [151]:

```
# Creating Vote Evaluation Table
vote_eval_table = pd.DataFrame({'model_accuracy': vote_accuracy_mean,
                                'model_f1_score': vote_f1_score_mean})

# Renaming rows of table
vote_eval_table = vote_eval_table.rename(index={0: "Vote 1"})
vote_eval_table
```

Out[151]:

	model_accuracy	model_f1_score
Vote 1	91.919192	84.83627

5. Present Results

Finally presenting our optimum result

In [152]:

```
# Setting up Final Voting Classifier Model
vote_clf = VotingClassifier(estimators=[('rf', rf_clf2),
                                        ('xgb', xgb_clf2),
                                        ('gb', gb_clf2)],
                            weights = None,
                            voting = "soft")

# Fitting Final Voting Classifier Model
vote_clf = vote_clf.fit(X_sm, y_sm)

# Predicting Values with the test set
y_pred_vot_test = vote_clf.predict(X_test)

# Accuracy score for Final Voting Classifier Model
fin_vot_accuracy = accuracy_score(y_test_final, y_pred_vot_test)
print('The Final Voting Classifier Model has an accuracy score of {:0.2f}%.'.format(100
*fin_vot_accuracy))

# F1 score for Final Voting Classifier Model
fin_vot_f1_score = f1_score(y_test_final, y_pred_vot_test, average='macro')
print('The Final Voting Classifier Model has an f1-score of {:0.2f}%.'.format(100*fin_v
ot_f1_score))
```

```
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:27:26] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
The Final Voting Classifier Model has an accuracy score of 92.00%.
The Final Voting Classifier Model has an f1-score of 84.31%.
```

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 [154]:

```
# Confusion Matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import plot_confusion_matrix
print(confusion_matrix(y_pred_vot_test, y_test_final))
```

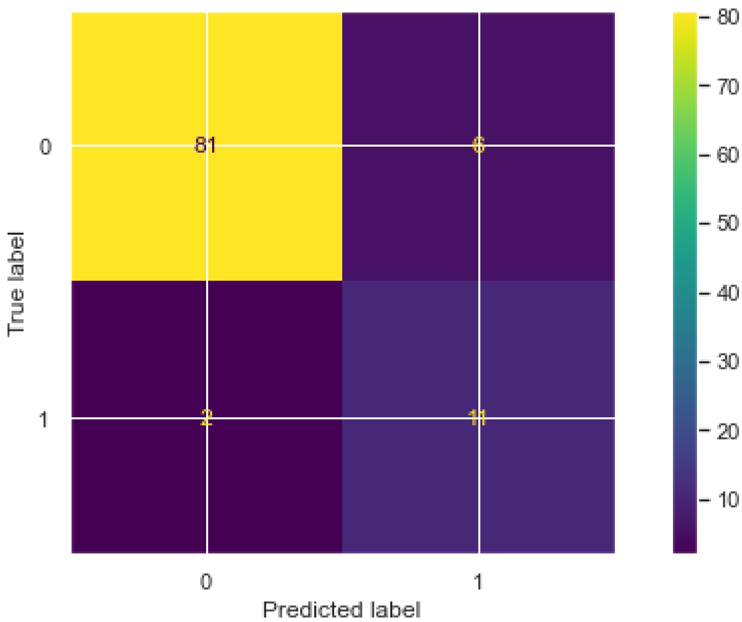
```
[[81  2]
 [ 6 11]]
```

In [155]:

```
# Plot Confusion Matrix
plot_confusion_matrix(vote_clf, X_test, y_test_final)
```

Out[155]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x21e818
b2700>
```



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.

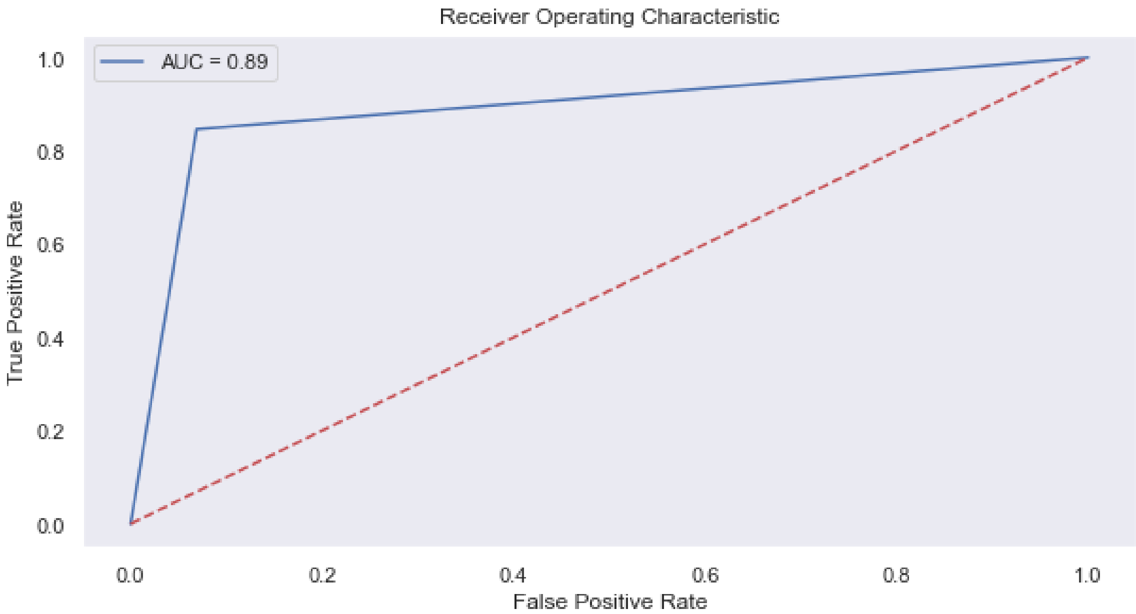
ACTION: ROC Curve

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

Explain any observations about the ROC results.

In [181]:

```
# Setting up ROC Curve
false_pos, true_pos, _ = roc_curve(y_test_final, y_pred_vot_test)

# Setting up AUC Score
auc = roc_auc_score(y_test_final, y_pred_vot_test)

# Plotting classifier ROC
plt.plot(false_pos, true_pos, label = 'AUC = %0.2f'% auc)
plt.plot([0,1],[0,1],'r--')

# Adding the labels and titles to figure
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend()
plt.show()
```



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.

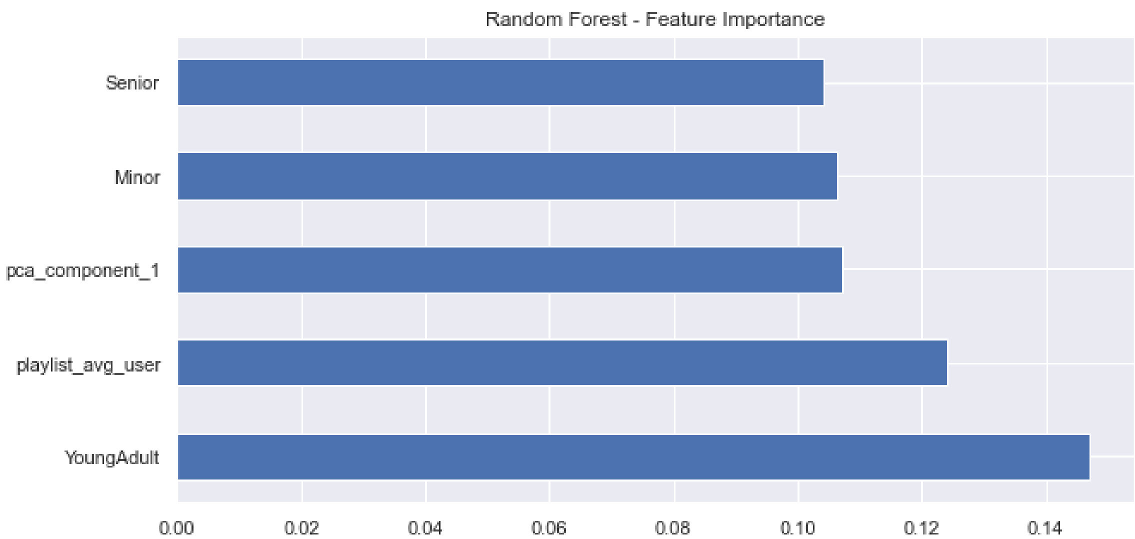
Explain any observations about the sensitivity of your final analysis.

In [195]:

```
# Feature Importance - Random Forest
# Extracting the relevant model
rf_imp = vote_clf.named_estimators['rf']

# Fitting the relevant model
rf_imp.fit(X_sm, y_sm)

# Obtaining the score of the relevant model
rf_imp.score(X_test, y_test_final)

# Plotting the Top 5 features of the relevant model
(pd.Series(rf_imp.feature_importances_, index = X_sm.columns).nlargest(5).plot(kind =
'barh'))
plt.title('Random Forest - Feature Importance')
```

Out[195]:

```
Text(0.5, 1.0, 'Random Forest - Feature Importance')
```



In [194]:

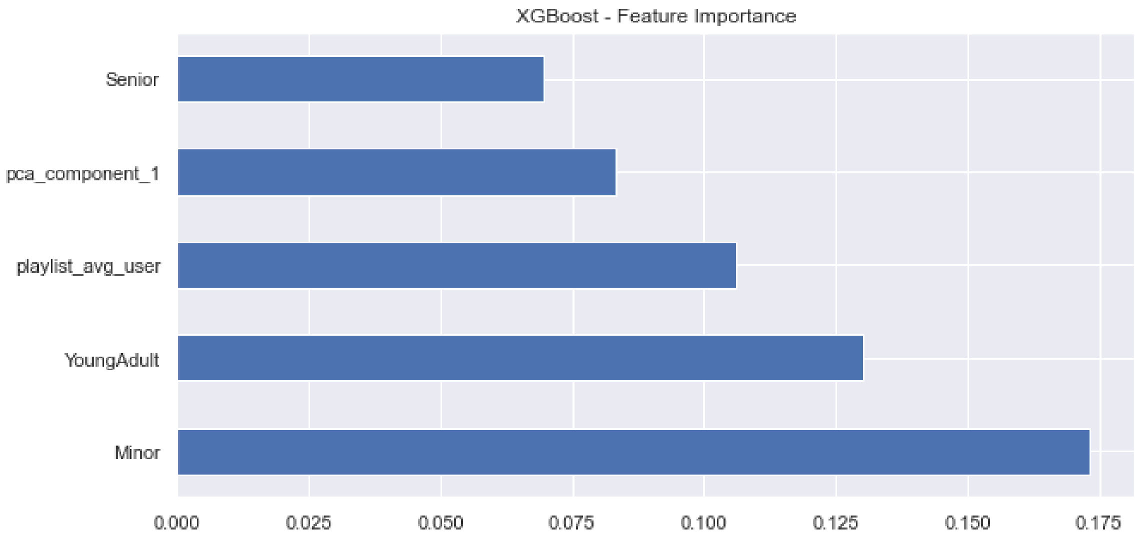
```
# Feature Importance - XGBoost
# Extracting the relevant model
xgb_imp = vote_clf.named_estimators['xgb']

# Fitting the relevant model
xgb_imp.fit(X_sm, y_sm)

# Obtaining the score of the relevant model
xgb_imp.score(X_test, y_test_final)

# Plotting the Top 5 features of the relevant model
(pd.Series(xgb_imp.feature_importances_, index = X_sm.columns).nlargest(5).plot(kind =
'barh'))
plt.title('XGBoost - Feature Importance')
```

```
C:\Users\jnlew\anaconda3\envs\Predictive Analytics\lib\site-packages\xgboo
st\sklearn.py:888: UserWarning: The use of label encoder in XGBClassifier
is deprecated and will be removed in a future release. To remove this warn
ing, do the following: 1) Pass option use_label_encoder=False when constru
cting XGBClassifier object; and 2) Encode your labels (y) as integers star
ting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

```
[01:12:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

Out[194]:

```
Text(0.5, 1.0, 'XGBoost - Feature Importance')
```

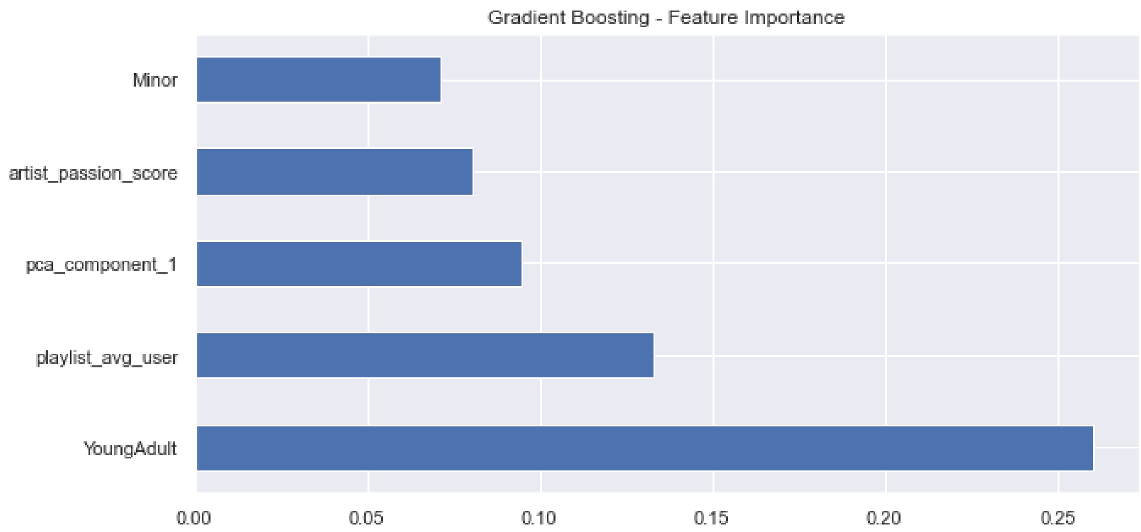


In [193]:

```
# Feature Importance - Gradient Boost
# Extracting the relevant model
gb_imp = vote_clf.named_estimators['gb']

# Fitting the relevant model
gb_imp.fit(X_sm, y_sm)

# Obtaining the score of the relevant model
gb_imp.score(X_test, y_test_final)

# Plotting the Top 5 features of the relevant model
(pd.Series(gb_imp.feature_importances_, index = X_sm.columns).nlargest(5).plot(kind =
'barh'))
plt.title('Gradient Boosting - Feature Importance')
```

Out[193]:

```
Text(0.5, 1.0, 'Gradient Boosting - Feature Importance')
```



Summary

Please provide summaries of the work completed and the outcomes of the analysis

Tips completing the coursework

- **Faculty** - You are free to run the code on your local machine, but if training timings and memory become an issue then use Faculty to complete the coursework. Technical support for using Faculty will be provided as necessary.
- **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.
- **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 contribute to improved 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 relatively good model performance (which ever metric you use to measure this) and give you confidence about the ML project structure and workflow. 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** - Do not limit your analysis to the instructions provided in Guidelines cells, feel free to expand your analysis beyond them.