In [138]:
```
# File Management
import os

########################################## API Calls ##############################
import requests # to make TMDB API calls
import locale # to format currency as USD
locale.setlocale( locale.LC_ALL, '' )

######################## Data Analysis and Machine Learning #####################
import numpy as np
import pandas as pd

# Plotting Libraries
import seaborn as sb
import matplotlib.pyplot as plt
```

In [140]:
```
# Either manually create a folder called "plots" or run this code
if "plots" not in os.listdir(): # If folder called "plots" doesnt exist in currer
    os.mkdir("plots") # Make a folder called "plots". mkdir = make directory
```

Interesting Problem

Is your movie going to be successful?

There are many factors that can create a good movie

.

We will be looking at these 3 common assumptions

1. Certain genres bring about higher success rate
2. Popular cast usually mean that movies are more successful
3. Higher budget would equate to higher success

In this project, we will assume that only these 3 factors would have a major effect on the *success* of a movie

These factors would be then be compared against a **Success** which would include either

- Revenue
- Vote Average

---

1. Data Extraction and Cleaning

Steps taken

1. **get_year_detail** calls **get_page_detail** to retrieve 10 pages of top movies of a year(by revenue/vote)
2. **get_page_detail** uses API to retrieve top movies of a certain page
3. Using list of movie names from **page details**, get individual movie details using **get_movie_detail**
4. Concat all info into 1 dataframe **(movie_data)**
5. Remove all movies that have no budget or casts

[API Documentation Site (https://developers.themoviedb.org/3/authentication/how-do-i-generate-a-session-id)](https://developers.themoviedb.org/3/authentication/how-do-i-generate-a-session-id)

In [2]:
```
api_key = 'INSERT YOUR OWN API KEY HERE' # Required to make API calls
```

Functions Required for data collection

In [8]:
```
def get_movie_detail(ID,api_key):
    # Getting Movie Details
    movie = requests.get(f'https://api.themoviedb.org/3/movie/{ID}?api_key={api_k
    movie = movie.json()

    # Getting Cast Names
    casts = requests.get(f'https://api.themoviedb.org/3/movie/{ID}/credits?api_ke
    casts = list(cast['name'] for cast in casts if cast['popularity']>10) #Gettin

    # Dictionary to store all details
    movie_dict = {}
    movie_dict['Name of Movie'] = movie['original_title']
    movie_dict['Genres'] = list(genre['name'] for genre in movie['genres']) # to
    movie_dict['Budget'] = movie['budget']
    movie_dict['Casts'] = casts
    movie_dict['Vote Count'] = movie['vote_count']
    movie_dict['Vote Average'] = movie['vote_average']
    movie_dict['Revenue'] = movie['revenue']

    return movie_dict

def get_page_detail(year,api_key,page,sort_factor):
    '''
        year : integer e.g. 2000
        api_key : string
        page : integer e.g. 10
        sort_factor : string either 'revenue' or 'vote_average'
    '''
    response = requests.get(f'https://api.themoviedb.org/3/discover/movie?api_key
    page_details = response.json()['results'] #response.json returns a dictionary
    ID_list = list(x['id'] for x in page_details) # to get movie IDs for each pag

    page_movies_list = []
    for ID in ID_list:
        page_movies_list.append(get_movie_detail(ID, api_key))


    return page_movies_list
```

In [9]:
```
def get_year_detail(year,api_key, sort_factor, total_page_num=10):
    '''
        year : integer e.g. 2000
        api_key : string
        generation : string e.g. 'x'
        sort_factor : string either 'revenue' or 'vote_average'
    '''
    year_list = []

    # Compiling page detail into the year_list
    for page in range(1,total_page_num+1):
        year_list.append(pd.DataFrame(get_page_detail(year,api_key,page,sort_fact

    year_detail = pd.concat(year_list).reset_index(drop=True)
    year_detail.drop(list(year_detail[year_detail['Budget']==0].index), inplace=T
    year_detail.drop(list(year_detail[year_detail['Casts'].map(len)==0].index), i

    return year_detail
```

Data Cleaning

> year_detail['Budget']==0

check for rows with budgets = 0

> year_detail['Casts'].map(len)==0

check for rows with no casts

year_detail.drop(list(year_detail[year_detail['Budget']==0].index), inplace=True) # Removing rows with no budget
year_detail.drop(list(year_detail[year_detail['Casts'].map(len)==0].index), inplace=True) # Removing rows with no casts info

---

Revenue vs Vote Average as a measure for good movie

In [10]:
```
# Sort by revenue
get_year_detail(2000,api_key, 'revenue')
```

...

In [6]:
```
# Sort by vote average
get_year_detail(2000,api_key, 'vote_average')
```

...

From the tables above, it is clear that **Revenue** is a better measure than **Vote Average** as a lot of the highly voted films has little to no information with very little vote count therefore are **not reliable** as datasets

Getting Dataframe of movie details

Do **NOT** run the bottom line of code if csv is already in the folder(Code takes 1hr+ to complete)

After confirming that **Revenue** is a better measure of a popular/good movie than **Vote Average**, we can continue analysing whole dataset

- 10 pages a year
- year range from 1981 to 2022
- removes outliers

Saves everything in csv file

In [223]:
```
# Getting Dataframe of 10 pages of movie from 1981 to 2022

data_list = []
for year in range(1981,2023):
    print(year)
    data_list.append(get_year_detail(year,api_key, 'revenue', gen))

movie_data = pd.concat(data_list)
del data_list #delete data list to free space
```

...

In [224]:
```
movie_data.to_csv("tmdb_topRevenueData.csv") # Saving to csv
```

2. Data Visualisation

Continuing from csv instead of reading API

if there is a csv file already made from the data, skip step 1 (**Data Extraction and Cleaning**) and go straight to this code

In [2]:
```
movie_data = pd.read_csv("tmdb_topRevenueData.csv", index_col = 'Unnamed: 0').res
movie_data
```

Out[2]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen
0	Raiders of the Lost Ark	['Adventure', 'Action']	18000000	['Harrison Ford', 'Karen Allen', 'Paul Freeman...	10400	7.922	389925971	X
1	For Your Eyes Only	['Adventure', 'Action', 'Thriller']	28000000	['Roger Moore', 'Carole Bouquet', 'Lynn-Holly ...	1478	6.477	195312802	X
2	Porky's	['Comedy']	4000000	['Kim Cattrall']	690	6.419	125728258	X
3	On Golden Pond	['Adventure', 'Drama', 'Romance']	15000000	['Henry Fonda', 'Jane Fonda', 'Dabney Coleman']	359	7.333	119285432	X
4	Arthur	['Comedy', 'Drama', 'Romance']	7000000	['Paul Gleason', 'Mark Margolis']	335	6.530	95461682	X
...	...	...	...	...	...	...	...	...
5354	Infinite Storm	['Drama', 'Thriller']	4749917	['Naomi Watts', "Denis O'Hare"]	90	6.206	1564696	Z
5355	Les passagers de la nuit	['Drama']	4300000	['Charlotte Gainsbourg', 'Emmanuelle Béart']	44	7.023	1396831	Z
5356	Terrifier 2	['Horror', 'Thriller']	250000	['Lauren LaVera', 'David Howard Thornton', 'Gr...	5	7.000	1200000	Z
5357	Gold	['Thriller', 'Action']	6500000	['Zac Efron']	393	6.295	176048	Z
5358	The Good Neighbor	['Thriller']	105	['Jonathan Rhys Meyers', 'Luke Kleintank', 'Br...	65	7.231	94909	Z

5359 rows × 8 columns

Measure of a good movie

- As a measure of good movie, we will be seeing how much profit was made with reference to budget
- For profit, equation would be : `profit = Revenue - Budget`
- For success, equation would be : `Success = profit/budget`

In [3]:
```
movie_data['Profit'] = movie_data['Revenue'] - movie_data['Budget']
movie_data['Success'] = round(movie_data['Profit']/movie_data['Budget'],4) # Rour
movie_data
```

Out[3]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen	Profit
0	Raiders of the Lost Ark	['Adventure', 'Action']	18000000	['Harrison Ford', 'Karen Allen', 'Paul Freeman...	10400	7.922	389925971	X	371925971
1	For Your Eyes Only	['Adventure', 'Action', 'Thriller']	28000000	['Roger Moore', 'Carole Bouquet', 'Lynn-Holly ...	1478	6.477	195312802	X	167312802
2	Porky's	['Comedy']	4000000	['Kim Cattrall']	690	6.419	125728258	X	121728258
3	On Golden Pond	['Adventure', 'Drama', 'Romance']	15000000	['Henry Fonda', 'Jane Fonda', 'Dabney Coleman']	359	7.333	119285432	X	104285432
4	Arthur	['Comedy', 'Drama', 'Romance']	7000000	['Paul Gleason', 'Mark Margolis']	335	6.530	95461682	X	88461682
...	...	...	...	...	...	...	...	...	...
5354	Infinite Storm	['Drama', 'Thriller']	4749917	['Naomi Watts', "Denis O'Hare"]	90	6.206	1564696	Z	-3185221
5355	Les passagers de la nuit	['Drama']	4300000	['Charlotte Gainsbourg', 'Emmanuelle Béart']	44	7.023	1396831	Z	-2903169
5356	Terrifier 2	['Horror', 'Thriller']	250000	['Lauren LaVera', 'David Howard Thornton', 'Gr...	5	7.000	1200000	Z	950000
5357	Gold	['Thriller', 'Action']	6500000	['Zac Efron']	393	6.295	176048	Z	-6323952
5358	The Good Neighbor	['Thriller']	105	['Jonathan Rhys Meyers', 'Luke Kleintank', 'Br...	65	7.231	94909	Z	94804

5359 rows × 10 columns

Visualising Success

Seeing the distribution of Success from all movies

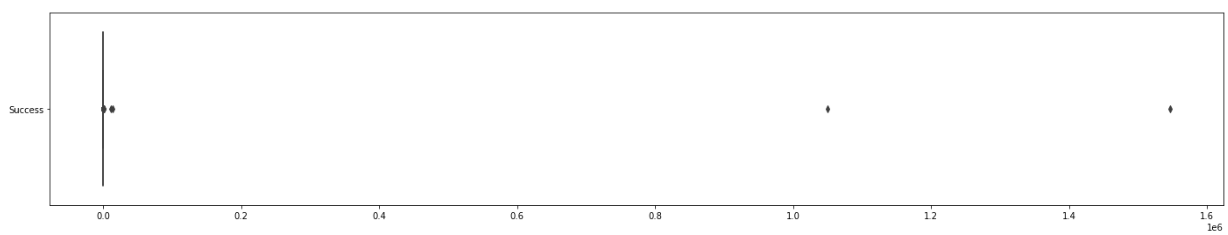
In [4]:
```
success_df = pd.DataFrame(movie_data['Success'])
success_df.describe() # Written Description of success
```

Out[4]:

	Success
count	5.359000e+03
mean	4.922176e+02
std	2.552029e+04
min	-9.986000e-01
25%	7.700000e-03
50%	1.190000e+00
75%	3.136950e+00
max	1.545929e+06

In [5]:
```
f = plt.figure(figsize=(24, 4))
sb.boxplot(data = success_df, orient = "h")
```

Out[5]: `<matplotlib.axes._subplots.AxesSubplot at 0x250ed3fad30>`



From this boxplot, some outliers can be identified(values that are >10) and removed for better visualisation

Cleaning Data
Inspecting `Budget` further as there could be the contributing factor to these outliers

In [6]:
```
movie_data['Budget'].describe()
```

Out[6]:
```
count    5.359000e+03
mean     3.820260e+07
std      4.428827e+07
min      7.000000e+00
25%      1.000000e+07
50%      2.300000e+07
75%      5.000000e+07
max      5.000000e+08
Name: Budget, dtype: float64
```

From the description, it can be seen that the minimum budget is $7 however, this is not feasible. Hence, we would be filtering out any movies with `Budget` < 100,000

In [7]:
```
movie_data.drop(movie_data.loc[movie_data['Budget']<100_000].index, inplace=True)
movie_data.reset_index(drop=True,inplace=True) # Reset Index
```

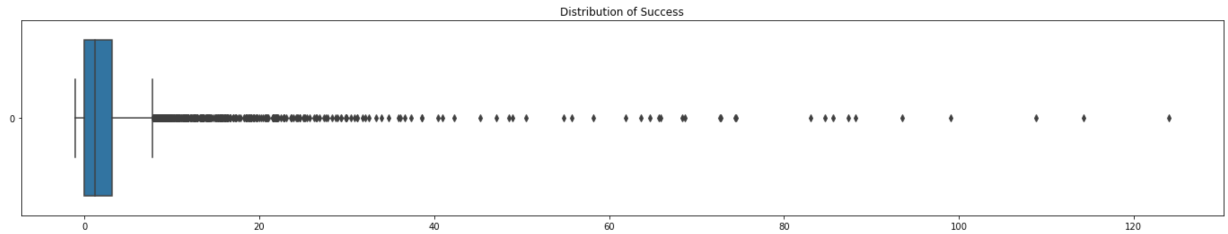
In [8]:
```
movie_data
```

Out[8]:

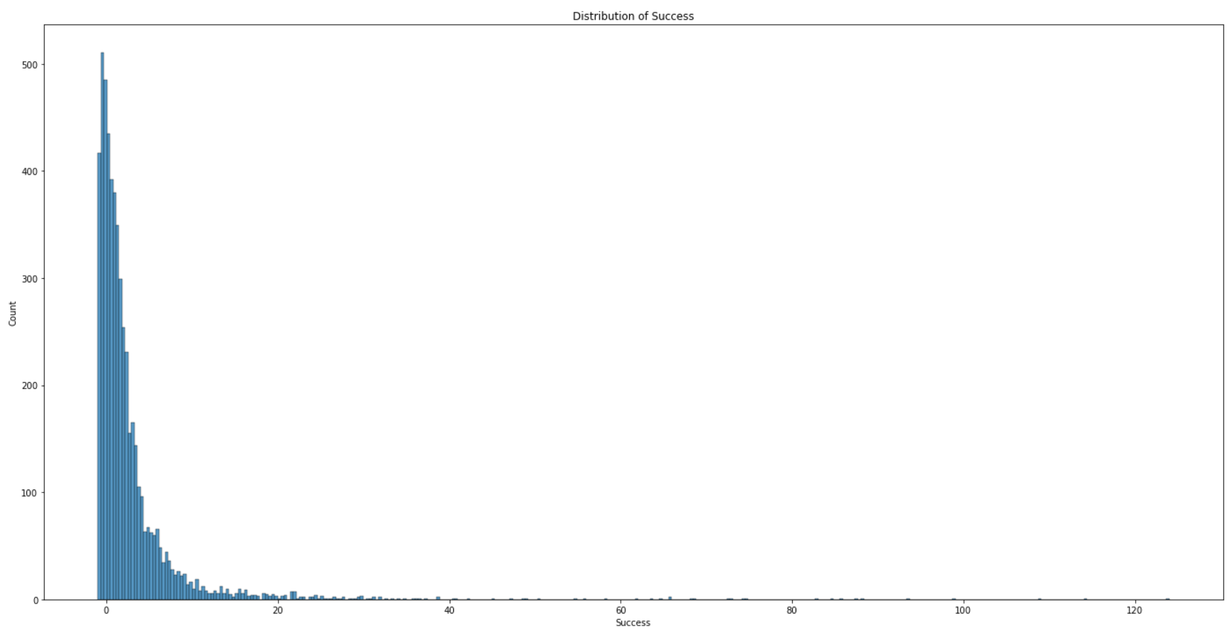
	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen	Profit
0	Raiders of the Lost Ark	['Adventure', 'Action']	18000000	['Harrison Ford', 'Karen Allen', 'Paul Freeman...	10400	7.922	389925971	X	371925971
1	For Your Eyes Only	['Adventure', 'Action', 'Thriller']	28000000	['Roger Moore', 'Carole Bouquet', 'Lynn-Holly ...	1478	6.477	195312802	X	167312802
2	Porky's	['Comedy']	4000000	['Kim Cattrall']	690	6.419	125728258	X	121728258
3	On Golden Pond	['Adventure', 'Drama', 'Romance']	15000000	['Henry Fonda', 'Jane Fonda', 'Dabney Coleman']	359	7.333	119285432	X	104285432
4	Arthur	['Comedy', 'Drama', 'Romance']	7000000	['Paul Gleason', 'Mark Margolis']	335	6.530	95461682	X	88461682
...	...	...	...	...	...	...	...	...	...
5335	The King's Daughter	['Fantasy', 'Drama', 'Romance', 'History']	40500000	['Pierce Brosnan', 'Kaya Scodelario', 'Benjami...	574	7.251	2182492	Z	-38317508
5336	Infinite Storm	['Drama', 'Thriller']	4749917	['Naomi Watts', "Denis O'Hare"]	90	6.206	1564696	Z	-3185221
5337	Les passagers de la nuit	['Drama']	4300000	['Charlotte Gainsbourg', 'Emmanuelle Béart']	44	7.023	1396831	Z	-2903169
5338	Terrifier 2	['Horror', 'Thriller']	250000	['Lauren LaVera', 'David Howard Thornton', 'Gr...	5	7.000	1200000	Z	950000
5339	Gold	['Thriller', 'Action']	6500000	['Zac Efron']	393	6.295	176048	Z	-6323952

5340 rows × 10 columns

In [9]:
```
# Plotting
f = plt.figure(figsize=(24, 4))
plt.title("Distribution of Success")
sb.boxplot(data = movie_data['Success'], orient = "h")
plt.savefig("plots/success_boxplot.png") #Save plot
```



In [10]:
```
# Plotting
f = plt.figure(figsize=(24, 12))
plt.title("Distribution of Success")
sb.histplot(data = movie_data['Success'])
plt.savefig("plots/success_histplot.png") #Save plot
```



From these plots, we have decided that a movie with **"Success" > 1** would be considered a **good movie**, else it is considered a bad movie. Hence now an edit will be done to the main dataframe to reflect this decision.

In [11]:
```
success_threshold = 1

# Editing Movie Dataframe such that "Success > success_threshold" would be counte
movie_data['Successful'] = True # Creating a new column by setting everything to
movie_data.loc[movie_data['Success'] < success_threshold,'Successful'] = False #
movie_data
```

Out[11]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen	Profit
0	Raiders of the Lost Ark	['Adventure', 'Action']	18000000	['Harrison Ford', 'Karen Allen', 'Paul Freeman...	10400	7.922	389925971	X	371925971
1	For Your Eyes Only	['Adventure', 'Action', 'Thriller']	28000000	['Roger Moore', 'Carole Bouquet', 'Lynn-Holly ...	1478	6.477	195312802	X	167312802
2	Porky's	['Comedy']	4000000	['Kim Cattrall']	690	6.419	125728258	X	121728258
3	On Golden Pond	['Adventure', 'Drama', 'Romance']	15000000	['Henry Fonda', 'Jane Fonda', 'Dabney Coleman']	359	7.333	119285432	X	104285432
4	Arthur	['Comedy', 'Drama', 'Romance']	7000000	['Paul Gleason', 'Mark Margolis']	335	6.530	95461682	X	88461682
...	...	...	...	...	...	...	...	...	...
5335	The King's Daughter	['Fantasy', 'Drama', 'Romance', 'History']	40500000	['Pierce Brosnan', 'Kaya Scodelario', 'Benjami...	574	7.251	2182492	Z	-38317508
5336	Infinite Storm	['Drama', 'Thriller']	4749917	['Naomi Watts', "Denis O'Hare"]	90	6.206	1564696	Z	-3185221
5337	Les passagers de la nuit	['Drama']	4300000	['Charlotte Gainsbourg', 'Emmanuelle Béart']	44	7.023	1396831	Z	-2903169
5338	Terrifier 2	['Horror', 'Thriller']	250000	['Lauren LaVera', 'David Howard Thornton', 'Gr...	5	7.000	1200000	Z	950000
5339	Gold	['Thriller', 'Action']	6500000	['Zac Efron']	393	6.295	176048	Z	-6323952

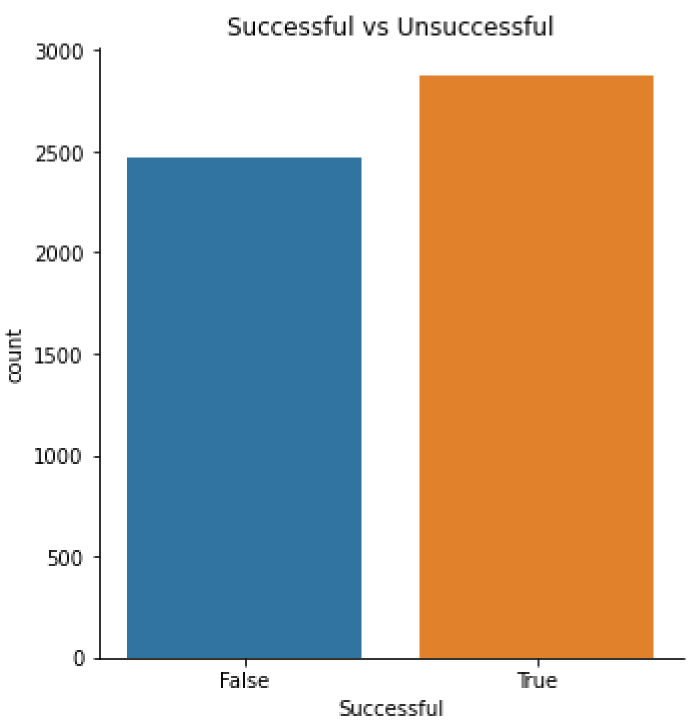
5340 rows × 11 columns

In [12]:
```
movie_data['Successful'].value_counts()
```

Out[12]:
```
True     2874
False    2466
Name: Successful, dtype: int64
```

In [13]:
```
# Plotting
f = plt.figure(figsize=(30, 16))
sb.catplot(x = 'Successful',data = pd.DataFrame(movie_data['Successful']), kind =
plt.title("Successful vs Unsuccessful")
plt.savefig("plots/SuccessvsUnsuccessful.png") #Save plot
```

```
<Figure size 2160x1152 with 0 Axes>
```



Visualising Factors

- Genres
- Casts
- Budget

2.1 Genres

Function to convert string to list

- dataframe issues where list are stored as strings

In [14]:
```
# Issue with list in Dataframe
string_list = "['Adventure', 'Action']"

def string_to_list(str):
    lst = []
    temp_word = ""
    for char in str :
        if char == ',': # If there is a comma, append word to list
            lst.append(temp_word)
            temp_word = ''

        elif char in ["'", "[","]", " ", ""]: # Ignore these characters
            pass

        else:
            temp_word += char

    lst.append(temp_word) #Appending last word cos no comma
    return lst

string_to_list(string_list)
```

Out[14]:
```
['Adventure', 'Action']
```

In [15]:
```
# Dictionary of Genres
Genre_dict ={}
for string_rows in movie_data['Genres'] :
    list_row = string_to_list(string_rows) # Issue is that the list of genres is
    for genre in list_row :
        if genre == "": # Some identify themselves as genreless
            genre = "Genreless"
        try:
            Genre_dict[genre] += 1
        except KeyError :
            Genre_dict[genre] = 1

Genre_df = pd.DataFrame(Genre_dict, index =['Count'])
Genre_df
```

Out[15]:

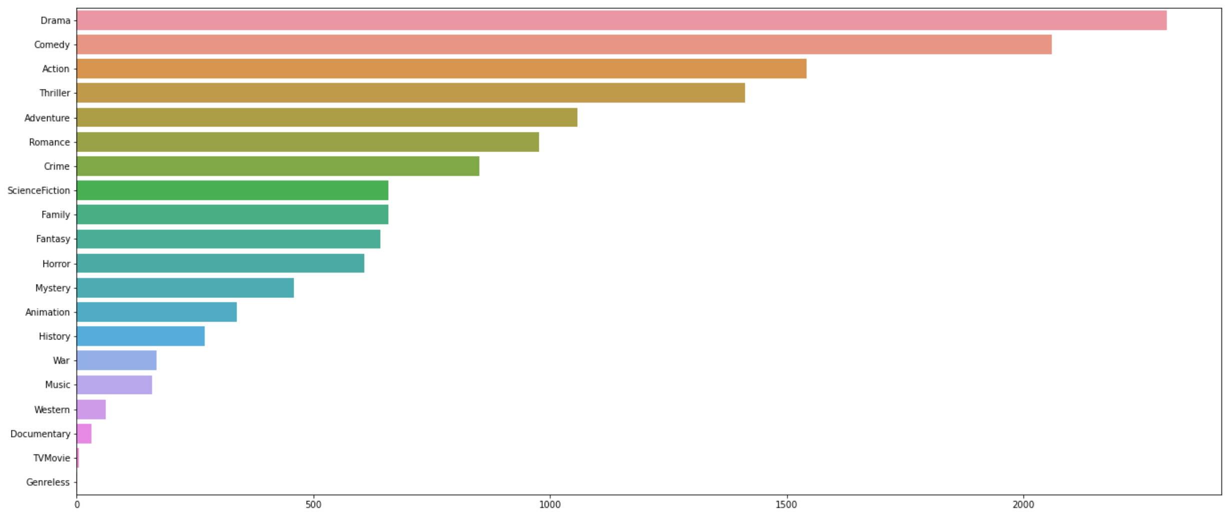
	Adventure	Action	Thriller	Comedy	Drama	Romance	History	War	ScienceFiction	Fami
Count	1057	1541	1411	2060	2302	977	271	168	659	6ŧ

In [16]:
```
# Sorting Genres for easier visualisation
Genre_sorted = Genre_df.T.sort_values(by="Count",ascending=False).T
Genre_sorted
```

Out[16]:

	Drama	Comedy	Action	Thriller	Adventure	Romance	Crime	ScienceFiction	Family	Far
Count	2302	2060	1541	1411	1057	977	850	659	658	

In [17]:
```
# Plotting
f = plt.figure(figsize=(23, 10))
sb.barplot(data = Genre_sorted, orient = "h")
plt.savefig("plots\genre_barplot.png")
```



From the plot, we can tell that **Drama** and **Comedy** are the most popular genres while **TV Movies** and **Genre-less** are least popular genres

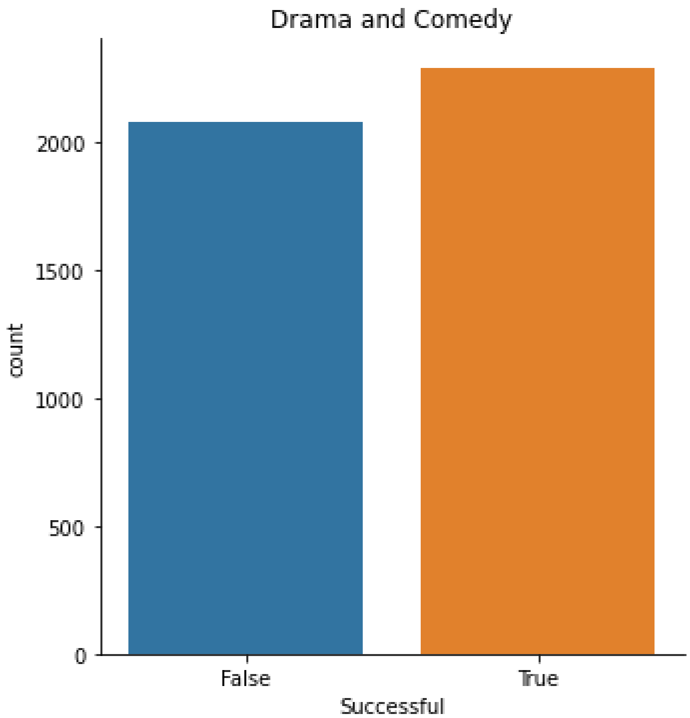
Finding the Success distribution for both Drama and Comedy movies

In [18]:
```
# Popular Genres analysis ("Drama and Comedy")
popular_list = []
for i,string_rows in enumerate(movie_data['Genres']) :
    list_row = string_to_list(string_rows) # Issue is that the list of genres is
    for genre in list_row :
        if genre == "Drama" or genre == 'Comedy':
            popular_list.append(movie_data[i:i+1])

popular_df = pd.concat(popular_list).reset_index(drop = True)
popular_success = pd.DataFrame(popular_df["Successful"])
popular_df["Successful"].value_counts()
```

Out[18]:
```
True     2287
False    2075
Name: Successful, dtype: int64
```

In [19]:
```
# Plotting
f = plt.figure(figsize=(30, 16))
sb.catplot(x = 'Successful',data = popular_success, kind = "count", orient ="h")
plt.title("Drama and Comedy")
plt.savefig("plots/popular_genre_success.png") #Save plot
```

```
<Figure size 2160x1152 with 0 Axes>
```



From the plots we can determine that Success of Drama and Comedy genres is not directly correlated as Success is equally distributed

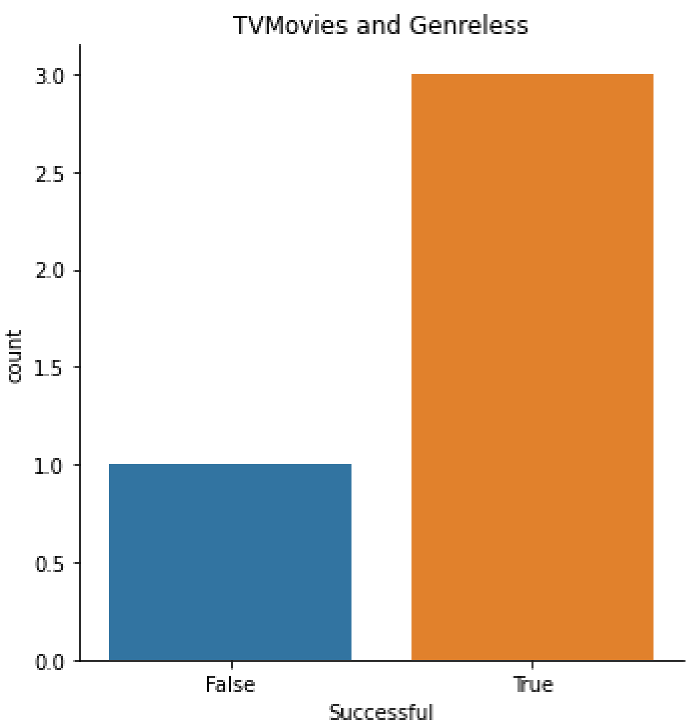
Finding the Success distribution for both TVMovie and Genreless movies

In [20]:
```
# Popular Genres analysis ("Drama and Comedy")
notpopular_list = []
for i,string_rows in enumerate(movie_data['Genres']) :
    list_row = string_to_list(string_rows) # Issue is that the list of genres is
    for genre in list_row :
        if genre == "TVMovie" or genre == 'Genreless':
            notpopular_list.append(movie_data[i:i+1])

notpopular_df = pd.concat(notpopular_list).reset_index(drop = True)
notpopular_success = pd.DataFrame(notpopular_df["Successful"])
notpopular_df["Successful"].value_counts()
```

Out[20]:
```
True     3
False    1
Name: Successful, dtype: int64
```

In [21]:
```
# Plotting
f = plt.figure(figsize=(30, 16))
sb.catplot(x = 'Successful',data = notpopular_success, kind = "count", orient ="h
plt.title("TVMovies and Genreless")
plt.savefig("plots/unpopular_genre_success.png") #Save plot
```

```
<Figure size 2160x1152 with 0 Axes>
```



Unpopular genres are more successful according to the plots however, there are also less movie with such genres hence these deductions are **not conclusive**

2.2 Cast

Finding the top 10 most popular cast members and the bottom 10 least popular cast members

In [22]:
```
cast_dict = {}

for i,string_rows in enumerate(movie_data['Casts']) :
    list_row = string_to_list(string_rows) # Issue is that the list of casts is s
    for cast in list_row :
        try:
            cast_dict[cast] += 1
        except KeyError :
            cast_dict[cast] = 1

# Converting from dictionary to dataframe for easier visualistion
cast_df = pd.DataFrame(cast_dict, index = ["count"]) # Add column called count
cast_df = cast_df.T.sort_values(by="count", ascending=False) # Sort dataframe
cast_df
```

Out[22]:

	count
FrankWelker	95
SamuelL.Jackson	86
BruceWillis	65
RobertDeNiro	62
LiamNeeson	61
...	...
ZlatkoBurić	1
JohnHamburg	1
JoeTurkel	1
CharlesBaker	1
GriffinSantopietro	1

5543 rows × 1 columns

Top 100 most popular cast members

In [23]:
```
cast_df[:100]
```

Out[23]:

	count
FrankWelker	95
SamuelL.Jackson	86
BruceWillis	65
RobertDeNiro	62
LiamNeeson	61
...	...
JimCarrey	34
JimBroadbent	34
MichellePfeiffer	34
BrianCox	34
SigourneyWeaver	34

100 rows × 1 columns

Bottom 100 most popular cast members

In [24]:
```
cast_df[-100:]
```

Out[24]:

	count
UhmJung-hwa	1
LeeMin-ki	1
KimYou-jung	1
NinavanPallandt	1
TomLipinski	1
...	...
ZlatkoBurić	1
JohnHamburg	1
JoeTurkel	1
CharlesBaker	1
GriffinSantopietro	1

100 rows × 1 columns

Checking for movies that popular cast members play in

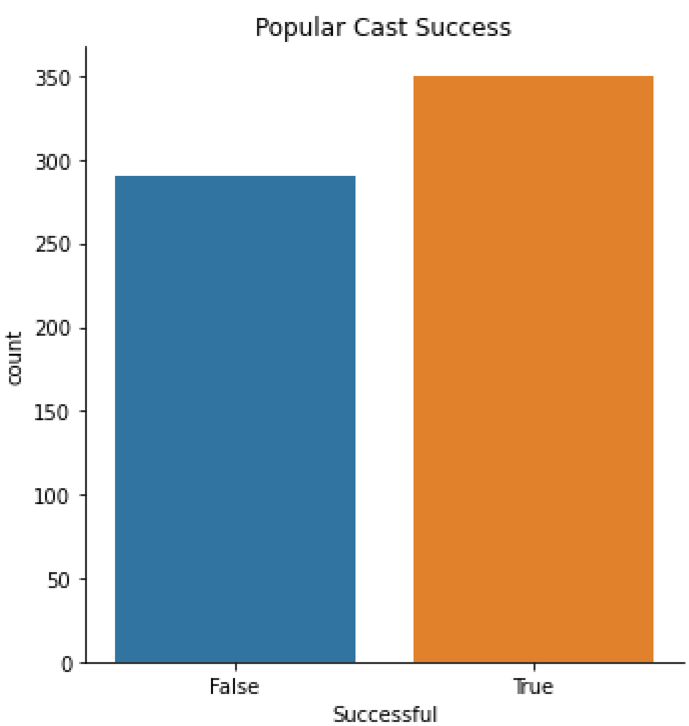
Seeing if the movies they played are successful

In [25]:
```
# Popular Cast analysis
popular_cast_list = []
for i,string_rows in enumerate(movie_data['Casts']) :
    list_row = string_to_list(string_rows) # Issue is that the list of casts is s
    for cast in list_row :
        if cast in cast_df[:10].index: # Top 10 popular cast
            popular_cast_list.append(movie_data[i:i+1])

popular_cast_df = pd.concat(popular_cast_list).reset_index(drop = True)
popular_cast_success = pd.DataFrame(popular_cast_df["Successful"])
popular_cast_df["Successful"].value_counts()
```

Out[25]:
```
True     350
False    290
Name: Successful, dtype: int64
```

In [26]:
```
# Plotting
f = plt.figure(figsize=(30, 16))
sb.catplot(x = 'Successful',data = popular_cast_df, kind = "count", orient ="h")
plt.title("Popular Cast Success")
plt.savefig("plots/popular_cast_success.png") #Save plot
```

```
<Figure size 2160x1152 with 0 Axes>
```



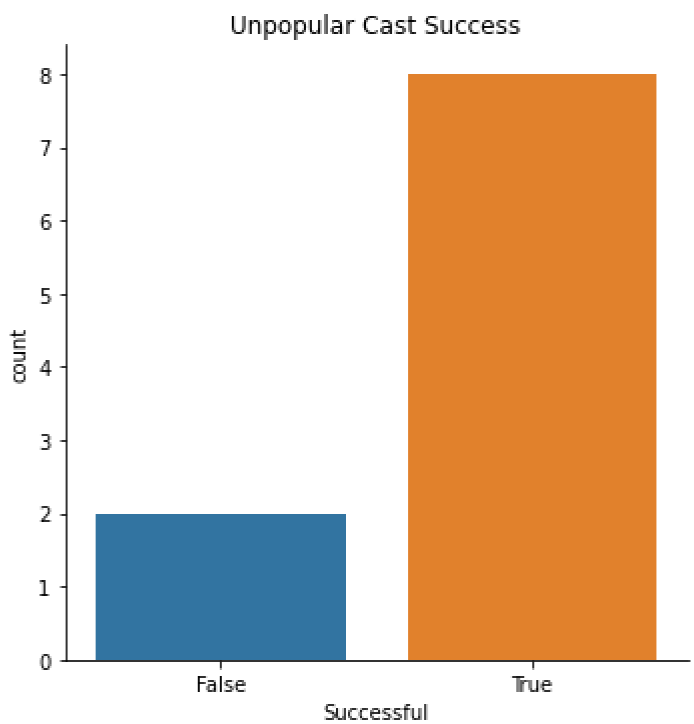
These results goes against conventional thought process of **popular casts brings good movies** as there are still a significant amount of "unsuccesful" movies despite having popular casts. However, there are slightly more successful movies than unsuccessful movies hence there is still some weight to this claim

In [27]:
```
# Popular Cast analysis
unpopular_cast_list = []
for i,string_rows in enumerate(movie_data['Casts']) :
    list_row = string_to_list(string_rows) # Issue is that the list of casts is s
    for cast in list_row :
        if cast in cast_df[-10:].index: # Top 10 popular cast
            unpopular_cast_list.append(movie_data[i:i+1])

unpopular_cast_df = pd.concat(unpopular_cast_list).reset_index(drop = True)
unpopular_cast_success = pd.DataFrame(unpopular_cast_df["Successful"])
unpopular_cast_df["Successful"].value_counts()
```

Out[27]:
```
True     8
False    2
Name: Successful, dtype: int64
```

In [28]:
```
# Plotting
f = plt.figure(figsize=(30, 16))
sb.catplot(x = 'Successful',data = unpopular_cast_df, kind = "count", orient ="h'
plt.title("Unpopular Cast Success")
plt.savefig("plots/unpopular_cast_success.png") #Save plot
```

```
<Figure size 2160x1152 with 0 Axes>
```



These results further **disprove** the claim that only popular cast make successful movies as there are more successful movie than unsuccessful movie with the bottom 10 most popular cast members

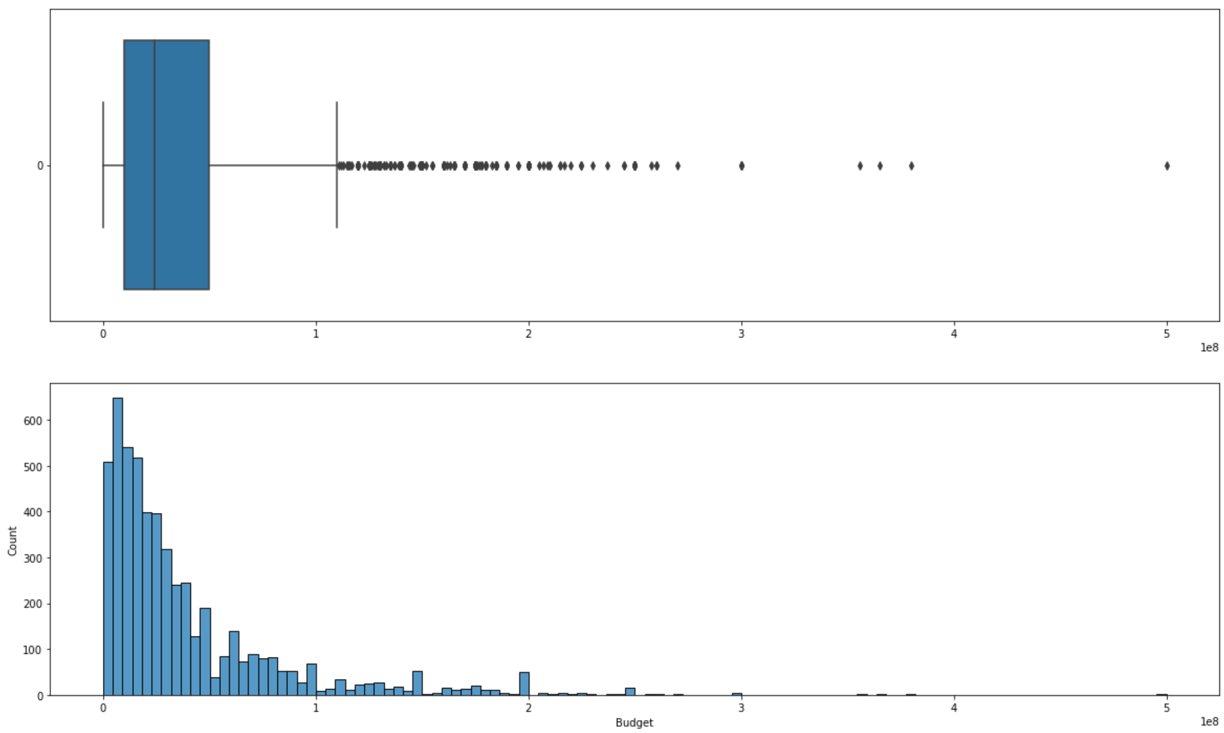
2.3 Budget

Analyzing the claim that a bigger budget would make a better movie

In [29]:
```
movie_data["Budget"].describe()
```

Out[29]:
```
count    5.340000e+03
mean     3.833844e+07
std      4.430830e+07
min      1.000000e+05
25%      1.000000e+07
50%      2.400000e+07
75%      5.000000e+07
max      5.000000e+08
Name: Budget, dtype: float64
```

In [30]:
```
# Distribution of Budget
f,axes = plt.subplots(2,1,figsize=(20, 12))
sb.boxplot(data = movie_data["Budget"], orient = "h", ax=axes[0])
sb.histplot(data = movie_data["Budget"], ax=axes[1])

plt.savefig("plots/budget_distribution.png")
```



From the analysis of budget above, we can consider movies with a budget of **more than 100 million as high budget** as most movies within the 75 and 25 percentile only have a budget of 10 to 50 million. Those films with less than **5 million dollar with be considered as low budget.**

High Budget Movies

Movies that have a budget of **more than USD$100 Million**

In [31]:
```
high_budget = movie_data.loc[movie_data['Budget'] >= 1*(10**8)]
high_budget
```

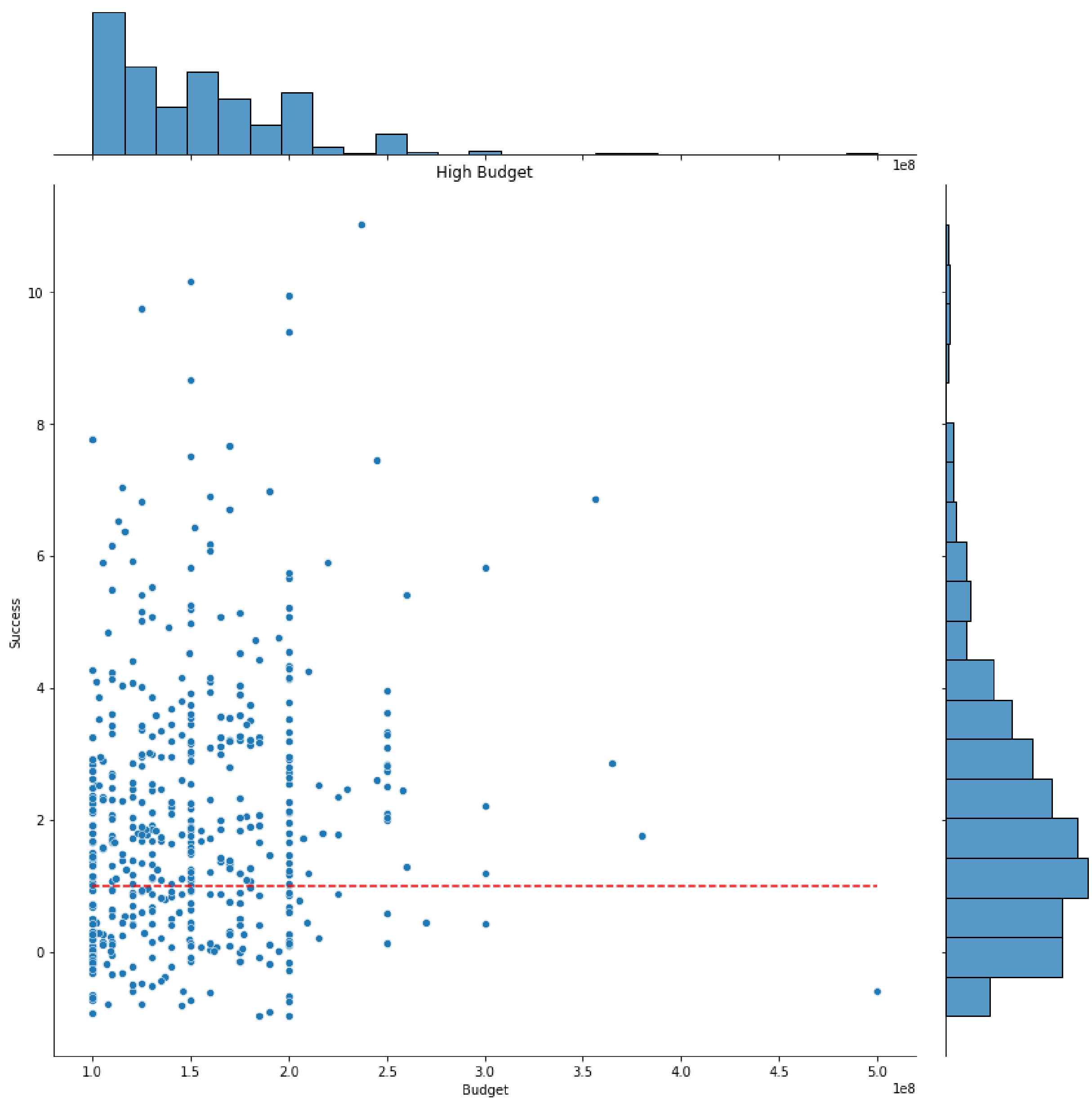
Out[31]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen	
779	Terminator 2: Judgment Day	['Action', 'Thriller', 'Science Fiction']	102000000	['Arnold Schwarzenegger', 'Linda Hamilton', 'E...	10732	8.081	520000000	X	418
1095	True Lies	['Action', 'Thriller']	115000000	['Arnold Schwarzenegger', 'Jamie Lee Curtis', ...	3330	7.040	378882411	X	263
1194	Batman Forever	['Action', 'Crime', 'Fantasy']	100000000	['Val Kilmer', 'Tommy Lee Jones', 'Jim Carrey'...	4437	5.398	336529144	X	236
1197	Waterworld	['Adventure', 'Action', 'Science Fiction']	175000000	['Kevin Costner', 'Dennis Hopper', 'Jeanne Tri...	3041	6.158	264218220	X	89
1324	The Hunchback of Notre Dame	['Drama', 'Animation', 'Family']	100000000	['Tom Hulce', 'Demi Moore', 'Tony Jay', 'Kevin...	4302	7.092	325338851	X	225
...	...	...	...	...	...	...	...	...	
5285	Uncharted	['Action', 'Adventure']	120000000	['Tom Holland', 'Mark Wahlberg', 'Sophia Ali',...	3663	7.108	401748820	Z	281
5289	Lightyear	['Animation', 'Action', 'Adventure', 'Family',...	200000000	['Chris Evans', 'Keke Palmer', 'Taika Waititi'...	2202	7.200	226400000	Z	26
5308	Moonfall	['Science Fiction']	146000000	['Halle Berry', 'Patrick Wilson', 'Charlie Plu...	1917	6.402	59100000	Z	-86
5321	Turning Red	['Animation', 'Family', 'Comedy', 'Fantasy']	190000000	['Sandra Oh', 'Maitreyi Ramakrishnan', 'James ...	3392	7.531	18879922	Z	-171
5330	Black Adam	['Action', 'Fantasy', 'Adventure']	185000000	['Dwayne Johnson', 'Aldis Hodge', 'Pierce Bros...	0	0.000	5000000	Z	-180

479 rows × 11 columns

In [32]:
```
# Distribution of Success of High budget film
f = plt.figure(figsize=(30, 16))
sb.jointplot(data = high_budget, x = "Budget", y = "Success", height = 12)

#plt.plot([range of x], [range of y], style, color)
plt.plot([high_budget['Budget'].min(),high_budget['Budget'].max()],[1,1],'--',col

plt.title("High Budget")
plt.savefig("plots\HighBudgetvsSuccess_plot.png")
```

```
<Figure size 2160x1152 with 0 Axes>
```



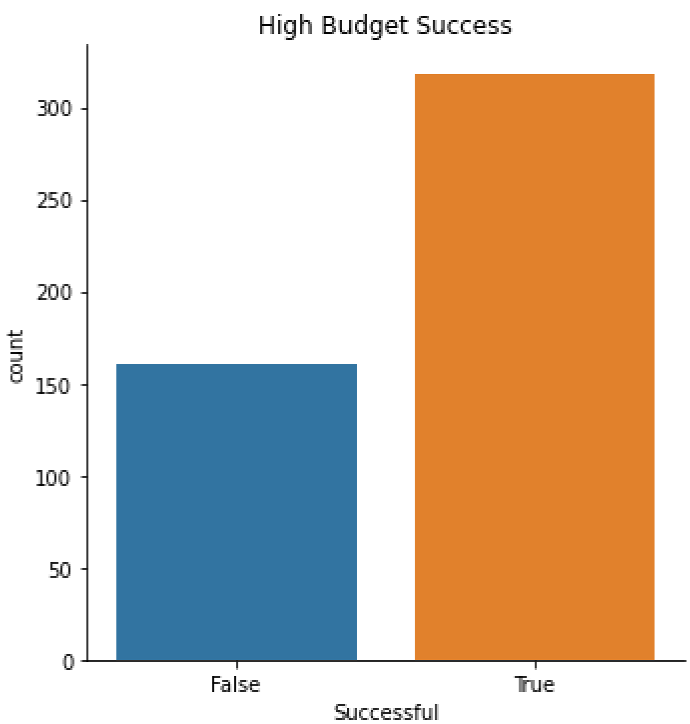
- As can be seen from the plot above, Budget and Success do not have much of a correlation as success is **evenly distributed around the 100 to 200 million dollar budget range**.
- However, above 200 million dollars, most movie tend to be more successful with Success >= 1.

In [33]:
```
# Comparison of Successful vs Unsuccessful
high_budget_success = high_budget['Successful']
high_budget_success.value_counts()
```

Out[33]:
```
True     318
False    161
Name: Successful, dtype: int64
```

In [34]:
```
# Plotting
f = plt.figure(figsize=(30, 16))
sb.catplot(x = 'Successful',data = high_budget, kind = "count", orient ="h")
plt.title("High Budget Success")
plt.savefig("plots/high_budget_success.png") #Save plot
```

```
<Figure size 2160x1152 with 0 Axes>
```



- From these analysis, it is fair to say that a higher budget **definitely has an impact on success** as there are almost <u>twice as many successful movies as there are unsuccessful movie</u> with a high budget

Low Budget Movies

Movies with less than $5 Million budget

In [35]:
```
low_budget = movie_data.loc[movie_data['Budget'] < 5*(10**6)]
low_budget
```

Out[35]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen	Profit	S
2	Porky's	['Comedy']	4000000	['Kim Cattrall']	690	6.419	125728258	X	121728258	
11	Hardly Working	['Comedy']	3400000	['Jerry Lewis']	18	4.500	49000000	X	45600000	
25	The Evil Dead	['Horror']	350000	['Bruce Campbell', 'Ted Raimi', 'Sam Raimi']	3096	7.313	29400000	X	29050000	
27	Private Lessons	['Comedy', 'Romance']	2800000	['Sylvia Kristel', 'Howard Hesseman', 'Ed Begl...	73	5.726	26279000	X	23479000	
29	Halloween II	['Horror', 'Thriller']	2500000	['Jamie Lee Curtis', 'Donald Pleasence', 'Pame...	1594	6.550	25533818	X	23033818	
...	...	...	...	...	...	...	...	...	...	
5319	Father Stu	['Drama']	4000000	['Mark Wahlberg', 'Mel Gibson', 'Jacki Weaver'...	302	7.500	21591034	Z	17591034	
5326	Fall	['Thriller']	3000000	['Grace Caroline Currey', 'Virginia Gardner', ...	1354	7.402	11900000	Z	8900000	
5336	Infinite Storm	['Drama', 'Thriller']	4749917	['Naomi Watts', "Denis O'Hare"]	90	6.206	1564696	Z	-3185221	
5337	Les passagers de la nuit	['Drama']	4300000	['Charlotte Gainsbourg', 'Emmanuelle Béart']	44	7.023	1396831	Z	-2903169	
5338	Terrifier 2	['Horror', 'Thriller']	250000	['Lauren LaVera', 'David Howard Thornton', 'Gr...	5	7.000	1200000	Z	950000	

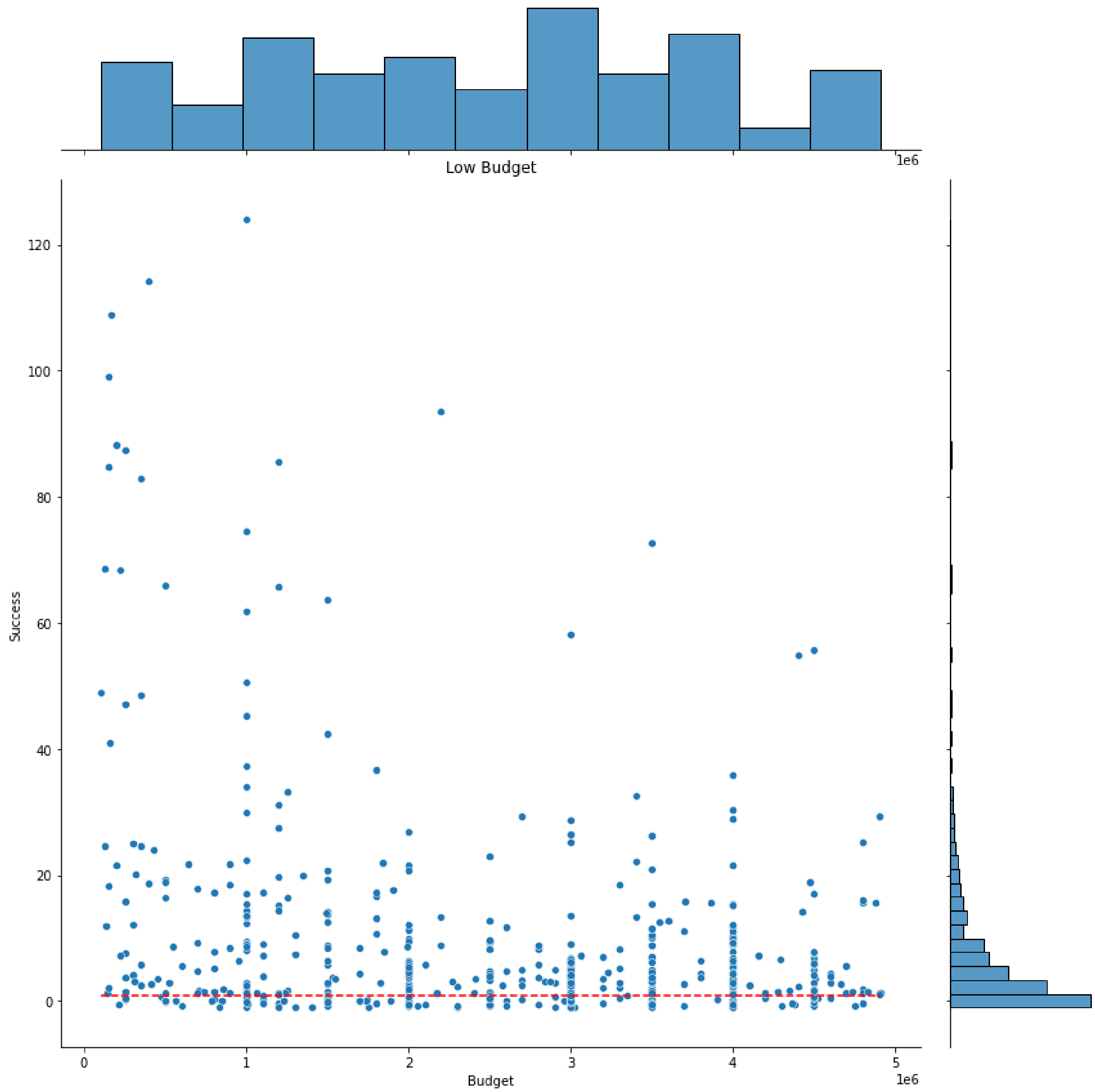
527 rows × 11 columns

In [36]:
```
low_budget['Success'].describe()
```

Out[36]:
```
count    527.00000
mean       9.45578
std       17.26949
min       -0.99170
25%        0.73215
50%        3.54940
75%        9.63355
max      124.00280
Name: Success, dtype: float64
```

In [37]:
```
# Distribution of Success of High budget film
f = plt.figure(figsize=(30, 16))
sb.jointplot(data = low_budget, x = "Budget", y = "Success", height = 12)

#plt.plot([range of x], [range of y], style, color)
plt.plot([low_budget['Budget'].min(),low_budget['Budget'].max()],[1,1],'--',color
plt.title("Low Budget")
plt.savefig("plots\LowBudgetvsSuccess_plot.png")
```

```
<Figure size 2160x1152 with 0 Axes>
```



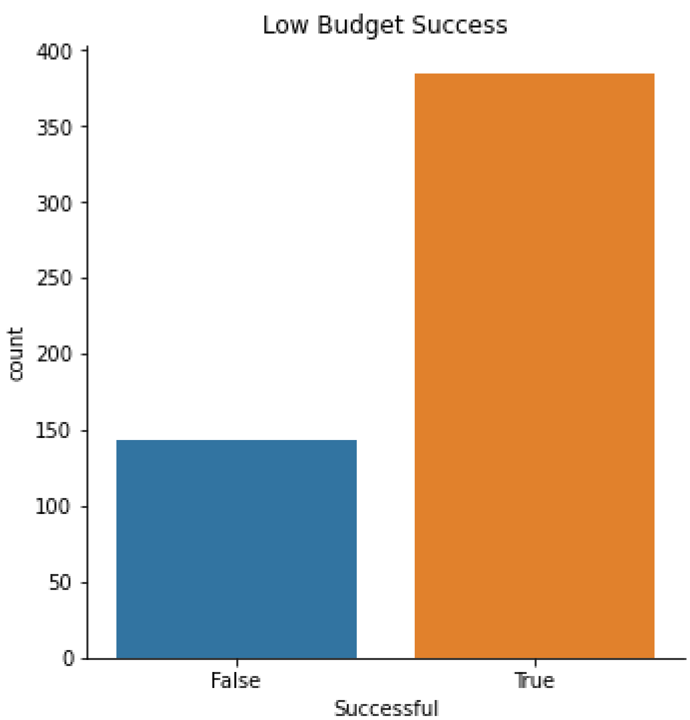
From this plot, it can be seen that lower budget films(<5mil) have less movies under the threshold(Success<1) than higher budget movies.

In [38]:
```
# Comparison of Successful vs Unsuccessful
low_budget_success = low_budget['Successful']
low_budget_success.value_counts()
```

Out[38]:
```
True     384
False    143
Name: Successful, dtype: int64
```

In [39]:
```
# Plotting
f = plt.figure(figsize=(30, 16))
sb.catplot(x = 'Successful',data = low_budget, kind = "count", orient ="h")
plt.title("Low Budget Success")
plt.savefig("plots/low_budget_success.png") #Save plot
```

```
<Figure size 2160x1152 with 0 Axes>
```



With more than twice as many successful movies than unsuccessful movies, it goes to show that low budget films **does not** equate to unsuccessful film and that the correlation might be that higher budget movies have a higher chance of failure instead

---

3. Machine Learning

Table of Contents

Models used

1. Decision Tree Classifier

2. Random Forest Classifier
3. TPOT Classifier

Model Optimization

1. Manually Find Best Parameter Value
2. GridSearchCV
3. Tpot vs GridSearchCV

Creating New Dataset

As `Casts` and `Genres` are categorical data, they are stored as strings

- For example genres = `'["Adventure","Action"]`, therefore genres[0] will output `[`
- Need to create individual columns for each genre

Adventure	Action	Drama	...
1	0	1	...
0	0	1	...
1	1	0	...

- For `Genres`, check whether Movie contains the top 1000 cast
- create a column that shows whether it has popular cast

Popular Cast
1
0
0
1

Genre Appending

In [40]:
```
# Creating dictionary of genres
genre_ml_dict = {}
for genre in Genre_df.columns:
    genre_ml_dict[genre] = []

# Looping through movie data to append value
for i,string_rows in enumerate(movie_data['Genres']) :
    list_row = string_to_list(string_rows)

    # Loop through genre dictionary
    for genre in genre_ml_dict:
        if genre in list_row :
            genre_ml_dict[genre].append(1)
        else :
            genre_ml_dict[genre].append(0)

# Dataframe of only genres
genre_ml_df = pd.DataFrame(genre_ml_dict)
genre_ml_df
```

Out[40]:

	Adventure	Action	Thriller	Comedy	Drama	Romance	History	War	ScienceFiction	Family
0	1	1	0	0	0	0	0	0	0	0
1	1	1	1	0	0	0	0	0	0	0
2	0	0	0	1	0	0	0	0	0	0
3	1	0	0	0	1	1	0	0	0	0
4	0	0	0	1	1	1	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
5335	0	0	0	0	1	1	1	0	0	0
5336	0	0	1	0	1	0	0	0	0	0
5337	0	0	0	0	1	0	0	0	0	0
5338	0	0	1	0	0	0	0	0	0	0
5339	0	1	1	0	0	0	0	0	0	0

5340 rows × 20 columns

In [41]:
```
# Join the genre dataframe with main dataframe
ml_df = movie_data.join(genre_ml_df)
ml_df
```

Out[41]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen	Profit
0	Raiders of the Lost Ark	['Adventure', 'Action']	18000000	['Harrison Ford', 'Karen Allen', 'Paul Freeman...	10400	7.922	389925971	X	371925971
1	For Your Eyes Only	['Adventure', 'Action', 'Thriller']	28000000	['Roger Moore', 'Carole Bouquet', 'Lynn-Holly ...	1478	6.477	195312802	X	167312802
2	Porky's	['Comedy']	4000000	['Kim Cattrall']	690	6.419	125728258	X	121728258
3	On Golden Pond	['Adventure', 'Drama', 'Romance']	15000000	['Henry Fonda', 'Jane Fonda', 'Dabney Coleman']	359	7.333	119285432	X	104285432
4	Arthur	['Comedy', 'Drama', 'Romance']	7000000	['Paul Gleason', 'Mark Margolis']	335	6.530	95461682	X	88461682
...	...	...	...	...	...	...	...	...	...
5335	The King's Daughter	['Fantasy', 'Drama', 'Romance', 'History']	40500000	['Pierce Brosnan', 'Kaya Scodelario', 'Benjami...	574	7.251	2182492	Z	-38317508
5336	Infinite Storm	['Drama', 'Thriller']	4749917	['Naomi Watts', "Denis O'Hare"]	90	6.206	1564696	Z	-3185221
5337	Les passagers de la nuit	['Drama']	4300000	['Charlotte Gainsbourg', 'Emmanuelle Béart']	44	7.023	1396831	Z	-2903169
5338	Terrifier 2	['Horror', 'Thriller']	250000	['Lauren LaVera', 'David Howard Thornton', 'Gr...	5	7.000	1200000	Z	950000
5339	Gold	['Thriller', 'Action']	6500000	['Zac Efron']	393	6.295	176048	Z	-6323952

5340 rows × 31 columns

Top 700 cast column

In [42]:
```
top_casts = list(cast_df[:700].index)

popular_cast_list = []

for i,string_rows in enumerate(movie_data['Casts']) :
    list_row = string_to_list(string_rows)
    common_names = [name for name in list_row if name in top_casts] # if names in
    if common_names :
        popular_cast_list.append(1)
    else :
        popular_cast_list.append(0)

ml_df['Popular Casts'] = popular_cast_list
ml_df
```

Out[42]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen	Profit
0	Raiders of the Lost Ark	['Adventure', 'Action']	18000000	['Harrison Ford', 'Karen Allen', 'Paul Freeman...	10400	7.922	389925971	X	371925971
1	For Your Eyes Only	['Adventure', 'Action', 'Thriller']	28000000	['Roger Moore', 'Carole Bouquet', 'Lynn-Holly ...	1478	6.477	195312802	X	167312802
2	Porky's	['Comedy']	4000000	['Kim Cattrall']	690	6.419	125728258	X	121728258
3	On Golden Pond	['Adventure', 'Drama', 'Romance']	15000000	['Henry Fonda', 'Jane Fonda', 'Dabney Coleman']	359	7.333	119285432	X	104285432
4	Arthur	['Comedy', 'Drama', 'Romance']	7000000	['Paul Gleason', 'Mark Margolis']	335	6.530	95461682	X	88461682
...	...	...	...	...	...	...	...	...	...
5335	The King's Daughter	['Fantasy', 'Drama', 'Romance', 'History']	40500000	['Pierce Brosnan', 'Kaya Scodelario', 'Benjami...	574	7.251	2182492	Z	-38317508
5336	Infinite Storm	['Drama', 'Thriller']	4749917	['Naomi Watts', "Denis O'Hare"]	90	6.206	1564696	Z	-3185221
5337	Les passagers de la nuit	['Drama']	4300000	['Charlotte Gainsbourg', 'Emmanuelle Béart']	44	7.023	1396831	Z	-2903169

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue	Gen	Profit
5338	Terrifier 2	['Horror', 'Thriller']	250000	['Lauren LaVera', 'David Howard Thornton', 'Gr...	5	7.000	1200000	Z	950000
5339	Gold	['Thriller', 'Action']	6500000	['Zac Efron']	393	6.295	176048	Z	-6323952

5340 rows × 32 columns

In [43]:
```
ml_df['Popular Casts'].value_counts()
```

Out[43]:
```
1    4484
0     856
Name: Popular Casts, dtype: int64
```

There are 4483 movies with popular casts while only 856 movies without.

3.1 Decision Tree Classifier

In [116]:
```
# Import Decision Tree Classifier model from Scikit-Learn
from sklearn.tree import DecisionTreeClassifier

# Plot the trained Decision Tree
from sklearn.tree import plot_tree

# Import essential models and functions from sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix

# For Exporting trained models
import pickle
```

For train-test split, change random_state to try different mix up the dataset. Every random_state is a specific combination of train-test data, hence change the number to **any integer** and test the accuracy. Remember the state with the best accuracy and always use that state

In [117]:
```
# Columns Required
columns_required = [idx for idx in ml_df.columns[11:]] # All columns from index 1
columns_required.append('Budget') # Adding Budget to part of dataframe column

# Extract Response and Predictors
y = pd.DataFrame(ml_df['Successful'])
X = pd.DataFrame(ml_df[columns_required])

# Split the Dataset into Train and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, randon
```

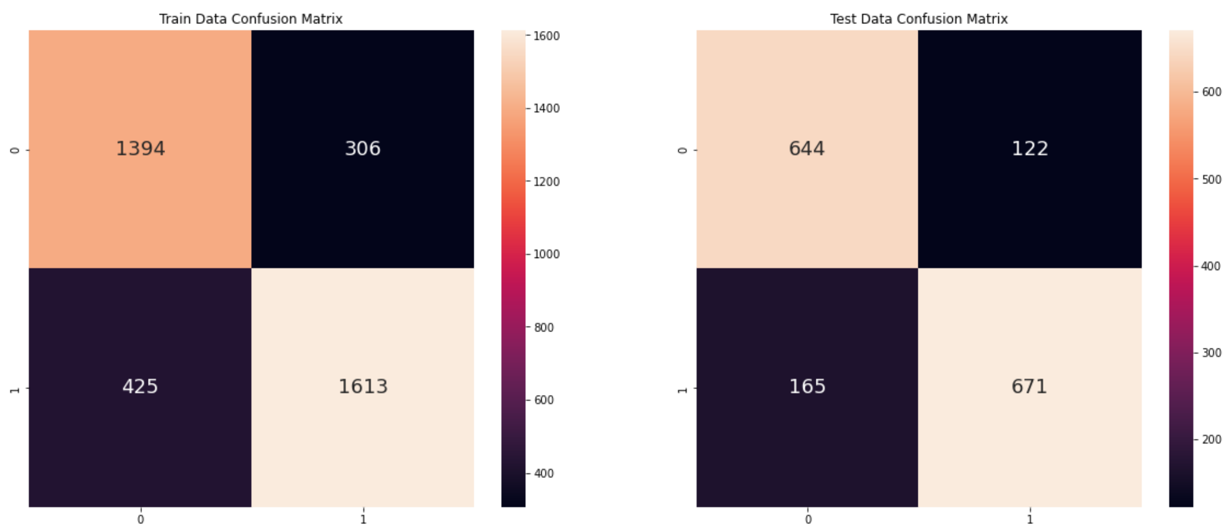
In [127]:
```
# Creating Decision Tree Model
dectree = DecisionTreeClassifier(max_depth = 100)  # create the decision tree moc
dectree.fit(X_train, y_train)                     # train the decision tree model

# Exporting Model so that do not need to re-train model with each refresh
with open('dectree_untuned.pkl', 'wb') as f:
    pickle.dump(dectree , f)
```

In [398]:
```
# Plotting the Tree for visualisation
# Do NOT plot if more than depth of 4 because it lags and nothing can be seen any
f = plt.figure(figsize=(24,24))
plot_tree(dectree, filled=True, rounded=True,
          feature_names=X_train.columns,
          class_names=["0","1"])
```

...

In [132]:
```
# Predict Legendary values corresponding to Total
y_train_pred = dectree.predict(X_train)
y_test_pred = dectree.predict(X_test)


# Confusion Matrix
cm_train = confusion_matrix(y_train, y_train_pred)
cm_test = confusion_matrix(y_test, y_test_pred)

# Plot the Confusion Matrix
fig, ax = plt.subplots(1,2,figsize=(20, 8))

# CM for Train Data
sb.heatmap(cm_train,
           annot = True, fmt=".0f", annot_kws={"size": 18},ax=ax[0])
ax[0].set_title("Train Data Confusion Matrix")

# CM for Test Data
sb.heatmap(cm_test,
           annot = True, fmt=".0f", annot_kws={"size": 18},ax=ax[1])
ax[1].set_title("Test Data Confusion Matrix")
```

Out[132]:
```
Text(0.5, 1.0, 'Test Data Confusion Matrix')
```



Classification Accuracy

- `TPR = TP / (TP + FN)` : True Positive Rate = True Positives / All Positives
- `TNR = TN / (TN + FP)` : True Negative Rate = True Negatives / All Negatives
- `FPR = FP / (TN + FP)` : False Positive Rate = False Positives / All Negatives
- `FNR = FN / (TP + FN)` : False Negative Rate = False Negatives / All Positives

In [133]:
```
# Number of Rows for each dataset
length_train = X_train.shape[0]
length_test = X_test.shape[0]

# Train data accuracy
tn_train, fp_train, fn_train, tp_train = cm_train[0][0],cm_train[0][1],cm_train[1

# Accuracy Measures
train_tr_neg = tn_train/(tn_train+fp_train)
train_fa_pos = (fp_train/(tn_train+fp_train))
train_fa_neg = (fn_train/(fn_train+tp_train))
train_tr_pos = (tp_train/(fn_train+tp_train))
train_acc = (tp_train+tn_train)/length_train
train_inacc = 1 - train_acc

# Test data accuracy
tn_test, fp_test, fn_test, tp_test= cm_test[0][0],cm_test[0][1],cm_test[1][0],cm_

# Accuracy Measures
test_tr_neg = tn_test/(tn_test+fp_test)
test_fa_pos = (fp_test/(tn_train+fp_test))
test_fa_neg = (fn_test/(fn_test+tp_test))
test_tr_pos = (tp_test/(fn_test+tp_test))
test_acc = (tp_test+tn_test)/length_test
test_inacc = 1 - test_acc
```

In [134]:
```
# Printing Dataframe of accuracy measures

# Dictionary of measures
accuracy_dict = {'class_acc': ['tr_neg', 'fa_pos', 'fa_neg','tr_pos', 'acc', 'ina
       'train': [train_tr_neg, train_fa_pos, train_fa_neg,train_tr_pos, train_acc
       'test': [test_tr_neg, test_fa_pos, test_fa_neg,test_tr_pos, test_acc, test

# Dictionary to dataframe
accuracy_df = pd.DataFrame(accuracy_dict)
accuracy_df
```

Out[134]:

	class_acc	train	test
0	tr_neg	0.820000	0.840731
1	fa_pos	0.180000	0.080475
2	fa_neg	0.208538	0.197368
3	tr_pos	0.791462	0.802632
4	acc	0.804441	0.820849
5	inacc	0.195559	0.179151

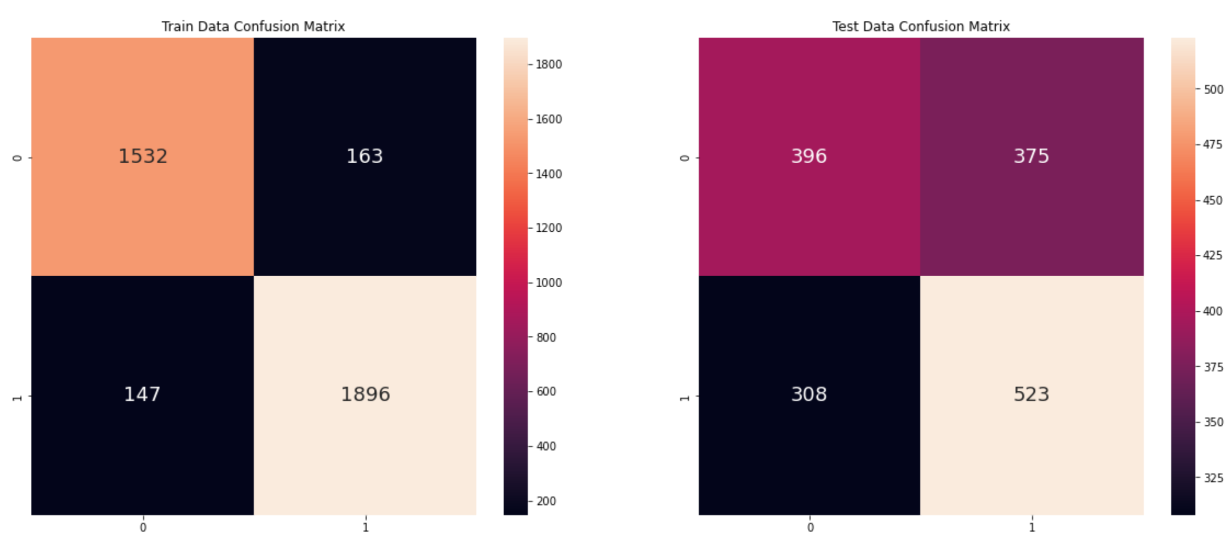
With a depth of **100**, the accuracy on the test data is around 56%, there is **not enough evidence** to show a direct impact on **Success** by the factors mentioned. However, the train data accuracy is 91% which would mean that there is some correlation between the factors and its "Successful-ness"

3.2 Random Forest Classifier

In [60]:
```
from sklearn.ensemble import RandomForestClassifier

# Creating the model
randomforest = RandomForestClassifier(max_depth=100, random_state=0, n_estimators
randomforest.fit(X_train, y_train['Successful']) #Used y_train['Successful'] inst

# Exporting Model so that do not need to re-train model with each refresh
with open('randomforest_untuned.pkl', 'wb') as f:
    pickle.dump(randomforest , f)
```

In [61]:
```
# Predicting Results
y_train_pred = randomforest.predict(X_train)
y_test_pred = randomforest.predict(X_test)

# Confusion Matrix
cm_train = confusion_matrix(y_train, y_train_pred)
cm_test = confusion_matrix(y_test, y_test_pred)

# Plot the Confusion Matrix
fig, ax = plt.subplots(1,2,figsize=(20, 8))

# CM for Train Data
sb.heatmap(cm_train,
           annot = True, fmt=".0f", annot_kws={"size": 18},ax=ax[0])
ax[0].set_title("Train Data Confusion Matrix")

# CM for Test Data
sb.heatmap(cm_test,
           annot = True, fmt=".0f", annot_kws={"size": 18},ax=ax[1])
ax[1].set_title("Test Data Confusion Matrix")
```

Out[61]:
```
Text(0.5, 1.0, 'Test Data Confusion Matrix')
```



In [62]:
```
# Number of Rows for each dataset
length_train = X_train.shape[0]
length_test = X_test.shape[0]

# Train data accuracy
tn_train, fp_train, fn_train, tp_train = cm_train[0][0],cm_train[0][1],cm_train[1

# Accuracy Measures
train_tr_neg = tn_train/(tn_train+fp_train)
train_fa_pos = (fp_train/(tn_train+fp_train))
train_fa_neg = (fn_train/(fn_train+tp_train))
train_tr_pos = (tp_train/(fn_train+tp_train))
train_acc = (tp_train+tn_train)/length_train
train_inacc = 1 - train_acc

# Test data accuracy
tn_test, fp_test, fn_test, tp_test= cm_test[0][0],cm_test[0][1],cm_test[1][0],cm_

# Accuracy Measures
test_tr_neg = tn_test/(tn_test+fp_test)
test_fa_pos = (fp_test/(tn_train+fp_test))
test_fa_neg = (fn_test/(fn_test+tp_test))
test_tr_pos = (tp_test/(fn_test+tp_test))
test_acc = (tp_test+tn_test)/length_test
test_inacc = 1 - test_acc
```

In [63]:
```
# Printing Dataframe of accuracy measures

# Dictionary of measures
accuracy_dict = {'class_acc': ['tr_neg', 'fa_pos', 'fa_neg','tr_pos', 'acc', 'ina
       'train': [train_tr_neg, train_fa_pos, train_fa_neg,train_tr_pos, train_acc
       'test': [test_tr_neg, test_fa_pos, test_fa_neg,test_tr_pos, test_acc, test

# Dictionary to dataframe
accuracy_df = pd.DataFrame(accuracy_dict)
accuracy_df
```

Out[63]:

	class_acc	train	test
0	tr_neg	0.903835	0.513619
1	fa_pos	0.096165	0.196644
2	fa_neg	0.071953	0.370638
3	tr_pos	0.928047	0.629362
4	acc	0.917068	0.573658
5	inacc	0.082932	0.426342

With a depth of **100**, the accuracy on the test data is around 57%, there is **not enough evidence** to show a direct impact on **Success** by the factors mentioned however, as the accuracy of train data is around 91.5%, it shows that there is a correlation and therefore could be tuned to achieve better results

3.3 TPOT Classifier

- Tpot is an automated machine learning package in python that uses genetic programming concepts to optimize the machine learning pipeline
- Automates the machine learning by intelligently exploring thousands of the possible to find the best possible parameter that suits data
- TPOT Documentation Site (http://epistasislab.github.io/tpot/api/)
- RepeatedKFolds Documentation Site (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RepeatedKFold.html)

In [204]:
```
# Required libraries
from tpot import TPOTClassifier
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import SelectFromModel, SelectKBest, f_regression
from sklearn.linear_model import Lasso
"""For Optimization of ML by KFolds"""
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import cross_val_score

# 1st Tpot try
cv = RepeatedKFold(n_splits=5, n_repeats=10, random_state=1)
tpot = TPOTClassifier(template = 'Classifier', generations=20, population_size=20
```

In [206]:
```
tpot.fit(X_train, y_train['Successful'])
```

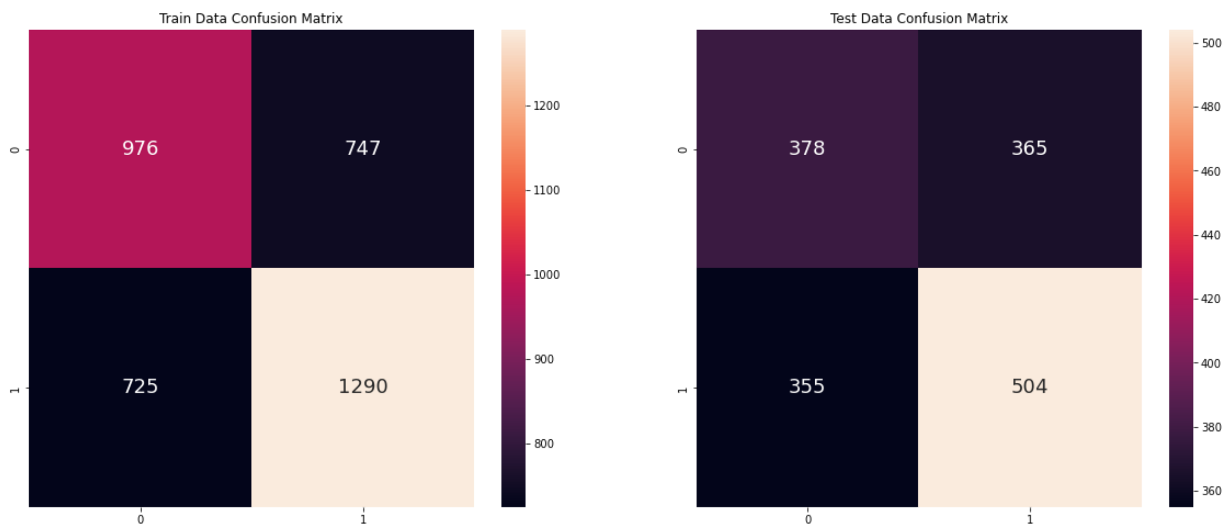
```
HBox(children=(FloatProgress(value=0.0, description='Optimization Progress', ma
x=4200.0, style=ProgressStyle(d…


Generation 1 - Current best internal CV score: -0.4021105455690857

Generation 2 - Current best internal CV score: -0.4021105455690857

Generation 3 - Current best internal CV score: -0.40186958171366394

Generation 4 - Current best internal CV score: -0.40186958171366394


TPOT closed during evaluation in one generation.
WARNING: TPOT may not provide a good pipeline if TPOT is stopped/interrupted in
a early generation.


TPOT closed prematurely. Will use the current best pipeline.

Best pipeline: XGBClassifier(input_matrix, learning_rate=0.1, max_depth=1, min_
child_weight=18, n_estimators=100, n_jobs=1, subsample=0.8500000000000001, verb
osity=0)
```

Out[206]:
```
TPOTClassifier(cv=RepeatedKFold(n_repeats=10, n_splits=5, random_state=1),
               generations=20, n_jobs=-1, population_size=200, random_state=1,
               scoring='neg_mean_squared_error', template='Classifier',
               verbosity=2)
```

In [211]:
```
TPOT_model = model.fitted_pipeline_
with open('tpot_new.pkl', 'wb') as f: #Exporting model to a pickle file so that t
    pickle.dump(TPOT_model , f)
```

In [207]:
```
# Predicting Results
y_train_pred = tpot.predict(X_train)
y_test_pred = tpot.predict(X_test)

# Confusion Matrix
cm_train = confusion_matrix(y_train, y_train_pred)
cm_test = confusion_matrix(y_test, y_test_pred)

# Plot the Confusion Matrix
fig, ax = plt.subplots(1,2,figsize=(20, 8))

# CM for Train Data
sb.heatmap(cm_train,
           annot = True, fmt=".0f", annot_kws={"size": 18},ax=ax[0])
ax[0].set_title("Train Data Confusion Matrix")

# CM for Test Data
sb.heatmap(cm_test,
           annot = True, fmt=".0f", annot_kws={"size": 18},ax=ax[1])
ax[1].set_title("Test Data Confusion Matrix")
```

Out[207]:
```
Text(0.5, 1.0, 'Test Data Confusion Matrix')
```



In [208]:
```
# Number of Rows for each dataset
length_train = X_train.shape[0]
length_test = X_test.shape[0]

# Train data accuracy
tn_train, fp_train, fn_train, tp_train = cm_train[0][0],cm_train[0][1],cm_train[1

# Accuracy Measures
train_tr_neg = tn_train/(tn_train+fp_train)
train_fa_pos = (fp_train/(tn_train+fp_train))
train_fa_neg = (fn_train/(fn_train+tp_train))
train_tr_pos = (tp_train/(fn_train+tp_train))
train_acc = (tp_train+tn_train)/length_train
train_inacc = 1 - train_acc

# Test data accuracy
tn_test, fp_test, fn_test, tp_test= cm_test[0][0],cm_test[0][1],cm_test[1][0],cm_

# Accuracy Measures
test_tr_neg = tn_test/(tn_test+fp_test)
test_fa_pos = (fp_test/(tn_train+fp_test))
test_fa_neg = (fn_test/(fn_test+tp_test))
test_tr_pos = (tp_test/(fn_test+tp_test))
test_acc = (tp_test+tn_test)/length_test
test_inacc = 1 - test_acc
```

In [209]:
```
# Printing Dataframe of accuracy measures

# Dictionary of measures
accuracy_dict = {'class_acc': ['tr_neg', 'fa_pos', 'fa_neg','tr_pos', 'acc', 'ina
       'train': [train_tr_neg, train_fa_pos, train_fa_neg,train_tr_pos, train_acc
       'test': [test_tr_neg, test_fa_pos, test_fa_neg,test_tr_pos, test_acc, test

# Dictionary to dataframe
accuracy_df = pd.DataFrame(accuracy_dict)
accuracy_df
```

Out[209]:

	class_acc	train	test
0	tr_neg	0.566454	0.508748
1	fa_pos	0.433546	0.272185
2	fa_neg	0.359801	0.413271
3	tr_pos	0.640199	0.586729
4	acc	0.606207	0.550562
5	inacc	0.393793	0.449438

After training and optimising a model using TPOT, the accuracy of the test data **remains similar** at 55% accuracy.

Optimising Models

Decision Tree Model

In [120]:
```
# Creating a function to call for prediction

def Dec_tree_pred(max_depth, X_train, y_train, X_test, y_test):
    # Creating Decision Tree Model
    dectree = DecisionTreeClassifier(max_depth = max_depth)  # create the decisio
    dectree.fit(X_train, y_train)                            # train the decision tree mo

    # Predict Legendary values corresponding to Total
    y_train_pred = dectree.predict(X_train)
    y_test_pred = dectree.predict(X_test)


    # Confusion Matrix
    cm_train = confusion_matrix(y_train, y_train_pred)
    cm_test = confusion_matrix(y_test, y_test_pred)

    # Number of Rows for each dataset
    length_train = X_train.shape[0]
    length_test = X_test.shape[0]

    # Train data accuracy
    tn_train, fp_train, fn_train, tp_train = cm_train[0][0],cm_train[0][1],cm_tra

    # Accuracy Measures
    train_tr_neg = tn_train/(tn_train+fp_train)
    train_fa_pos = (fp_train/(tn_train+fp_train))
    train_fa_neg = (fn_train/(fn_train+tp_train))
    train_tr_pos = (tp_train/(fn_train+tp_train))
    train_acc = (tp_train+tn_train)/length_train
    train_inacc = 1 - train_acc

    # Test data accuracy
    tn_test, fp_test, fn_test, tp_test= cm_test[0][0],cm_test[0][1],cm_test[1][0]

    # Accuracy Measures
    test_tr_neg = tn_test/(tn_test+fp_test)
    test_fa_pos = (fp_test/(tn_train+fp_test))
    test_fa_neg = (fn_test/(fn_test+tp_test))
    test_tr_pos = (tp_test/(fn_test+tp_test))
    test_acc = (tp_test+tn_test)/length_test
    test_inacc = 1 - test_acc

    # Dictionary of measures
    accuracy_dict = {'class_acc': ['tr_neg', 'fa_pos', 'fa_neg','tr_pos', 'acc',
           'train': [train_tr_neg, train_fa_pos, train_fa_neg,train_tr_pos, trair
           'test': [test_tr_neg, test_fa_pos, test_fa_neg,test_tr_pos, test_acc,

    # Dictionary to dataframe
    accuracy_df = pd.DataFrame(accuracy_dict)

    return test_acc, accuracy_df, dectree
```

In [121]:
```
# Manually looping Through all the max_depth to see which produces best results
max_depth_range = [2,3,4,5,7,10,20,50,60,75,80,100,125,150,175,200,250,300,400,50

max_acc = 0
acc_list = [] # For plotting
for depth in max_depth_range:
    acc, acc_df, dec_model = Dec_tree_pred(depth, X_train, y_train, X_test, y_tes
    acc_list.append(acc)
    if acc > max_acc :
        max_acc = acc
        best_df = acc_df
        best_depth = depth

        #Saving Tuned Model
        with open('dectree_tuned.pkl', 'wb') as f:
            pickle.dump(dec_model , f)

print(f"Best Accuracy : {max_acc}, best depth : {best_depth}")
best_df
```

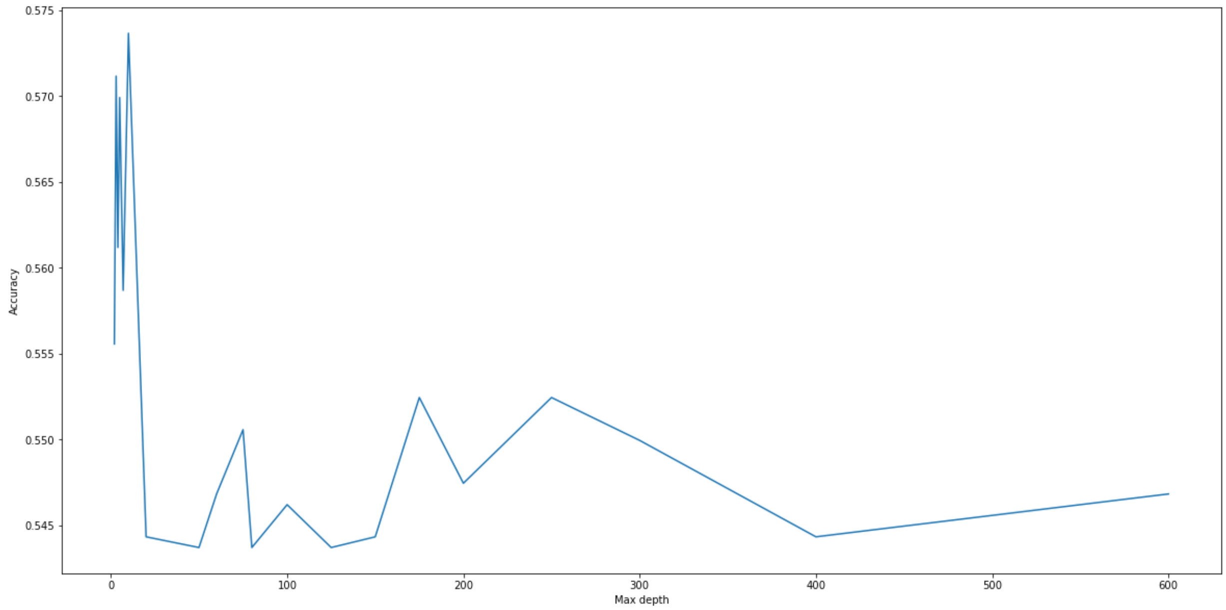
```
Best Accuracy : 0.5736579275905118, best depth : 10
```

Out[121]:

	class_acc	train	test
0	tr_neg	0.678235	0.588773
1	fa_pos	0.321765	0.214578
2	fa_neg	0.322866	0.440191
3	tr_pos	0.677134	0.559809
4	acc	0.677635	0.573658
5	inacc	0.322365	0.426342

In [122]:
```
f = plt.figure(figsize=(20,10))
plt.plot(max_depth_range,acc_list)
plt.ylabel("Accuracy")
plt.xlabel("Max depth")
```

Out[122]:
```
Text(0.5, 0, 'Max depth')
```



As can be seen from the accuracy plot, we can see that after max_depth > 80, the graph starts to saturate and max_depth does not affect the accuracy of the model as much. Therefore, we can conclude that **max depth > 100** is the optimal depth for an accurate prediction

---

Random Forest Model

- Finding the best 3 values for each parameter
- Using `GridSearchCV` to choose the best value for the best accuracy

In [73]:
```
# Creating a function to call for prediction

def Rand_For_pred(X_train, y_train, X_test, y_test, max_depth=100, n_estimators=1
                  min_samples_split=2, bootstrap=True, random_state=0, max_featur
    # Creating the model
    clf = RandomForestClassifier( max_depth=max_depth,
                                  n_estimators=n_estimators,
                                  min_samples_leaf=min_samples_leaf,
                                  min_samples_split=min_samples_split,
                                  bootstrap=bootstrap,
                                  random_state= random_state,
                                  max_features=max_features)

    clf.fit(X_train, y_train['Successful']) #Used y_train['Successful'] instead o

    # Predict Legendary values corresponding to Total
    y_train_pred = clf.predict(X_train)
    y_test_pred = clf.predict(X_test)


    # Confusion Matrix
    cm_train = confusion_matrix(y_train, y_train_pred)
    cm_test = confusion_matrix(y_test, y_test_pred)

    # Number of Rows for each dataset
    length_train = X_train.shape[0]
    length_test = X_test.shape[0]

    # Train data accuracy
    tn_train, fp_train, fn_train, tp_train = cm_train[0][0],cm_train[0][1],cm_tra

    # Accuracy Measures
    train_tr_neg = tn_train/(tn_train+fp_train)
    train_fa_pos = (fp_train/(tn_train+fp_train))
    train_fa_neg = (fn_train/(fn_train+tp_train))
    train_tr_pos = (tp_train/(fn_train+tp_train))
    train_acc = (tp_train+tn_train)/length_train
    train_inacc = 1 - train_acc

    # Test data accuracy
    tn_test, fp_test, fn_test, tp_test= cm_test[0][0],cm_test[0][1],cm_test[1][0]

    # Accuracy Measures
    test_tr_neg = tn_test/(tn_test+fp_test)
    test_fa_pos = (fp_test/(tn_train+fp_test))
    test_fa_neg = (fn_test/(fn_test+tp_test))
    test_tr_pos = (tp_test/(fn_test+tp_test))
    test_acc = (tp_test+tn_test)/length_test
    test_inacc = 1 - test_acc

    # Dictionary of measures
    accuracy_dict = {'class_acc': ['tr_neg', 'fa_pos', 'fa_neg','tr_pos', 'acc',
           'train': [train_tr_neg, train_fa_pos, train_fa_neg,train_tr_pos, train
           'test': [test_tr_neg, test_fa_pos, test_fa_neg,test_tr_pos, test_acc,

    # Dictionary to dataframe
```

```
    accuracy_df = pd.DataFrame(accuracy_dict)

    return test_acc, accuracy_df
```

max_depth

In [74]:
```
# Manually Looping Through all the max_depth to see which produces best results
max_depth_range = [2,3,4,5,7,10,20,50,60,75,80,100,125,150,175,200,250,300,400,50

max_acc = 0
acc_depth_list = [] # For plotting
for depth in max_depth_range:
    acc, acc_df = Rand_For_pred(X_train, y_train, X_test, y_test,max_depth=depth)
    acc_depth_list.append(acc)
    if acc > max_acc :
        max_acc = acc
        best_df = acc_df
        best_depth = depth

print(f"Best Accuracy : {max_acc}, best depth : {best_depth}")
best_df
```

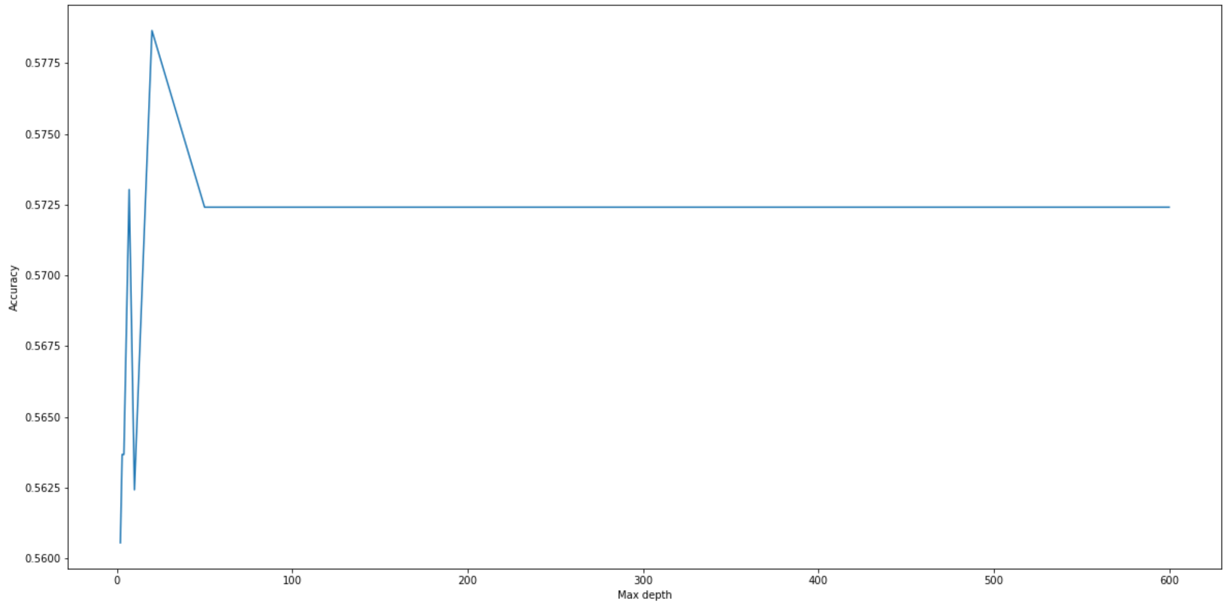
```
Best Accuracy : 0.5786516853932584, best depth : 20
```

Out[74]:

	class_acc	train	test
0	tr_neg	0.900885	0.512322
1	fa_pos	0.099115	0.197583
2	fa_neg	0.072442	0.359807
3	tr_pos	0.927558	0.640193
4	acc	0.915463	0.578652
5	inacc	0.084537	0.421348

In [75]:
```
f = plt.figure(figsize=(20,10))
plt.plot(max_depth_range,acc_depth_list)
plt.ylabel("Accuracy")
plt.xlabel("Max depth")
```

Out[75]: Text(0.5, 0, 'Max depth')



n_estimators

In [325]:
```
n_estimators_range = [50,100,200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 20

max_acc = 0
acc_nest_list = [] # For plotting
for n_estimator in n_estimators_range:
    acc, acc_df = Rand_For_pred(X_train, y_train, X_test, y_test,n_estimators=n_e
    acc_nest_list.append(acc)
    if acc > max_acc :
        max_acc = acc
        best_df = acc_df
        best_n_estimator = n_estimator

print(f"Best Accuracy : {max_acc}, best_n_estimator : {best_n_estimator}")
best_df
```

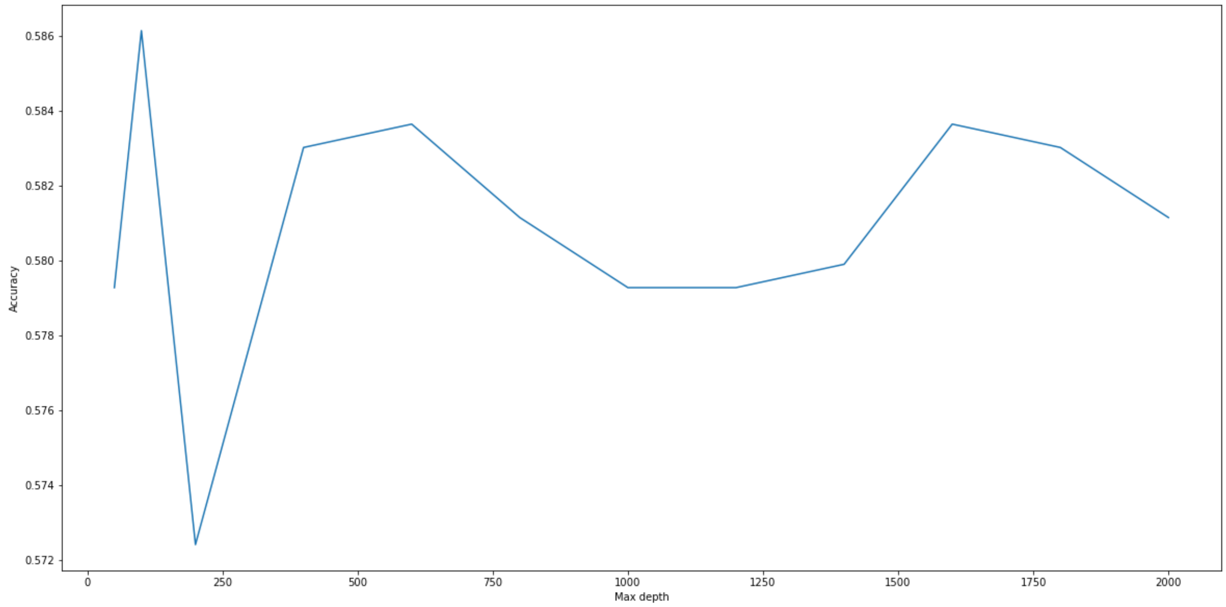
```
Best Accuracy : 0.5861423220973783, best_n_estimator : 100
```

Out[325]:

	class_acc	train	test
0	tr_neg	0.907719	0.549125
1	fa_pos	0.092281	0.176409
2	fa_neg	0.078412	0.381839
3	tr_pos	0.921588	0.618161
4	acc	0.915195	0.586142
5	inacc	0.084805	0.413858

In [326]:
```
f = plt.figure(figsize=(20,10))
plt.plot(n_estimators_range,acc_nest_list)
plt.ylabel("Accuracy")
plt.xlabel("N estimator")
```

Out[326]: Text(0.5, 0, 'Max depth')



min samples leaf

In [444]:
```
min_samples_leaf_range = [1, 2, 4,8, 10, 15, 17, 19 ,23]

max_acc = 0
acc_samLeaf_list = [] # For plotting
for samp_leaf in min_samples_leaf_range:
    acc, acc_df = Rand_For_pred(X_train, y_train, X_test, y_test,min_samples_leaf
    acc_samLeaf_list.append(acc)
    if acc > max_acc :
        max_acc = acc
        best_df = acc_df
        best_min_samples_leaf = samp_leaf

print(f"Best Accuracy : {max_acc}, best min_samples_leaf : {best_min_samples_leaf
best_df
```

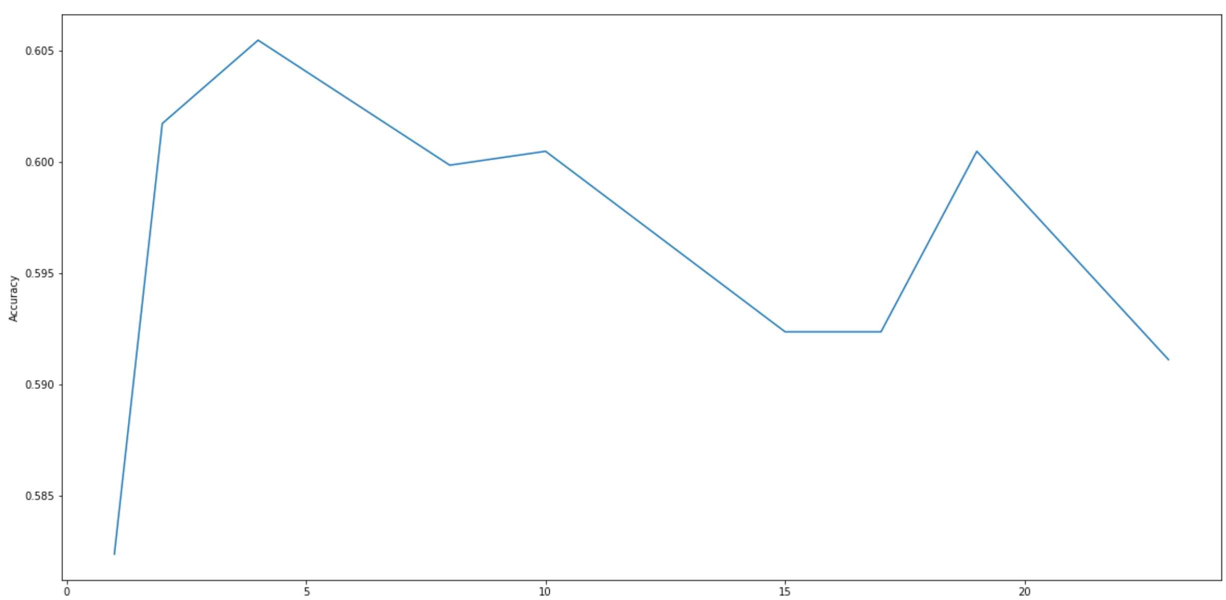
```
Best Accuracy : 0.6054931335830213, best min_samples_leaf : 4
```

Out[444]:

	class_acc	train	test
0	tr_neg	0.605568	0.494609
1	fa_pos	0.394432	0.264271
2	fa_neg	0.198113	0.298837
3	tr_pos	0.801887	0.701163
4	acc	0.711343	0.605493
5	inacc	0.288657	0.394507

In [445]:
```
f = plt.figure(figsize=(20,10))
plt.plot(min_samples_leaf_range,acc_samLeaf_list)
plt.ylabel("Accuracy")
plt.xlabel("Min sample leaf")
```

Out[445]: Text(0.5, 0, 'Max depth')



min samples split

In [447]:
```
min_samples_split_range = [2, 4,8, 10, 15, 17, 19 ,23]

max_acc = 0
acc_samSplit_list = [] # For plotting
for split in min_samples_split_range:
    acc, acc_df = Rand_For_pred(X_train, y_train, X_test, y_test,min_samples_spli
    acc_samSplit_list.append(acc)
    if acc > max_acc :
        max_acc = acc
        best_df = acc_df
        best_min_samples_split = split

print(f"Best Accuracy : {max_acc}, best min_samples_split : {best_min_samples_spl
best_df
```

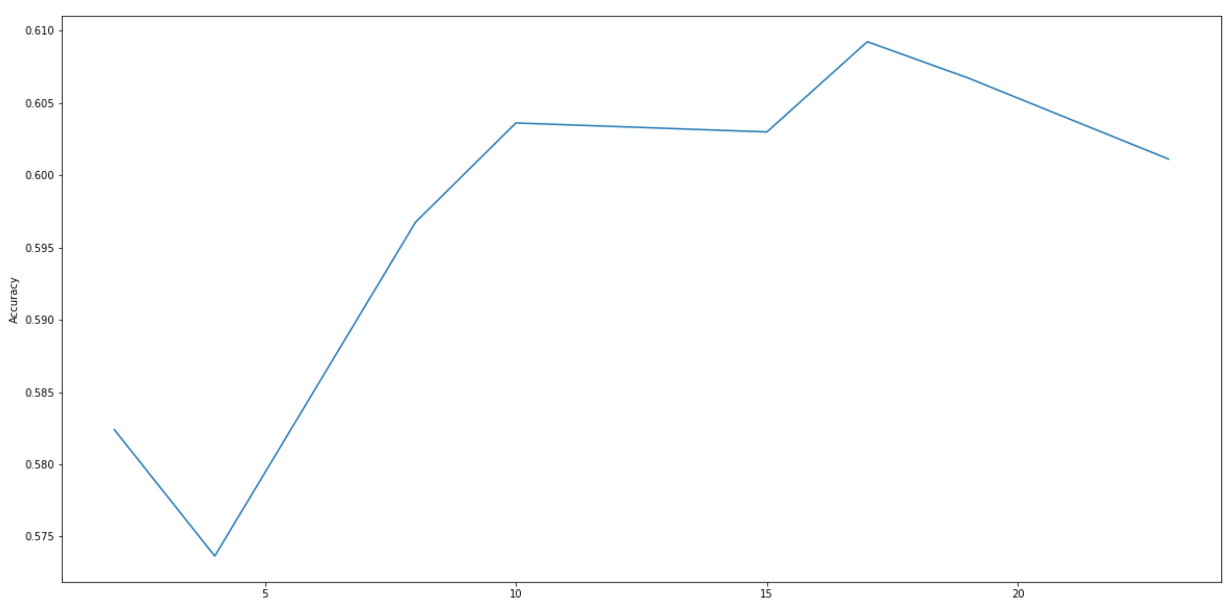
```
Best Accuracy : 0.6092384519350812, best min_samples_split : 17
```

Out[447]:

	class_acc	train	test
0	tr_neg	0.722158	0.528302
1	fa_pos	0.277842	0.219436
2	fa_neg	0.177259	0.320930
3	tr_pos	0.822741	0.679070
4	acc	0.776351	0.609238
5	inacc	0.223649	0.390762

In [448]:
```
f = plt.figure(figsize=(20,10))
plt.plot(min_samples_split_range, acc_samSplit_list)
plt.ylabel("Accuracy")
plt.xlabel("Min sample split")
```

Out[448]:
```
Text(0.5, 0, 'Max depth')
```



max features

In [453]:
```
max_features_range = [0.1,0.3,0.7,1,2,"sqrt","log2",None]

max_acc = 0
acc_max_features_list = [] # For plotting
for feature in max_features_range:
    acc, acc_df = Rand_For_pred(X_train, y_train, X_test, y_test,max_features=fea
    acc_max_features_list.append(acc)
    if acc > max_acc :
        max_acc = acc
        best_df = acc_df
        best_max_features = feature

print(f"Best Accuracy : {max_acc}, best max_features : {feature}")
best_df
```

```
Best Accuracy : 0.5873907615480649, best max_features : None
```

Out[453]:

	class_acc	train	test
0	tr_neg	0.892691	0.513477
1	fa_pos	0.107309	0.190000
2	fa_neg	0.058093	0.348837
3	tr_pos	0.941907	0.651163
4	acc	0.919208	0.587391
5	inacc	0.080792	0.412609

Random State

In [442]:
```
import random
rand_list = [random.randrange(0,1000) for i in range(50)]
rand_list
```

Out[442]:
```
[948,
 22,
 426,
 857,
 938,
 569,
 944,
 657,
 102,
 190,
 644,
 741,
 880,
 303,
 123,
 760,
 340,
 917,
 738,
```

In [443]:
```
max_acc = 0
acc_rand_list = [] # For plotting
for ran_num in rand_list:
    acc, acc_df = Rand_For_pred(X_train, y_train, X_test, y_test,random_state=rar
    acc_rand_list.append(acc)
    if acc > max_acc :
        max_acc = acc
        best_df = acc_df
        best_random_state = ran_num

print(f"Best Accuracy : {max_acc}, best random_state : {best_random_state}")
best_df
```

```
Best Accuracy : 0.5848938826466916, best random_state : 873
```

Out[443]:

	class_acc	train	test
0	tr_neg	0.893852	0.516173
1	fa_pos	0.106148	0.188947
2	fa_neg	0.059086	0.355814
3	tr_pos	0.940914	0.644186
4	acc	0.919208	0.584894
5	inacc	0.080792	0.415106

GridSearchCV

- Exhaustive search the best parameters
- Compare with Best tpot model

In [351]:
```
from sklearn.model_selection import GridSearchCV
```

In [369]:
```
# Function to get the top 3 most accurate value for a parameter
def top3params(params_list, acc_list ):
    sorted_acc_lst = sorted(acc_list, reverse=True)[:3] #Get top 3 most accurate

    duplicate_idx = 0 # to loop through same number e.g. acc = [0.63,0.73,0.63,0.
    best_params = [] # List of best parameters
    for best_acc in sorted_acc_lst:
        index = acc_list.index(best_acc)
        value = params_list[index]

        if value not in best_params:
            best_params.append(value) # If there is a duplicate accuracy so it wo
            duplicate_idx = 0

        else :
            print(value)
            duplicate_idx += 1

            # Find the next index of the same value; e.g. in the above statement,
            actual_index = [i for i,n in enumerate(acc_list) if n == best_acc][du
            best_params.append(params_list[actual_index]) # Duplicate accuracy me


    return best_params

# Example : Depth
top3params(max_depth_range,acc_depth_list)
```

Out[369]: [60, 300, 75]

In [473]:
```
parameters = {
    'max_depth' : top3params(max_depth_range,acc_depth_list),
    'n_estimators' : top3params(n_estimators_range,acc_nest_list),
    'random_state' : top3params(rand_list,acc_rand_list),
    'criterion' : ["gini", "entropy", "log_loss"],
    'min_samples_leaf' : top3params(min_samples_leaf_range,acc_samLeaf_list),
    'min_samples_split' : top3params(min_samples_split_range, acc_samSplit_list),
    'max_features' : top3params(max_features_range,acc_max_features_list)

}

parameters
```

```
600
432
```

Out[473]:
```
{'max_depth': [60, 300, 75],
 'n_estimators': [100, 600, 1600],
 'random_state': [873, 432, 194],
 'criterion': ['gini', 'entropy', 'log_loss'],
 'min_samples_leaf': [4, 2, 10],
 'min_samples_split': [17, 19, 10],
 'max_features': [0.3, 1, 'sqrt']}
```

In [474]:
```
# Creating a Gridsearch of the parameters using Random Forest
# Will probably take super long maybe 5hr ?
randFor_tuned= GridSearchCV(RandomForestClassifier(), parameters)
randFor_tuned.fit(X_train, y_train['Successful'])
```

...

In [ ]:
```
with open('GridSearch_RF_tuned.pkl', 'wb') as f: #Exporting model to a pickle fil
    pickle.dump(randFor_tuned , f)
```

In [475]:
```
pd.DataFrame(randFor_tuned.cv_results_).sort_values(by='rank_test_score',ignore_i
```

Out[475]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_criterion	param_max_d
0	0.212909	0.009541	0.015463	0.003846	gini	
1	0.232979	0.018437	0.018350	0.001016	gini	
2	0.216043	0.003889	0.017026	0.004091	gini	
3	0.249670	0.019432	0.021216	0.006587	gini	
4	0.212740	0.004919	0.018148	0.000401	gini	
...	...	...	...	...	...	
2182	0.031915	0.003232	0.000000	0.000000	log_loss	
2183	0.196512	0.026987	0.000000	0.000000	log_loss	
2184	0.179867	0.015562	0.000000	0.000000	log_loss	
2185	0.440933	0.004065	0.000000	0.000000	log_loss	
2186	0.451313	0.018233	0.000000	0.000000	log_loss	

2187 rows × 20 columns

In [476]:
```
# Predict Legendary values corresponding to Total
y_train_pred = randFor_tuned.predict(X_train)
y_test_pred = randFor_tuned.predict(X_test)


# Confusion Matrix
cm_train = confusion_matrix(y_train, y_train_pred)
cm_test = confusion_matrix(y_test, y_test_pred)

# Number of Rows for each dataset
length_train = X_train.shape[0]
length_test = X_test.shape[0]

# Train data accuracy
tn_train, fp_train, fn_train, tp_train = cm_train[0][0],cm_train[0][1],cm_train[

# Accuracy Measures
train_tr_neg = tn_train/(tn_train+fp_train)
train_fa_pos = (fp_train/(tn_train+fp_train))
train_fa_neg = (fn_train/(fn_train+tp_train))
train_tr_pos = (tp_train/(fn_train+tp_train))
train_acc = (tp_train+tn_train)/length_train
train_inacc = 1 - train_acc

# Test data accuracy
tn_test, fp_test, fn_test, tp_test= cm_test[0][0],cm_test[0][1],cm_test[1][0],cm_

# Accuracy Measures
test_tr_neg = tn_test/(tn_test+fp_test)
test_fa_pos = (fp_test/(tn_train+fp_test))
test_fa_neg = (fn_test/(fn_test+tp_test))
test_tr_pos = (tp_test/(fn_test+tp_test))
test_acc = (tp_test+tn_test)/length_test
test_inacc = 1 - test_acc

# Dictionary of measures
accuracy_dict = {'class_acc': ['tr_neg', 'fa_pos', 'fa_neg','tr_pos', 'acc', 'ina
       'train': [train_tr_neg, train_fa_pos, train_fa_neg,train_tr_pos, train_acc
       'test': [test_tr_neg, test_fa_pos, test_fa_neg,test_tr_pos, test_acc, test

# Dictionary to dataframe
accuracy_df = pd.DataFrame(accuracy_dict)

accuracy_df
```

Out[476]:

	class_acc	train	test
0	tr_neg	0.568445	0.491914
1	fa_pos	0.431555	0.277819
2	fa_neg	0.239821	0.312791
3	tr_pos	0.760179	0.687209
4	acc	0.671750	0.596754
5	inacc	0.328250	0.403246

Despite tuning the hyper parameters, the model accuracy is only 59.6%

Comparing All Model Accuracy

In [89]:
```
# Function to predict data and show accuracy automatically

def model_accuracy(model_path, X_train,X_test,y_train,y_test):

    model_name = model_path[:-4] # Model name is the same as filename but without

    # Importing Model
    with open(model_path, 'rb') as f:
        model = pickle.load(f)

    # Predict Legendary values corresponding to Total
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)


    # Confusion Matrix
    cm_train = confusion_matrix(y_train, y_train_pred)
    cm_test = confusion_matrix(y_test, y_test_pred)

    # Number of Rows for each dataset
    length_train = X_train.shape[0]
    length_test = X_test.shape[0]

    # Train data accuracy
    tn_train, fp_train, fn_train, tp_train = cm_train[0][0],cm_train[0][1],cm_tra

    # Accuracy Measures
    train_tr_neg = tn_train/(tn_train+fp_train)
    train_fa_pos = (fp_train/(tn_train+fp_train))
    train_fa_neg = (fn_train/(fn_train+tp_train))
    train_tr_pos = (tp_train/(fn_train+tp_train))
    train_acc = (tp_train+tn_train)/length_train
    train_inacc = 1 - train_acc

    # Test data accuracy
    tn_test, fp_test, fn_test, tp_test= cm_test[0][0],cm_test[0][1],cm_test[1][0]

    # Accuracy Measures
    test_tr_neg = tn_test/(tn_test+fp_test)
    test_fa_pos = (fp_test/(tn_train+fp_test))
    test_fa_neg = (fn_test/(fn_test+tp_test))
    test_tr_pos = (tp_test/(fn_test+tp_test))
    test_acc = (tp_test+tn_test)/length_test
    test_inacc = 1 - test_acc

    # Dictionary of measures
    accuracy_dict = {
           model_name+'_train': [train_tr_neg, train_fa_pos, train_fa_neg,train_t
           model_name+'_test': [test_tr_neg, test_fa_pos, test_fa_neg,test_tr_pos
    }

    # Dictionary to dataframe
    accuracy_df = pd.DataFrame(accuracy_dict)

    return accuracy_df
```

In [90]:
```
pd.concat([model_accuracy('tpot_randomforest.pkl', X_train,X_test,y_train,y_test)
          model_accuracy('GridSearch_RF_tuned.pkl', X_train,X_test,y_train,y_test
```

Out[90]:

	tpot_randomforest_train	tpot_randomforest_test	GridSearch_RF_tuned_train	GridSearch_RF_tunec
0	0.611799	0.618677	0.549263	0.5:
1	0.388201	0.220887	0.450737	0.2
2	0.276554	0.273165	0.252570	0.2(
3	0.723446	0.726835	0.747430	0.7
4	0.672820	0.674782	0.657571	0.6:
5	0.327180	0.325218	0.342429	0.3

In [109]:
```
# listing all the model together
model_list = [file for file in os.listdir() if ".pkl" in file]
model_list
```

Out[109]:
```
['dectree_tuned.pkl',
 'dectree_untuned.pkl',
 'GridSearch_RF_tuned.pkl',
 'randomforest_untuned.pkl',
 'tpot_extratree.pkl',
 'tpot_randomforest.pkl']
```

In [118]:
```
import warnings
warnings.filterwarnings('ignore') # Warnings keep coming up but output is correct

# Initializing a dataframe
all_model_df = pd.DataFrame({
    'class_acc' : ['tr_neg', 'fa_pos', 'fa_neg','tr_pos', 'acc', 'inacc']
})

for model_path in model_list:
    all_model_df = pd.concat([all_model_df, model_accuracy(model_path, X_train,X_
```

Analysis of all models

In [119]:
```
all_model_df
```

Out[119]:

	class_acc	dectree_tuned_train	dectree_tuned_test	dectree_untuned_train	dectree_untuned_test
0	tr_neg	0.561765	0.567885	0.820000	0.840731
1	fa_pos	0.438235	0.257387	0.180000	0.080475
2	fa_neg	0.375368	0.381579	0.208538	0.197368
3	tr_pos	0.624632	0.618421	0.791462	0.802632
4	acc	0.596041	0.594257	0.804441	0.820849
5	inacc	0.403959	0.405743	0.195559	0.179151

Untuned Decision Tree Model has the **best accuracy** as compared to any other model with an accuracy of 82%
(Train-Test split: random_state = 73, test_size =0.3).

Testing Model on movies I want to create

Things I want in my movie

1. Genre : Action and Comedy
2. Cast : No popular casts, just a group of friends
3. Budget : 500,000

In [135]:
```
# Importing Best Model from above analysis
with open("dectree_untuned.pkl", 'rb') as f:
    model_selected = pickle.load(f)

model_selected
```

Out[135]:
```
DecisionTreeClassifier(max_depth=100)
```

In [136]:
```
# Creating DataFrame
genre_wanted = ['Action','Comedy']
popular_cast = 0
budget = 500_000

# Creating dictionary of genres
genre_ml_dict = {}
for genre in Genre_df.columns:
    if genre in genre_wanted :
        genre_ml_dict[genre] = 1

    else :
        genre_ml_dict[genre] = 0

my_movie_df = pd.DataFrame(genre_ml_dict, index = [0])
my_movie_df['Popular Casts'] = popular_cast
my_movie_df['Budget'] = budget

result = model_selected.predict(my_movie_df)

if result[0] : # If results is true
    print(f"My Movie is successful")

else :
    print(f"My Movie is unsuccessful")
```

```
My Movie is successful
```

Example of Unsuccessful movie

In [137]:

```
# Creating DataFrame
genre_wanted = ['Drama','ScienceFiction']
popular_cast = 1
budget = 40_000_000

# Creating dictionary of genres
genre_ml_dict = {}
for genre in Genre_df.columns:
    if genre in genre_wanted :
        genre_ml_dict[genre] = 1

    else :
        genre_ml_dict[genre] = 0

my_movie_df = pd.DataFrame(genre_ml_dict, index = [0])
my_movie_df['Popular Casts'] = popular_cast
my_movie_df['Budget'] = budget

result = model_selected.predict(my_movie_df)

if result[0] : # If results is true
    print(f"My Movie is successful")

else :
    print(f"My Movie is unsuccessful")
```

```
My Movie is unsuccessful
```

Code Graveyard

Just for testing purpose

In [94]:
```
# 1.1 Response for API get
response = requests.get('https://api.themoviedb.org/3/movie/top_rated?api_key=aaa
print(response) #If response = 200, it is working; check http status code for oth
```

```
<Response [200]>
```

In [95]:
```python
# 1.2 Print response JSON
# Returns a dictionary
result = response.json()
result
```

Out[95]:

```
{'page': 1,
 'results': [{'adult': False,
   'backdrop_path': '/rSPw7tgCH9c6NqICZef4kZjFOQ5.jpg',
   'genre_ids': [18, 80],
   'id': 238,
   'original_language': 'en',
   'original_title': 'The Godfather',
   'overview': 'Spanning the years 1945 to 1955, a chronicle of the fictional
Italian-American Corleone crime family. When organized crime family patriarc
h, Vito Corleone barely survives an attempt on his life, his youngest son, Mi
chael steps in to take care of the would-be killers, launching a campaign of
bloody revenge.',
   'popularity': 100.336,
   'poster_path': '/3bhkrj58Vtu7enYsRolD1fZdja1.jpg',
   'release_date': '1972-03-14',
   'title': 'The Godfather',
   'video': False,
   'vote_average': 8.7,
   'vote_count': 16719},
```


In [72]:
```python
pd.DataFrame(result['results'])
```

Out[72]:

	adult	backdrop_path	genre_ids	id	original_language	original
0	False	/qjGrUmKW78MCFG8PTLDBp67S27p.jpg	[16, 28, 12, 14]	635302	ja	劇場版 の刃」無
1	False	/lRN1JuNwr1VKp88Dscgja2uR8H.jpg	[10752, 36, 18, 28]	508935	zh	
2	False	/ddygUzXBHGqnlBPcUI70ih7QOW0.jpg	[10402]	715904	en	Met World Tour - L Manche

In [96]:
```
# 1.3 Movie Details
movie_detail = requests.get('https://api.themoviedb.org/3/movie/'+ '911046' +'?ap
movie_detail = movie_detail.json()
movie_detail
```

Out[96]:

```
{'adult': False,
 'backdrop_path': '/pNx7Tsc0moO9mII939rv4IHeGiz.jpg',
 'belongs_to_collection': {'id': 935616,
  'name': 'In Search of Walt Whitman Collection',
  'poster_path': '/wr2EZX9R7f8f8IvVqG06vuKLzlP.jpg',
  'backdrop_path': '/pNx7Tsc0moO9mII939rv4IHeGiz.jpg'},
 'budget': 0,
 'genres': [{'id': 99, 'name': 'Documentary'}, {'id': 36, 'name': 'History'}],
 'homepage': '',
 'id': 911046,
 'imdb_id': 'tt13905906',
 'original_language': 'en',
 'original_title': 'In Search of Walt Whitman, Part Two: The Civil War and Beyo
nd (1861-1892)',
 'overview': 'The poet moves to Washington to care for injured Civil War soldie
rs but is disillusioned by the Gilded Age after the war. He recovers from a deb
ilitating stroke to live out his days in Camden NJ, where he continues to write
poetry.',
 'popularity': 0.6,
 'poster_path': '/lp4pR7Aw7se5zbBPv8asO2vW43Y.jpg',
 'production_companies': [],
 'production_countries': [],
 'release_date': '2020-04-19',
 'revenue': 0,
 'runtime': 89,
 'spoken_languages': [],
 'status': 'Released',
 'tagline': '',
 'title': 'In Search of Walt Whitman, Part Two: The Civil War and Beyond (1861-
1892)',
 'video': False,
 'vote_average': 10.0,
 'vote_count': 1}
```

In [98]:
```
# 1.4 Getting Cast Names
ID = 577922
casts = requests.get('https://api.themoviedb.org/3/movie/'+ str(ID) + '/credits'
list(cast['name'] for cast in casts if cast['popularity']>10) #Getting list of ca
```

Out[98]:
```
['John David Washington',
 'Robert Pattinson',
 'Elizabeth Debicki',
 'Kenneth Branagh',
 'Himesh Patel',
 'Aaron Taylor-Johnson',
 'Michael Caine',
 'Clémence Poésy',
 'Martin Donovan',
 'Fiona Dourif',
 'Jefferson Hall',
 'Josh Stewart']
```

In [99]:
```
# 1.5 Printing Movie details (Function)
get_movie_detail(ID, api_key)
```

Out[99]:
```
{'Name of Movie': 'Tenet',
 'Genres': ['Action', 'Thriller', 'Science Fiction'],
 'Budget': 205000000,
 'Casts': ['John David Washington',
  'Robert Pattinson',
  'Elizabeth Debicki',
  'Kenneth Branagh',
  'Himesh Patel',
  'Aaron Taylor-Johnson',
  'Michael Caine',
  'Clémence Poésy',
  'Martin Donovan',
  'Fiona Dourif',
  'Jefferson Hall',
  'Josh Stewart'],
 'Vote Count': 7629,
 'Vote Average': 7.213,
 'Revenue': 363129000}
```

In [115]:
```
# 1.6 Printing Year page detail (Function)
year = 2000
page = 1 # Goes to 10, didnt really try beyond that
sort_factor = 'revenue'
yr_pg = get_page_detail(year,api_key,page,sort_factor)
yr_pg
```

Out[115]:
```
[{'Name of Movie': 'Mission: Impossible II',
  'Genres': ['Adventure', 'Action', 'Thriller'],
  'Budget': 125000000,
  'Casts': ['Tom Cruise',
   'Dougray Scott',
   'Thandiwe Newton',
   'Ving Rhames',
   'Richard Roxburgh',
   'Brendan Gleeson',
   'Rade Šerbedžija',
   'William Mapother',
   'Dominic Purcell',
   'Anthony Hopkins',
   'Alison Araya',
   'Tory Mussett'],
  'Vote Count': 5497,
  'Vote Average': 6.109,
  'Revenue': 546388105},
 {'Name of Movie': 'Gladiator',
```

In [116]:
```
pd.DataFrame(yr_pg)
```

Out[116]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue
0	Mission: Impossible II	[Adventure, Action, Thriller]	125000000	[Tom Cruise, Dougray Scott, Thandiwe Newton, V...	5497	6.109	546388105
1	Gladiator	[Action, Drama, Adventure]	103000000	[Russell Crowe, Joaquin Phoenix, Connie Nielse...	15633	8.202	465361176
2	Cast Away	[Adventure, Drama]	90000000	[Tom Hanks, Helen Hunt, Elden Henson, Jenifer ...	9719	7.656	429632142
3	What Women Want	[Comedy, Romance]	70000000	[Mel Gibson, Helen Hunt, Marisa Tomei, Alan Al...	3338	6.410	374111707
4	Dinosaur	[Family, Animation]	127500000	[D.B. Sweeney, Alfre Woodard, Max Casella, Hay...	2105	6.493	354248063
5	Meet the Parents	[Comedy, Romance]	55000000	[Ben Stiller, Robert De Niro, Teri Polo, Blyth...	5138	6.665	330444045
6	The Perfect Storm	[Action, Adventure, Drama, Thriller]	120000000	[George Clooney, Mark Wahlberg, Diane Lane, Jo...	1855	6.401	325756637
7	Le Roi Danse	[Drama, History, Music]	21000000	[Benoît Magimel, Tchéky Karyo]	34	6.600	320300000
8	X-Men	[Adventure, Action, Science Fiction]	75000000	[Patrick Stewart, Hugh Jackman, Ian McKellen, ...	9865	6.986	296339527
9	What Lies Beneath	[Drama, Horror, Mystery, Thriller]	100000000	[Harrison Ford, Michelle Pfeiffer, Diana Scarw...	1505	6.402	291420351
10	Scary Movie	[Comedy]	19000000	[Anna Faris, Marlon Wayans, Shawn Wayans, Regi...	5759	6.312	278019771
11	Charlie's Angels	[Action, Adventure, Comedy, Crime, Thriller]	92000000	[Cameron Diaz, Drew Barrymore, Lucy Liu, Bill ...	3602	5.824	264105545
12	Erin Brockovich	[Drama]	52000000	[Julia Roberts, Aaron Eckhart, Marg Helgenberg...	2575	7.406	256271286
13	Unbreakable	[Thriller, Drama, Mystery]	75000000	[Bruce Willis, Samuel L. Jackson, Robin Wright...	8016	7.132	248118121
14	Gone in Sixty Seconds	[Action, Crime, Thriller]	90000000	[Nicolas Cage, Giovanni Ribisi, Angelina Jolie...	3687	6.383	237202299
15	Chicken Run	[Animation, Comedy, Family]	45000000	[Mel Gibson, Julia Sawalha, Miranda Richardson...	4148	6.730	224834564
16	Vertical Limit	[Adventure, Action, Thriller]	75000000	[Chris O'Donnell, Robin Tunney, Bill Paxton, S...	864	6.006	215663859

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue
17	The Patriot	[Drama, History, War, Action]	110000000	[Mel Gibson, Heath Ledger, Joely Richardson, J...	3255	7.154	215294342
18	卧虎藏龍	[Adventure, Drama, Action, Romance]	17000000	[Chow Yun-Fat, Michelle Yeoh, Zhang Ziyi, Chan...	2644	7.394	213525736
19	Miss Congeniality	[Comedy, Crime, Action]	45000000	[Sandra Bullock, Benjamin Bratt, Michael Caine...	3290	6.509	212000000

In [ ]:

In [ ]:

In [ ]:

In [152]:
```
lst = []
for page in range(1,3):
    lst.append(pd.DataFrame(get_page_detail(2000,api_key,page,'vote_average')))

pd.concat(lst).reset_index(drop=True)
```

Out[152]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue
0	Raid	[Crime, Drama, TV Movie]	0	[]	1	10.0	0
1	René Vautier, le maquisard à la caméra	[Documentary]	0	[]	1	10.0	0
2	King George and the Ducky	[Family, Animation]	0	[]	1	10.0	0
3	René Vautier, le rebelle	[Documentary]	0	[]	1	10.0	0
4	Young Guns Go For It - Soft Cell	[Documentary, Music]	0	[]	1	10.0	0
5	Hunks on Haunted Hill	[Comedy, Horror, Mystery, Action]	0	[]	1	10.0	0
6	Carnophage	[]	0	[]	1	10.0	0
7	Der Puppenschänder 2	[]	0	[]	1	10.0	0
8	The League of Gentlemen - Yule Never Leave!	[]	0	[]	1	10.0	0
9	Teddy, der kleine Bär	[Animation, Family]	0	[]	1	10.0	0
10	The Acting Class	[Comedy]	0	[Jill Hennessy, Will Arnett, Jerry Orbach, Ale...	1	10.0	0
11	Whoa Whoa Studio (for Courbet)	[]	0	[]	1	10.0	0
12	Dracula XXI	[Comedy, Horror]	11000	[]	1	10.0	0
13	Sydney 2000 Olympics Closing Ceremony	[]	40000000	[]	1	10.0	0
14	Las Vegas	[]	0	[]	1	10.0	0
15	La grande aventure de Marcelino : l'ami des an...	[Animation]	0	[]	1	10.0	0
16	Cuốc Xe Đêm	[]	0	[]	1	10.0	0
17	Özallı Yıllar	[Documentary]	0	[]	1	10.0	0
18	Ek Ajooba	[Family]	0	[]	1	10.0	0
19	Austria 3 - Live vor dem Schloss Schönbrunn	[]	0	[]	1	10.0	0

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue
20	Offending Angels	[Romance]	88608	[Andrew Lincoln, Jack Davenport]	2	10.0	100
21	Bibleman: Shattering The Prince Of Pride	[]	0	[]	1	10.0	0
22	Silence Broken: Korean Comfort Women	[Documentary]	0	[]	1	10.0	0
23	Кончина	[Documentary, History]	0	[]	2	10.0	0
24	Mana-mana Tiba-tiba	[Comedy]	0	[]	1	10.0	0
25	Alien technology	[Documentary]	0	[Stacy Keach]	1	10.0	0
26	پر پرواز	[Drama, Romance]	0	[]	1	10.0	0
27	Le savon lave	[Animation, Family]	2883	[]	1	10.0	2883
28	Jack the Ripper: An On-Going Mystery	[Documentary]	0	[]	1	10.0	0
29	Shaheed Uddham Singh	[Drama, History, Music]	0	[]	1	10.0	0
30	MxPx - It Came From Bremerton!	[Documentary]	0	[]	1	10.0	0
31	The Man Who Came to Dinner	[]	0	[Nathan Lane, Jean Smart, Harriet Sansom Harris]	1	10.0	0
32	Fyren	[Documentary]	0	[]	1	10.0	0
33	Utopia Blues	[Drama]	0	[]	1	10.0	0
34	Нет смерти для меня	[Documentary]	0	[]	1	10.0	0
35	The Wake	[]	0	[]	1	10.0	0
36	Coppélia (The Royal Ballet)	[Fantasy, Music]	0	[]	1	10.0	0
37	Abandonada	[Drama]	0	[]	2	10.0	0
38	Déjà-Vu	[Thriller]	0	[]	1	10.0	0
39	Scandalize My Name: Stories from the Blacklist	[Documentary]	1000000	[Morgan Freeman]	1	10.0	100000

In [209]:
```
pg_detail.drop(list(pg_detail[pg_detail['Casts'].map(len)<1].index),inplace=True)
```

In [213]:
```
list(pg_detail[pg_detail['Budget']<1].index)
```

Out[213]:
```
[10, 25, 31]
```

In [216]:
```
pg_detail = pd.concat(lst).reset_index(drop=True)
pg_detail.drop(list(pg_detail[pg_detail['Budget']<1].index), inplace=True)
pg_detail.drop(list(pg_detail[pg_detail['Casts'].map(len)<1].index), inplace=True
pg_detail
```

Out[216]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue
20	Offending Angels	[Romance]	88608	[Andrew Lincoln, Jack Davenport]	2	10.0	100
39	Scandalize My Name: Stories from the Blacklist	[Documentary]	1000000	[Morgan Freeman]	1	10.0	100000

In [183]:
```
pg_detail = pd.concat(lst).reset_index(drop=True)
#pg_detail.drop(pg_detail[pg_detail['Budget']<1].index, inplace=True)
#pg_detail.drop(pg_detail[pg_detail['Casts'].size<1].index, inplace=True)
pg_detail
```

Out[183]:

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue
0	Raid	[Crime, Drama, TV Movie]	0	[]	1	10.0	0
1	René Vautier, le maquisard à la caméra	[Documentary]	0	[]	1	10.0	0
2	King George and the Ducky	[Family, Animation]	0	[]	1	10.0	0
3	René Vautier, le rebelle	[Documentary]	0	[]	1	10.0	0
4	Young Guns Go For It - Soft Cell	[Documentary, Music]	0	[]	1	10.0	0
5	Hunks on Haunted Hill	[Comedy, Horror, Mystery, Action]	0	[]	1	10.0	0
6	Carnophage	[]	0	[]	1	10.0	0
7	Der Puppenschänder 2	[]	0	[]	1	10.0	0
8	The League of Gentlemen - Yule Never Leave!	[]	0	[]	1	10.0	0
9	Teddy, der kleine Bär	[Animation, Family]	0	[]	1	10.0	0
10	The Acting Class	[Comedy]	0	[Jill Hennessy, Will Arnett, Jerry Orbach, Ale...	1	10.0	0
11	Whoa Whoa Studio (for Courbet)	[]	0	[]	1	10.0	0
12	Dracula XXI	[Comedy, Horror]	11000	[]	1	10.0	0
13	Sydney 2000 Olympics Closing Ceremony	[]	40000000	[]	1	10.0	0
14	Las Vegas	[]	0	[]	1	10.0	0
15	La grande aventure de Marcelino : l'ami des an...	[Animation]	0	[]	1	10.0	0
16	Cuốc Xe Đêm	[]	0	[]	1	10.0	0
17	Özallı Yıllar	[Documentary]	0	[]	1	10.0	0
18	Ek Ajooba	[Family]	0	[]	1	10.0	0
19	Austria 3 - Live vor dem Schloss Schönbrunn	[]	0	[]	1	10.0	0

	Name of Movie	Genres	Budget	Casts	Vote Count	Vote Average	Revenue
20	Offending Angels	[Romance]	88608	[Andrew Lincoln, Jack Davenport]	2	10.0	100
21	Bibleman: Shattering The Prince Of Pride	[]	0	[]	1	10.0	0
22	Silence Broken: Korean Comfort Women	[Documentary]	0	[]	1	10.0	0
23	Кончина	[Documentary, History]	0	[]	2	10.0	0
24	Mana-mana Tiba-tiba	[Comedy]	0	[]	1	10.0	0
25	Alien technology	[Documentary]	0	[Stacy Keach]	1	10.0	0
26	پر پرواز	[Drama, Romance]	0	[]	1	10.0	0
27	Le savon lave	[Animation, Family]	2883	[]	1	10.0	2883
28	Jack the Ripper: An On-Going Mystery	[Documentary]	0	[]	1	10.0	0
29	Shaheed Uddham Singh	[Drama, History, Music]	0	[]	1	10.0	0
30	MxPx - It Came From Bremerton!	[Documentary]	0	[]	1	10.0	0
31	The Man Who Came to Dinner	[]	0	[Nathan Lane, Jean Smart, Harriet Sansom Harris]	1	10.0	0
32	Fyren	[Documentary]	0	[]	1	10.0	0
33	Utopia Blues	[Drama]	0	[]	1	10.0	0
34	Нет смерти для меня	[Documentary]	0	[]	1	10.0	0
35	The Wake	[]	0	[]	1	10.0	0
36	Coppélia (The Royal Ballet)	[Fantasy, Music]	0	[]	1	10.0	0
37	Abandonada	[Drama]	0	[]	2	10.0	0
38	Déjà-Vu	[Thriller]	0	[]	1	10.0	0
39	Scandalize My Name: Stories from the Blacklist	[Documentary]	1000000	[Morgan Freeman]	1	10.0	100000

In [194]:
```
pg_detail = pd.concat(lst)
pg_detail.drop(pg_detail[pg_detail['Budget']<1].index() or pg_detail[pg_detail['C
pg_detail.reset_index(drop=True)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-194-c379e1b84a6d> in <module>
      1 pg_detail = pd.concat(lst)
----> 2 pg_detail.drop(pg_detail[pg_detail['Budget']<1].index() or pg_detail[pg
_detail['Casts'].map(len)<1].index(), inplace=True)
      3 pg_detail.reset_index(drop=True)

TypeError: 'Int64Index' object is not callable
```

In [188]:
```
pg_detail['Casts'][2].length()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-188-67ed4ccb5782> in <module>
----> 1 pg_detail['Casts'][2].length()

AttributeError: 'list' object has no attribute 'length'
```

In [182]:
```
len(pg_detail['Casts'][2])
```

Out[182]: 0

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [368]:
```
top3params(n_estimators_range,acc_nest_list)
```

600

Out[368]: [100, 600, 1600]

In [364]:
```
[i for i,n in enumerate(acc_list) if n == 0.581772784019975][1]
```

Out[364]: 6

In [361]:
```
acc_list
```

Out[361]:
```
[0.5792759051186017,
 0.5786516853932584,
 0.5755305867665418,
 0.583645443196005,
 0.5855181023720349,
 0.581772784019975,
 0.581772784019975,
 0.5780274656679151,
 0.581772784019975,
 0.5861423220973783,
 0.5805243445692884,
 0.579900124843945]
```