Final Project Submission

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- Blog post URL:

INTRODUCTION

This proposition includes an evaluation of different movie information aimed at guiding executive decision-making for Microsoft's hypothetical new movie studio. The analysis offers practical recommendations on the kinds of films the studio should prioritize making in order to achieve the highest possible box office success. The primary findings indicate that box office revenues are linked to genre, duration, and rating. By utilizing this analysis, Microsoft can generate successful films and establish its new studio as a profitable and competitive entity within the film industry.

BUSINESS PROBLEM

Microsoft has noticed that major companies are producing unique video content and they are interested in joining the trend. They have concluded to launch a novel movie production studio. However, they lack knowledge in film-making. My task is to investigate the types of movies that are presently performing well at the box office. Afterward, I will interpret the results into useful information that can assist the leader of Microsoft's new movie studio in determining the type of movies to generate.

OBJECTIVES

- To determine if there is any correlation between production budget and profit of a movie
- To determine which movie title has the highest total gross
- To determine which genre of movie has the highest rating
- To determine which movie titles are the most profitable

1.LOADING DATASET

In [1]:
```
#Importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import sqlite3
import matplotlib.pyplot as plt
%matplotlib inline

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

Opening the all the datasets to see what I am working with.

In [2]:
```
bom_movie_gross = pd.read_csv('Data/bom.movie_gross.csv')
bom_movie_gross
```

Out[2]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

In [3]:
```
tmdb_movies = pd.read_csv('Data/tmdb.movies.csv')
tmdb_movies
```

Out[3]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16
...	...	...	...	...	...	...	...
26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13
26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01
26514	26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01
26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22
26516	26516	[53, 27]	309885	en	The Church	0.600	2018-10-05

26517 rows × 10 columns

In [4]:
```
movie_budgets =  pd.read_csv('Data/tn.movie_budgets.csv')
movie_budgets
```

Out[4]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of	$5,000	$1,338	$1,338

In [5]:
```
rt_movie_info = pd.read_csv('Data/rt.movie_info.tsv', delimiter="\t")
rt_movie_info
```

Out[5]:

	id	synopsis	rating	genre	director	writer	theater_c
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1
		Michael Douglas					

In [6]:
```
rt_reviews_tsv = pd.read_csv('Data/rt.reviews.tsv', delimiter="\t", encodin
rt_reviews_tsv
```

Out[6]:

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com	May 23, 2018
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI	November 16, 2017
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope	October 12, 2017

In [7]:
```
#Opening movie_ratings from SQL data set
conn = sqlite3.connect('Data/im.db')
movie_rating=pd.read_sql("""SELECT *
                         FROM movie_ratings;""", conn)
movie_rating
```

Out[7]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

In [8]:
```
#Opening movive_basics from the SQL data set
movie_basics=pd.read_sql("""SELECT *
                         FROM movie_basics;""", conn)
movie_basics.head()
```

Out[8]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

2. EXPLORATORY DATA ANALYSIS

Going back to the objective, I want to explore on the different datasets that have gross margin profit for movies, the genres and budget needed

In [9]:
```
#checking missing values  and data type in the bom_movie_gross dataset
bom_movie_gross.info()
bom_movie_gross.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

Out[9]:

	domestic_gross	year
count	3.359000e+03	3387.000000
mean	2.874585e+07	2013.958075
std	6.698250e+07	2.478141

From the above analysis i can see that foreign gross,domestic gross and studio have missing values.Foreign gross is also not in the correct data types.

In [10]:
```
#checking for missing values and data type in the movie_budgets dataset
movie_budgets.info()
movie_budgets.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

Out[10]:

	id
count	5782.000000
mean	50.372363

The movie_budgets dataset has production_budget and worldwide_gross, which will help me achieve my objective of finding the correlation between budget and profit made from a movie. Also, to note is that it does not have any missing values

In [11]:
```
movie_basics.info()
movie_basics.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

Out[11]:

	start_year	runtime_minutes
count	146144.000000	114405.000000
mean	2014.621798	86.187247

The movie_basics dataset contains genres, which will help in understanding the most common genre

In [12]:
```
movie_rating.info()
movie_rating.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   movie_id       73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

Out[12]:

	averagerating	numvotes
count	73856.000000	7.385600e+04
mean	6.332729	3.523662e+03
std	1.474978	3.029402e+04
min	1.000000	5.000000e+00
25%	5.500000	1.400000e+01
50%	6.500000	4.900000e+01
75%	7.400000	2.820000e+02
max	10.000000	1.841066e+06

The movie_rating contains movie id and average rating and votes of the most liked movie

3. DATA CLEANING

In [13]:
```
#join the moving rating data set and movie basics since they both have movi
joint_genre = movie_basics.join(movie_rating.set_index('movie_id'),
                                how = 'inner', on = 'movie_id', rsuffix
joint_genre.head()
```

Out[13]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averager
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	

In [14]:
```
joint_genre.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 146134
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         73856 non-null  object 
 1   primary_title    73856 non-null  object 
 2   original_title   73856 non-null  object 
 3   start_year       73856 non-null  int64  
 4   runtime_minutes  66236 non-null  float64
 5   genres           73052 non-null  object 
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 5.1+ MB
```

In [15]:
```
joint_genre.isna().sum()
```

Out[15]:
```
movie_id              0
primary_title         0
original_title        0
start_year            0
runtime_minutes    7620
genres              804
averagerating         0
numvotes              0
dtype: int64
```

In [16]:
```
#dropping the runtime_minutes column because it has so many missing values

joint_genre.dropna(subset=['runtime_minutes'],inplace=True)
joint_genre.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 66236 entries, 0 to 146134
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         66236 non-null  object 
 1   primary_title    66236 non-null  object 
 2   original_title   66236 non-null  object 
 3   start_year       66236 non-null  int64  
 4   runtime_minutes  66236 non-null  float64
 5   genres           65720 non-null  object 
 6   averagerating    66236 non-null  float64
 7   numvotes         66236 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB
```

In [17]:
```
#Find the most popular genre based on average ratings
most_popular_genre = joint_genre.loc[0:25, ['genres', 'averagerating']].gro
most_popular_genre
```

Out[17]:
```
['Adventure,Animation,Comedy',
 'Animation,Drama,History',
 'Documentary',
 'Biography,Drama',
 'Action,Crime,Drama',
 'Drama',
 'Comedy,Drama,Fantasy',
 'Biography,Comedy,Drama',
 'History',
 'Drama,Mystery',
 'Action,Animation,Comedy']
```

Based on the average rating, the most popular genre is "Adventure,Animation,Comedy", "Animation, Drama, History" and "Documentary" among others

Cleaning movie_budgets data set by removing dollar sign and

In [18]:
```
#removing comma and $ sign in worldwide_gross and changing it to a float
movie_budgets['worldwide_gross'] = movie_budgets['worldwide_gross'].str.rep
movie_budgets['worldwide_gross'] = movie_budgets['worldwide_gross'].str.rep
movie_budgets['worldwide_gross'] = movie_budgets['worldwide_gross'].astype(
```

In [19]:
```
#removing comma and $ sign in domestic_gross and changing it to a integer
movie_budgets['domestic_gross'] = movie_budgets['domestic_gross'].str.repla
movie_budgets['domestic_gross'] = movie_budgets['domestic_gross'].str.repla
movie_budgets['domestic_gross'] = movie_budgets['domestic_gross'].astype(in
```

In [20]:
```
#removing comma and $ sign in production_budget and changing it to a intege
movie_budgets['production_budget'] = movie_budgets['production_budget'].str
movie_budgets['production_budget'] = movie_budgets['production_budget'].str
movie_budgets['production_budget'] = movie_budgets['production_budget'].ast
```

In [21]:
```
#Confirm that the $ and comma are removed from the data set
movie_budgets.head()
```

Out[21]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2.776345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1.045664e+09
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	1.497624e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1.403014e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1.316722e+09

In [22]:
```
#creating new column for profit and profit margin so as to know how much pr
movie_budgets['Profit'] = movie_budgets['worldwide_gross'] - movie_budgets[

movie_budgets['Profit_Margin'] = (movie_budgets['worldwide_gross'] -
                                  movie_budgets['production_budget'])/mov
```

In [23]:
```
#Confirming that the columns were added for profit and proft margin
movie_budgets.head()
```

Out[23]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	Profit
0	1	Dec 18, 2009	Avatar	425000000	760507625	2.776345e+09	2.351345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1.045664e+09	6.350639e+08
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	1.497624e+08	-2.002376e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1.403014e+09	1.072414e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1.316722e+09	9.997217e+08

The dataset now shows the profit and profit margin for each movie

Data cleaning on bom_movie_gross data set

In [24]:
```
#Fill NaN values with 0 and find total gross
bom_movie_gross["foreign_gross"]=bom_movie_gross["foreign_gross"].fillna(0)
bom_movie_gross["foreign_gross"] = pd.to_numeric(bom_movie_gross["foreign_g
bom_movie_gross['Total_gross'] = bom_movie_gross['domestic_gross'] + bom_mo
bom_movie_gross.sort_values('Total_gross', ascending= False).head(5)
```

Out[24]:

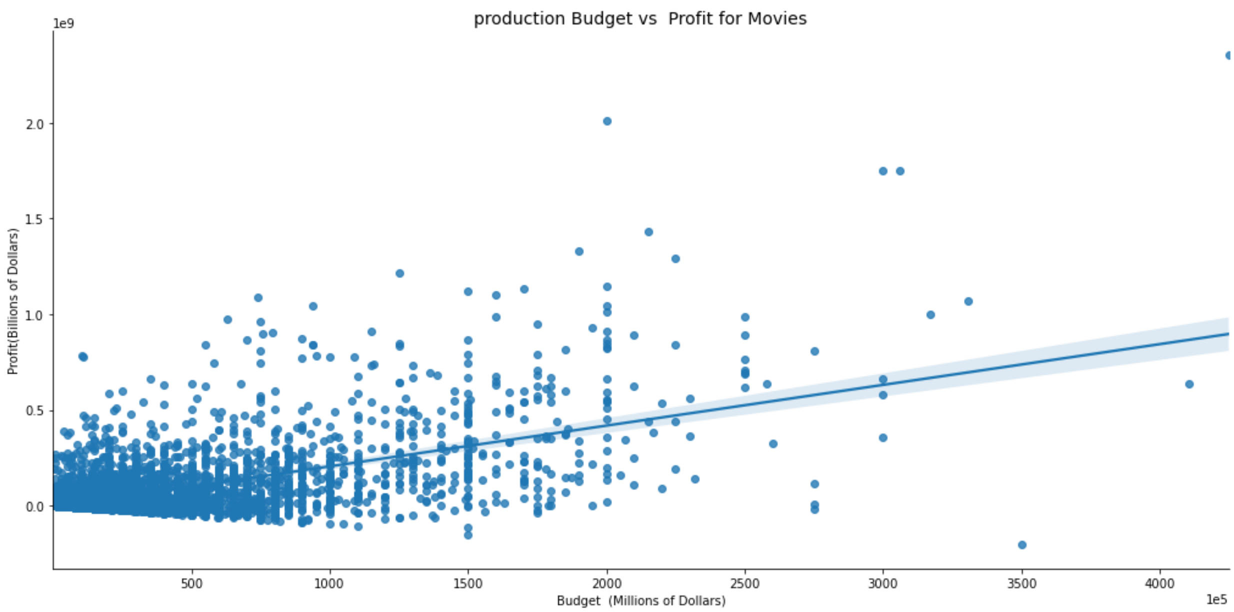
	title	studio	domestic_gross	foreign_gross	year	Total_gross
727	Marvel's The Avengers	BV	623400000.0	895500000.0	2012	1.518900e+09
1875	Avengers: Age of Ultron	BV	459000000.0	946400000.0	2015	1.405400e+09
3080	Black Panther	BV	700100000.0	646900000.0	2018	1.347000e+09
328	Harry Potter and the Deathly Hallows Part 2	WB	381000000.0	960500000.0	2011	1.341500e+09
2758	Star Wars: The Last Jedi	BV	620200000.0	712400000.0	2017	1.332600e+09

4. DATA ANALYSIS

1. Is there any correlation between production_budget and profit?

In [25]:
```
#determining the relationship between budget and profit
ax1 = sns.lmplot(x='production_budget', y='Profit', data=movie_budgets, hei

plt.xlabel('Budget  (Millions of Dollars)', fontsize=10)
plt.ticklabel_format(axis='x', style='sci', scilimits=(5,5))
plt.ylabel('Profit(Billions of Dollars)', fontsize=10)
plt.title('production Budget vs  Profit for Movies', fontsize=14)
plt.savefig('BudgetVProfit');
```

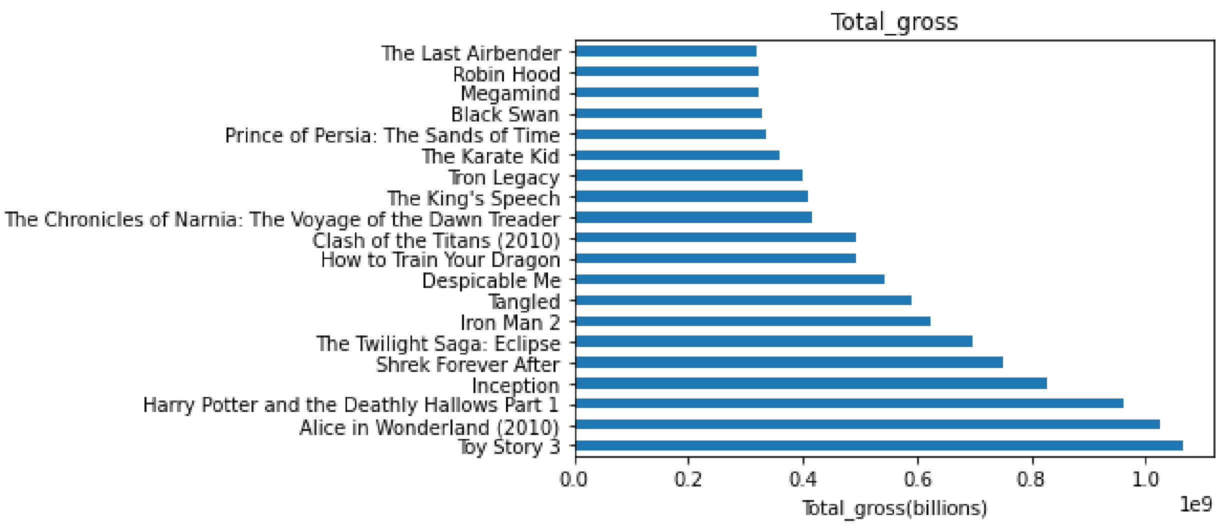


The scatter plot above shows that there is a weak positive correlation.As the budget increases the profit also increases. However, there some outliers in the data

2. Which movie title has the highest total gross?

In [26]:
```
#bar graph to see highest gross profit
bom_movie_gross.head(20).plot.barh("title","Total_gross")
plt.title("Total_gross")
plt.xlabel("Total_gross(billions)")
plt.ylabel("")
plt.legend().remove()
plt.show
```

Out[26]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Toy story,Alice in Wonderland(2010) and Harry Potter and the Deathly Hallows part 1 have the highest total gross.

3. Which genre of movie has the highest rating?

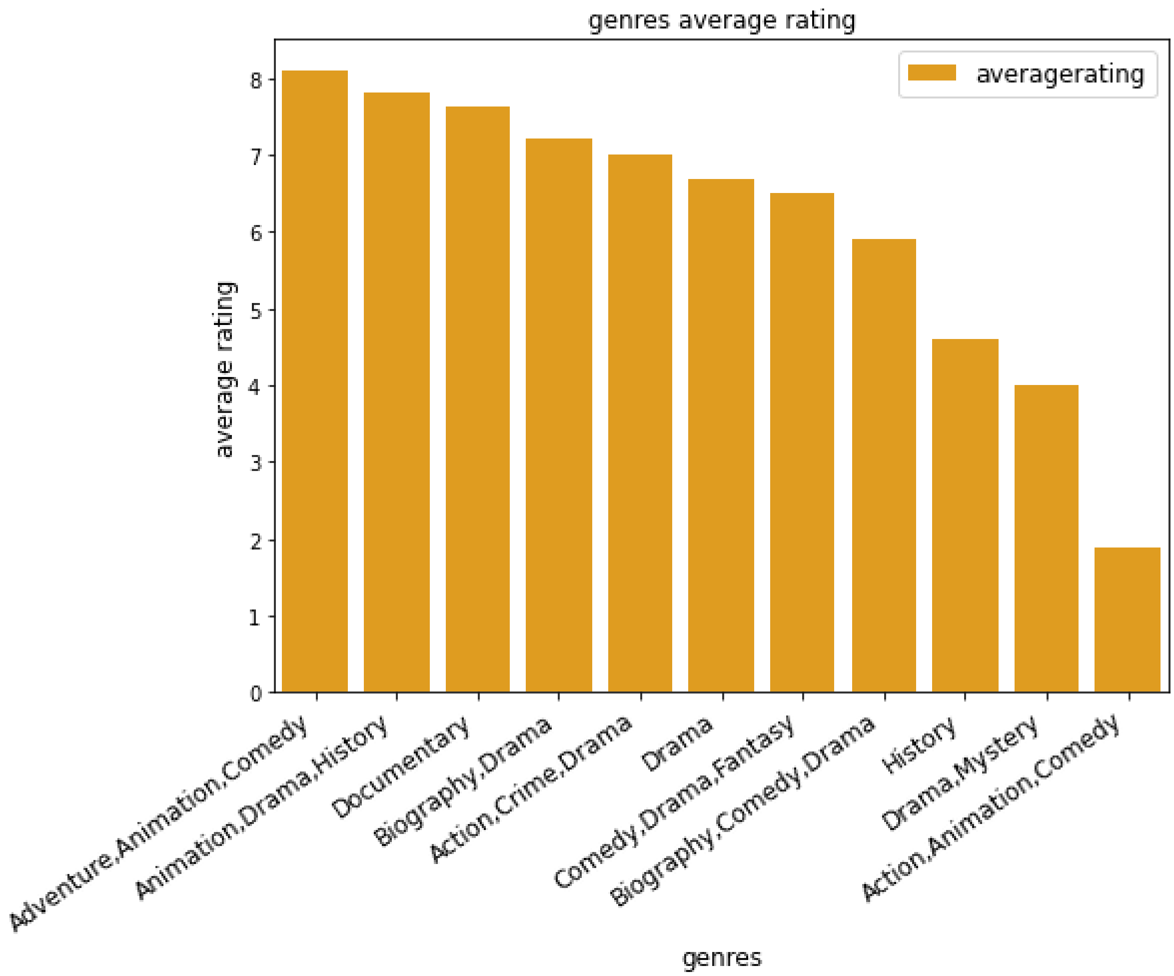
In [27]:
```
# sort the genres by average rating in descending order
genres_sorted = joint_genre.loc[0:25, ['genres', 'averagerating']].groupby(

plt.figure(figsize=(8,6))

# add the order parameter to the barplot method
sns.barplot(x=joint_genre.loc[0:25, 'genres'], y=joint_genre.loc[0:25, 'ave
            color='orange', label='averagerating', ci=None, order=genres_so

plt.xlabel('genres', fontsize=12)
plt.title("genres average rating", fontsize=12)
plt.ylabel('average rating', fontsize=12)
plt.xticks(rotation=35, horizontalalignment='right', fontsize=12)
plt.legend(fontsize=12)

plt.savefig('genres vs average rating')
```



'Adventure, Animation, Comedy','Animation,Drama,History' and 'Documentary are the highest rated as per the above analysis meaning that they are the most liked.

4. What are the most profitable movie titles?

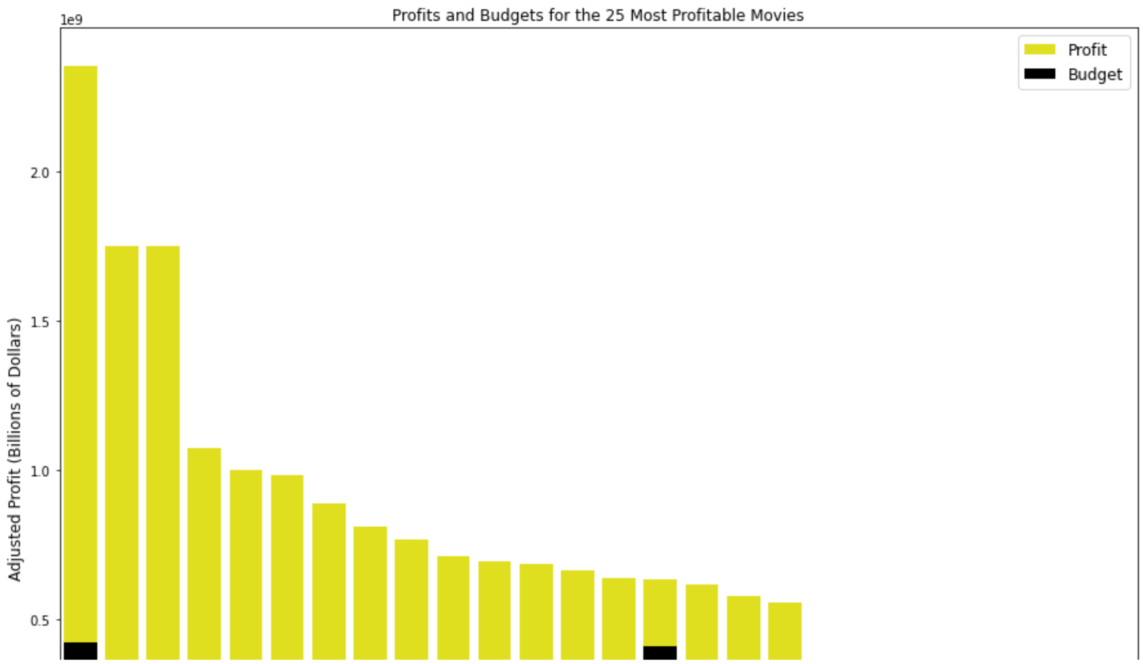
In [28]:
```
movie_budgets.loc[0:25].sort_values('Profit', ascending=False)
```

Out[28]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	Profi
0	1	Dec 18, 2009	Avatar	425000000	760507625	2.776345e+09	2.351345e+0
6	7	Apr 27, 2018	Avengers: Infinity War	300000000	678815482	2.048134e+09	1.748134e+0
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2.053311e+09	1.747311e+0
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1.403014e+09	1.072414e+0
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1.316722e+09	9.997217e+0
22	23	Apr 14, 2017	The Fate of the Furious	250000000	225764765	1.234846e+09	9.848463e+0

In [29]:
```
#plotting the 25 most profitable movies
x = movie_budgets.loc[0:25].sort_values('Profit', ascending=False)

plt.figure(figsize=(15,12))
sns.barplot(x=x['movie'],y=x['Profit'],
            color='yellow', label='Profit', ci=None)
sns.barplot(x=x['movie'],y=x['production_budget'],
            color='black', label='Budget', ci=None)
plt.xlabel('movie', fontsize=12)
plt.title("Profits and Budgets for the 25 Most Profitable Movies", fontsize
plt.ylabel('Adjusted Profit (Billions of Dollars)', fontsize=12)
plt.xticks(rotation=35, horizontalalignment='right', fontsize=12)
plt.legend(fontsize=12)
plt.savefig('ProfitBudgetTop25');
```



Based on the above, Avatar and Avengers:Infinity War are the most profitable movies while Dark Phoenix incurred losses.

5. CONCLUSION AND RECOMMENDATIONS

-In conclusion, the scatter plot analysis indicates a weak positive correlation between production_budget and profit, suggesting that investing more in a movie production does not guarantee high profits. -It is also noteworthy that movies such as Toy Story, Alice In Wonderland(2010), and Harry Potter and the Deathly Hallows have generated the highest total gross, while "Adventure, Animation, Comedy", and "Animation, Drama, History" are the most popular genres.

Furthermore, Avatar and Avengers:Infinity War have proved to be the most profitable movies, while Dark Phoenix incurred losses.

From this analysis,I would recommended Microsoft to consider factors beyond budget when deciding on movie production. Additionally, investing in popular genres such as "adventure, animation,comedy", among others, could lead to more significant profits. Finally, attention to detail

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