Semester 1 Project Submission

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AI Academy Capstone Project

Introduction:

Computing Vision is looking to enter the movie studio business. We have been tasked to utilize readily available data to determine trends in the movie industry, and formulate three business recommendations for them to follow if they decide to enter the movie studio industry.

Project Goal

The goal for this project is to recommend three key business insights for the company Computing Vision passed on our Exploratory data analysis, data visualizations, and statistical inference

Loading in python dependencies and packages for data manipulation and visualizations

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
import numpy as np
import zipfile
import sqlite3
from scipy import stats

%matplotlib inline
```

Begin loading in datasets and preparing for mergers

Prepare data for merging by making sure the right types are in place and renaming columns for easier joining on index

Box office movies provides us with the domestic and foreign grosses for movies as well as the studios. Since we will be looking at profitability this is an important dataset to incorporate into our analysis.

In [2]:
```
movie_bom = pd.read_csv("zippedData/bom.movie_gross.csv.gz")
movie_bom = movie_bom.rename(columns={'title':"movie"})
movie_bom['movie'] = movie_bom['movie'].map(lambda x: "Harry Potter and th
movie_bom.head()
```

Out[2]:

	movie	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

In [3]:
```
#pulling in movie budgets dataset and preparing it for joining by changing
```

Load in The Number data set, cleanup column information and prepare for join

The Number dataset provides us valuable information regarding worldwide gross as well as the production budgets for the movies. Once again this will be valuable as we look into the financial impact of these things on the financial success of a potential studio.

In [4]:

```
"
ta was formulated as string with $ signs and commas, to merge, we needed to
 do this we used lambda functions to recode over the specific columns and t
ta frame typing.
"
viebudgets = pd.read_csv("zippedData/tn.movie_budgets.csv.gz")
viebudgets["production_budget"] = moviebudgets['production_budget'].map(lam
viebudgets["production_budget"] = moviebudgets['production_budget'].map(lam

viebudgets["domestic_gross"] = moviebudgets['domestic_gross'].map(lambda x:
viebudgets["domestic_gross"] = moviebudgets['domestic_gross'].map(lambda x:

viebudgets["worldwide_gross"] = moviebudgets['worldwide_gross'].map(lambda
viebudgets["worldwide_gross"] = moviebudgets['worldwide_gross'].map(lambda


viebudgets= moviebudgets.astype({'production_budget': np.int64, 'domestic_g
viebudgets.head(10)
```

Out[4]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220
6	7	Apr 27, 2018	Avengers: Infinity War	300000000	678815482	2048134200
7	8	May 24, 2007	Pirates of the Caribbean: At Worldâ□□s End	300000000	309420425	963420425
8	9	Nov 17, 2017	Justice League	300000000	229024295	655945209
9	10	Nov 6, 2015	Spectre	300000000	200074175	879620923

Join Box office movies and the numbers dataset on index movie

In [5]:
```
#joining movie budgets dataset with bom movie gross so we can have the stu
# and worldwide gross
```

In [6]:
```
movie_total_gross = movie_bom.join(moviebudgets.set_index("movie"), on= ['
movie_total_gross = movie_total_gross.set_index('id')
movie_total_gross
```

Out[6]:

	movie	studio	domestic_gross	foreign_gross	year	release_date	production
id							
47.0	Toy Story 3	BV	415000000.0	652000000	2010	Jun 18, 2010	200(
NaN	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010	NaN	
NaN	Harry Potter and the Deathly Hallows: Part 1	WB	296000000.0	664300000	2010	NaN	
38.0	Inception	WB	292600000.0	535700000	2010	Jul 16, 2010	160(
27.0	Shrek Forever After	P/DW	238700000.0	513900000	2010	May 21, 2010	165(
...	...	...	...	...	...	...	
NaN	The Quake	Magn.	6200.0	NaN	2018	NaN	
NaN	Edward II (2018 re-release)	FM	4800.0	NaN	2018	NaN	
NaN	El Pacto	Sony	2500.0	NaN	2018	NaN	
NaN	The Swan	Synergetic	2400.0	NaN	2018	NaN	
NaN	An Actor Prepares	Grav.	1700.0	NaN	2018	NaN	

3396 rows × 9 columns

In [7]:
```
movie_tmdb = pd.read_csv('zippedData/tmdb.movies.csv.gz')
```

In [8]:
```
movie_tmdb= movie_tmdb.rename(columns={'original_title':"movie"})
movie_tmdb = movie_tmdb.set_index("movie")
```

Pull in tmdb movie dataset and prepare for merger with the existing data frame

Another point of our analysis is success based on ratings, so we pulled in the TMDb ratings in order to investigate this relationship.

In [9]:
```
#pullin in tmdb ratings so we have budget info and ratings
```

In [10]:
```
movies_and_rating = movie_total_gross.join(movie_tmdb, on = 'movie', how =
```

In [11]:
```
movies_and_rating
```

Out[11]:

	movie	studio	domestic_gross	foreign_gross	year	release_date__	produc
17.0	Toy Story 3	BV	415000000.0	652000000	2010.0	Jun 18, 2010	:
NaN	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010.0	NaN	
NaN	Harry Potter and the Deathly Hallows: Part 1	WB	296000000.0	664300000	2010.0	NaN	
38.0	Inception	WB	292600000.0	535700000	2010.0	Jul 16, 2010	
27.0	Shrek Forever After	P/DW	238700000.0	513900000	2010.0	May 21, 2010	
...	...	...	...	...	...	...	
NaN	Laboratory Conditions	NaN	NaN	NaN	NaN	NaN	
NaN	_EXHIBIT_84xxx_	NaN	NaN	NaN	NaN	NaN	
NaN	The Last One	NaN	NaN	NaN	NaN	NaN	
NaN	Trailer Made	NaN	NaN	NaN	NaN	NaN	
NaN	The Church	NaN	NaN	NaN	NaN	NaN	

7975 rows × 18 columns

In [12]:
```
#dropping unnecessary columns
```

Continue to clean data by dropping unused and/or redundant columns

In [13]:
```
movies_and_rating.drop(["Unnamed: 0",'id','title', 'genre_ids', 'title'],
```

In [14]:
```
movies_and_rating = movies_and_rating.set_index('movie')
```

In [15]:
```
movies_and_rating
```

Out[15]:

	studio	domestic_gross	foreign_gross	year	release_date__	productio
movie						
Toy Story 3	BV	415000000.0	652000000	2010.0	Jun 18, 2010	200
Alice in Wonderland (2010)	BV	334200000.0	691300000	2010.0	NaN	
Harry Potter and the Deathly Hallows: Part 1	WB	296000000.0	664300000	2010.0	NaN	
Inception	WB	292600000.0	535700000	2010.0	Jul 16, 2010	160
Shrek Forever After	P/DW	238700000.0	513900000	2010.0	May 21, 2010	165
...	...	...	...	...	...	
Laboratory Conditions	NaN	NaN	NaN	NaN	NaN	
_EXHIBIT_84xxx_	NaN	NaN	NaN	NaN	NaN	
The Last One	NaN	NaN	NaN	NaN	NaN	
Trailer Made	NaN	NaN	NaN	NaN	NaN	
The Church	NaN	NaN	NaN	NaN	NaN	

27975 rows × 13 columns

In [16]:
```
#dropping movies that don't have enough information to be of use
```

Dropping Na's from the dataset using 6 empty columns in a row as the threshold

We found that at this threshold we can complete the necessary calculations and visualizations with still enough datapoints. At a higher threshold there are a lot of entries that only have a couple columns worth of data and these were not valuable to the insights that we created

In [17]:
```
movies_and_rating.dropna(axis = 0, thresh = 6, inplace = True)
```

In [18]:
```
movies_and_rating
```

Out[18]:

movie	studio	domestic_gross	foreign_gross	year	release_date__	production_budge
Toy Story 3	BV	415000000.0	652000000	2010.0	Jun 18, 2010	200000000.(
Harry Potter and the Deathly Hallows: Part 1	WB	296000000.0	664300000	2010.0	NaN	NaN
Inception	WB	292600000.0	535700000	2010.0	Jul 16, 2010	160000000.(
Shrek Forever After	P/DW	238700000.0	513900000	2010.0	May 21, 2010	165000000.(
The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010.0	Jun 30, 2010	68000000.(
...	...	...	...	...	...	..
Loving Pablo	Uni.	22000.0	NaN	2018.0	NaN	NaN
The Escape	IFC	14000.0	NaN	2018.0	NaN	NaN
The Escape	IFC	14000.0	NaN	2018.0	NaN	NaN
Souvenir	Strand	11400.0	NaN	2018.0	NaN	NaN
An Actor Prepares	Grav.	1700.0	NaN	2018.0	NaN	NaN

2374 rows × 13 columns

Pulling in the IMDb ratings using SQL

Merge the desired columns from the tables of interest and prepare for joinging into the master dataset

We also wanted to pull in IMDb for ratings so that we can compare the ratings between the two datasets to see if they are consistent or if there are discrepancies.

In [19]:
```
"""
Pulling in the zipped IMDb database and setting up a cursor object to exec
"""

with zipfile.ZipFile("zippedData/im.db.zip", 'r') as imdb_zip:
    imdb_zip.extractall("zippedData")
conn = sqlite3.connect('zippedData/im.db')
cur = conn.cursor()
cur.execute("""SELECT name FROM sqlite_master WHERE type = 'table';""")
```

Out[19]:
```
<sqlite3.Cursor at 0x1acef15cd40>
```

In [20]:
```
"""Creating pandas dataframes out of sql data bases"""
movie_basics = pd.DataFrame(
    data=cur.execute("""SELECT * FROM movie_basics;""").fetchall(),
    columns=[x[0] for x in cur.description]
)
```

In [21]:
```
movie_ratings = pd.DataFrame(
    data=cur.execute("""SELECT * FROM movie_ratings;""").fetchall(),
    columns=[x[0] for x in cur.description]
)
```

In [22]:

```
#Merging the two sql databases into one larger pandas dataframe
merged = pd.merge(movie_ratings, movie_basics, on='movie_id')
merged = merged.rename(columns={'primary_title':"movie"})
merged = merged.set_index('movie')
merged
```

Out[22]:

	movie_id	averagerating	numvotes	original_title	start_year	runtime_minutes
movie						
Laiye Je Yaarian	tt10356526	8.3	31	Laiye Je Yaarian	2019	117.(
Borderless	tt10384606	8.9	559	Borderless	2019	87.(
Just Inès	tt1042974	6.4	20	Just Inès	2010	90.(
The Legend of Hercules	tt1043726	4.2	50352	The Legend of Hercules	2014	99.(
Até Onde?	tt1060240	6.5	21	Até Onde?	2011	73.(
...	...	...	...	...	...	..
Caisa	tt9805820	8.1	25	Caisa	2018	84.(
Code Geass: Lelouch of the Rebellion - Glorification	tt9844256	7.5	24	Code Geass: Lelouch of the Rebellion Episode III	2018	120.(
Sisters	tt9851050	4.7	14	Sisters	2019	NaN
The Projectionist	tt9886934	7.0	5	The Projectionist	2019	81.(
Sathru	tt9894098	6.3	128	Sathru	2019	129.(

73856 rows × 7 columns

In [23]:

```
master_df = movies_and_rating.join(merged, on = 'movie', how = 'outer', ls
```

Drop redundant columns for readability, and Create new columns of interest for calculations visualizations, and metrics

In [24]:
```
master_df.head()
```

Out[24]:

	movie	studio	domestic_gross	foreign_gross	year	release_date__	product
Toy Story 3	Toy Story 3	BV	415000000.0	652000000	2010.0	Jun 18, 2010	2
Harry Potter and the Deathly Hallows: Part 1	Harry Potter and the Deathly Hallows: Part 1	WB	296000000.0	664300000	2010.0	NaN	
Inception	Inception	WB	292600000.0	535700000	2010.0	Jul 16, 2010	1
Shrek Forever After	Shrek Forever After	P/DW	238700000.0	513900000	2010.0	May 21, 2010	1
The Twilight Saga: Eclipse	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010.0	Jun 30, 2010	

5 rows × 21 columns

In [25]:
```
master_df.dropna(axis = 0, thresh = 9, inplace = True)
```

In [26]:
```
master_df = master_df.set_index("movie")
```

In [27]:
```
master_df.drop(["domestic_gross___",'movie_id','original_title', 'year', '
                 ,"release_date", "start_year","popularity"],  axis=1, inpl
```

In [28]:
```
master_df["Total_Profit"] = (master_df.worldwide_gross - master_df.product
master_df["Profit%"] = ((master_df.Total_Profit)/master_df.production_budg
```

In [29]:
```
master_df.shape
```

Out[29]: (2989, 13)

Resulting dataset has 6,857 entries

Limitations of this dataset are that they do not contain the entire population, there are missing values throughout that would be challenging to fill so we have chosen to omit them when conducting statistical tesing and visualizations.

With any statistical analysis these pose risks for the validity of the conclusions, but given our sample size we feel we still have enough observations to determine trends among movies that can be reasonably representative of the population.

Descriptive statistics for all features used in analysis

Since we are examining the profit percentage and audience ratings as forms of "Success" the remaining features in the dataset will be valuable in our suggestions and recommendations for the path that Computing Vision should take.

In [30]:
```
master_df.describe() #descriptive statistics for all features used in anal
```

Out[30]:

	domestic_gross	production_budget	worldwide_gross	vote_average	vote_count
count	2.963000e+03	1.832000e+03	1.832000e+03	2912.000000	2912.000000
mean	4.085259e+07	4.430199e+07	1.471707e+08	6.335886	1463.480082
std	7.884126e+07	5.432862e+07	2.295861e+08	1.018145	2469.254428
min	1.000000e+02	5.000000e+04	0.000000e+00	0.000000	1.000000
25%	3.560000e+05	9.350000e+06	1.634077e+07	5.800000	87.000000
50%	7.600000e+06	2.500000e+07	6.428288e+07	6.300000	474.000000
75%	4.690000e+07	5.500000e+07	1.697664e+08	7.000000	1692.000000
max	9.367000e+08	4.106000e+08	2.048134e+09	10.000000	22186.000000

Runtime Visualizations

Creating Bins for Runtime

There is a wide range of runtime so we wanted to condense them into a categorical variable to better examine trends in runtime based on ranges that we created of common movie durations.

In [31]:

```
"""
Converting runtimes into runtime bins for common movie duration runtime in
"""
binned_df = master_df.copy()
bins = [90, 150, 210, 270] # bins of under 1.5 hours, 1.5-2.5 hours, 2.5-3
runtime_bins = []
for index, row in binned_df.iterrows():
    runtime = row['runtime_minutes']
    if runtime < bins[0]:
        runtime_bins.append(0)
    elif runtime < bins[1]:
        runtime_bins.append(1)
    elif runtime < bins[2]:
        runtime_bins.append(2)
    else:
        runtime_bins.append(3)
binned_df['runtime_bins'] = runtime_bins
binned_df[binned_df['runtime_bins'] == 0] # examples of runtimes under 1.5
```

Out[31]:

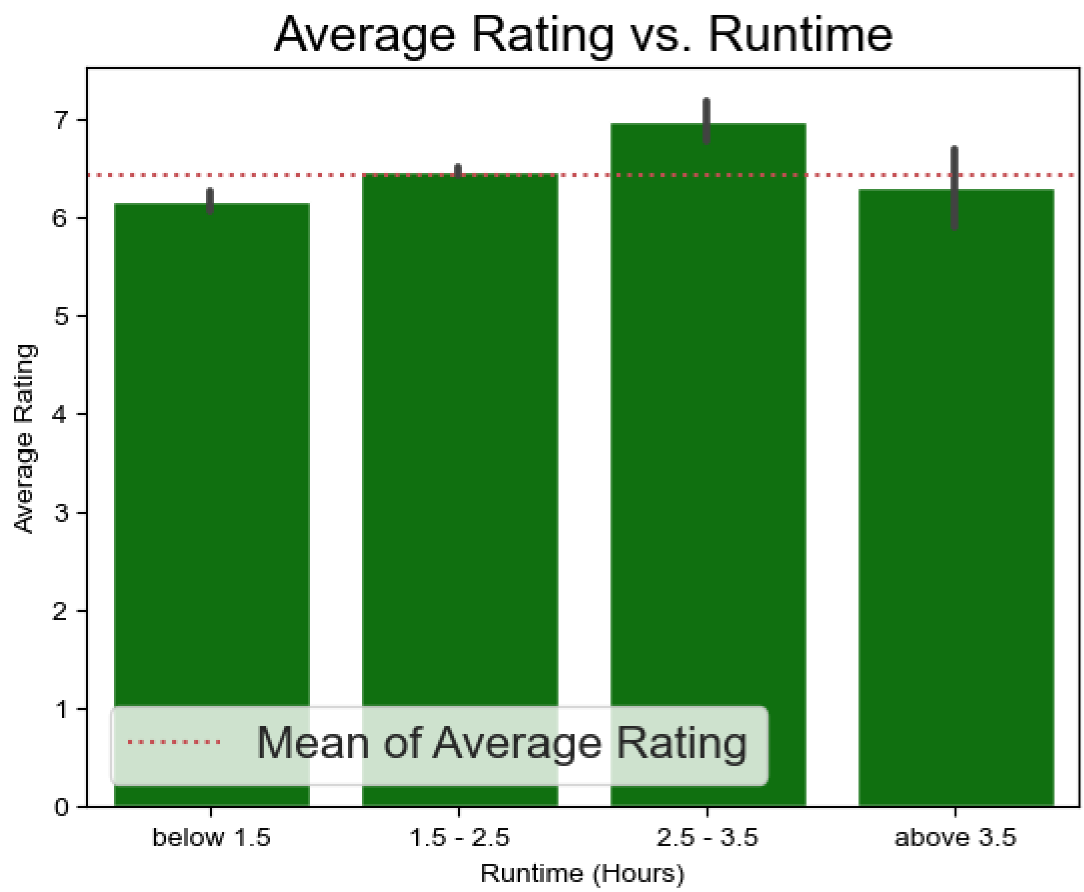
	studio	domestic_gross	foreign_gross	production_budget	worldwide_gros
movie					
Gulliver's Travels	Fox	42800000.0	194600000	112000000.0	232017848.
Yogi Bear	WB	100200000.0	101300000	80000000.0	204774690.
Unstoppable	Fox	81600000.0	86200000	95000000.0	165720921.
Unstoppable	Fox	81600000.0	86200000	95000000.0	165720921.
Unstoppable	Fox	81600000.0	86200000	95000000.0	165720921.
...	...	...	...	...	.
Beast	RAtt.	800000.0	NaN	NaN	Na
Beast	RAtt.	800000.0	NaN	NaN	Na
Mountain	Greenwich	365000.0	NaN	NaN	Na
Mountain	Greenwich	365000.0	NaN	NaN	Na
Souvenir	Strand	11400.0	NaN	NaN	Na

452 rows × 14 columns

Average Rating vs. Runtime

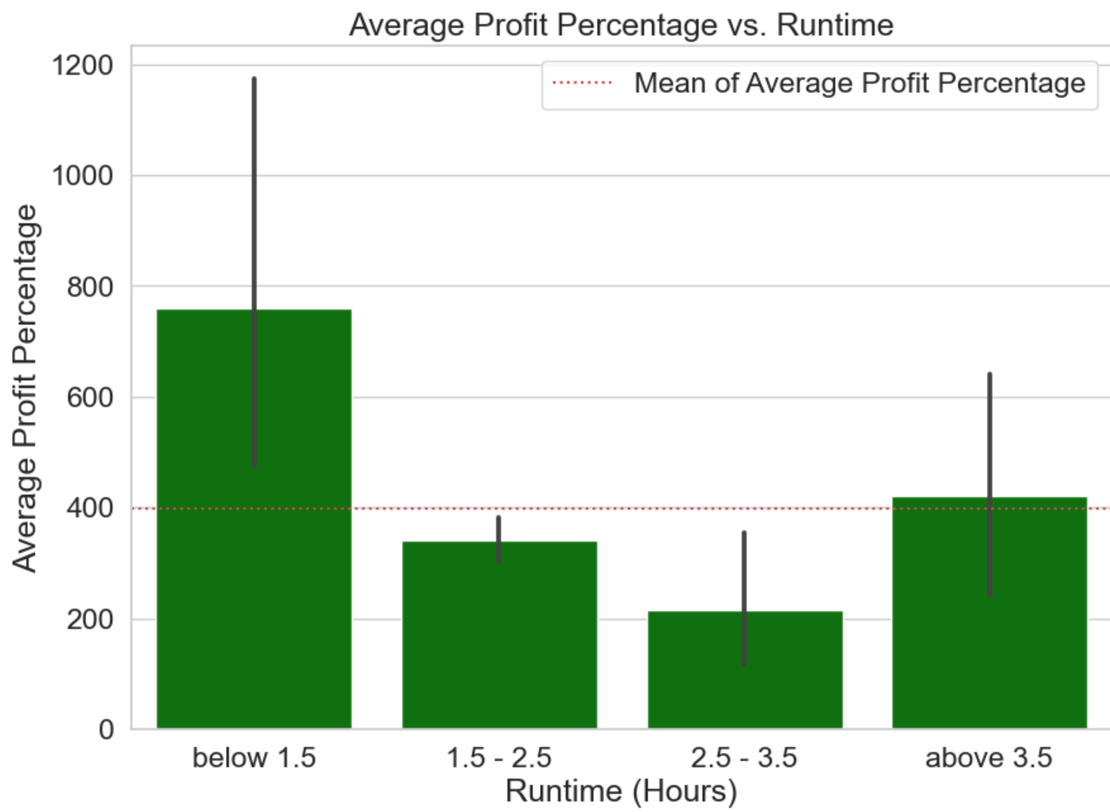
In [32]:

```
fix, ax = plt.subplots()
sns.set(rc={"figure.figsize":(10, 7)})
sns.set_theme(style="whitegrid", font_scale=1.5)
runtime_df = binned_df[binned_df['runtime_bins'] != 0]
plot = sns.barplot(data = binned_df, x = 'runtime_bins', y = 'averageratin
                   color = 'green').set(title = 'Average Rating vs. Runtim
ax.set_xticklabels(["below 1.5","1.5 - 2.5","2.5 - 3.5","above 3.5"])
ax.axhline(y = binned_df['averagerating'].mean(), color='r',
               linestyle='dotted', label = "Mean of Average Rating")
ax.legend()
ax.set_xlabel("Runtime (Hours)")
ax.set_ylabel("Average Rating")
plt.show()
```



Average Profit Percentage vs. Runtime

In [33]:
```
fix, ax = plt.subplots()
sns.set(rc={"figure.figsize":(10, 7)})
sns.set_theme(style="whitegrid", font_scale=1.5)
plot = sns.barplot(data = binned_df, x = 'runtime_bins', y = 'Profit%',
                   color = 'green').set(title = 'Average Profit Percentage
ax.set_xticklabels(["below 1.5","1.5 - 2.5","2.5 - 3.5","above 3.5"])
ax.set_xlabel("Runtime (Hours)")
ax.set_ylabel("Average Profit Percentage")
ax.axhline(y = binned_df['Profit%'].mean(), color='r', linestyle='dotted',
ax.legend()
plt.show()
```



Recommendation

Based on the above visualizations, if the goal of Computing Vision is higher ratings, we recommend a longer movie runtime of 2.5-3.5 hours. If their goal is higher profits, we recommend a shorter movie runtime of below 1.5 hours.

Cleaning up genres column and initial visualizations with transformed data

We cleaned genres because one movie can have multiple genres. There was no indication of what a primary genre was, so there was no way to decipher which was the primary so we made sure to give each of the movies all of their respective genres so that we could determine which performed the best in terms of profit percentage and audience ratings.

This allowed us to group the genres together and examine features amongst each individual genre and draw conclusions based on the results.

In [34]:

```
# Split genres into new rows
master_df_genre = master_df.copy()

# Used later for sub-genre analysis
master_df_genre_sg = merged
master_df_genre_sg = master_df_genre_sg[master_df_genre_sg['genres'].str.c
                                         | master_df_genre_sg['genres'].str
                                         | master_df_genre_sg['genres'].str

master_df_genre['genres'] = master_df_genre['genres'].map(lambda x: x.spli
master_df_genre_sg['genres'] = master_df_genre_sg['genres'].map(lambda x:
master_df_genre = master_df_genre.explode('genres')
master_df_genre_sg = master_df_genre_sg.explode('genres')
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\2719726769.py:1
1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#return
ing-a-view-versus-a-copy)
  master_df_genre_sg['genres'] = master_df_genre_sg['genres'].map(lambda
x: x.split(',') if type(x) is str else x)
```

In [35]:

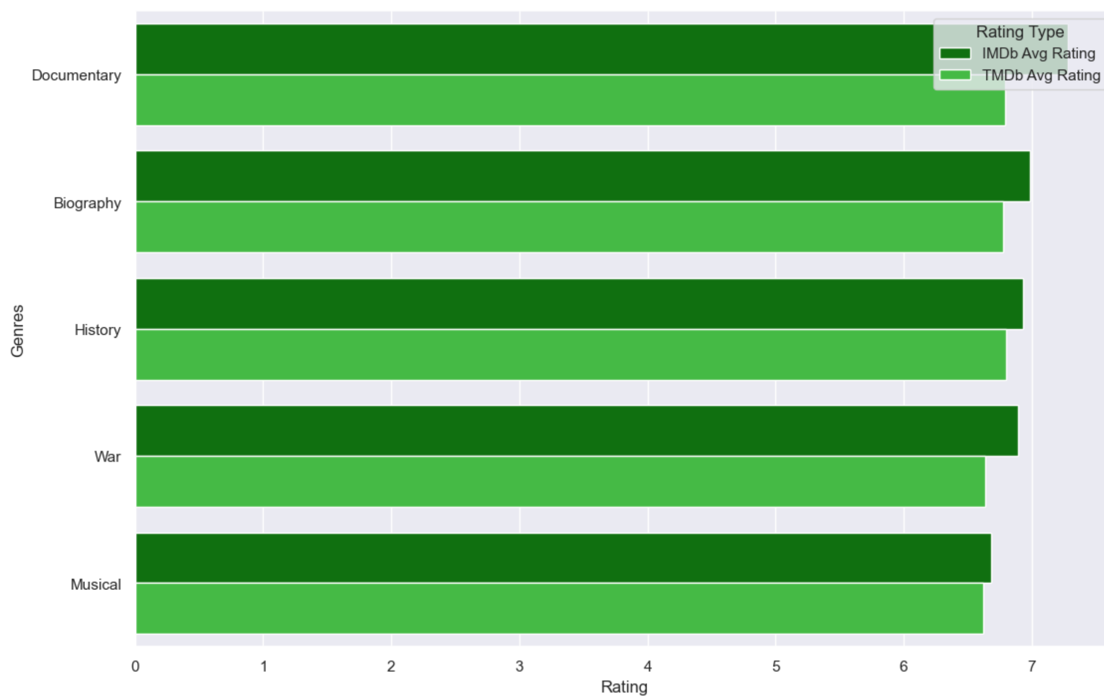
```
# Drop irrelevant genres
drop_list = ['Talk-Show','Reality-TV','Game-Show','News', 'Short']

for dropg in drop_list:
    master_df_genre = master_df_genre[master_df_genre['genres'] != dropg].
    master_df_genre_sg = master_df_genre_sg[master_df_genre_sg['genres'] !

# Merge Musical and Musically
master_df_genre['genres'] = master_df_genre['genres'].map(lambda x: x if x
master_df_genre_sg['genres'] = master_df_genre_sg['genres'].map(lambda x:
```

Average Overall Rating by Genre

In [36]:
```
# Get top 5 rated genres
master_df_genre_grp = master_df_genre.groupby(['genres']).mean().sort_valu
                    by=['averagerating','vote_average'], ascending=False).

# Rename columns for plot
master_df_genre_grp = master_df_genre_grp.rename(
    columns={'averagerating':'IMDb Avg Rating','vote_average':'TMDb Avg Ra

# Convert to vertical format for seaborn
master_df_genre_grp = master_df_genre_grp[
    ['IMDb Avg Rating','TMDb Avg Rating']].stack().to_frame('value').reset

master_df_genre_grp.rename(columns={'level_1':'Rating Type'},inplace=True)

# Plot
sns.set(rc={'figure.figsize':(12.7,8.27)})
sns.barplot(palette=['green','limegreen'],data=master_df_genre_grp,orient=
            x='value',hue='Rating Type').set(xlabel='Rating',ylabel='Genre
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\3168255354.py:2:
FutureWarning: The default value of numeric_only in DataFrameGroupBy.mea
n is deprecated. In a future version, numeric_only will default to Fals
e. Either specify numeric_only or select only columns which should be va
lid for the function.
  master_df_genre_grp = master_df_genre.groupby(['genres']).mean().sort_
values(
```

Out[36]:
```
[Text(0.5, 0, 'Rating'), Text(0, 0.5, 'Genres')]
```



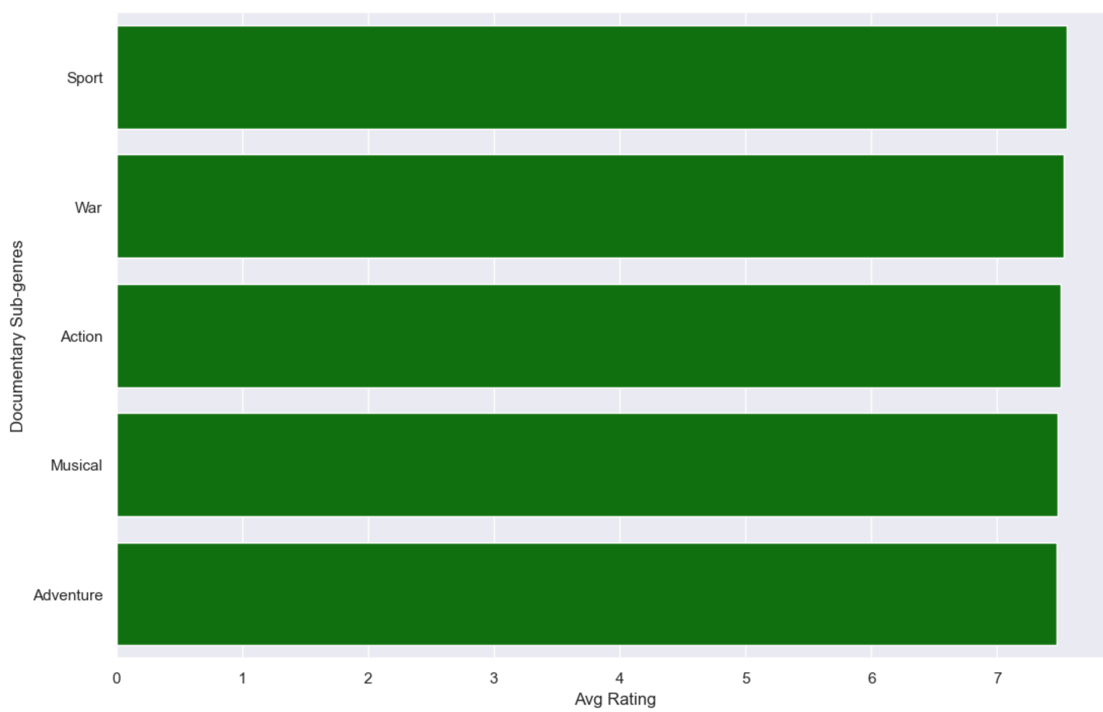
Plotting sub-genres by average rating

In [37]:

```
# Sub genre count
df_doc = master_df_genre_sg.drop(master_df_genre_sg[(master_df_genre_sg['g
                                                    | (master_df_genre_sg[

df_bio = master_df_genre_sg.drop(master_df_genre_sg[(master_df_genre_sg['g
                                                    | (master_df_genre_sg[

df_his = master_df_genre_sg.drop(master_df_genre_sg[(master_df_genre_sg['g
                                                    | (master_df_genre_sg[

#
df_doc = df_doc[df_doc['genres'] != 'Documentary']
df_bio = df_bio[df_bio['genres'] != 'Biography']
df_his = df_his[df_his['genres'] != 'History']

# Plot
sns.barplot(data=df_doc.rename(columns={'genres':'Documentary Sub-genres',
            'averagerating':'Avg Rating'}).groupby(['Documentary Sub-genre
            by='Avg Rating', ascending=False).head().reset_index(),
            y='Documentary Sub-genres',orient='h',x='Avg Rating',color='gr
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\1723305244.py:1
8: FutureWarning: The default value of numeric_only in DataFrameGroupBy.
mean is deprecated. In a future version, numeric_only will default to Fa
lse. Either specify numeric_only or select only columns which should be
valid for the function.
  'averagerating':'Avg Rating'}).groupby(['Documentary Sub-genres']).mea
n().sort_values(
```

Out[37]: <Axes: xlabel='Avg Rating', ylabel='Documentary Sub-genres'>



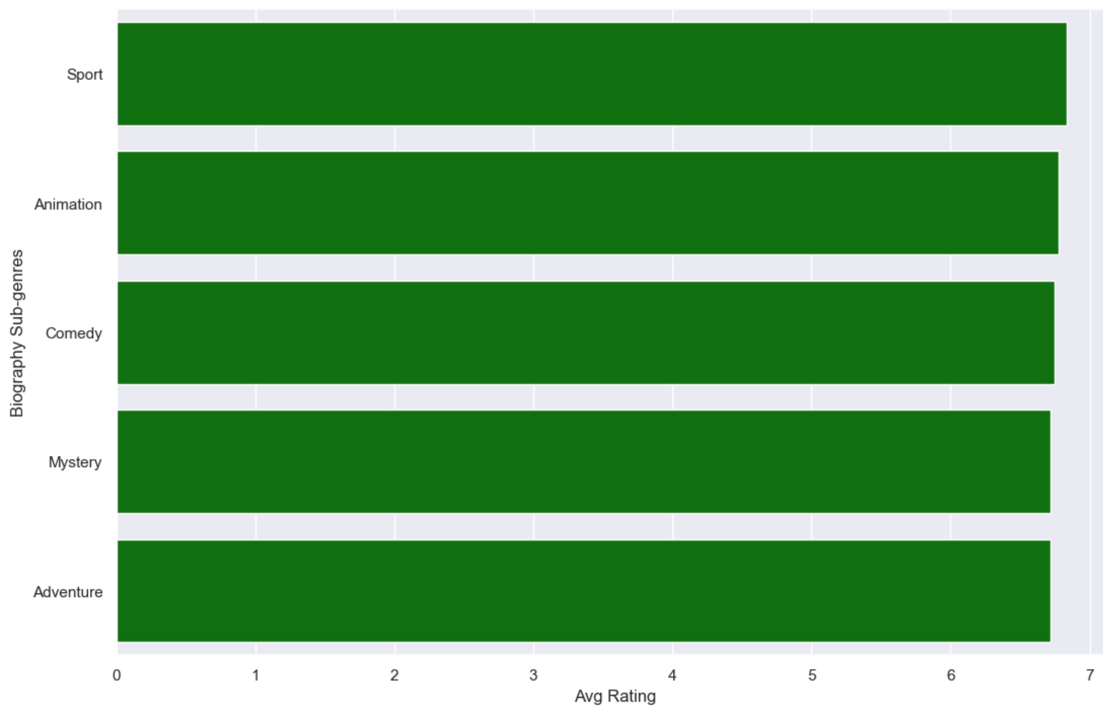
In [38]:

```
sns.barplot(data=df_bio.rename(columns={'genres':'Biography Sub-genres',
            'averagerating':'Avg Rating'}).groupby(['Biography Sub-genres'
            by='Avg Rating',ascending=False).head().reset_index(),
            y='Biography Sub-genres',orient='h',x='Avg Rating',color='gree
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\2840321267.py:2:
FutureWarning: The default value of numeric_only in DataFrameGroupBy.mea
n is deprecated. In a future version, numeric_only will default to Fals
e. Either specify numeric_only or select only columns which should be va
lid for the function.
  'averagerating':'Avg Rating'}).groupby(['Biography Sub-genres']).mean
().sort_values(
```

Out[38]:

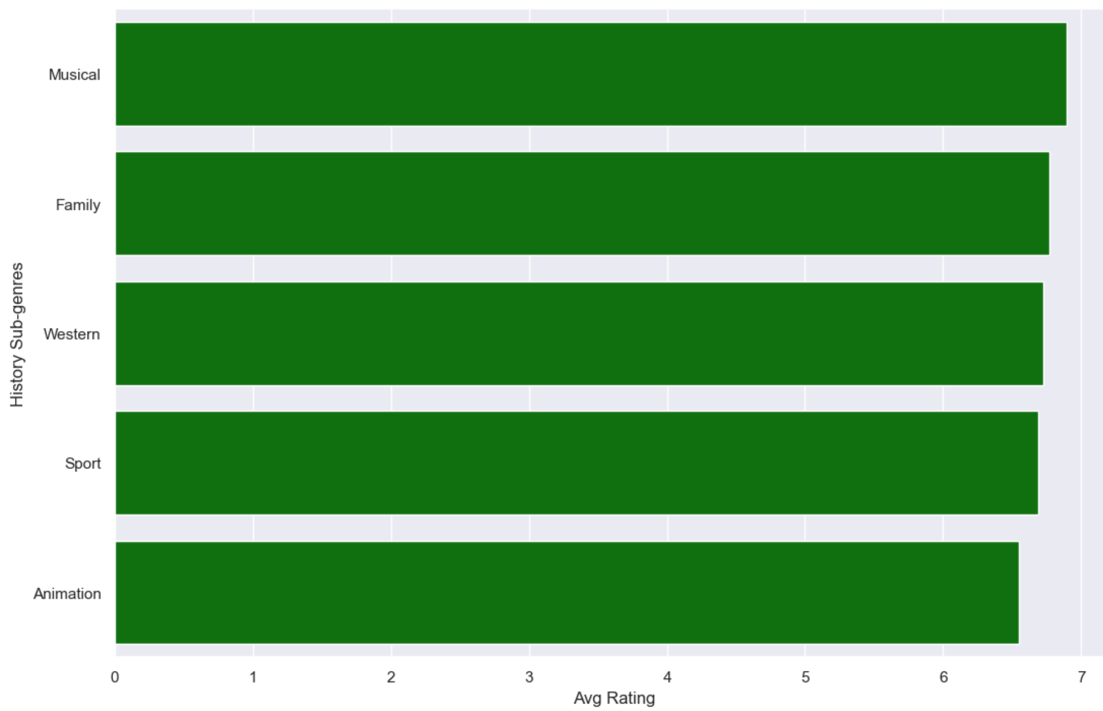
```
<Axes: xlabel='Avg Rating', ylabel='Biography Sub-genres'>
```



In [39]:
```
sns.barplot(data=df_his.rename(columns={'genres':'History Sub-genres',
            'averagerating':'Avg Rating'}).groupby(['History Sub-genres'])
            by='Avg Rating', ascending=False).head().reset_index(),
            y='History Sub-genres',orient='h',x='Avg Rating',color='green'
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\2989694421.py:2:
FutureWarning: The default value of numeric_only in DataFrameGroupBy.mea
n is deprecated. In a future version, numeric_only will default to Fals
e. Either specify numeric_only or select only columns which should be va
lid for the function.
  'averagerating':'Avg Rating'}).groupby(['History Sub-genres']).mean().
sort_values(
```

Out[39]:
```
<Axes: xlabel='Avg Rating', ylabel='History Sub-genres'>
```



In [40]:
```
master_df = master_df_genre.copy()
```

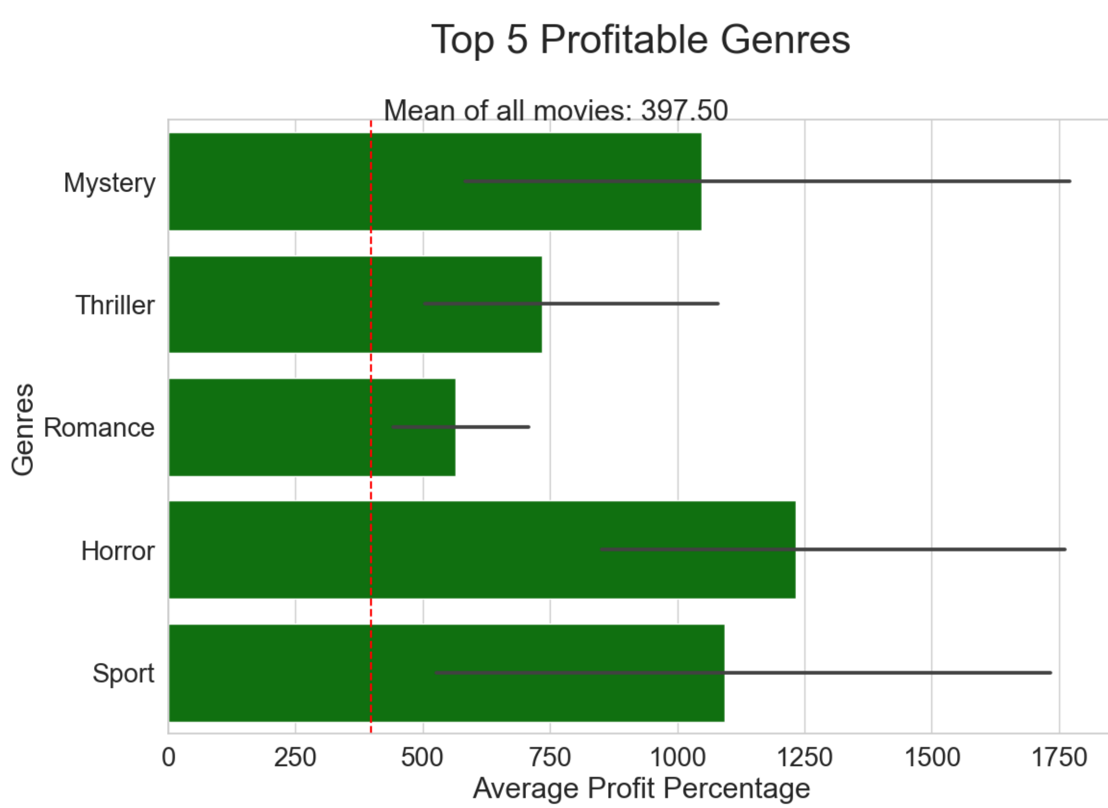
In [41]:
```
master_df_genre_grp = master_df.groupby(['genres'])
```

Genre Visualizations:

In [42]:
```
#Create Group of top 5 profit percentage genres in order to plot
new_df = master_df.copy()
new_df_top_5 = master_df[(master_df.genres == "Horror") | (master_df.genre
                         (master_df.genres == "Romance") | (master_df.genr
                         | (master_df.genres == "Sport")]
new_df_genre_grp = new_df_top_5.groupby("genres")
```

In [43]:
```
#Create Seaborn plot of the highest profiting genres
sns.set_theme(style="whitegrid",palette= "deep", font_scale=1.8)

ax = sns.barplot(data=new_df_top_5,y='genres',x='Profit%', color = "green"
ax.set_ylabel("Genres")
ax.set_xlabel("Average Profit Percentage")
ax.set_title("Top 5 Profitable Genres", size = 30, pad = 50)
ax.axvline(master_df["Profit%"].mean(), ls = '--', color = "red")
plt.text(master_df["Profit%"].mean()+25,-.5,  "Mean of all movies: {:.2f}"
;
```

Out[43]: ''



Recommendation:

Based on these visualizations we recommend that Computing Vision focuses on Mystery, Thriller, Romance, Horror, and Sport genres if their goal is profit percentages.

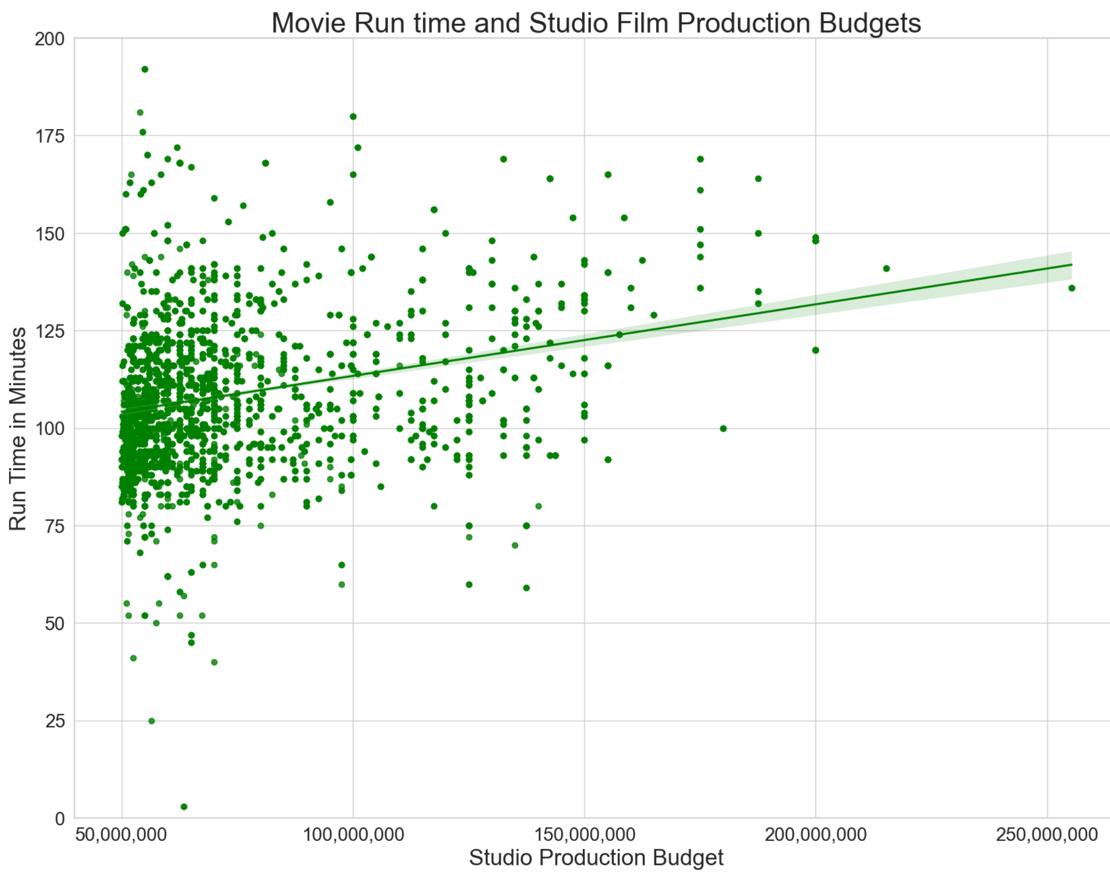
If there goal is audience ratings and reception, we reccomend that Computing Vision focuses on History, War, Musical, Biography, and Documentary genre movies.

Budget Visualizations

In [44]:

```
#Creating a scatter plot with a line of best fit
sns.set(rc={"figure.figsize":(20, 15)})
sns.set_theme(style="whitegrid", font_scale=1.8)
ax = sns.regplot(x="production_budget",
                 y="runtime_minutes",
                 data=master_df,
                 color = "green")
# Set y limit as no movies are over 200 minutes
plt.ylim(0, 200)
plt.title("Movie Run time and Studio Film Production Budgets",size =30 )
plt.xlabel("Studio Production Budget", size = 24)
plt.ylabel("Run Time in Minutes", size = 24)
#Create ticks for x axis based on budget range
ax.set_xticklabels(["0",'50,000,000', "100,000,000",
                    "150,000,000","200,000,000","250,000,000",
                    '300,000,000',"350,000,000","400,000,000","450,000,000
```

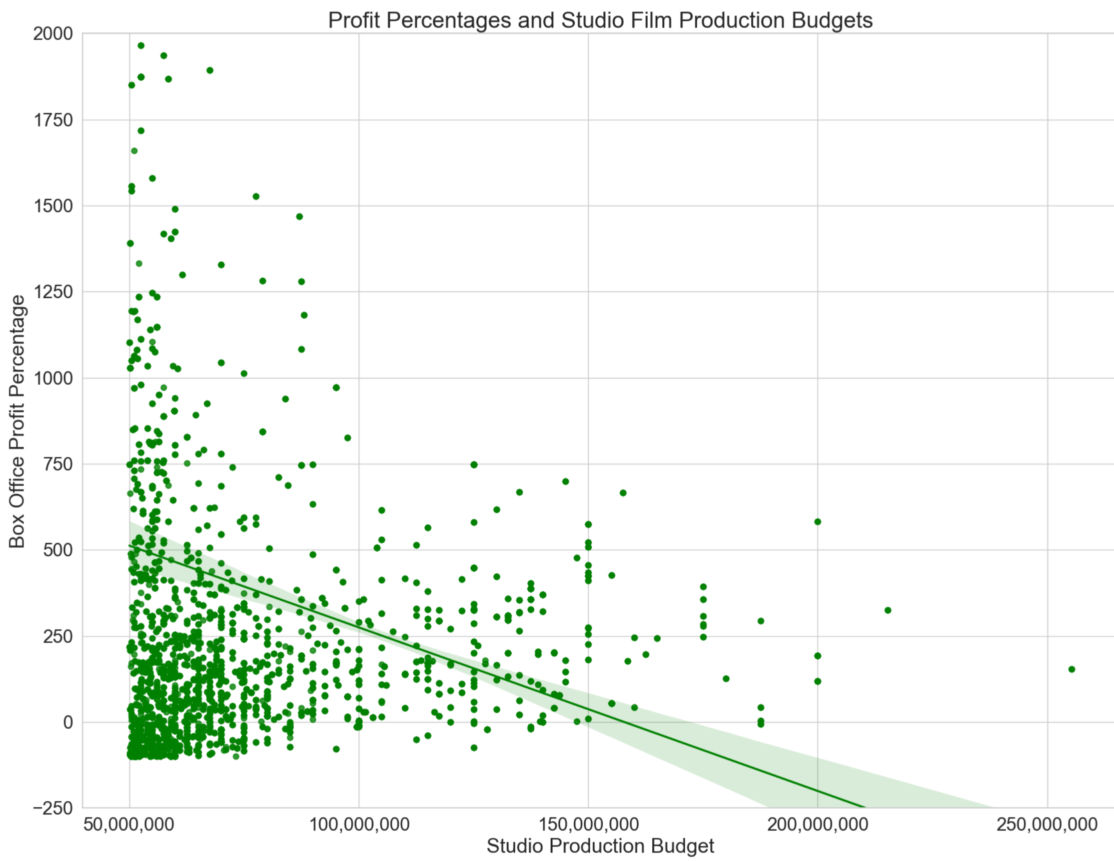
```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\162721585.py:14:
UserWarning: FixedFormatter should only be used together with FixedLocat
or
  ax.set_xticklabels(["0",'50,000,000', "100,000,000",
```



In [45]:

```
#Creating a scatter plot with a line of best fit

sns.set_theme(style="whitegrid", font_scale=1.8)
ax = sns.regplot(x="production_budget",
                 y="Profit%",
                 data=master_df,
                 color = "green")
plt.ylim(-250, 2000)
plt.title("Profit Percentages and Studio Film Production Budgets",size =24
plt.xlabel("Studio Production Budget")
plt.ylabel("Box Office Profit Percentage")
#Create ticks for x axis based on budget range
ax.set_xticklabels(["0",'50,000,000', "100,000,000",
                    "150,000,000","200,000,000","250,000,000",
                    '300,000,000',"350,000,000","400,000,000","450,000,000
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\2541216104.py:1
3: UserWarning: FixedFormatter should only be used together with FixedLo
cator
  ax.set_xticklabels(["0",'50,000,000', "100,000,000",
```



Recommendation:

Based on these visualizations we recommend that Computing Vision focuses on smaller budgets if their goal is profit percentages.

If there goal is audience ratings and reception, and budget is less of a concern, then we recommend using larger budgets to achieve this.

Calculating sample statistics like correlation to determine general trends among key quantitative variables of interest

In [46]:
```
master_df.production_budget.corr(master_df.Total_Profit)
```
Out[46]: 0.6452383068974963

In [47]:
```
master_df.production_budget.corr(master_df.averagerating)
```
Out[47]: 0.14159000612679057

In [48]:
```
master_df.production_budget.corr(master_df['Profit%'])
```
Out[48]: -0.09983003381523183

In [49]:
```
master_df.runtime_minutes.corr(master_df.averagerating)
```
Out[49]: 0.2647187702866116

In [50]:
```
master_df.runtime_minutes.corr(master_df["Profit%"])
```
Out[50]: -0.07883337549573378

Exploratory Statistical Testings on genres

Construct new data sets using genres of interest to create samples to compare to the general population

Explored several different variables and their statistical relationship with the general movies population to determine relationships of interest and determine the extent of these relationships.

Given the nature of genres being samples of our general dataset we settled on one sample t-tests to determine if individual samples were statistically higher than the general movie population.

For all five of these tests, we had the same hypotheses

Null-Hypothesis: The average profit percentage of each genre was less than or equal to the rest of the movies

Alternative Hypothesis: The average profit percentage of each genre was greater than the rest of the movies.

All of our testing revealed that these genres have a statistically higher profit percentage at the alpha level of .05.

Statistical testing for horror genre with variables: Profit Percentage

In [ ]:

```

```

In [51]:

```
df_horror = master_df[master_df.genres == "Horror"]
```

In [52]:

```
df_horror["Profit%"].mean()
```

Out[52]:

```
1233.1011563119691
```

In [53]:

```
stats.ttest_1samp(df_horror['Profit%'], popmean=master_df["Profit%"].mean(
```

Out[53]:

```
TtestResult(statistic=3.5384016386399404, pvalue=0.0005037350881016739,
df=194)
```

In [54]:

```
stats.t.interval(alpha = .95, df = len(df_horror)-1, loc = df_horror["Prof
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\1717214429.py:1:
DeprecationWarning: Use of keyword argument 'alpha' for method 'interva
l' is deprecated and wil be removed in SciPy 1.11.0. Use first positiona
l argument or keyword argument 'confidence' instead.
  stats.t.interval(alpha = .95, df = len(df_horror)-1, loc = df_horror
["Profit%"].mean(), scale = df_horror["Profit%"].std())
```

Out[54]:

```
(-5257.722730797311, 7723.925043421249)
```

Statistical testing for mystery genre with variable: Profit Percentage

In [55]:

```
df_mystery = master_df[master_df.genres == "Mystery"]
```

In [56]:
```
df_mystery["Profit%"].mean()
```

Out[56]: 1047.7253384458588

In [57]:
```
stats.t.interval(alpha = .95, df = len(df_mystery)-1, loc = df_mystery["Pr
                 scale =df_mystery["Profit%"].std())
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\1663007215.py:1:
DeprecationWarning: Use of keyword argument 'alpha' for method 'interva
l' is deprecated and wil be removed in SciPy 1.11.0. Use first positiona
l argument or keyword argument 'confidence' instead.
  stats.t.interval(alpha = .95, df = len(df_mystery)-1, loc = df_mystery
["Profit%"].mean(),
```

Out[57]: (-6319.355459118147, 8414.806136009865)

In [58]:
```
stats.ttest_1samp(df_mystery['Profit%'], popmean=master_df["Profit%"].mear
```

Out[58]: TtestResult(statistic=2.0138774368039543, pvalue=0.04603971305391123, df=133)

In [59]:
```
#Statistically cheaper to make than other movies
```

In [60]:
```
#mystery movies are statistically lower rated but statistically more profi
```

Statistical testing for Sport genre with variables: Profit Percentage

In [61]:
```
df_sport = master_df[master_df.genres == "Sport"]
```

In [62]:
```
df_sport["Profit%"].mean()
```

Out[62]: 1093.128317480592

In [63]:
```
stats.t.interval(alpha = .95, df = len(df_sport)-1, loc = df_sport["Profit
                 scale =df_sport["Profit%"].std())
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\1759420779.py:1:
DeprecationWarning: Use of keyword argument 'alpha' for method 'interva
l' is deprecated and wil be removed in SciPy 1.11.0. Use first positiona
l argument or keyword argument 'confidence' instead.
  stats.t.interval(alpha = .95, df = len(df_sport)-1, loc = df_sport["Pr
ofit%"].mean(),
```

Out[63]: (-3057.282009395951, 5243.538644357135)

In [64]:
```
stats.ttest_1samp(df_sport['Profit%'], popmean=master_df["Profit%"].mean()
```

Out[64]:
```
TtestResult(statistic=2.2454402542510925, pvalue=0.029813618814152426, d
f=44)
```

Statistical testing for Thriller genre with variables: Profit Percentage

In [65]:
```
df_thriller = master_df[master_df.genres == "Thriller"]
```

In [66]:
```
df_thriller["Profit%"].mean()
```

Out[66]:
```
733.7430978347663
```

In [67]:
```
stats.t.interval(alpha = .95, df = len(df_thriller)-1, loc = df_thriller["
                 scale =df_thriller["Profit%"].std())
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\349095963.py:1:
DeprecationWarning: Use of keyword argument 'alpha' for method 'interva
l' is deprecated and wil be removed in SciPy 1.11.0. Use first positiona
l argument or keyword argument 'confidence' instead.
  stats.t.interval(alpha = .95, df = len(df_thriller)-1, loc = df_thrill
er["Profit%"].mean(),
```

Out[67]:
```
(-4388.160373276534, 5855.646568946067)
```

In [68]:
```
stats.ttest_1samp(df_thriller['Profit%'], popmean=master_df["Profit%"].mea
```

Out[68]:
```
TtestResult(statistic=2.2675385944072293, pvalue=0.024049969365415032, d
f=308)
```

Statistical testing for Romance genre with variables: Profit Percentage

In [69]:
```
df_romance = master_df[master_df.genres == "Romance"]
```

In [70]:
```
df_romance["Profit%"].mean()
```

Out[70]:
```
563.7883368777519
```

In [71]:
```
stats.t.interval(alpha = .95, df = len(df_romance)-1, loc = df_romance["Pr
                 scale =df_romance["Profit%"].std())
```

```
C:\Users\usethuraman\AppData\Local\Temp\ipykernel_25944\2409525155.py:1:
DeprecationWarning: Use of keyword argument 'alpha' for method 'interva
l' is deprecated and wil be removed in SciPy 1.11.0. Use first positiona
l argument or keyword argument 'confidence' instead.
  stats.t.interval(alpha = .95, df = len(df_romance)-1, loc = df_romance
["Profit%"].mean(),
```

Out[71]:
```
(-1392.5182404865009, 2520.094914242005)
```

In [72]:
```
stats.ttest_1samp(df_romance['Profit%'], popmean=master_df["Profit%"].mear
```

Out[72]:
```
TtestResult(statistic=2.444339916049215, pvalue=0.01532469962099076, df=
213)
```

Recommendation:

Following our plotting of the average profit percentages against genres, we concluded these genres have statistically higher profit percentages. As a result, if Computing Vision's focus is on profit percentages, then we advise focusing on these 3 genres.

Conclusion:

After joining together 4 popular datasets with information regardin movie performance across ratings and financials we have come up with the following business insights based on what Computing Vision's priorities could be.

Audience Ratings and Reception

If their main priority is for high quality and received films from audiences, then we recommend using a run time between 2.5-3.5 hours in non-fiction genres like Documentary, History, and Biograph, using a higher production budget to achieve this goal.

Profit Percentages:

If their main priority is profit percentages, then we recommend using a shorter run time less than 1.5 hours in genres like horror, mystery, or sport, and to use a lower production budget to achieve this goal.