Movie Status Report: Computing Vision

I.- Introduction

A) Overview

We have been tasked with determining which type of movie would be the best investment for a new movie studio. Based on empirical data collected over the past couple of years. We want your initial investment in a movie to be successful so you can hit the ground running in your new and exciting venture. For that to be a success, we have taken a deep dive into the data to determine how long a movie should be, what rating, and how much to spend to insure a hit in the box office.

B) Members

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2. Rico Gutierrez
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C) Objectives

1. Analyze empirical data based on the last few years
2. Visualize the analyzed data
3. Explain the vizualizations
4. Determine the best course of action for the initial investment

II.- Determining Data

A) What production metrics makes a movie successful?

1. Runtime - How long a movie lasts
2. Age Rating - The age bracket and potential age restrictions determined by the MPAA
3. Movie Budget - The amount invested in film production

B) What metrics are affected by production?

1. Domestic gross - Gross revenue made released within a country
2. Foreign gross - Gross revenue made by the movie outside of the origin country
3. Worldwide gross - Gross revenue made by the movie worldwide
4. Box Office - The amount of money raised by ticket sales
5. Popularity Rating - How high would an audience rate a movie

C) Where does the data come from?

1. Box Office Mojo - Domestic gross, foreign gross, release year
2. Rotten Tomatoes - MPAA rating, runtime, box office
3. The Movie Database - Popularity rating, average popularity vote
4. The Numbers - Production budget, domestic gross, worldwide gross

III.- Cleaning and Modifying Data

A) Importing data into dataframes and respective libraries

In [215]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from scipy import stats
bom_movies = pd.read_csv('zippedData/bom.movie_gross.csv.gz', index_col=0)
rt_reviews = pd.read_csv("zippedData/rt.reviews.tsv.gz", sep = '\t', encodi
rt_movies = pd.read_csv("zippedData/rt.movie_info.tsv.gz", sep = '\t', encc
tmdb = pd.read_csv('zippedData/tmdb.movies.csv.gz', index_col=7)
tn = pd.read_csv('zippedData/tn.movie_budgets.csv.gz', index_col=2)
```

B) Removing data that would potentially skew results

1. Non applicable data
2. Data containing synonymous values like zero

In [216]:

```
bom_movies.dropna(inplace=True)
rt_movies.dropna(inplace=True)
```

C) Change data types

1. Changing a string into a manageable integer type

In [217]:

```

rt_movies['box_office'] = rt_movies['box_office'].str.replace(',', '')
rt_movies['box_office'] = rt_movies['box_office'].astype(int)
```

D) Merging dataframes

1. Increases population for metrics such as gross revenue
2. Decreasing columns based on what information is valuable

In [218]:

```
df = pd.merge(bom_movies, tmdb, on = 'title')
df = df[['studio', 'domestic_gross', 'foreign_gross', 'year', 'popularity',
tn.index.name = 'title'
df = df.merge(tn, on='title', how='left' )
df.sort_index()
```

Out[218]:

title	studio	domestic_gross_x	foreign_gross	year	popularity	vote_average	id
'71	RAtt.	1300000.0	355000	2015	10.523	6.8	NaN
10 Cloverfield Lane	Par.	72100000.0	38100000	2016	17.892	6.9	54.0
11-11-11	Rocket	32800.0	5700000	2011	5.196	4.3	NaN
12 Strong	WB	45800000.0	21600000	2018	13.183	5.6	64.0
12 Years a Slave	FoxS	56700000.0	131100000	2013	16.493	7.9	18.0
...	...	...	...	...	...	...	...
Zero Dark Thirty	Sony	95700000.0	37100000	2012	14.239	6.9	66.0
Zookeeper	Sony	80400000.0	89500000	2011	10.764	5.3	71.0
Zoolander 2	Par.	28800000.0	27900000	2016	12.997	4.7	64.0
Zootopia	BV	341300000.0	682500000	2016	27.549	7.7	57.0
mother!	Par.	17800000.0	26700000	2017	15.227	7.0	59.0

1714 rows × 11 columns

D) Further formatting

```
1. Removing Duplicate columns
2. Removing Nan values again
3.Converting values
```

In [219]:

```python
#Removing duplicate columns
df = df.drop('domestic_gross_y', axis=1)
df = df.drop('release_date', axis=1)

#Removing Nan
df.dropna(inplace=True)

#Formatting and convertting values
pd.to_datetime(df.year, format='%Y')

df['production_budget'] = df['production_budget'].str.replace(',', '')
df['production_budget'] = df['production_budget'].str.replace('$', '')
df['production_budget'] = df['production_budget'].astype(int)

df['worldwide_gross'] = df['worldwide_gross'].str.replace(',', '')
df['worldwide_gross'] = df['worldwide_gross'].str.replace('$', '')
df['worldwide_gross'] = df['worldwide_gross'].astype(int)

df.drop_duplicates(inplace=True)
df= df.rename(columns={'domestic_gross_x':'domestic_gross'})

df.head()
```

Out[219]:

title	studio	domestic_gross	foreign_gross	year	popularity	vote_average	id	prod
Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	47.0	
Inception	WB	292600000.0	535700000	2010	27.920	8.3	38.0	
Shrek Forever After	P/DW	238700000.0	513900000	2010	15.041	6.1	27.0	
The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	20.340	6.0	53.0	
Iron Man 2	Par.	312400000.0	311500000	2010	28.515	6.8	15.0	

IV.- Analyzing Data

A 1.1) Analyzing MPAA Age Rating: Graphing

In [220]:

```python
#Calculating how much average box office each rating made
ratings_df = rt_movies.groupby(by='rating').mean().sort_values(by=['box_off
ratings_df.drop(['id'], inplace=True, axis = 1)
ratings_df.reset_index(inplace=True)
ratings_df.head()
```

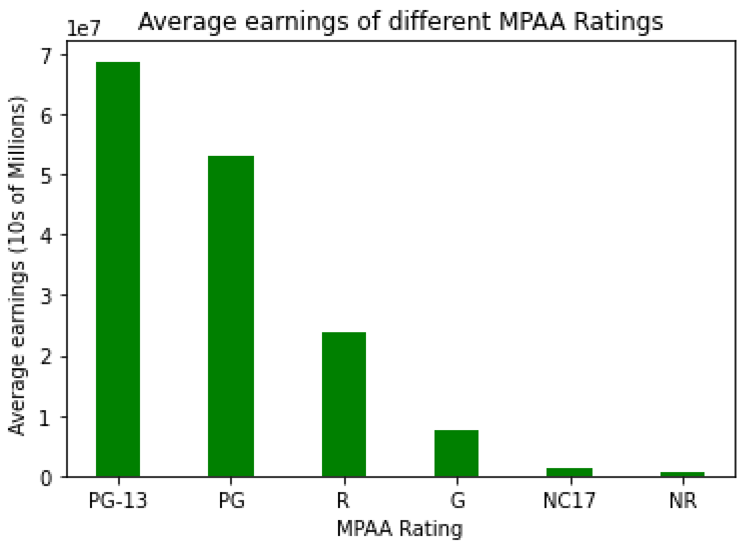
Out[220]:

	rating	box_office
0	PG-13	6.872359e+07
1	PG	5.289280e+07
2	R	2.394827e+07
3	G	7.402788e+06
4	NC17	1.260219e+06

In [221]:

```python
#Graphing
x = ratings_df.rating
y = ratings_df.box_office
plt.bar(x, y, color ='green',
        width = 0.4)

plt.xlabel("MPAA Rating")
plt.ylabel("Average earnings (10s of Millions) ")
plt.title("Average earnings of different MPAA Ratings")
plt.show()
```



A 1.2) Analyzing Movie Runtime: Conclusions

```
1. The biggest standout for recommending earnings are PG-13 and PG mov
ies
```

A 1.3) Analyzing Movie Runtime: T-test Graphing

```
1. We are comparing a sample mean with a population mean, 1 sample t-t
est
2. We are trying to determing if the sample is making more than the po
pulation, 1 tail t-test
3. We are trying to look for a 95% significance level, alpha = .05
4. The null hypothesis would be that a PG-13 movie does not significan
tly increase revenue
```

In [222]:

```
population_df = rt_movies[["rating", "box_office"]]
population_df.reset_index(inplace=True)
population_df = population_df.drop("index", axis=1)
population_df.head()
```

Out[222]:

	rating	box_office
0	R	600000
1	PG-13	41032915
2	R	224114
3	R	1039869
4	PG-13	20518224

In [223]:

```
population_df['rating'].value_counts()
```

Out[223]:

```
R         105
PG-13      77
PG         38
NR          9
G           5
NC17        1
Name: rating, dtype: int64
```

In [224]:

```
sample_df = population_df[population_df['rating'] == "PG-13"]
sample_df.reset_index(inplace=True)
sample_df = sample_df.drop("index", axis=1)
sample_df.head()
```

Out[224]:

	rating	box_office
0	PG-13	41032915
1	PG-13	20518224
2	PG-13	35565975
3	PG-13	42929971
4	PG-13	37431431

In [225]:

```
sample_df['rating'].value_counts()
```

Out[225]:

```
PG-13    77
Name: rating, dtype: int64
```

In [226]:

```
degrees = len(sample_df)-1
t_crit = stats.t.ppf(1 - 0.025, degrees)
t_crit
```

Out[226]:

```
1.9916726093523487
```

In [227]:

```
population_mean = population_df["box_office"].mean()
results = stats.ttest_1samp(
    a       = list(sample_df["box_office"]),
    popmean = population_mean
)

t = results.statistic
results
```

Out[227]:

```
Ttest_1sampResult(statistic=3.120504262968141, pvalue=0.002552049772706054
3)
```

A 1.4) Analyzing Movie Runtime: T-test Conclusions

```
1. The observed t-statistic > the critical t value
2. Null Hypothesis is rejected
3. The increase in box office sales is statistically significant with
a 97.5% confidence
```

In [228]:

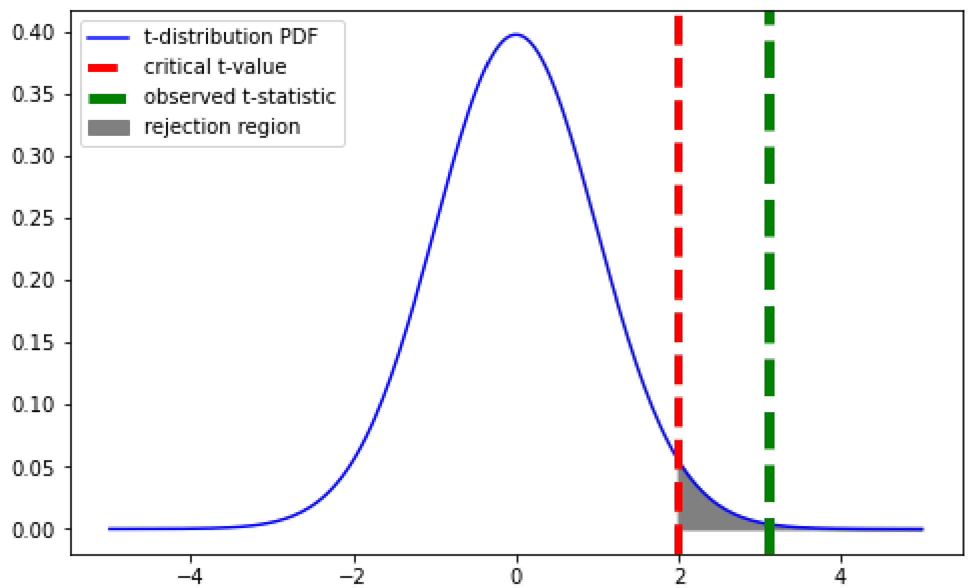
```
# Set up figure and axes
fig, ax = plt.subplots(figsize=(8,5))
x = np.linspace(-5, 5, 200)
y = stats.t.pdf(x, degrees, 0, 1)
# Plot the PDF as a line graph
# (x and y were created in previous plotting code)
ax.plot(x, y, color='blue', label="t-distribution PDF")

# Graphing Critical t-value
ax.axvline(t_crit,color='red',linestyle='--',lw=4,label='critical t-value')

# Filling Rejection Region
ax.fill_betweenx(y,x,t_crit,where=x > t_crit,color="gray",label="rejection

#Graphing observed t-stat
ax.axvline(t, color='green', linestyle='--', lw=5,label='observed t-statist

#Graphing Legend
ax.legend();
```



B 1.1) Analyzing Movie Budget: Cleaning

```
1. We want to analyze movies that have a high earning of at least 400,
000,000 dollars
2. We need to analyze the studio, the production budget, and the world
wide gross.
3. A stacked bar chart will depict the budget a studio allocates and h
ow much revenue they recieve
3. Some studios have are in the dataset multiple times but under a dif
ferent name
```

In [229]:

```
df.head()
```

Out[229]:

title	studio	domestic_gross	foreign_gross	year	popularity	vote_average	id	prod
Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	47.0	
Inception	WB	292600000.0	535700000	2010	27.920	8.3	38.0	
Shrek Forever After	P/DW	238700000.0	513900000	2010	15.041	6.1	27.0	
The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	20.340	6.0	53.0	
Iron Man 2	Par.	312400000.0	311500000	2010	28.515	6.8	15.0	

In [230]:

```
movie_budget_df = df[df['worldwide_gross'] > 400000000]
movie_budget_df = movie_budget_df[['production_budget', 'worldwide_gross',
movie_budget_df.reset_index(inplace=True)
movie_budget_df
```

Out[230]:

	studio	production_budget	worldwide_gross
0	BV	6.831200e+09	3.176650e+10
1	WB	3.271000e+09	1.324274e+10
2	Fox	2.937000e+09	1.378231e+10
3	Uni.	1.974000e+09	1.440055e+10
4	Sony	1.440000e+09	6.862027e+09
5	Par.	1.394000e+09	4.907887e+09
6	P/DW	9.500000e+08	4.341653e+09
7	WB (NL)	8.950000e+08	4.076665e+09
8	LGF	4.950000e+08	2.958353e+09
9	Wein.	1.000000e+08	4.499483e+08
10	Sum.	6.800000e+07	7.061028e+08
11	LG/S	2.000000e+07	4.263512e+08

In [231]:
```
#Combigning duplicate entries under LG and WB
movie_budget_df['studio'] = movie_budget_df['studio'].replace('^WB.*', 'WB'
movie_budget_df['studio'] = movie_budget_df['studio'].replace('^LG.*', 'LG'
movie_budget_df
```

Out[231]:

	studio	production_budget	worldwide_gross
0	BV	6.831200e+09	3.176650e+10
1	WB	3.271000e+09	1.324274e+10
2	Fox	2.937000e+09	1.378231e+10
3	Uni.	1.974000e+09	1.440055e+10
4	Sony	1.440000e+09	6.862027e+09
5	Par.	1.394000e+09	4.907887e+09
6	P/DW	9.500000e+08	4.341653e+09
7	WB	8.950000e+08	4.076665e+09
8	LG	4.950000e+08	2.958353e+09
9	Wein.	1.000000e+08	4.499483e+08
10	Sum.	6.800000e+07	7.061028e+08
11	LG	2.000000e+07	4.263512e+08

In [232]:
```
movie_budget_df = movie_budget_df.groupby(movie_budget_df["studio"], sort=F
movie_budget_df
```

Out[232]:

studio	production_budget	worldwide_gross
BV	6.831200e+09	3.176650e+10
WB	4.166000e+09	1.731940e+10
Fox	2.937000e+09	1.378231e+10
Uni.	1.974000e+09	1.440055e+10
Sony	1.440000e+09	6.862027e+09
Par.	1.394000e+09	4.907887e+09
P/DW	9.500000e+08	4.341653e+09
LG	5.150000e+08	3.384705e+09
Wein.	1.000000e+08	4.499483e+08
Sum.	6.800000e+07	7.061028e+08

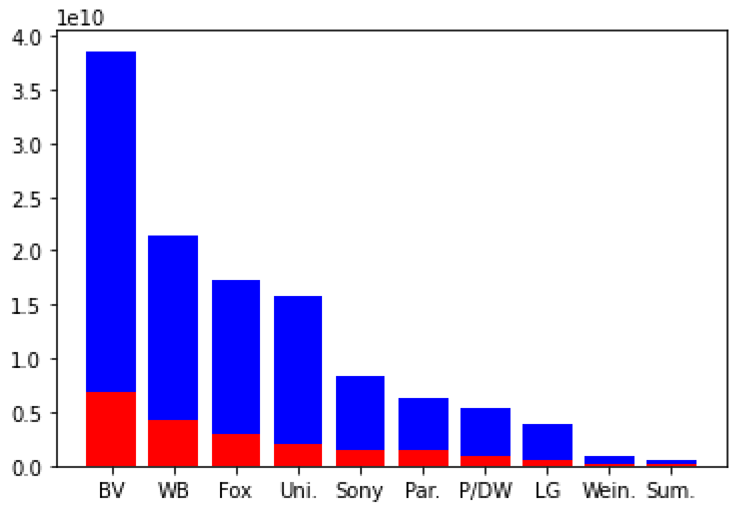
In [233]:

```
#Our X-Values will be the studios
x = list(movie_budget_df.index)

#We need 2 bars to make a stacked bar chart. The revenue will on average be
#Because of this, we will graph the expense on top of the revenue
revenue_y = movie_budget_df.groupby(by = 'studio').mean().sort_values(by=['
expense_y = movie_budget_df.groupby(by = 'studio').mean().sort_values(by=['
```

In [234]:

```
plt.bar(x, expense_y, color='r')
plt.bar(x, revenue_y, bottom=expense_y, color='b')
plt.show()
```



B 1.2) Analyzing Movie Budget: Conclusions

```
1. We are comparing the budgets vs the expenses
2. Studios with more potential expenses, would be expected to have mor
e return on revenue
3. A further step would be to determine the marginal returns for every
dollar invested to determine an optimal budget
```

C 1.1) Analyzing Movie Runtime: Graphing

In [235]:

```
runtime_df = rt_movies[['runtime', "box_office"]]
runtime_df['runtime'] = rt_movies['runtime'].str[:-8].astype(int)
runtime_df['Long'] = np.where(runtime_df['runtime']> 107, 'Y', 'N')
```

```
<ipython-input-235-20a045845f64>:2: 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-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://
pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
view-versus-a-copy)
  runtime_df['runtime'] = rt_movies['runtime'].str[:-8].astype(int)
<ipython-input-235-20a045845f64>:3: 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-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://
pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
view-versus-a-copy)
  runtime_df['Long'] = np.where(runtime_df['runtime']> 107, 'Y', 'N')
```

In [236]:

```
#Determining what makes a movie long
runtime_df
```

Out[236]:

	runtime	box_office	Long
1	108	600000	Y
6	82	41032915	N
7	123	224114	Y
15	108	1039869	Y
18	127	20518224	Y
...	...	...	...
1530	126	72700000	Y
1537	123	1320005	Y
1541	119	25335935	Y
1542	129	1416189	Y
1545	98	59371	N

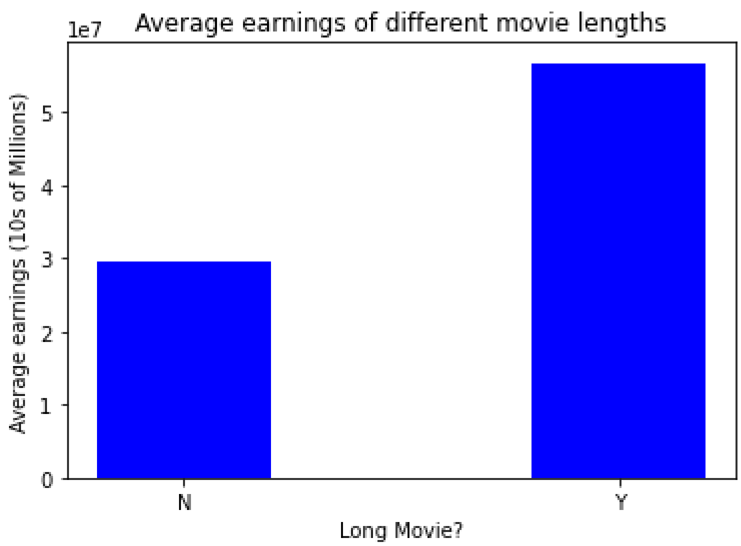
In [237]:

```
#The Average
runtime_df = runtime_df.groupby(by = 'Long').mean()
runtime_df.reset_index(inplace=True)

y = runtime_df.box_office
x = runtime_df.Long

plt.bar(x, y, color ='blue', width = 0.4)

plt.xlabel("Long Movie?")
plt.ylabel("Average earnings (10s of Millions)")
plt.title("Average earnings of different movie lengths")
plt.show()
```



C 1.2) Analyzing Movie Runtime: Conclusions

1. The average length of a movie was determined to be 107 minutes
2. Anything above 107 would be considered long, anything below would be short
3. The average earnings is used to avoid total earnings in case there are an abundance of long or short movies
4. The average earnings made by a long movie is SUBSTANTIALLY HIGHER than that made with a short movie

V.- Further Steps

A) Age Rating

1. We would recommend a targeted age rating of PG-13 or equivalent for other countries.
2. Avoid ratings that would restrict a potential viewerbase

B) Runtime

1. A longer movie on average would also increase potential revenue
2. The industry standard is 90 minutes, this is further evidence that a longer runtime is better

C) Funding

1. Movies with higher production budgets will also return greater revenue
2. It is important to to secure funding from investors