Multiple Regression Analysis on Video Game Movie Reviews and Sales Data

Aaron Hum - MAT 421 - Final Project

Introduction

This project tests the "so-bad-it's-good" effect, where people actively seek out "bad" movies in order to watch them for comedic or satirical purposes. In order to test this, I have found a dataset of 42 video game movies, including their titles, release date, worldwide box office earnings (in US dollars), Rotten Tomatoes score (percentage), Metacritic score (out of 100), film distributor, and publisher.

Data source: https://www.kaggle.com/bcruise/film-adaptations-of-video-games

Models and Numerical Methods

Models Used

Linear Regression, Multiple Linear Regression

Numerical Methods

The equation will measure Y, the box office sales of a movie in US dollars, in the equation:

Y = box office sales of a movie in US dollars

X1 = Metacritic score, X2 = Rotten Tomato score

B0 = Intercept, Bn = Slope of the regression line for each variable, e = error

$Y = B0 + B1X1 + B2X2 + e$

Expectations

I expect Metacritic scores and Rotten Tomatoes scores will have a negative correlation to box office sales, due to my hypothesised “so-bad-it’s-good” effect.

I expect the model will have a lot of error, due to the wide variance among video game movie box office sales and scores, and also, due to the relatively small sample size (42), there could be a lot of error as well.

Python Libraries in this Project

numpy: Numerical computations

pandas: Data manipulation

matplotlib: Data visualization

seaborn: Statistical data visualization

sklearn: Regression, machine learning, data analysis

```
# imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Uploading the Dataset

Upload 'video_game_films.csv' from the data source.

```
# upload 'video_game_films.csv'
from google.colab import files
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>

Saving video_game_films.csv to video_game_films.csv
```

```
dataset = pd.read_csv("video_game_films.csv")
dataset
```

```
                                              Title  ...      Original
game publisher
0                                 Super Mario Bros.  ...
Nintendo
1                                     Double Dragon  ...
Technōs Japan
2                                   Street Fighter  ...
Capcom
3                                     Mortal Kombat  ...
Midway
4                       Mortal Kombat: Annihilation  ...
Midway
5                                   Wing Commander  ...
Origin Systems
6                           Lara Croft: Tomb Raider  ...
Eidos
7                                     Resident Evil  ...
Capcom
8    Lara Croft: Tomb Raider – The Cradle of Life  ...
Eidos
9                                 House of the Dead  ...
Sega Sammy
10                          Resident Evil: Apocalypse  ...
Capcom
11                                Alone in the Dark  ...
Infogrames
12                                             Doom  ...
```

```
id Software
13                                      BloodRayne  ...        Majesco
Entertainment
14                                    Silent Hill  ...
Konami
15                              DOA: Dead or Alive  ...
Tecmo
16                        Resident Evil: Extinction  ...
Capcom
17                                         Postal  ...
Ripcord Games
18                                          Hitman  ...
Eidos
19  In the Name of the King: A Dungeon Siege Tale  ...
Microsoft Studios
20                                        Far Cry  ...
Ubisoft
21                                      Max Payne  ...
Rockstar Games
22          Street Fighter: The Legend of Chun-Li  ...
Capcom
23                                         Tekken  ...
Bandai Namco Games
24            Prince of Persia: The Sands of Time  ...
Ubisoft
25                         Resident Evil: Afterlife  ...
Capcom
26                       Resident Evil: Retribution  ...
Capcom
27                          Silent Hill: Revelation  ...
Konami
28                                   Need for Speed  ...
Electronic Arts
29                                Hitman: Agent 47  ...
Square Enix
30                                         Warcraft  ...       Blizzard
Entertainment
31                                Assassin's Creed  ...
Ubisoft
32               Resident Evil: The Final Chapter  ...
Capcom
33                                      Tomb Raider  ...
Square Enix
34                                          Rampage  ...
WB Games
35                                     Dead Trigger  ...
Madfinger Games
36                                Detective Pikachu  ...  NintendoThe
Pokémon Company
37                                Sonic the Hedgehog  ...
```

```
Sega Sammy
38                                  Monster Hunter  ...
Capcom
39                                   Mortal Kombat  ...
WB Games
40                                Werewolves Within  ...
Ubisoft
41         Resident Evil: Welcome to Raccoon City  ...
Capcom

[42 rows x 7 columns]
```

Removing Null Values from the Dataset

```
# Examining the dataset
dataset.shape
dataset.info()
dataset.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42 entries, 0 to 41
Data columns (total 7 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Title                    42 non-null     object
 1   Release date             42 non-null     object
 2   Worldwide box office     42 non-null     float64
 3   Rotten Tomatoes          40 non-null     float64
 4   Metacritic               38 non-null     float64
 5   Distributor              42 non-null     object
 6   Original game publisher  42 non-null     object
dtypes: float64(3), object(4)
memory usage: 2.4+ KB
```

```
                        Title  ... Original game publisher
0            Super Mario Bros.  ...                Nintendo
1                Double Dragon  ...           Technōs Japan
2               Street Fighter  ...                  Capcom
3                Mortal Kombat  ...                  Midway
4  Mortal Kombat: Annihilation  ...                  Midway

[5 rows x 7 columns]
```

```
# Finding out how many null values there are
dataset.isnull()
```

```
    Title  Release date  ...  Distributor  Original game publisher
0   False         False  ...        False                    False
1   False         False  ...        False                    False
2   False         False  ...        False                    False
3   False         False  ...        False                    False
4   False         False  ...        False                    False
```

```
5   False         False  ...        False                    False
6   False         False  ...        False                    False
7   False         False  ...        False                    False
8   False         False  ...        False                    False
9   False         False  ...        False                    False
10  False         False  ...        False                    False
11  False         False  ...        False                    False
12  False         False  ...        False                    False
13  False         False  ...        False                    False
14  False         False  ...        False                    False
15  False         False  ...        False                    False
16  False         False  ...        False                    False
17  False         False  ...        False                    False
18  False         False  ...        False                    False
19  False         False  ...        False                    False
20  False         False  ...        False                    False
21  False         False  ...        False                    False
22  False         False  ...        False                    False
23  False         False  ...        False                    False
24  False         False  ...        False                    False
25  False         False  ...        False                    False
26  False         False  ...        False                    False
27  False         False  ...        False                    False
28  False         False  ...        False                    False
29  False         False  ...        False                    False
30  False         False  ...        False                    False
31  False         False  ...        False                    False
32  False         False  ...        False                    False
33  False         False  ...        False                    False
34  False         False  ...        False                    False
35  False         False  ...        False                    False
36  False         False  ...        False                    False
37  False         False  ...        False                    False
38  False         False  ...        False                    False
39  False         False  ...        False                    False
40  False         False  ...        False                    False
41  False         False  ...        False                    False

[42 rows x 7 columns]
```

```
dataset.isnull().sum()
```

```
Title                     0
Release date              0
Worldwide box office      0
Rotten Tomatoes           2
Metacritic                4
Distributor               0
Original game publisher   0
dtype: int64
```

```
# Drop the null values of the dataset
dataset = dataset.dropna()
dataset
```

```
                                                Title  ...      Original
game publisher
0                                  Super Mario Bros.  ...
Nintendo
2                                     Street Fighter  ...
Capcom
3                                      Mortal Kombat  ...
Midway
4                        Mortal Kombat: Annihilation  ...
Midway
5                                     Wing Commander  ...
Origin Systems
6                             Lara Croft: Tomb Raider  ...
Eidos
7                                      Resident Evil  ...
Capcom
8    Lara Croft: Tomb Raider – The Cradle of Life  ...
Eidos
9                                  House of the Dead  ...
Sega Sammy
10                           Resident Evil: Apocalypse  ...
Capcom
11                                 Alone in the Dark  ...
Infogrames
12                                              Doom  ...
id Software
13                                         BloodRayne  ...        Majesco
Entertainment
14                                        Silent Hill  ...
Konami
15                                DOA: Dead or Alive  ...
Tecmo
16                           Resident Evil: Extinction  ...
Capcom
17                                            Postal  ...
Ripcord Games
18                                            Hitman  ...
Eidos
19  In the Name of the King: A Dungeon Siege Tale  ...
Microsoft Studios
21                                         Max Payne  ...
Rockstar Games
22          Street Fighter: The Legend of Chun-Li  ...
Capcom
24            Prince of Persia: The Sands of Time  ...
Ubisoft
```

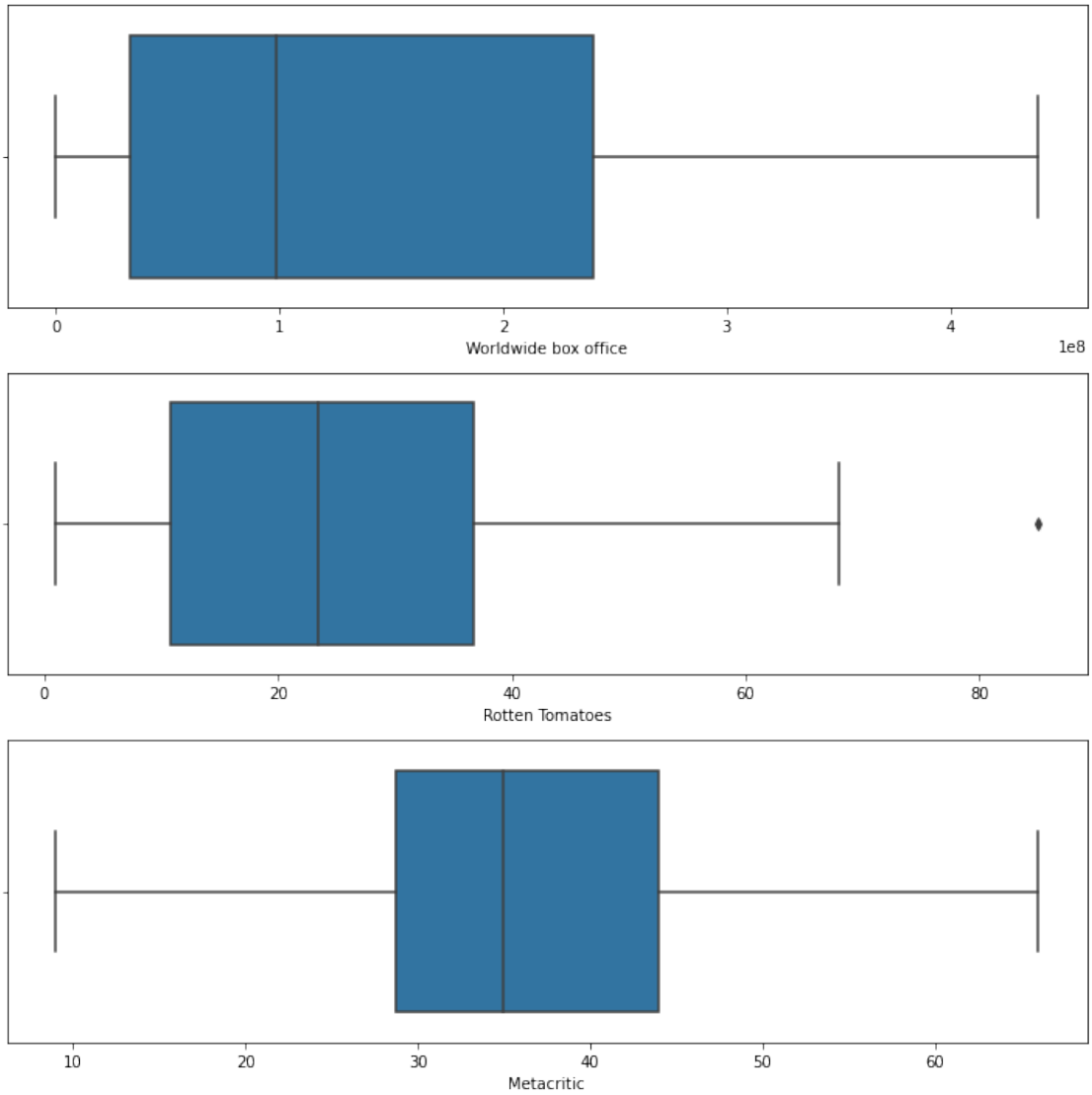
```
25                        Resident Evil: Afterlife  ...
Capcom
26                      Resident Evil: Retribution  ...
Capcom
27                         Silent Hill: Revelation  ...
Konami
28                                   Need for Speed  ...
Electronic Arts
29                                 Hitman: Agent 47  ...
Square Enix
30                                          Warcraft  ...       Blizzard
Entertainment
31                                 Assassin's Creed  ...
Ubisoft
32                 Resident Evil: The Final Chapter  ...
Capcom
33                                      Tomb Raider  ...
Square Enix
34                                          Rampage  ...
WB Games
36                                Detective Pikachu  ...  NintendoThe
Pokémon Company
37                               Sonic the Hedgehog  ...
Sega Sammy
38                                  Monster Hunter  ...
Capcom
39                                   Mortal Kombat  ...
WB Games
40                                Werewolves Within  ...
Ubisoft
41          Resident Evil: Welcome to Raccoon City  ...
Capcom

[38 rows x 7 columns]
```

Basic Plots, Data Visualization and Analysis

Using matplotlib and seaborn, I create several plots showing different aspects of the data.

Boxplots

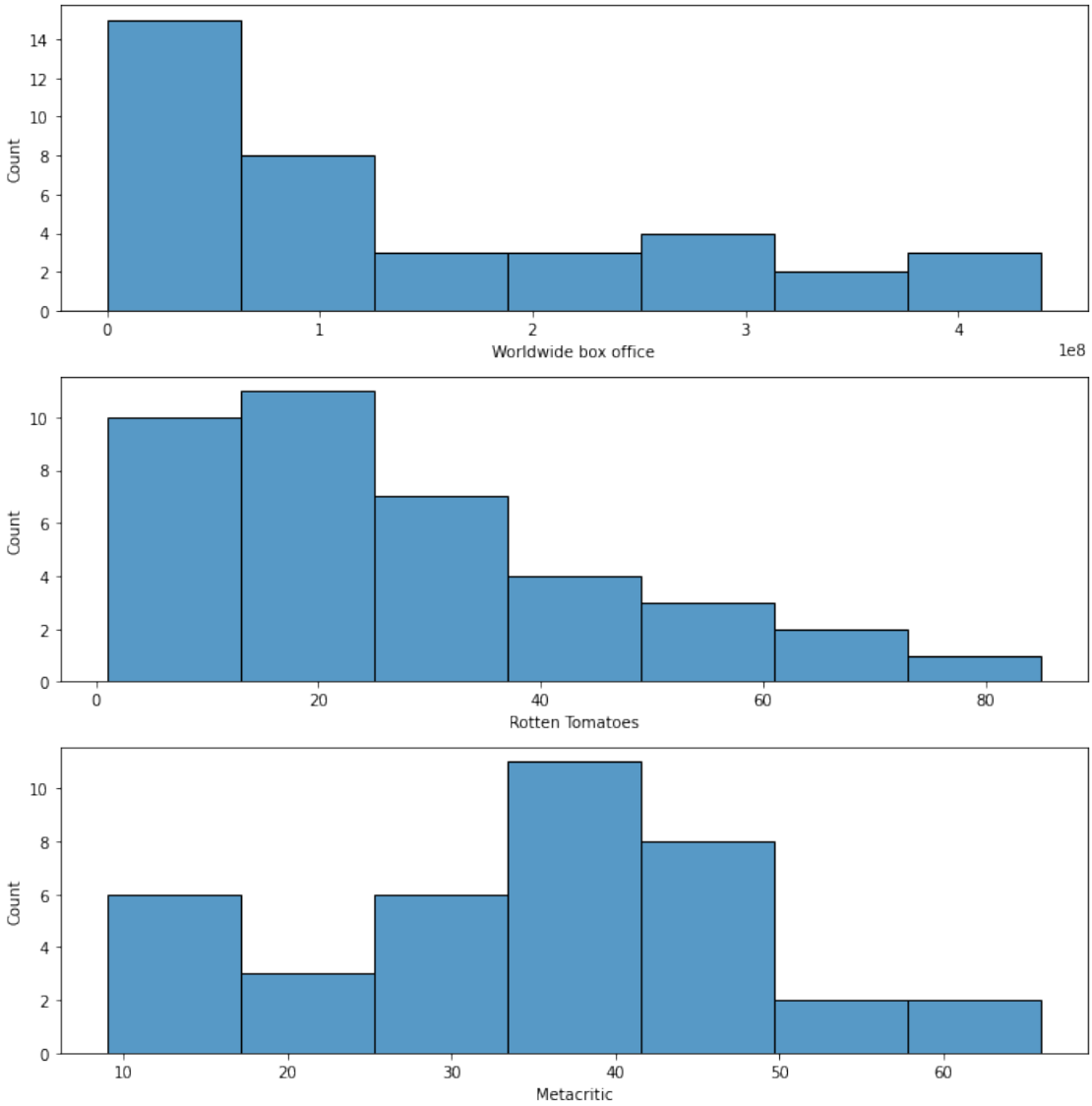
```
fig, axs = plt.subplots(3, figsize = (10,10))
plt1 = sns.boxplot(x = dataset['Worldwide box office'], ax = axs[0])
plt2 = sns.boxplot(x = dataset['Rotten Tomatoes'], ax = axs[1])
plt3 = sns.boxplot(x = dataset['Metacritic'], ax = axs[2])
plt.tight_layout()
```



Boxplot Conclusions: There are no extreme values except for one in Rotten Tomatoes. The Worldwide box office sales and Rotten Tomatoes scores are positive skewed in distribution, Metacritic is realtively unskewed or normal.

Histogram Plots

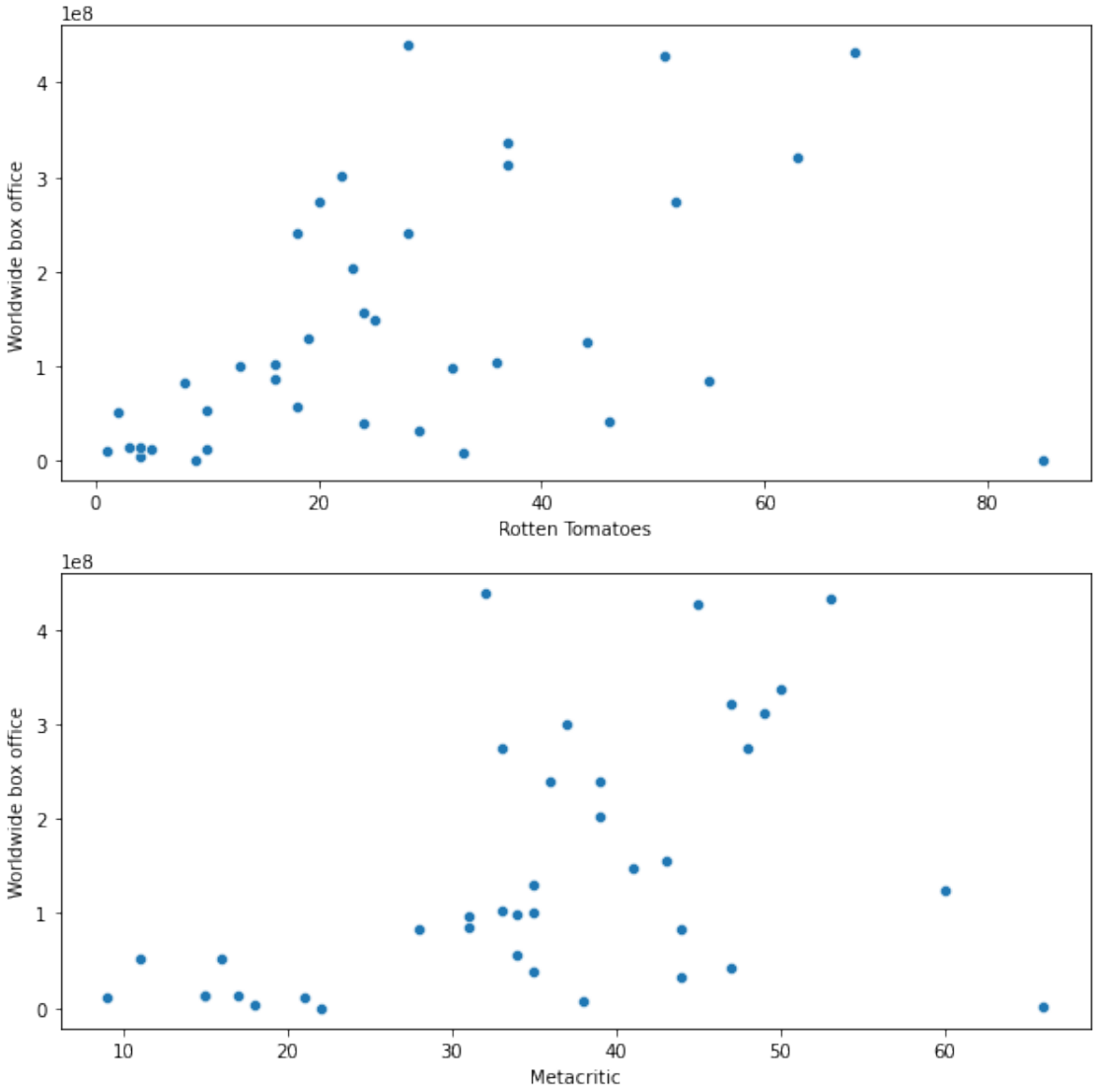
```
fig, axs = plt.subplots(3, figsize = (10,10))
plt1 = sns.histplot(x = dataset['Worldwide box office'], ax = axs[0])
plt2 = sns.histplot(x = dataset['Rotten Tomatoes'], ax = axs[1])
plt3 = sns.histplot(x = dataset['Metacritic'], ax = axs[2])
plt.tight_layout()
```



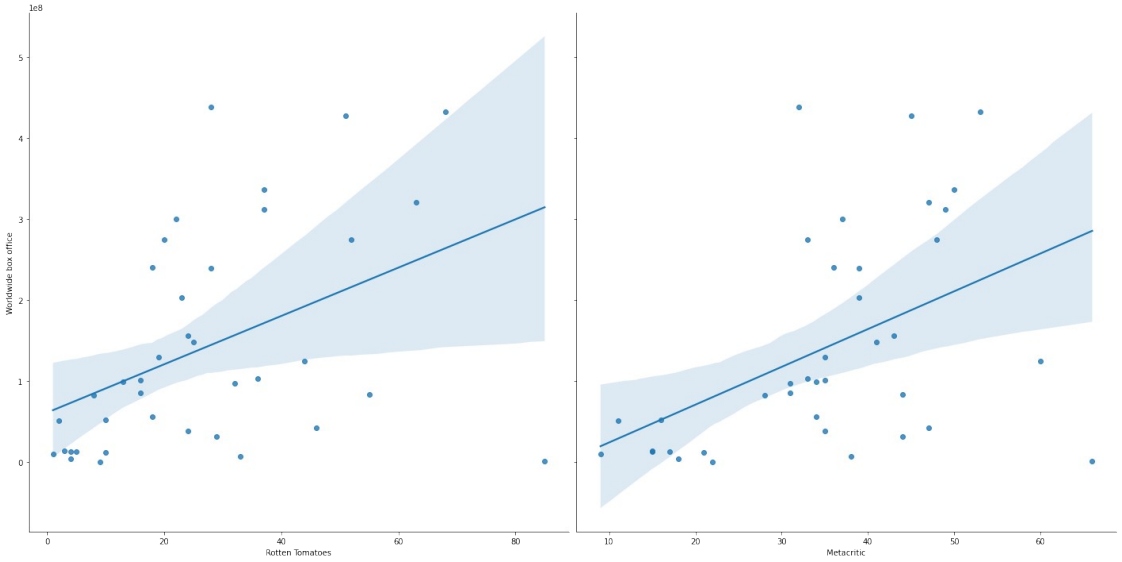
Histogram Conclusions: Similar conclusions to the boxplots. The Worldwide box office sales and Rotten Tomatoes scores are positive skewed in distribution, Metacritic is realtively unskewed or normal.

Scatter Plots

```
fig, axs = plt.subplots(2, figsize = (10,10))
plt1 = sns.scatterplot(x = dataset['Rotten Tomatoes'], y =
dataset['Worldwide box office'], ax = axs[0])
plt2 = sns.scatterplot(x = dataset['Metacritic'], y =
dataset['Worldwide box office'], ax = axs[1])
plt.show()
```



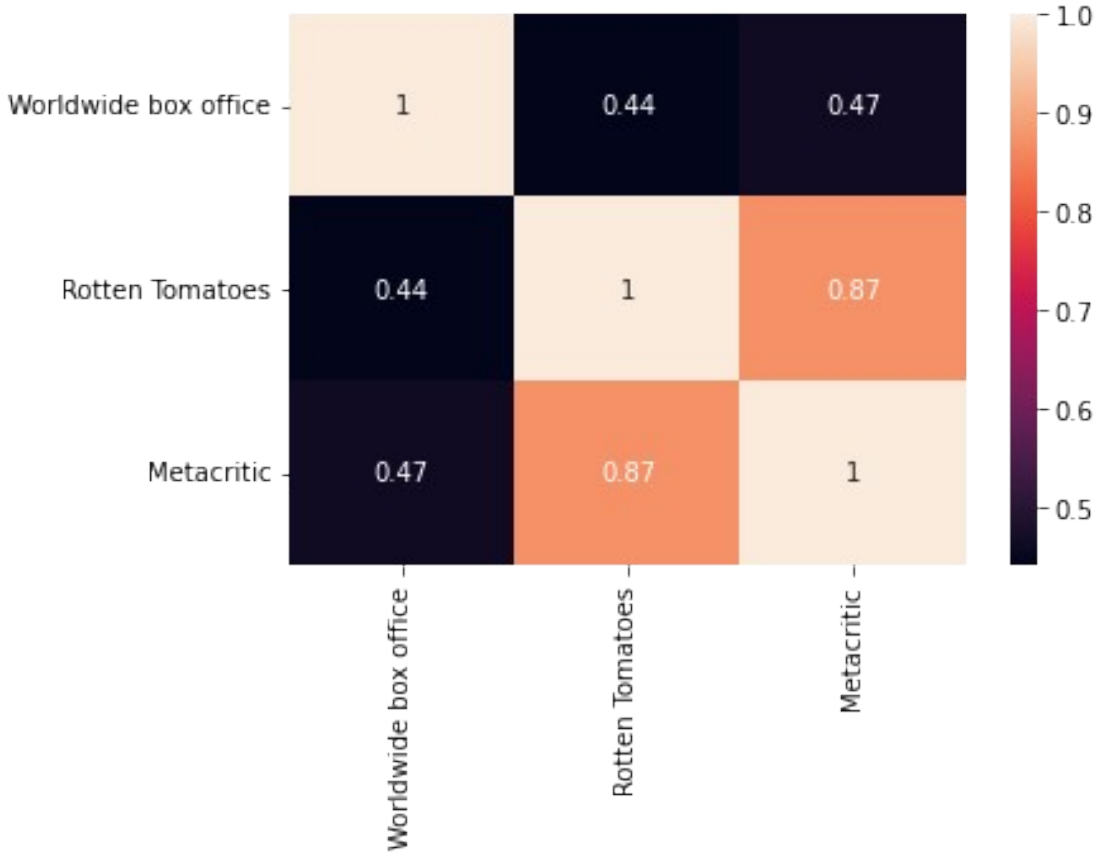

```
sns.pairplot(dataset, x_vars=['Rotten Tomatoes', 'Metacritic'],
y_vars='Worldwide box office', height=10, aspect=1, kind='reg')
plt.show()
```



Scatterplot Conclusions: The data, both Metacritic and Rotten Tomatoes scores, seems to be very loosely positively correlated to Worldwide box office.

Heatmap

```
sns.heatmap(dataset.corr(), annot = True)
plt.show()
```



Heatmap Conclusions: The heatmap shows that both Rotten Tomatoes and Metacritic are very loosley positively correlated.

Modeling

Using sklearn, I do linear regression and multiple regression modelling on the data.

Linear Regression

Imports for Linear Regression

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

Creating the Linear Regression Models

```
# Simple linear regression on the individual variables
x_rt = dataset[['Rotten Tomatoes']]
x_m = dataset[['Metacritic']]
y = dataset['Worldwide box office']

x_train_rt, x_test_rt, y_train_rt, y_test_rt = train_test_split(x_rt,
y, test_size = 0.3, random_state = 99)
x_train_m, x_test_m, y_train_m, y_test_m = train_test_split(x_m, y,
test_size = 0.3, random_state = 99)

reg_m = LinearRegression()
reg_m.fit(x_train_m, y_train_m)
int_m = reg_m.intercept_
coef_m = reg_m.coef_

reg_rt = LinearRegression()
reg_rt.fit(x_train_rt, y_train_rt)
int_rt = reg_rt.intercept_
coef_rt = reg_rt.coef_

eq_rt = 'Worldwide box office = %s + %s * (Rotten Tomatoes)'%
(int_rt,coef_rt)
eq_m = 'Worldwide box office = %s + %s * (Metacritic)'%(int_m,coef_m)
eq_rt
```

```
{"type":"string"}
```

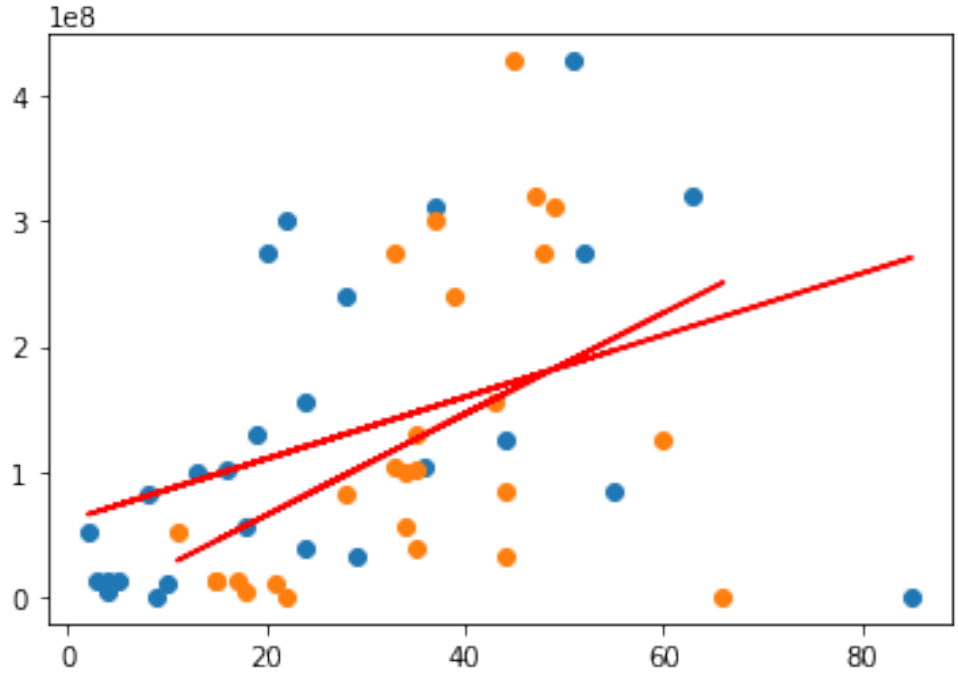
```
eq_m
```

```
{"type":"string"}
```

Visualizing the Regression Models

```
# Showing the scatter plots of the linear regression models
plt.scatter(x_train_rt, y_train_rt)
plt.plot(x_train_rt, int_rt + coef_rt * x_train_rt, 'r')
plt.scatter(x_train_m, y_train_m)
```

```
plt.plot(x_train_m, int_m + coef_m * x_train_m, 'r')
plt.show()
```



Prediction Based on the Model

```
# Testing Predictions
y_pred_reg_rt = reg_rt.predict(x_test_rt)
x_pred_reg_rt = reg_rt.predict(x_train_rt)

y_pred_reg_m = reg_m.predict(x_test_m)
x_pred_reg_m = reg_m.predict(x_train_m)

# Showing actual values vs predicted values of the data
prediction = pd.DataFrame({'Actual Value': y_test_rt, 'Prediction1':
y_pred_reg_rt, 'Prediction2': y_pred_reg_m})
prediction
```

	Actual Value	Prediction1	Prediction2
15	7516532.0	1.424006e+08	1.380138e+08
30	439048914.0	1.300486e+08	1.137736e+08
24	336365676.0	1.522822e+08	1.864940e+08
31	240558621.0	1.053447e+08	1.299337e+08
38	42145959.0	1.745158e+08	1.743739e+08
14	97607453.0	1.399302e+08	1.097336e+08
21	85416905.0	1.004039e+08	1.097336e+08
27	52302796.0	8.558149e+07	4.913335e+07
28	203277636.0	1.176967e+08	1.420538e+08
16	148412065.0	1.226375e+08	1.501338e+08
36	433005346.0	2.288645e+08	1.986140e+08
11	10442808.0	6.334791e+07	2.085322e+07

Accuracy of the Models

To test the accuracy, I will show the R squared values and error

```
# R squared value
r2_rt = reg_rt.score(x_rt,y)*100
r2_m = reg_m.score(x_m,y)*100

print('R squared value for the Rotten Tomatoes model: ', r2_rt)
print('R squared value for the Metacritic model: ', r2_m)
```

```
R squared value for the Rotten Tomatoes model:  17.882129476729137
R squared value for the Metacritic model:  19.993340114549763
```

```
mean_ab_er_rt = metrics.mean_absolute_error(y_test_rt, y_pred_reg_rt)
mean_sq_er_rt = metrics.mean_squared_error(y_test_rt, y_pred_reg_rt)
root_mean_er_rt = mean_sq_er_rt ** (1/2)

mean_ab_er_m = metrics.mean_absolute_error(y_test_m, y_pred_reg_m)
mean_sq_er_m = metrics.mean_squared_error(y_test_m, y_pred_reg_m)
root_mean_er_m = mean_sq_er_m ** (1/2)

print('Mean absolute error for the Rotten Tomatoes model: ',
mean_ab_er_rt)
print('Mean square error for the Rotten Tomatoes model: ',
mean_sq_er_rt)
print('Root mean square error for the Rotten Tomatoes model: ',
root_mean_er_rt)

print('Mean absolute error for the Metacritic model: ', mean_ab_er_m)
print('Mean square error for the Metacritic model: ', mean_sq_er_m)
print('Root mean square error for the Metacritic model: ',
root_mean_er_m)
```

```
Mean absolute error for the Rotten Tomatoes model:  112878463.25561361
Mean square error for the Rotten Tomatoes model:
1.9912528634891156e+16
Root mean square error for the Rotten Tomatoes model:
141111759.37848395
Mean absolute error for the Metacritic model:  99654727.96104068
Mean square error for the Metacritic model:  1.9547045344775624e+16
Root mean square error for the Metacritic model:  139810748.31634235
```

Linear Regression Conclusion

These data do not fit the Linear regrssion model generated here. As indicated by the R squared values, the Rotten Tomatoes and Metacritic models fit 18% and 20% of the data respectively. Additionally, the error is astronomically high. Overall, Rotten Tomatoes score and Metacritic scores individually seem to be not very good predictors of Worldwide box office sales on a linear regression model.

Multiple Linear Regression

Creating the Multiple Linear Regression Model

```
x = dataset[['Rotten Tomatoes', 'Metacritic']]
y = dataset['Worldwide box office']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =
0.3, random_state = 99)

mreg = LinearRegression()
mreg.fit(x_train, y_train)

LinearRegression()

coef_rt = mreg.coef_[0]
coef_m = mreg.coef_[1]
intercept = mreg.intercept_

eq = 'Worldwide box office = %s + %s * (Rotten Tomatoes) + %s *
(Metacritic)'%(intercept,coef_rt,coef_m)
eq

{"type":"string"}
```

Prediction Based on the Model

```
y_pred_mreg = mreg.predict(x_test)
x_pred_mreg = mreg.predict(x_train)

prediction = pd.DataFrame({'Actual Value': y_test, 'Prediction':
y_pred_mreg})
prediction
```

	Actual Value	Prediction
15	7516532.0	1.397295e+08
30	439048914.0	1.174893e+08
24	336365676.0	1.803339e+08
31	240558621.0	1.237029e+08
38	42145959.0	1.766427e+08
14	97607453.0	1.169048e+08
21	85416905.0	1.065690e+08
27	52302796.0	5.516749e+07
28	203277636.0	1.364380e+08
16	148412065.0	1.440667e+08
36	433005346.0	2.098647e+08
11	10442808.0	2.717497e+07

Accuracy of the Model

To test the accuracy, I will show the R squared values and error.

```
# R squared value
r2 = mreg.score(x,y)*100
```

```
print('R squared value for the Multiple Linear Regression model: ',
r2_rt)
```

```
R squared value for the Multiple Linear Regression model:
17.882129476729137
```

```
mean_ab_er = metrics.mean_absolute_error(y_test, y_pred_mreg)
mean_sq_er = metrics.mean_squared_error(y_test, y_pred_mreg)
root_mean_er = mean_sq_er ** (1/2)

print('Mean absolute error for the Rotten Tomatoes model: ',
mean_ab_er)
print('Mean square error for the Rotten Tomatoes model: ', mean_sq_er)
print('Root mean square error for the Rotten Tomatoes model: ',
root_mean_er)
```

```
Mean absolute error for the Rotten Tomatoes model:  101294075.84043245
Mean square error for the Rotten Tomatoes model:
1.9363130961420748e+16
Root mean square error for the Rotten Tomatoes model:
139151467.69409493
```

Multiple Linear Regression Conclusion

These data do not seem to fit the multiple linear regrssion model generated either. As indicated by the R squared value, the multiple regression model fits 18% of the data. Additionally, the error is astronomically high, just like the Linear regression model. Overall, Rotten Tomatoes score and Metacritic scores together seem to be not very good predictors of Worldwide box office sales on a multiple linear regression model.

Summary and Conclusion

Overall, it seems that Rotten Tomatoes and Metacritic scores are not valid predictors of Worldwide box office sales for Video Game Movies. This can be seen through their weak correlation in the scatter plots and heatmap, as well as the low R squared values and high error in both the linear regression model and multiple linear regression model.

Finally, the "so-bad-it's-good" effect seems to neither be proven nor disproven by this data.