GAMBIT STUDIOS

Linear Regression

Machine Learning Algorithm for Thrillers

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Art Company

Business Situation

A newly emerged production studio plans to make movies in the thriller genre and would like to know which characteristics of thrillers are predictors of US Box Office Gross.

Key Questions:

Does a set of features do a good job in predicting US Gross for thrillers?

Which features are significant predictors of US Gross for thrillers?

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Project Steps

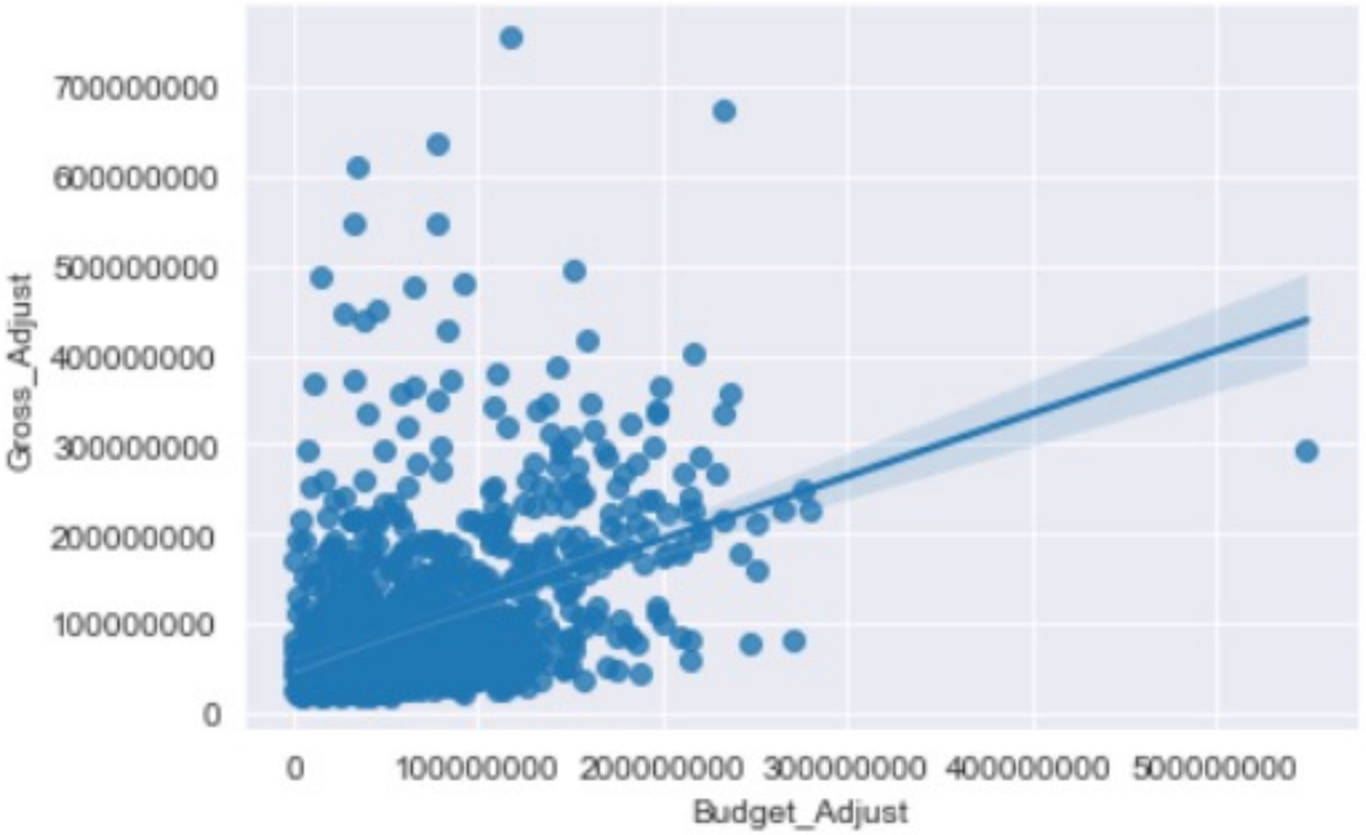
ACTION	TOOLS USED
WEBSCRAPING • Scraped IMDB Thrillers for target and feature data • 1100 thriller titles, 16 potential predictor variables	Request Module, BeautifulSoup Library
EDA & REGRESSION VIABILITY • Data cleanup, address missing values, etc • Create dummy variables for categorical features • Correlation matrix and regression plots to check linear relationships	Pandas, Seaborn, Statsmodels cpi library (to apply inflation to budget based on year)
Linear Regression Modeling • Fit data to the model • Train, Test, Score • Coefficients: most impactful features	Pandas, Sklearn
EDA & Continued Model Optimization • Predicted vs Actuals • Regularization	Sklearn, Matplotlib, Seaborn

Features Scraped From Thriller List IMDB

IMDB: Thrillers Categorized by Genre

Features scraped

Check Linear Relationships



Correlation Analysis of Feature with Target

Low correlation can contain signal that can be discovered

Positive Correlation with US Gross

Budget 0.72
Duration 0.56
Adventure 0.49
Action 0.42
PG 0.42
PG-13 0.33
Sci-Fi 0.24

Negative Correlation with US Gross

R Rating - 0.47
Horror -0.36
Crime -0.25
Drama -0.21
Mystery -0.21

Low Correlation

Range: .00 to .20 , .00 to -.20

Music 0.18
Family 0.01
Animation – 0.00
Romance -0.14
Sport -0.09
Comedy -0.03
History -0.03
Musical -0.06
Western -0.07
Fantasy -0.08
War -0.10
Biography -0.11

Keep all features in the modeling

Data: Pearson Correlation

Fit Data to Linear Regression Model

Scores

R^2

Slight overfitting expected

Train R^2	.318	
Test R^2	.276	**28% of variance explained by model's inputs**

MAE: Mean Absolute Error

Work to improve in future iterations of model

$46,825,271

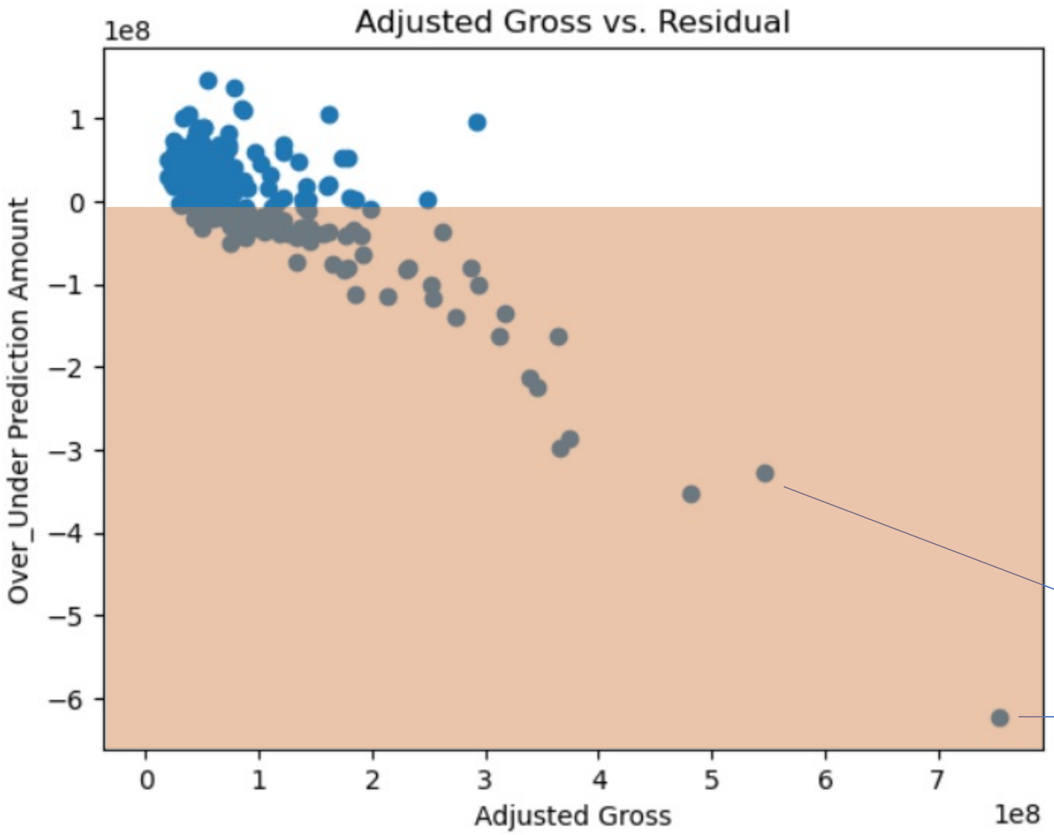
Definitions

Tells us how well the input data can explain the variation of US Gross (target aka response variable)

Represents the average of the difference between the actual and predicted values in dataset

Plot Actuals vs Residuals

Model is Underpredicting: hypothesize the blockbusters are underpredicting



Findings

- Model isn't reliable - Residuals are problematic
  - Heteroskedasticity: unequal variability

Future Work

- Address the blockbusters
- What's happening to create the underprediction?

Examples:

5.50 actual, predicting 2.25

7.5 actual, predicting 1.50

Regression Coefficients

What the model considers to be the most impactful features, and the per-unit impact on US Gross

Positive Impact on Thriller US Gross

PG	68,017,516.47
Adventure	19,793,585.00
Sci-Fi	19,450,110.29
Comedy	12,575,077.35

Categorical variables – binary values

US Gross prediction to increase by x amount

Duration	1,647,406.25

Minutes – Integer

US Gross Prediction to increase $1.6M per minute when at zero

Budget	0.39

Dollars – Continuous values

US Gross Prediction to increase by .39

Negative Impact on Thriller US Gross

History	-76,092,866.62
Musical	-67,808,047.35
Biography	-57,640,257.49
Animation	-54,468,082.93
R Rating	-40,303,575.50
Drama	-28,094,114.77
PG-13	-27,713,940.97
Romance	-29,425,524.70
Action	-20,658,701.63
Horror	-14,634,199.66
Mystery	-12,610,294.09
Crime	-10,495,540.63
Fantasy	-7,649,883.02

Neither Positive Nor Negative Impact

War	0.00
Sport	0.00
Western	0.00
Family	0.00
Music	0.00

Summary / Future Work

- The current model isn't reliable - Residuals are problematic
- Determine what's happening to create the underprediction
    - Look into the blockbuster films
- Upon resolution re-run the regression coefficients and conduct a deeper analysis