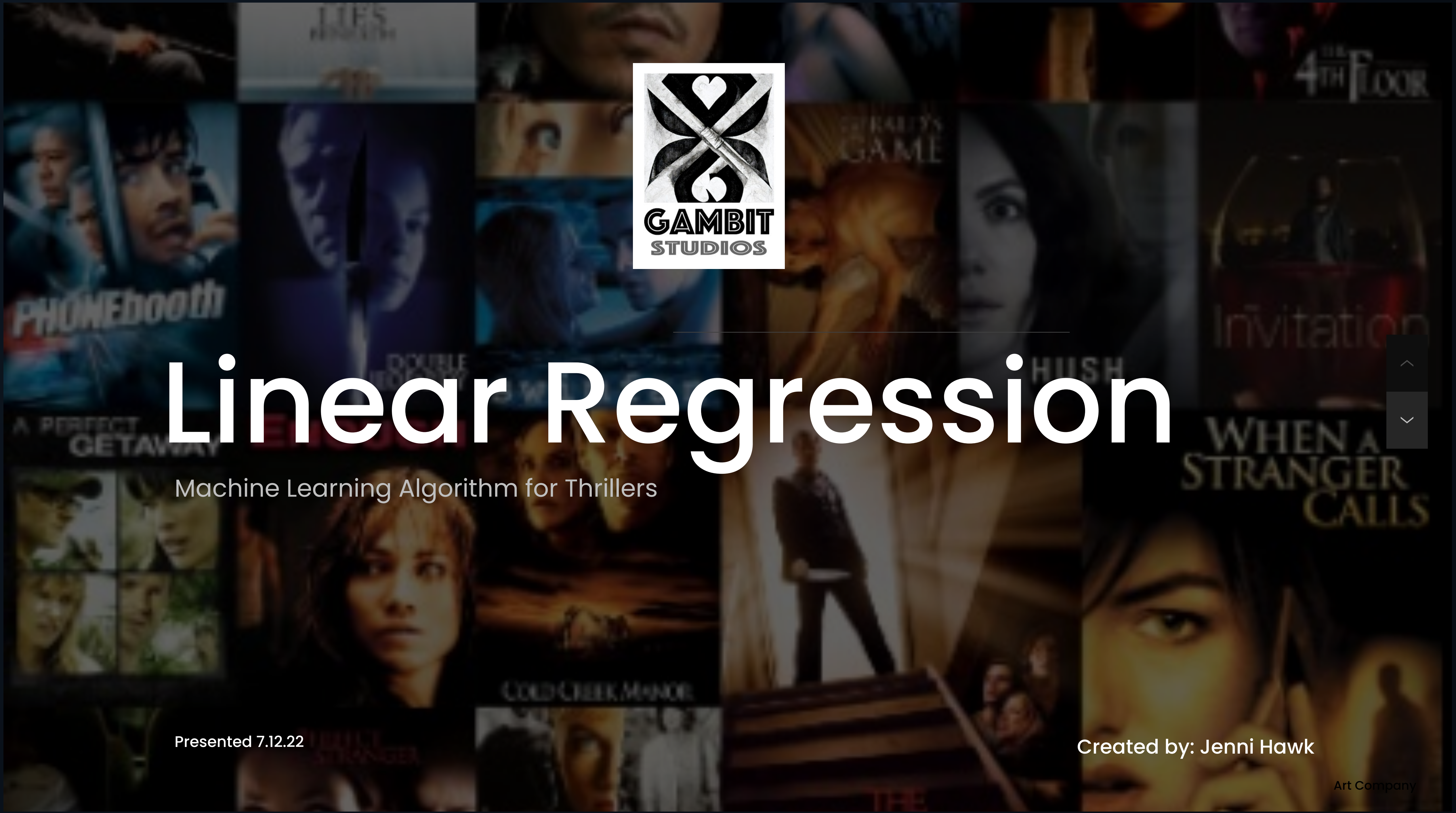

GAMBIT STUDIOS

Linear Regression

Machine Learning Algorithm for Thrillers

Presented 7.12.22

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Art Company

Assignment Goals

- Learn the fundamentals of linear regression
- Viability Analysis
- Instantiate model, Train + Test, Score
- Learn the fundamentals: Statsmodels, Sklearn, etc

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 • Ensure data correct and appears as expected. • Data cleanup, address missing values, etc • Correlation matrix, reg plots, R^2 score • Feature engineering	Pandas, Seaborn, Statsmodels cpi library (to apply inflation to budget based on year)
DETERMINE BASELINE MODEL • Tested log transform vs no transform • Tested regularization methods • Identified features with meaningful coefficients	Pandas, Sklearn
TRAIN – VALIDATE - TEST • Utilized cross validation • Tested two models	Sklearn

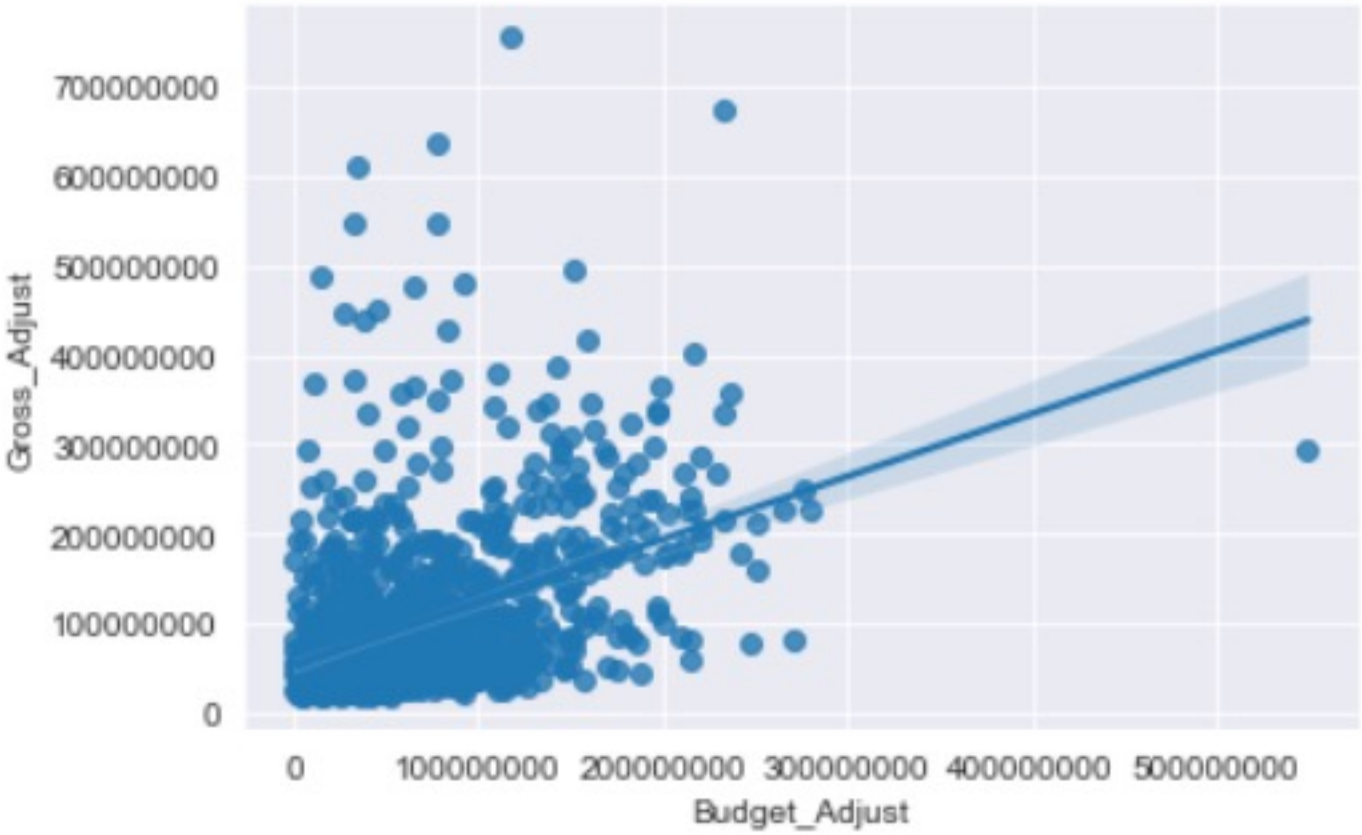
Features Scraped From Thriller List IMDB

IMDB: Thrillers Categorized by Genre

Features scraped

Linear Regression Model

Check Linear Relationships



Feature Target Correlation Analysis

Low correlation doesn't mean it won't contain signal

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
Music	0.18

Negative Correlation with US Gross

R Rating - 0.47

Horror -0.36

Crime -0.25

Drama -0.21

Mystery -0.21

Romance -0.14

Biography -0.11

Fantasy -0.08

Comedy -0.03

History -0.03

Close to zero -.10 to .10

War -0.10

Sport -0.09

Western -.07

Musical -0.06

Animation – 0.00

Family 0.01

Data: Pearson Correlation / Seaborn Heatmap

Let's look at coefficients to understand relative signal

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
Duration	1,647,406.25
Budget	0.39

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

R^2

Slight overfitting expected

Train R^2 .318

Test R^2 .276

28% of Variance explained by model

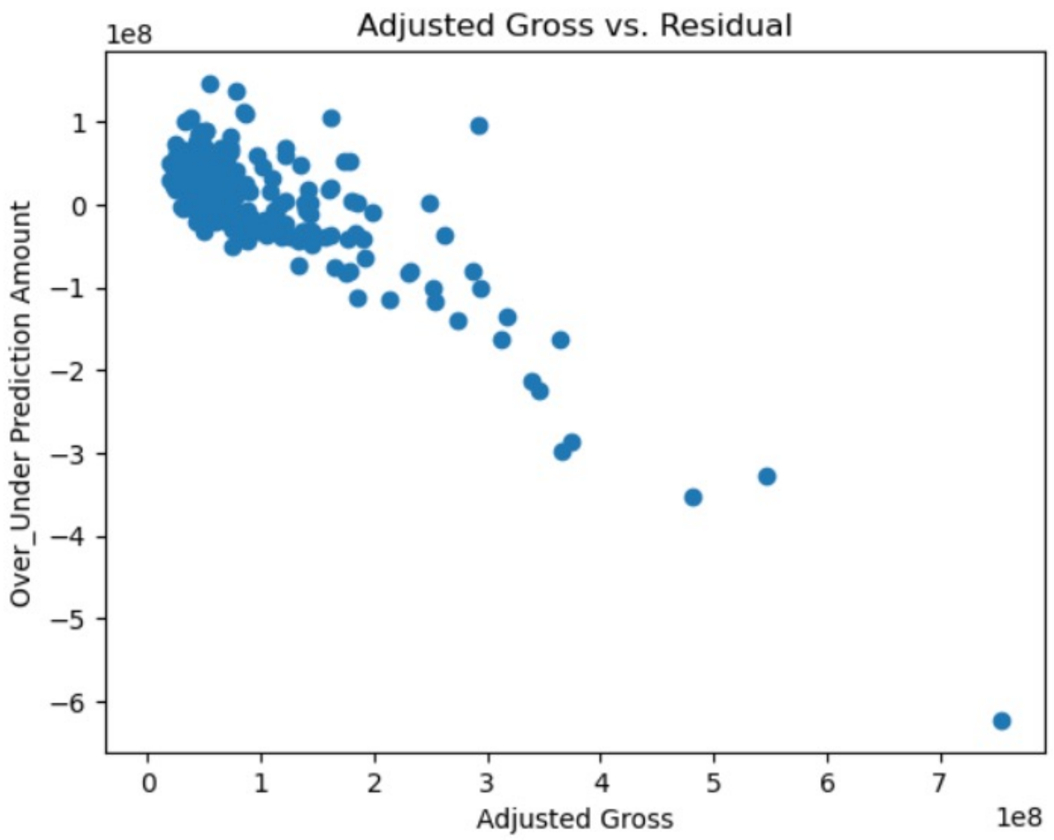
MAE: Mean Absolute Error

How close the prediction is against the real value

$46,825,271

Predicted vs Actuals

Underpredicting – big blockbusters may be the issue



Findings

- Residuals are problematic
  - Heteroskedasticity: unequal variability (scatter)
- Hypothesize that block busters are underpredicting

Future Work

- Going forward address blockbusters