# Predicting Total Movie Grosses Using Regression Modeling to Predict Total Movie Theater Grosses during the Calendar Year

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# Why is predicting total movie grosses important?

- It can help producers decide which month or season is best to release a film
- Allows the movie budget to be adjusted based on expected revenues
- Can help decide how many theaters would produce the most gross for the movie

#### AGENDA:

- 1. Approach
- 2. Methodology
- 3. The Data
- 4. Feature Engineering
- 5. Modeling
- 6. Results
- 7. Next Steps

#### 1. Approach: What makes a movie successful?

Let's look at total movie grosses to predict the best parameters to find maximum gross.

Target Data: Total Gross Revenue

Total data points: 3,191

Features: Monthly movie gross

Number of theaters

Release Month

Release Year (2019-2020)



#### **Data Source:**

All data was scraped from IMDb's BoxOfficeMojo



#### **Tools Used:**



#### 2. Methodology

- 1. Check for missing data
- 2. Create dummy variables
- 3. Run feature distributions
  - 4. Split the data
- 5. Plot all of the feature distributions
- 6. Remove all features with a correlation > 0.1
  - 7. Train-test split
- 8. Perform feature scaling and normalization
  - 9. Regression Modeling

#### 3. The Data: Coefficients

**Negative** 

**Positive** 

#### **Categorical Features:**

Rank

Release Date

Release Name (movie title)

Distributor

#### **Quantitative Features:**

Gross Estimate \$

Total Estimate \$

Theaters (total amount)

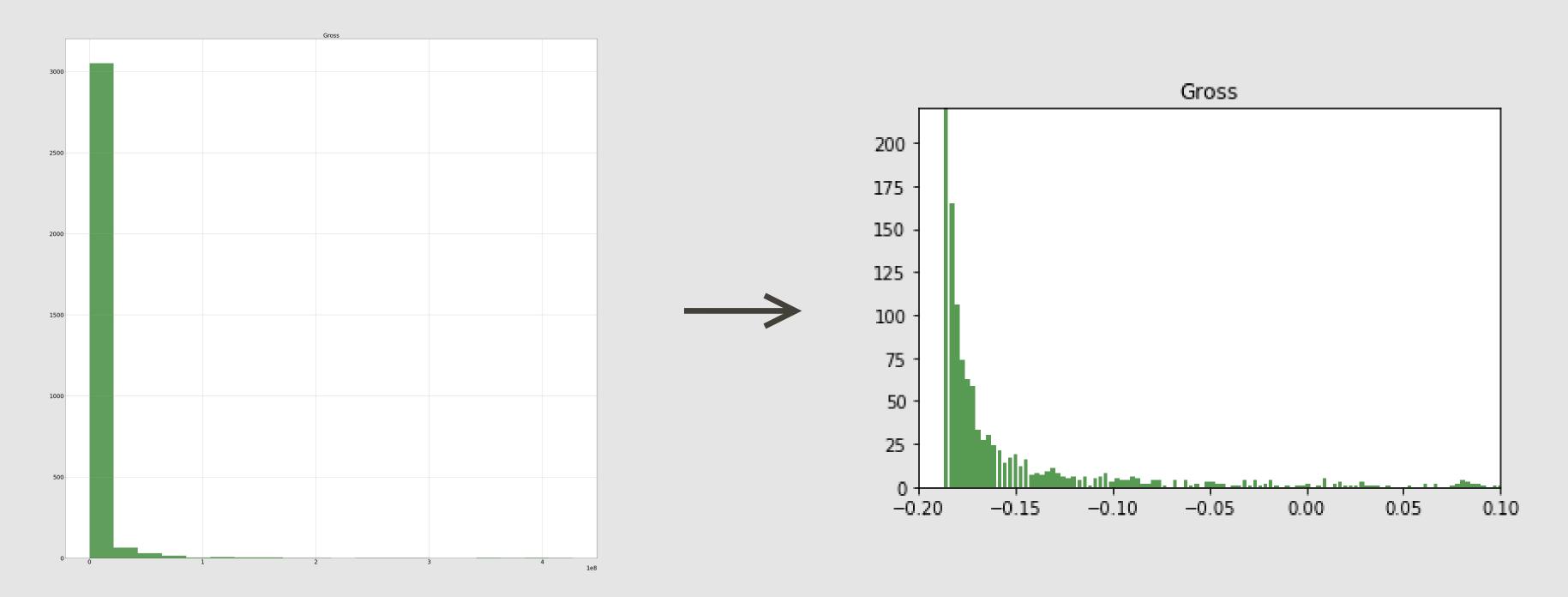
#### **Categorical Features:**

Months (1-12)

Years (2019-2020)

#### 4. Feature Engineering

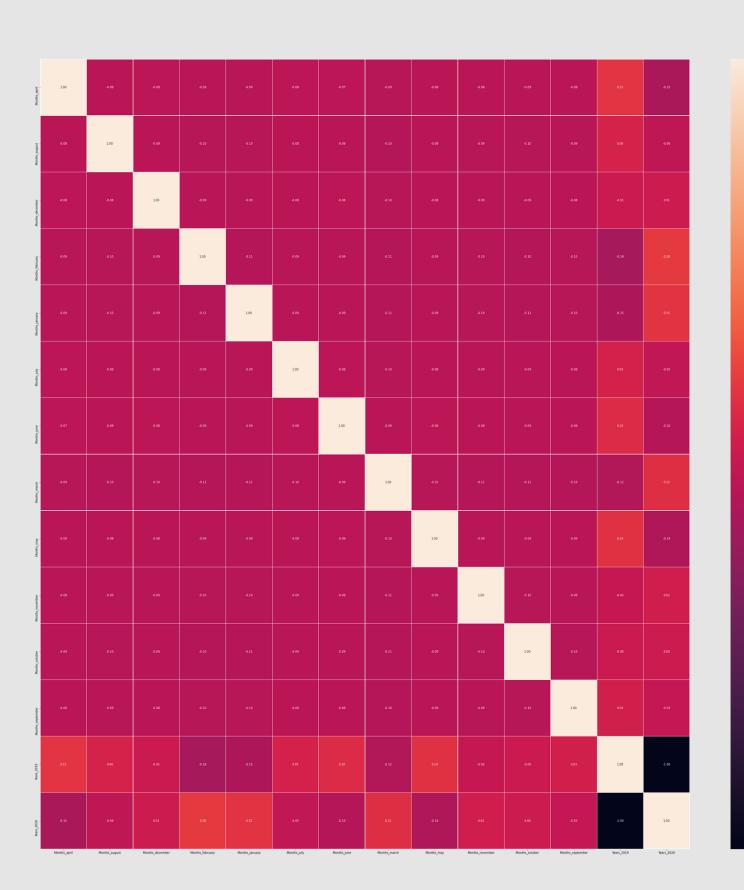
Feature distribution before and after normalization: Gross



<sup>\*\*</sup>See Appendix 'B' and 'C' for more images on this\*\*

#### Examine Features

# WEAK CORRELATIONS



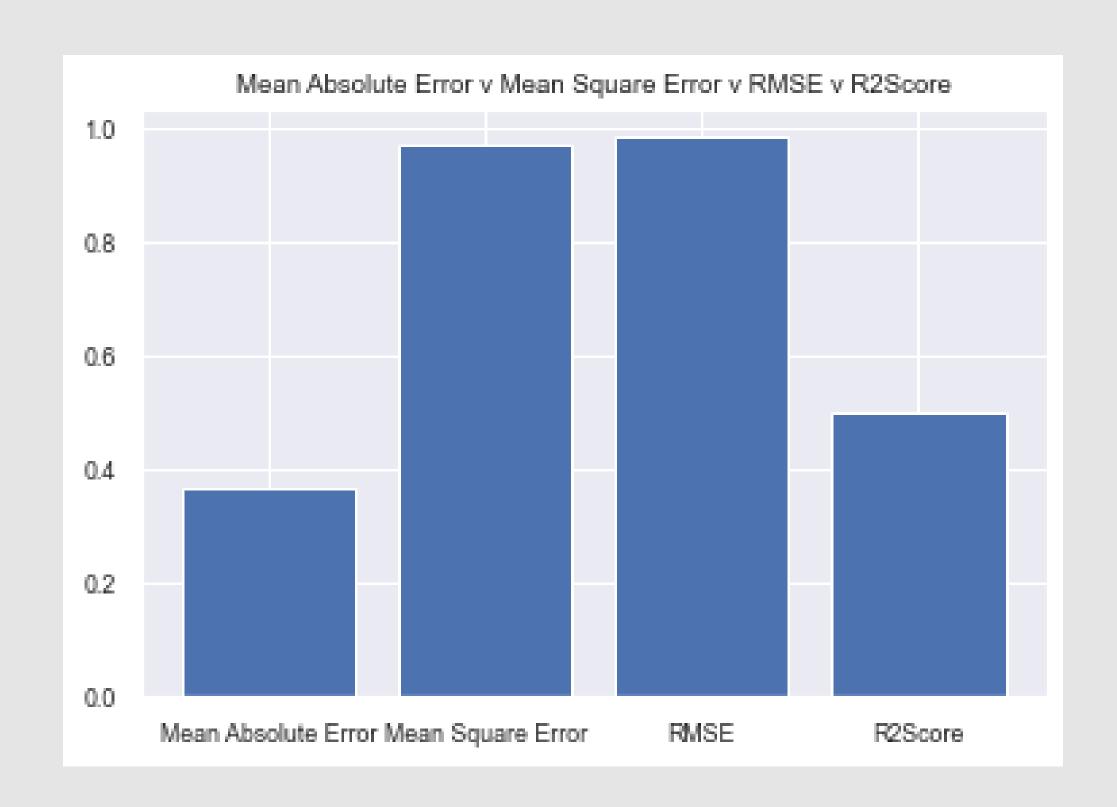
#### 5. MODELING: Linear Regression

 $R^2 = 0.5011$ 

MSE = 0.9703

MAE = 0.3681

RMSE = 0.9850



#### MODELING: Lasso Regression

#### **SLIGHTLY WORSE**

 $R^2 = 0.5009$ 

MSE = 0.9701

MAE = 0.3674

RMSE = 0.9851

### LASSO COEFFICIENTS: ('Gross', 1.0223928138889704), ('Theaters', 30182.39836992574),

('Months\_april', 3823821.8376515703),

('Months\_august', 4827778.961552109),

('Months\_december', -5519543.147972001), \( \)

('Months\_february', -322084.72346213204), 🔊

('Months\_january', -2062942.0395195826), <

('Months\_july', 6301807.080629837),

('Months\_june', 367673.1278506973),

('Months\_march', 895340.4868220205),

('Months\_may', -1805823.8099229618), <

('Months\_november', -1769041.533069785), //

('Months\_october', -2597390.9879438146), \( \sigma \)

('Months\_september', 3695347.566792137),

('Years\_2019', 3171720.5583540807),

('Years\_2020', -0.0)

#### MODELING: Ridge Regression

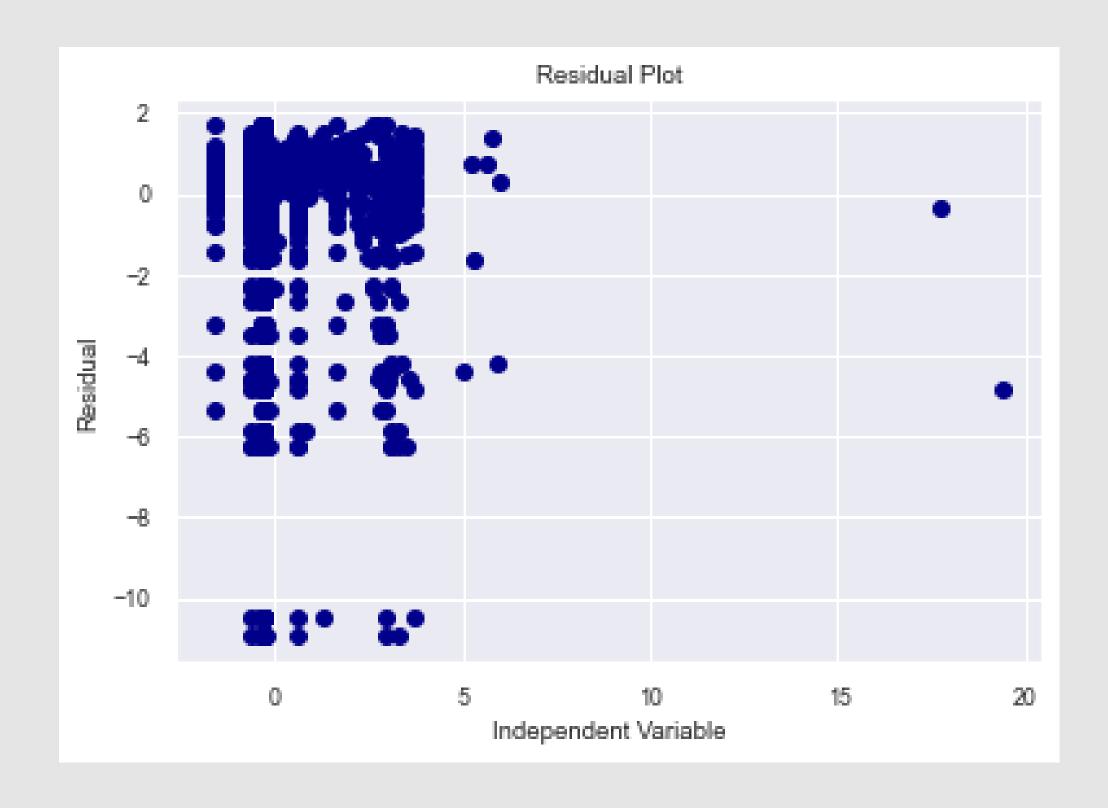
 $R^2 = 0.4988$ 

MSE = 0.9756

MAE = 0.3639

RMSE = 0.9872

Cross Validation Score: 0.4552



#### 6. Results: Final Model

Based off of this data the best predictive model for movie grosses is:

Linear Regression Model

$$R^2 = 0.50$$

In this case, simple is best.

#### 7. Next Steps



- 1. Scrape multiple websites to increase the data set
  - -IMDB, Rotten Tomatoes, AllMovie
- 2. Include additional features and regressions to observe the model's performance over more time
  - -features like MPAA ratings, reviews, runtime
  - -polynomial regressions
- 3. Look more specifically into genre
  - -see if this is seasonally correlated
  - -example: horror movies in October
- 4. Take into account location, holidays and major seasonal events

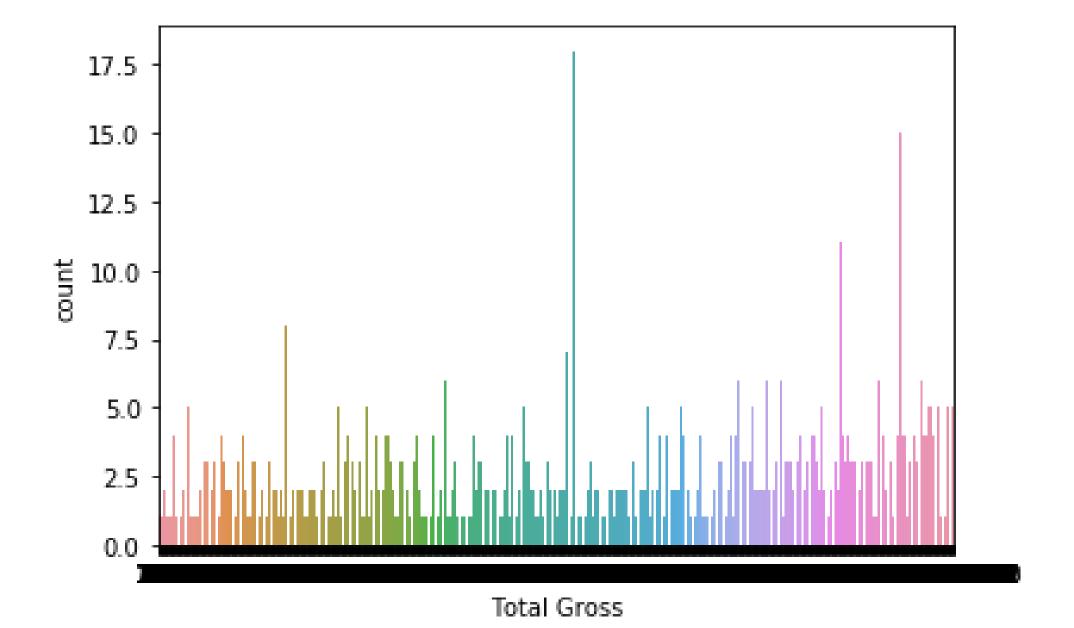
#### Thank you!

## Questions?

#### Appendix

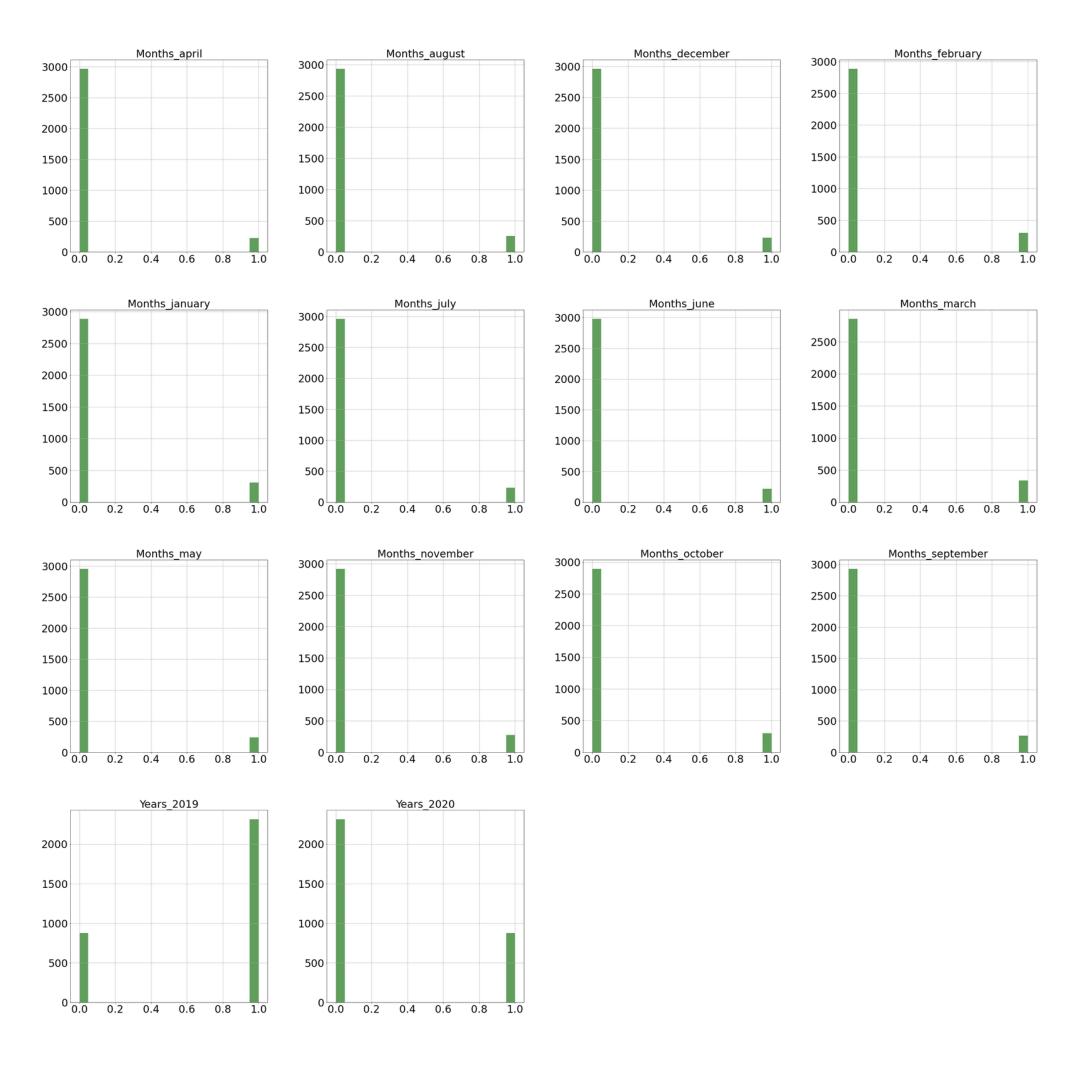
More information and more graphical representations are available via code.

#### A. Movies with total gross counts



#### Appendix

#### **B. Feature Distributions**



#### Appendix

#### C. Standard Scalar Data (transformed)

