



Lights, Camera, Analytics!

10|03|16

Elizabeth Carnahan
Kristopher Korte
Brian Malloy
Noreen Nagji
Karthik Subramanian

Agenda

- 1 Strategic Challenges
- 2 Metrics and Mental Models
- 3 Data and Analysis
- 4 Insights
- 5 Recommendation and Next Steps

Strategic Challenges



What factors are relevant in predicting box office revenue of a movie?

Our hypothesis is that movie production companies can predict revenues through careful selection of specific variables



1

\$2,783,918,982

9

\$1,274,234,980

3

\$1,837,932,841

5

\$1,519,479,547

11

\$1,163,595,387

2

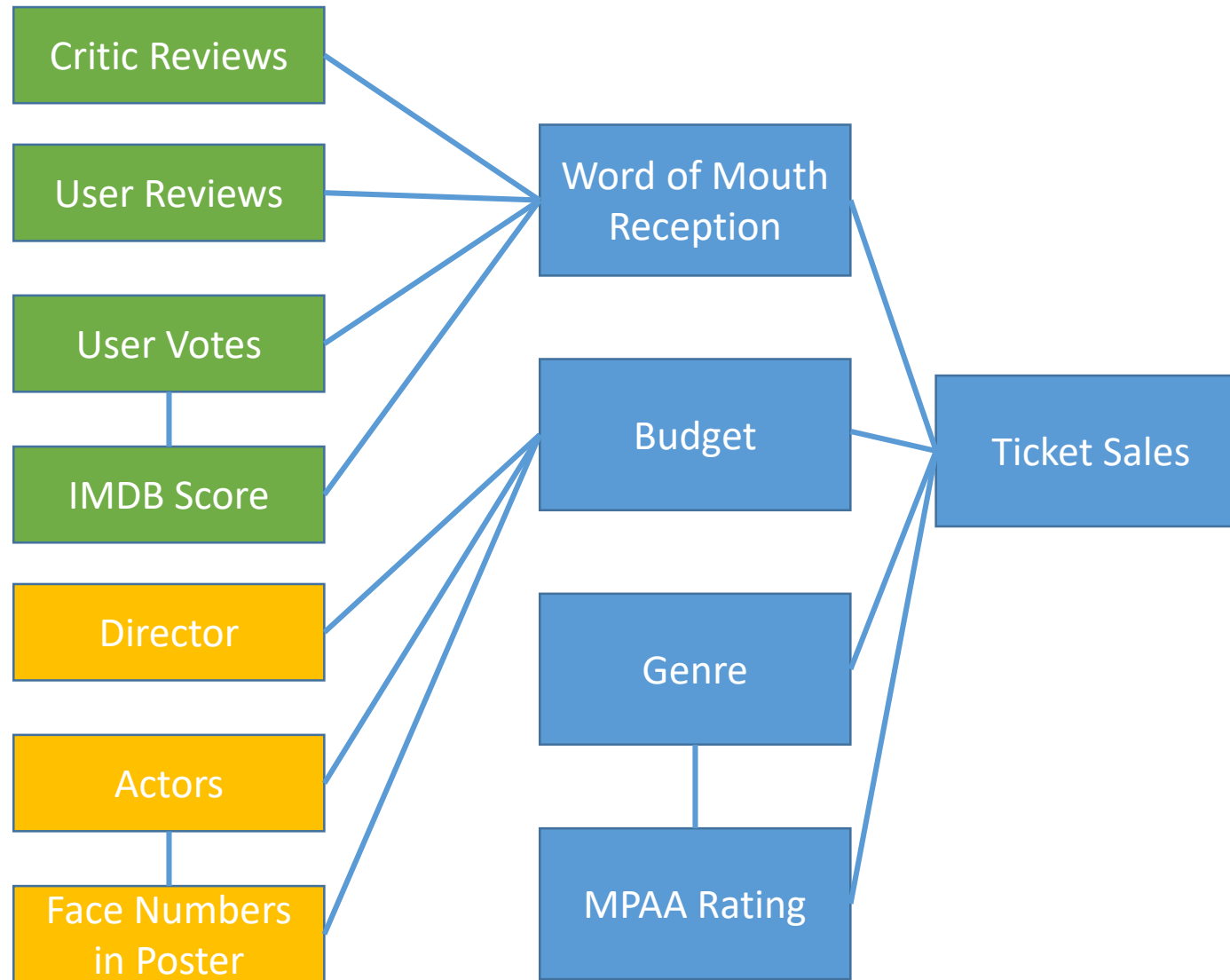
\$2,207,615,668

Metrics & Mental Models



Mental Model

Prior to running our regressions, we created a mental model of the variables that could significantly affect ticket sales

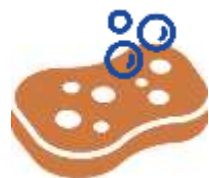


Data and Analysis



Data

We used complimentary datasets to create dummy variables and adjusted dollar amounts for an accurate comparison



- US Films
- English as Primary Language
- Released in 1990 or Later
- Eliminated duplicates
- Eliminated incomplete rows
- Eliminated films rated X & NC-17



- Created 3 Tiers Based on Vulture Ranks (Actor) & AMC Ratings (Director)



- Adjusted gross revenue for inflation using average ticket price per year of movie release



- Ratings
Ex. G, PG, PG-13, R
- Film Genres
Ex. Comedy, Drama, Horror
- Actor/Director Tiers
Ex. Tier 1, Tier 2, Tier 3

Analysis – Linear Regression

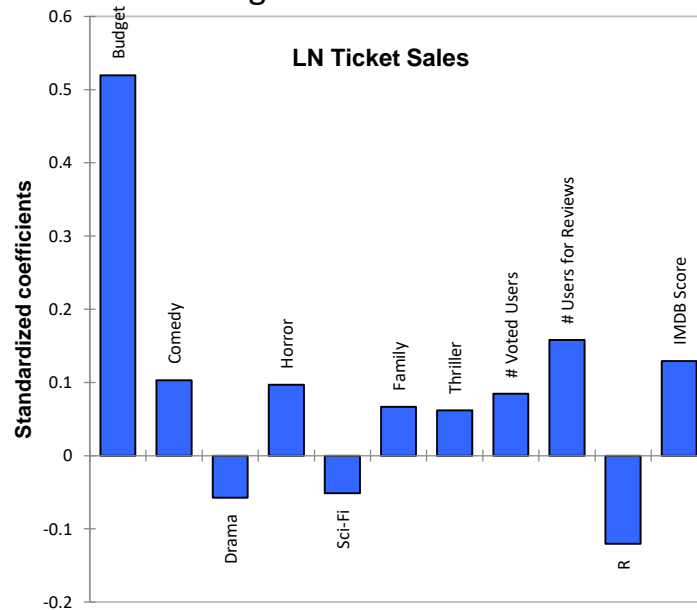
We used regression analysis to determine what factors contribute to a movie's box office revenues

Regression

Model Prediction

Goodness of Fit Statistics

- Test set (20% of data)
- Training set (80% of data)
- Ran a linear regression on log of ticket sales, second time eliminating all insignificant variables

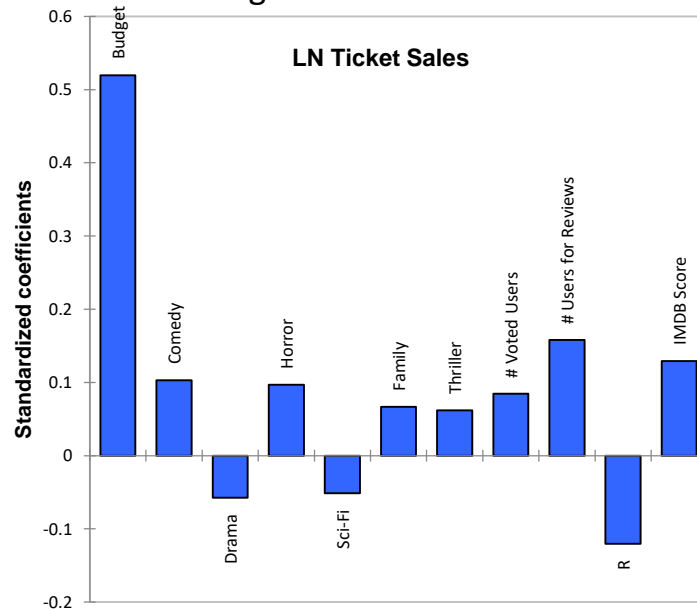


Analysis – Linear Regression

We used regression analysis to determine what factors contribute to a movie's box office revenues



- Test set (20% of data)
- Training set (80% of data)
- Ran a linear regression on log of ticket sales, second time eliminating all insignificant variables
- Used analysis to perform prediction for test data set
- Goal: to predict ticket sales and box office revenues with accuracy

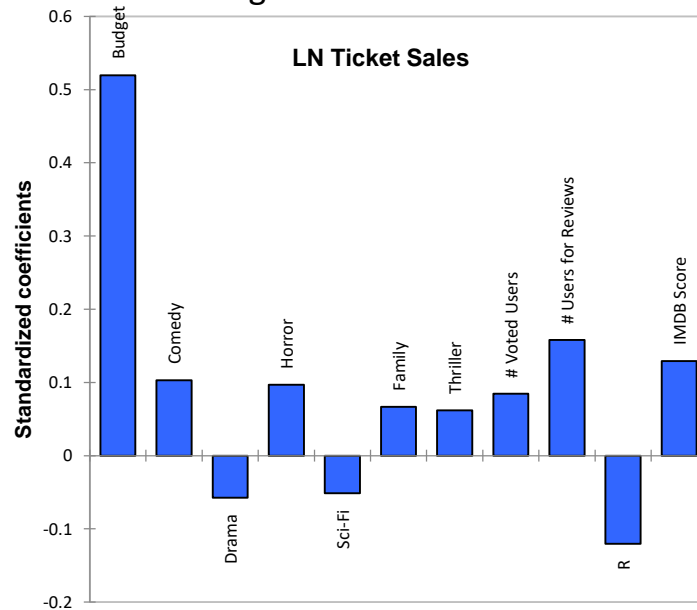


Analysis – Linear Regression

We used regression analysis to determine what factors contribute to a movie's box office revenues

Regression

- Test set (20% of data)
- Training set (80% of data)
- Ran a linear regression on log of ticket sales, second time eliminating all insignificant variables



Model Prediction

- Used analysis to perform prediction for test data set
- Goal: to predict ticket sales and box office revenues with accuracy

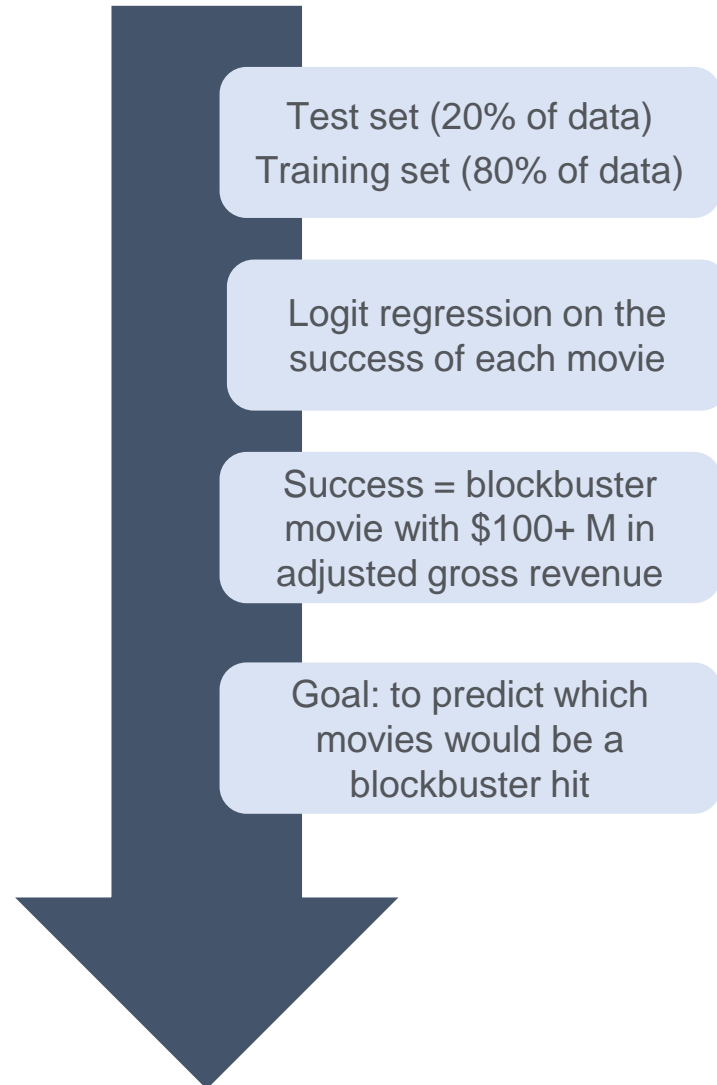


Goodness of Fit Statistics

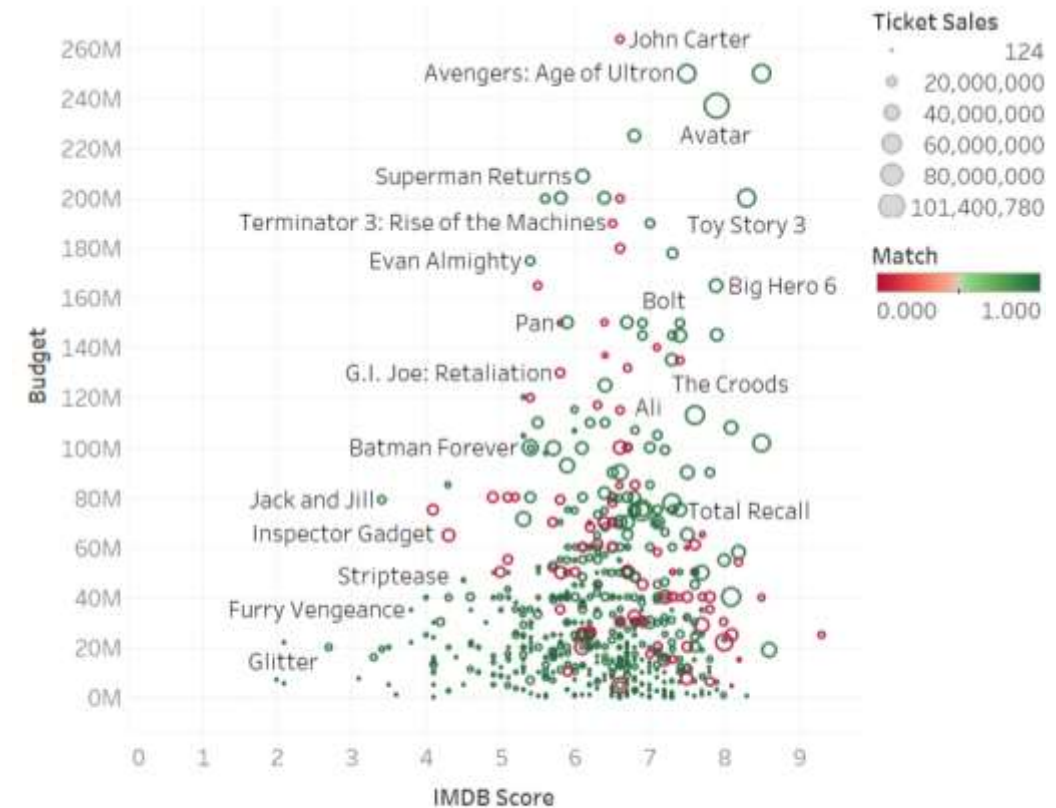
| | |
|-------------------------|----------|
| Observations | 2145.000 |
| Sum of weights | 2145.000 |
| DF | 2133.000 |
| R ² | 0.509 |
| Adjusted R ² | 0.51 |
| MSE | 1.891 |
| RMSE | 1.375 |
| MAPE | 7.24 |
| DW | 0.842 |
| Cp | 12.000 |
| AIC | 1378.900 |
| SBC | 1446.950 |
| PC | 0.496 |

Analysis – Logit Regression

We used regression analysis to determine what factors contribute to a movie's box office revenues.



Hit Rate = 84%








Sum of IMDB Score vs. sum of Budget. Color shows sum of Match. Size shows sum of Ticket Sales. The marks are labeled by Movie Title. Details are shown for Movie Title.



Sony Picture Studios: 4th Quarter 2015 Releases

In looking at a sample of recent releases, we see how effective the model is in predicting whether or not a movie will be a blockbuster

| Movie | Budget | Ln of Budget | # Critics for Reviews | Comedy | Drama | Sci-Fi | Family | # Voted Users | # Users for Review | IMDB Score | Blockbuster Prediction | Match? |
|---|--------|--------------|-----------------------|--------|-------|--------|--------|---------------|--------------------|------------|------------------------|--------|
|  | \$80M | \$18.20 | 156 | 1 | 0 | 0 | 1 | 59,884 | 100 | 6.7 | YES | ✓ |
|  | \$33M | \$17.31 | 36 | 1 | 0 | 1 | 0 | 6,063 | 30 | 5.9 | NO | ✓ |
|  | \$245M | \$19.32 | 604 | 0 | 1 | 0 | 0 | 283,170 | 1,003 | 6.8 | YES | ✓ |
|  | \$25M | \$17.03 | 154 | 1 | 0 | 0 | 0 | 34,274 | 87 | 6.5 | NO | ✓ |
|  | \$35M | \$17.37 | 222 | 0 | 1 | 0 | 0 | 48,889 | 143 | 7.1 | NO | ✓ |

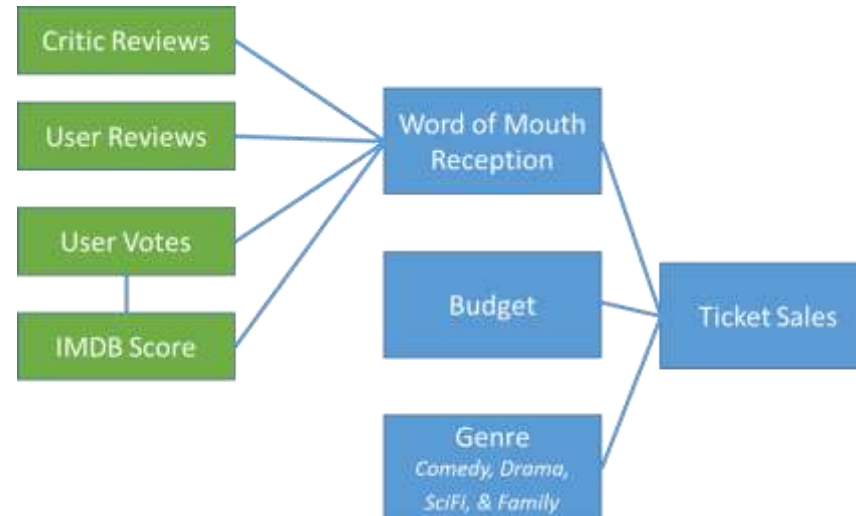
Factors that Govern Ticket Sales / Box Office Revenues

After identifying the variables that significantly effected the success of a movie, we adjusted our Mental Model accordingly

Significant Variables

- ✓ Movie Budget
- ✓ IMDB Score
- ✓ Movie Genre: *Comedy, Drama, Sci-Fi, and Family*
- ✓ User Engagement on IMDB: *Number of User Votes and Number of User Reviews*

New Mental Model



Insignificant Variables

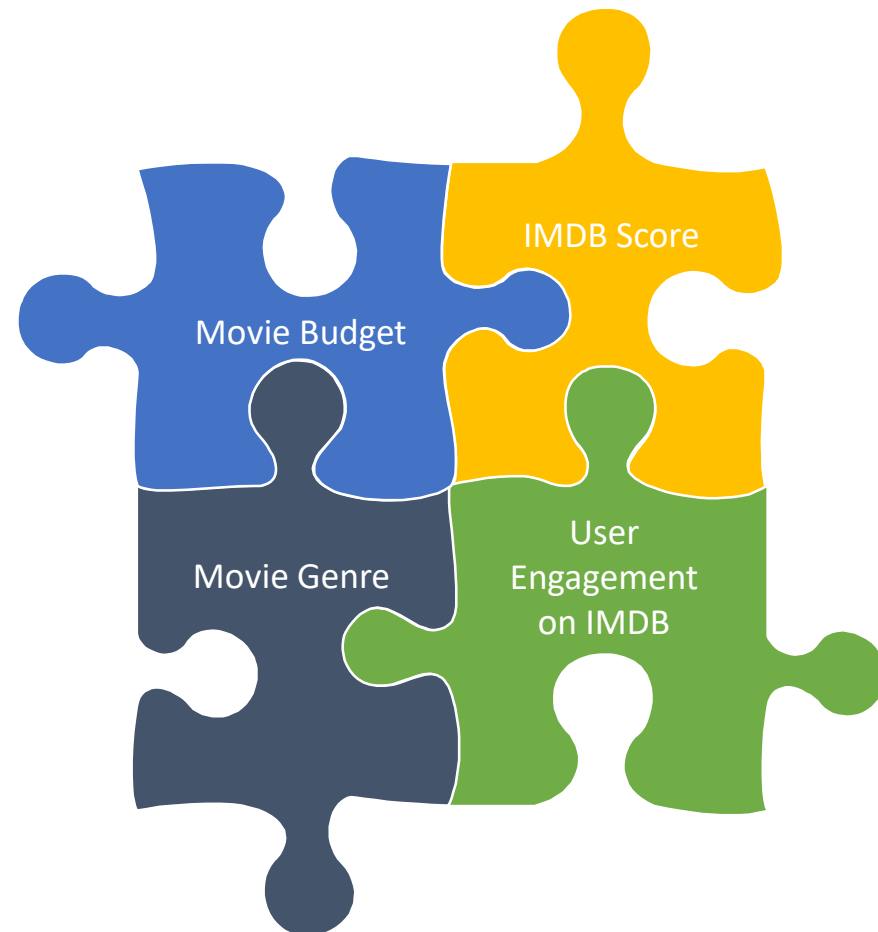
- x Popularity of Cast
- x Popularity of Director
- x Number of Critic Reviews on IMDB
- x Movie Genres (excluding the 4 listed above)
- x Number of Faces in Poster
- x Movie Ratings

Recommendations and Next Steps



Recommendations and Next Steps

To further investigate the actionable variables that our regression highlighted, we have outlined additional strategic challenges



IMDB Score

- What are the components of this rating?
- Are there any early indicators of the IMDB score?
- Can we test these indicators prior to the release of the movie?
- Is there a way to incentivize additional users and critics to review a movie?

Questions?

