

A Budding Data Scientist's First Modeling Journey: Japanese v. American Animated Films

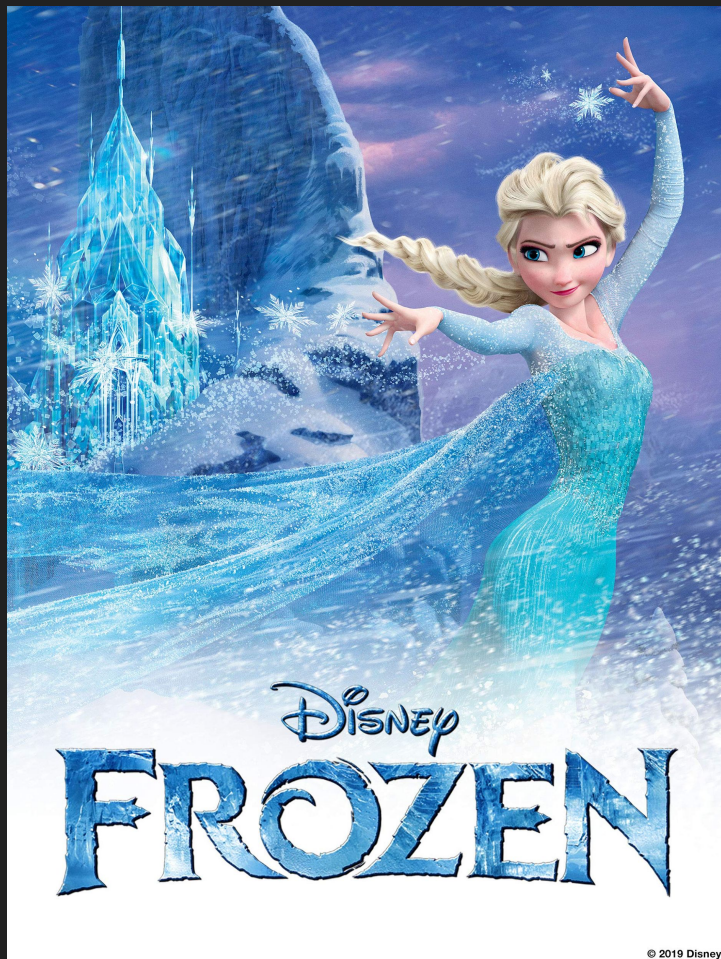
Binh Hoang

The challenge

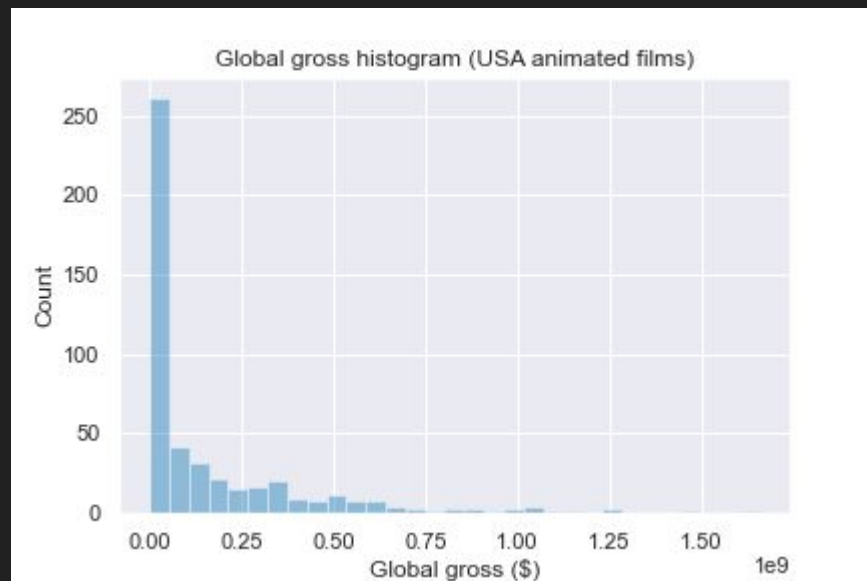
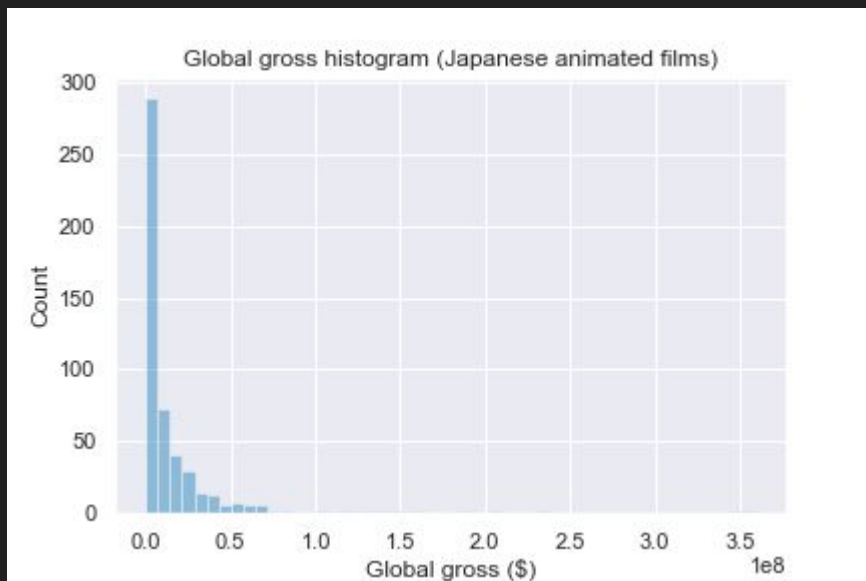
Can I predict the global box
office gross for...?

My Neighbor TOTORO





Modeling difficulty: medium




Methodology



Scrape Clean Model

Scrape

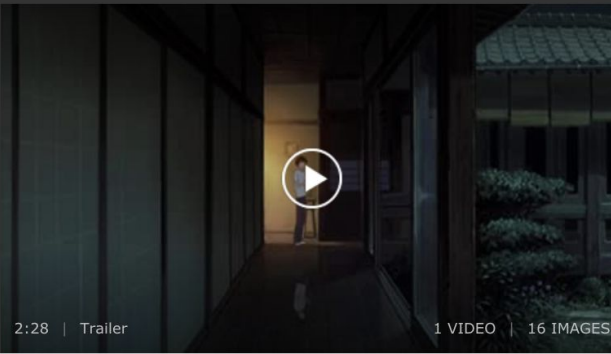

imdb.com

- 2,846 animated films
(almost evenly split
between US/Japan)
- Packages:
BeautifulSoup,
requests

FULL CAST AND CREW | TRIVIA | USER REVIEWS | IMDbPro | MORE  SHARE

**Summer Wars (2009)** ★ 7.5 ¹⁰_{25,191}  Rate This


Samâ uôzu (original title)
PG | 1h 54min | Animation, Action, Adventure | 1 August 2009 (Japan)




2:28 | Trailer 1 VIDEO | 16 IMAGES


A student tries to fix a problem he accidentally caused in OZ, a digital world, while pretending to be the fiancé of his friend at her grandmother's 90th birthday.


Director: Mamoru Hosoda
Writers: Mamoru Hosoda (original story), Satoko Okudera (screenplay) | [2 more credits »](#)
Stars: Ryûnosuke Kamiki, Nanami Sakuraba, Mitsuki Tanimura | [See full cast & crew »](#)

 Add to Watchlist

 63 Metascore
From metacritic.com

Reviews
63 user | 94 critic

IMDbPro View production, box office, & company info 

 10 wins & 5 nominations. [See more awards »](#)

Clean

- Dropped 1,796 (63% of all data) data points b/c missing global gross (target)
- Dropped another 80 data points b/c films were produced in Japan and US

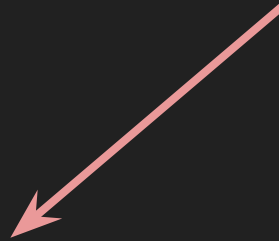
Final dataset

	American Films	Japanese Films
Data Points	474	496
Missing Budget Values	142	451

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	American Films	Japanese Films
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Missing Budget Values	142	451

Important point! Will
come back to this



Filled with median

Modeling approach

- OLS regression
- Two separate models (Japan model/US model)
- 5 k-fold cross-validation
- No regularization

US model

Feature coefficients:

budget	2.25
budget * is_summer_release	0.99
budget * is_xmas_release	0.19
oscar_wins	41,484,604.23
imdb_user_rating	10,066,891.63
imdb_user_rating_count	676.18
years_since_release	-760,422.17

US model

Training R^2 : 0.695

Val R^2 : 0.686

Test R^2 : 0.661

Training MAE (\$): 92,742,534.38

Test MAE (\$): 73,133,756.76

Decent R^2 , but high mean absolute error

Japan model

Feature coefficients:

imdb_user_rating_count	279.97
non_oscar_wins	3,596,523.12
years_since_release	-369,800.85
is_golden_week_release	-9,869,910.32
is_summer_release	6,034,622.74
is_xmas_release	2,255,158.46

No budget:

budget feature
reduced validation
 R^2 by .01
(incomplete budget
data caused issue)

Japan model

Training R^2 : 0.491

Val R^2 : 0.285

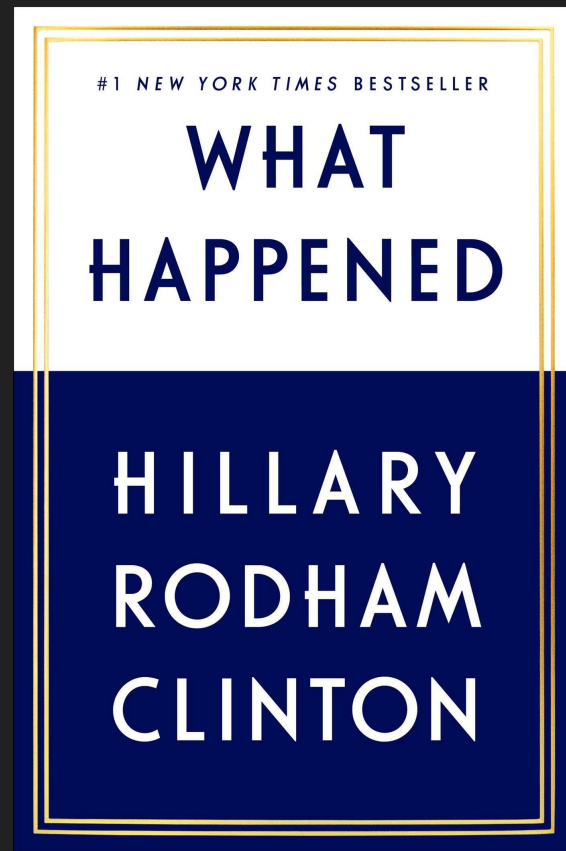
Test R^2 : 0.059

Training MAE (\$): 15,242,610.013

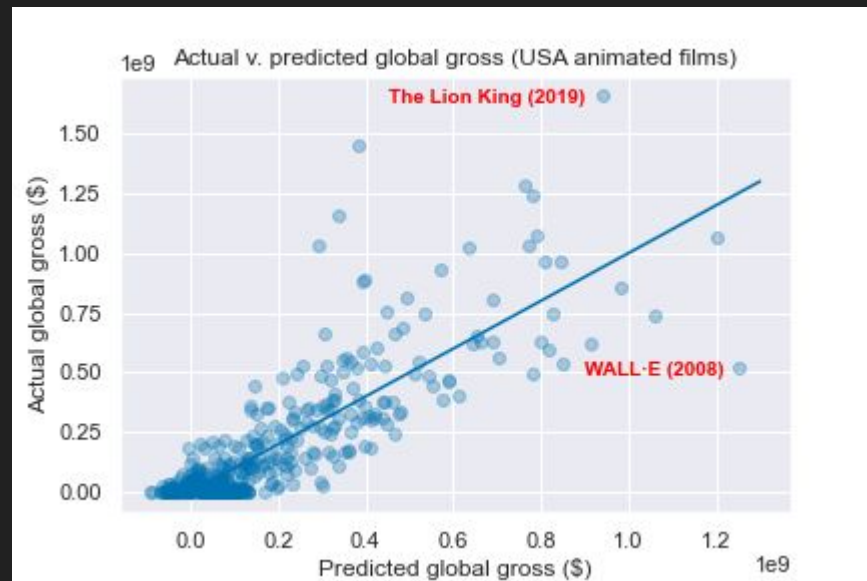
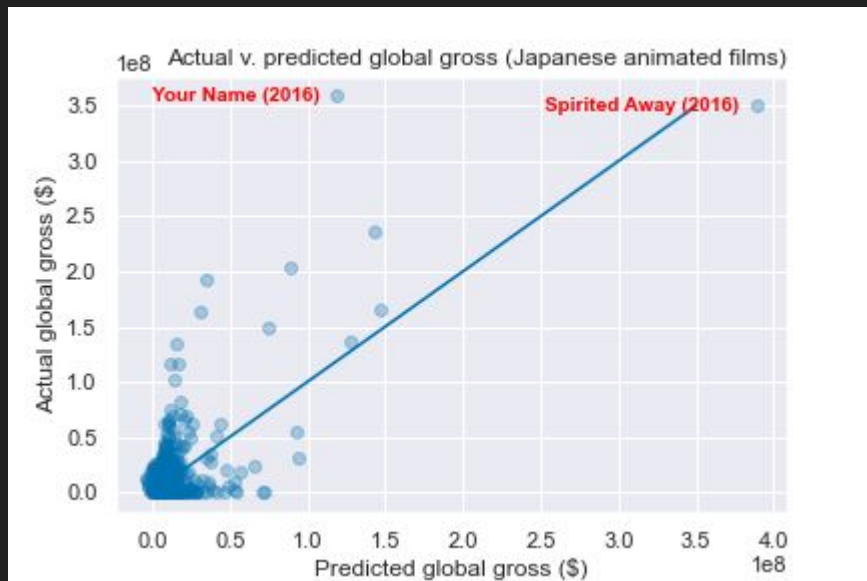
Test MAE (\$): 15,286,223.419

Two not so great models, with the Japan model almost having no predictive power

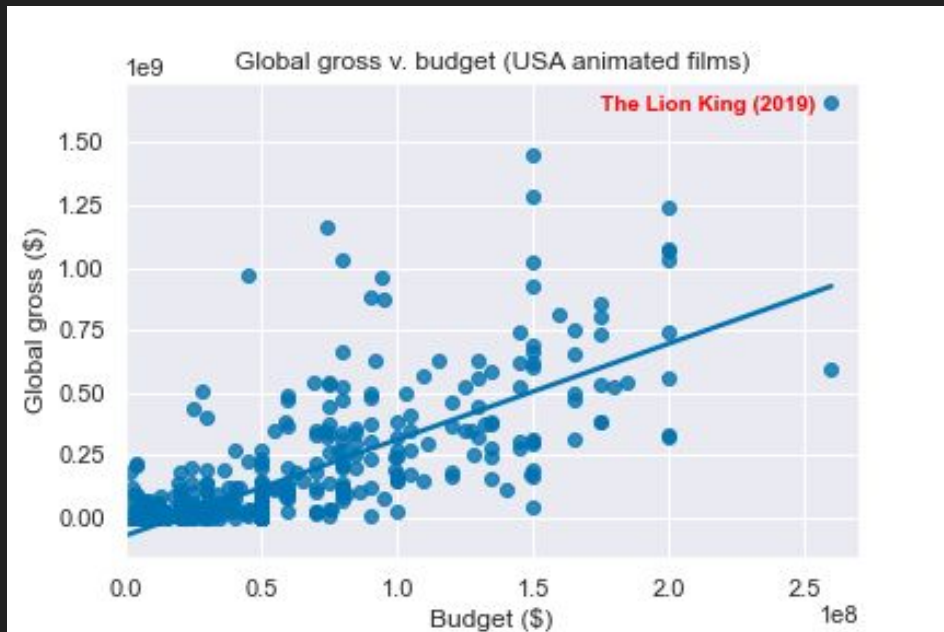
What happened?



Prediction error increases for films with higher global gross (error heteroskedasticity)



Missing important budget feature in Japan model (potentially losing $\sim .5$ in R^2)



Training R^2 : 0.511
Test R^2 : 0.476

Feature coefficients:

budget 3.84

Residual analysis (models mostly underpredicted)

US abs largest residuals:

1. Frozen II
2. Minions
3. Despicable Me 3
4. WALL·E
5. The Lion King (2019)

*Underpredicted by as high as
\$1.07 bn*

Japan abs largest residuals:

1. Your Name
2. Weathering With You
3. Pokémon: The First
Movie
4. Pokémon the Movie
2000
5. Ponyo

*Underpredicted by as
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**Models missing
an animation
company
feature!**

What I learned/takeaways

- Poor data produces poor models (obvious, but learned this the hard way)
- Do residual analysis earlier
- Scrape more than you need to
- An American website may not be the best data source for Japanese films

Future work

- Create two working models and compare/contrast them as way to gain business insights into Japanese v. American animated films (original project goal)

THANK YOU

**FOR LISTENING TO MY
PRESENTATION**

nemegenerator.net

Appendix

Literature review:

- [The determinants of box office performance in the film industry revisited \(N.A. Pangarker and E.v.d.M. Smit\)](#)
- [A study on box-office revenue: How user and expert ratings determine movie success \(Sylvain Dingenouts\)](#)

Appendix

Scraping issues:

1. mpaa_rating was not scraped properly (missing certain ratings like TV-G) due to improper scraping logic
2. usa_release_date was not scraped properly (some release dates from other countries were pulled in) due to improper scraping logic

Appendix

Created a function to record my cross-validation scores for each feature engineering/model selection iteration.

Helps systematize workflow.

```
• def record_cv(mean_train_score, mean_val_score):  
    cv_dict = {}  
    model = input("Model: ")  
    label = input("Iteration description: ")  
    cv_dict['model'] = model  
    cv_dict['label'] = label  
    cv_dict['mean_train_score'] = mean_train_score  
    cv_dict['mean_val_score'] = mean_val_score  
    return cv_dict
```