

Predicting the Ratings of Book to Film Adaptations

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Background

- Books - great
- Film adaptations - mixed bag

Problem

- Which films to watch or avoid?
-

Data Collection

- 2008-2017
- 216 points after cleaning



- **Rating**
- Runtime
- Director
- Studio
- Genre

Box Office
Mojo

- Avg gross of Director(s)
- Studio market share



WIKIPEDIA

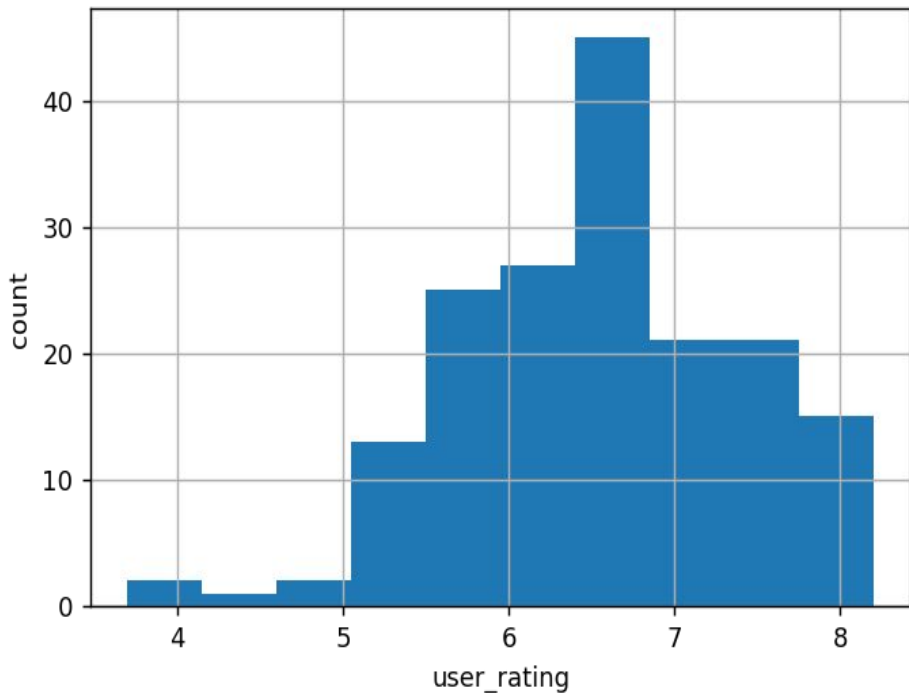
(Film to book link)

goodreads

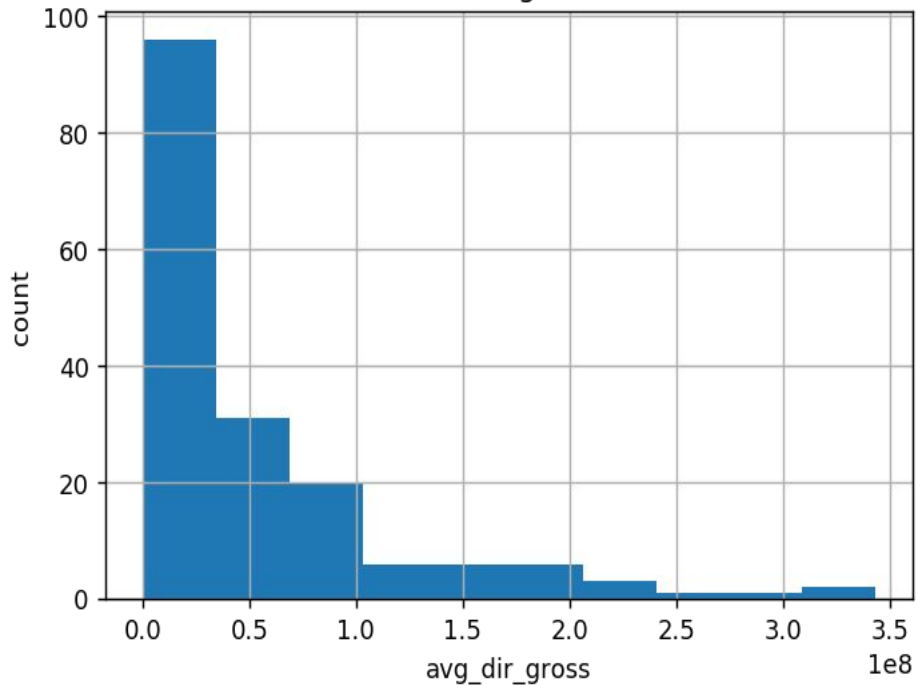
- Rating
- Reviewer count
- Years between publication and film

Data Cleaning/Transformation

Distribution of Film Ratings

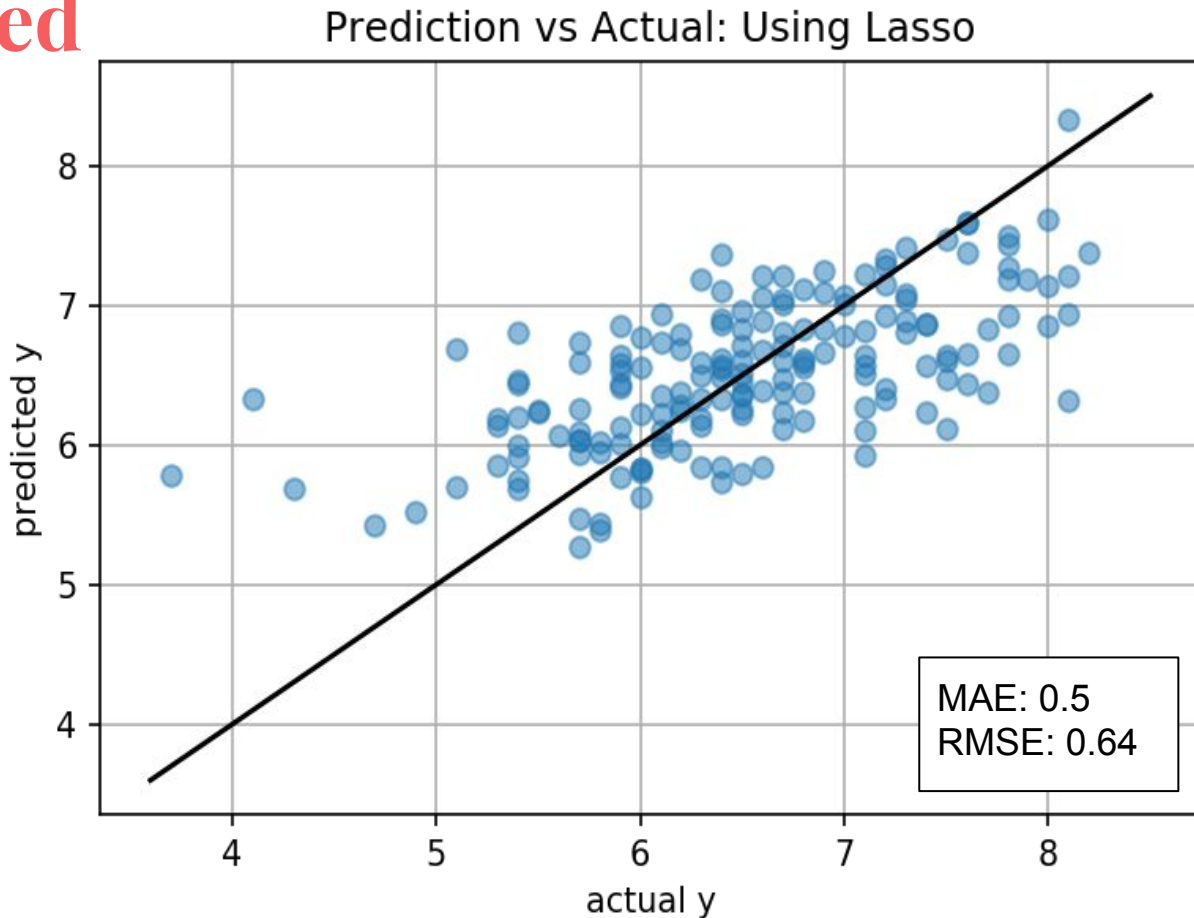


Distribution of Avg Director Gross

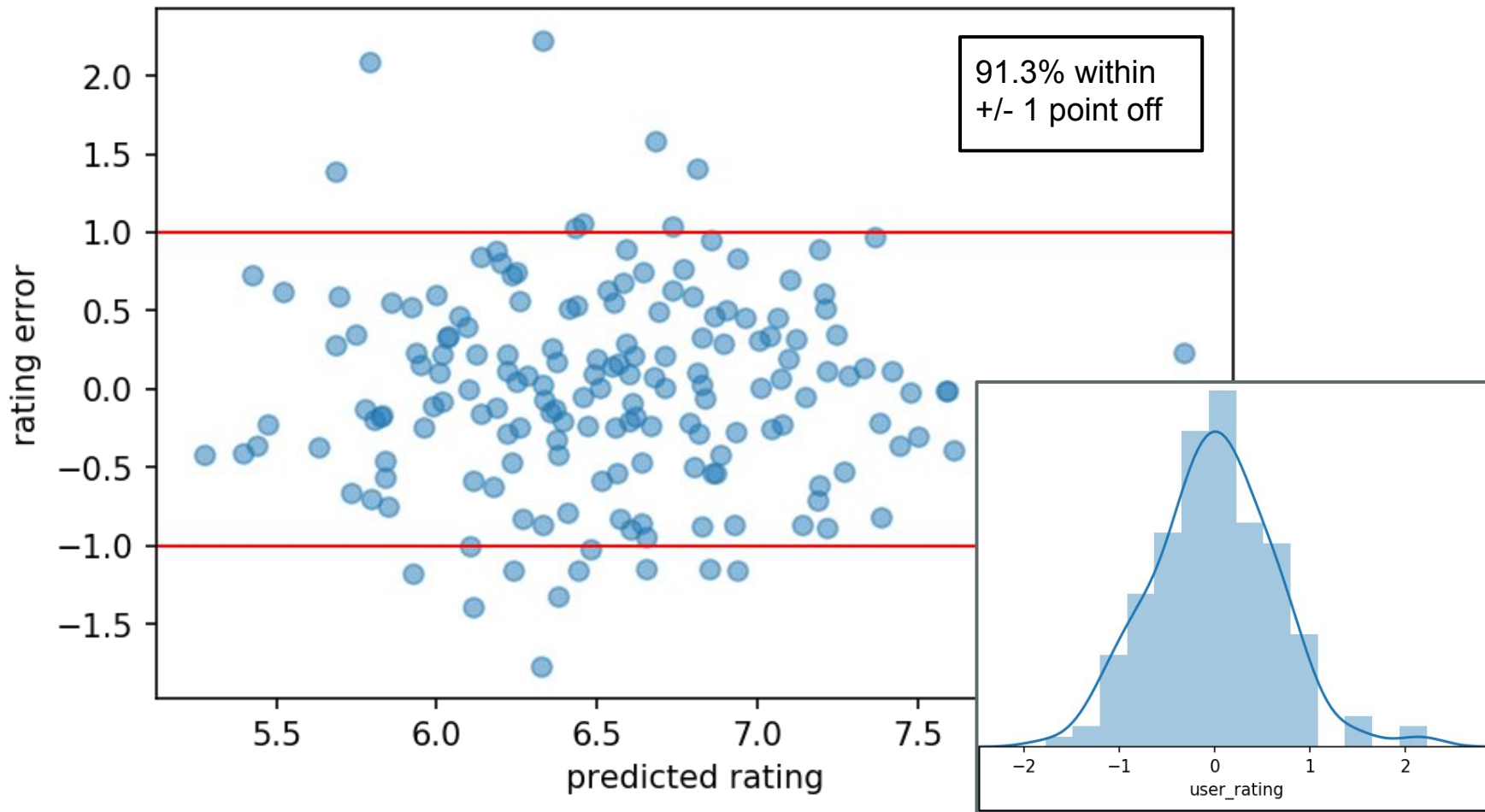


Models Attempted

- Linear Regression
- Linear with Lasso
- Polynomial Features with Lasso
- Polynomial Features with Ridge
- Linear with Ridge
- Lasso after removing features

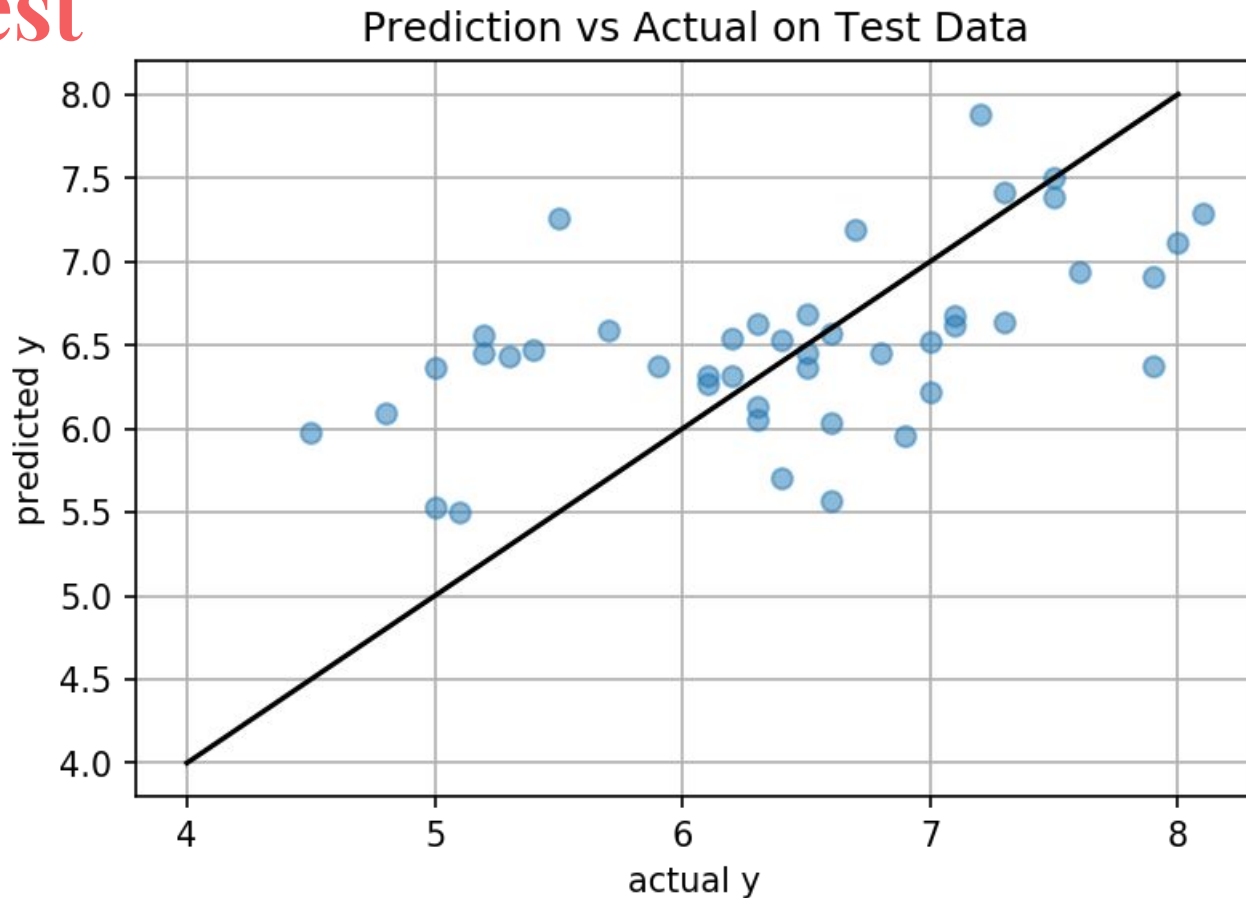


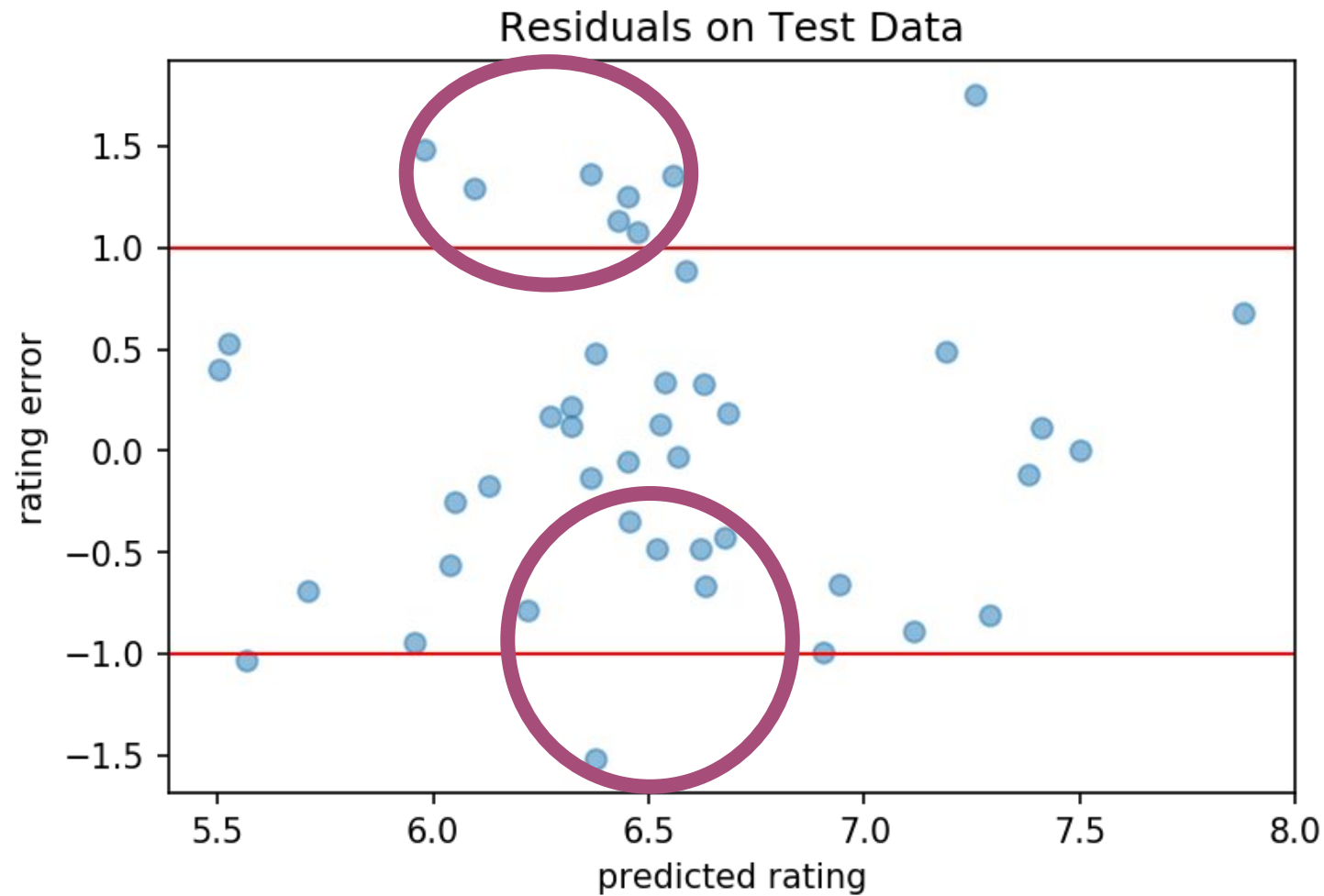
Residuals on Train Data using Lasso



Applying to test

- 44 datapoints
- 9 outside the ± 1 point tolerance
- MAE: 0.63
Compare to 0.5
- RMSE: 0.78
Compare to 0.64





Conclusion

- Model identifies bad movies, most good movies
- Avoid disappointment!

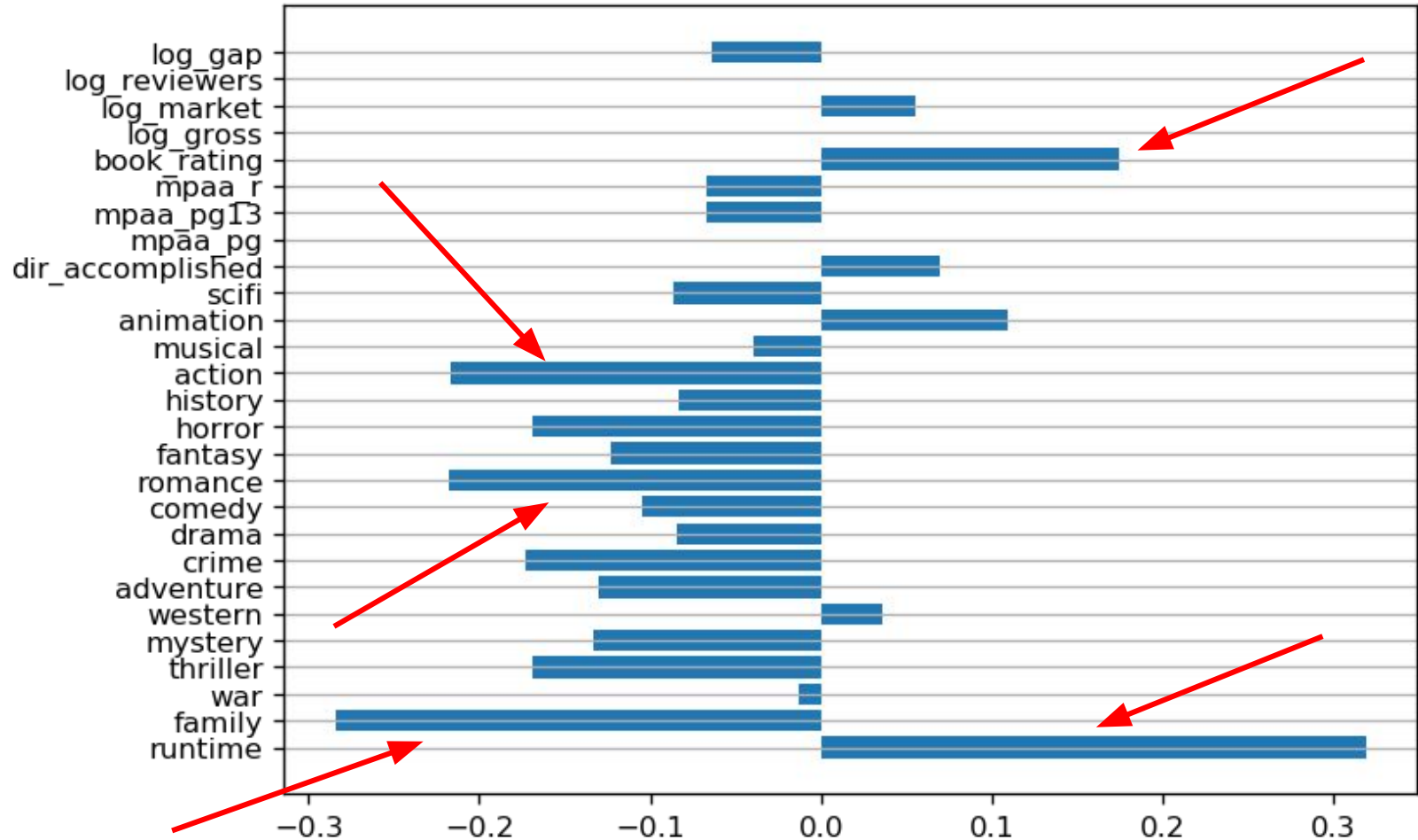


Next Steps

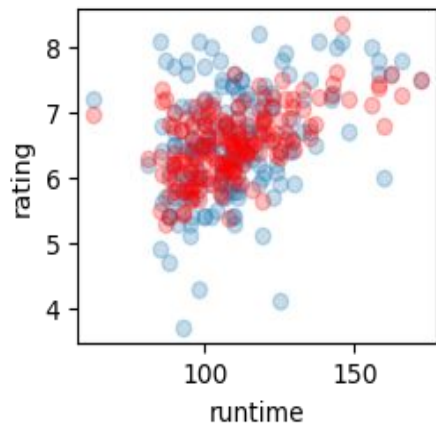
- Expand date range
- Different features/ feature engineering
- Explore per genre/clustering
- Set lower expectations

Appendix

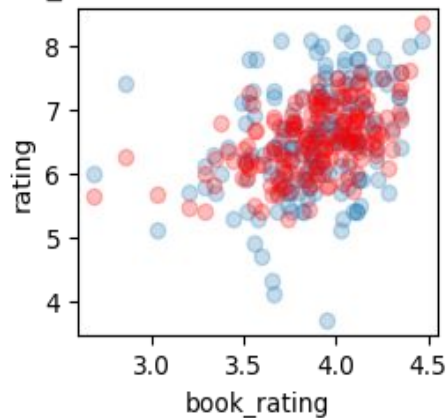
Coefficients from model



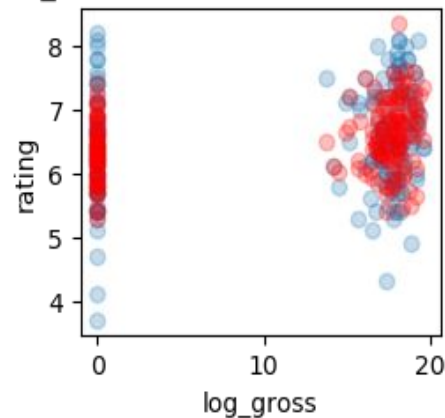
runtime vs predicted rating (train)



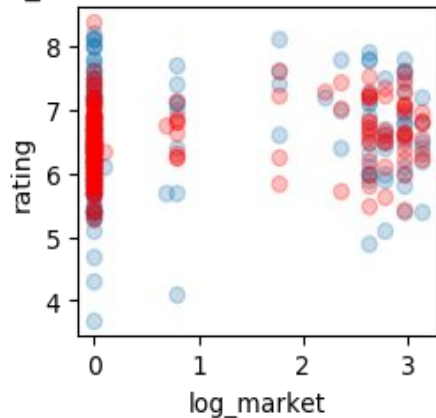
book_rating vs predicted rating (train)



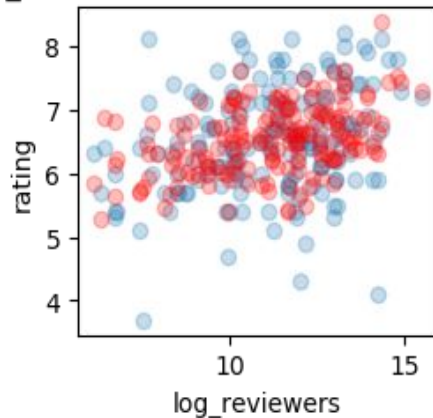
log_gross vs predicted rating (train)



log_market vs predicted rating (train)



log_reviewers vs predicted rating (train)



log_gap vs predicted rating (train)

