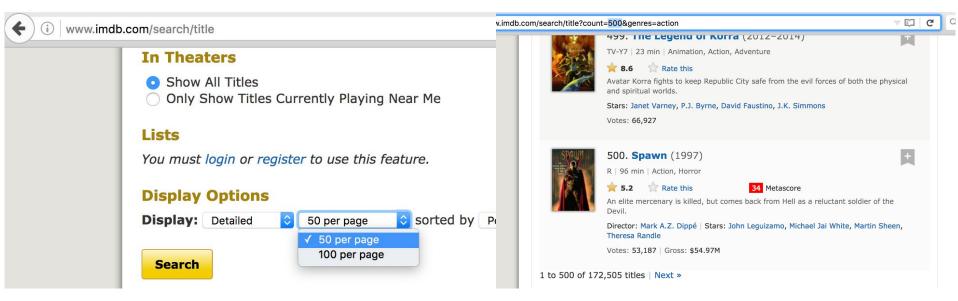
# **Predicting IMDb User Rating**

Kevin Du

# **Objective**

- Predict the IMDb user rating for movies
- User rating and reviews affect ticket sales, and thus revenue
- Netflix competition: \$1 mil prize
  - Predict user ratings for movies and TV shows

# **Data scraping**



Works with any number.

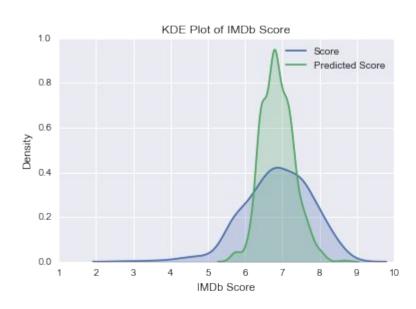
Too high might crash your browser.

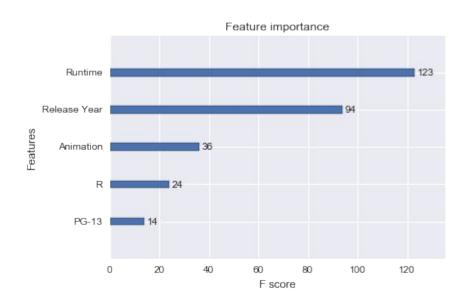
#### **Dataset**

- Scraped 2,332 movies from IMDb.com
- Only movies with over 50,000 ratings to preserve integrity
  - Avoids vote manipulation for less popular movies
- Features: actors, directors, genres, year, MPAA certification, runtime
- Will not use number of votes or gross revenue
  - Unknown before release
  - More suitable as label than feature

### **Results**

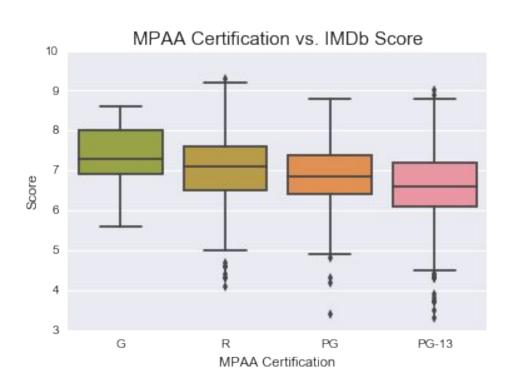
XGBoost  $R^2$  score = 0.275



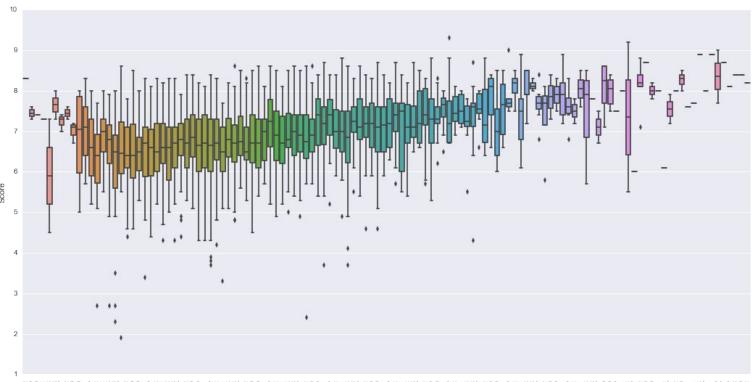


Predictions tend to be safe, near the mean

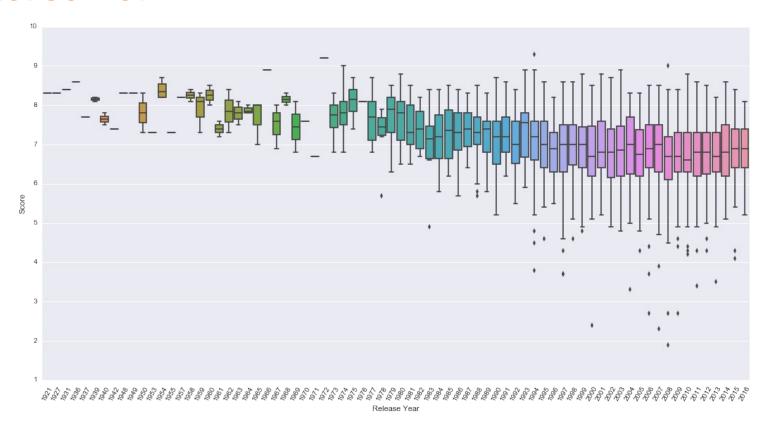
#### **MPAA Certification**



#### **Runtime**



#### **Release Year**



# **Feature Engineering**

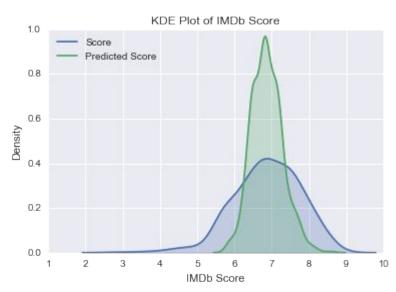
- Title contains '2', '3', or '4'?
- Title contains a colon?
- Title starts with 'The'?
- Length of movie title
- Number of directors
- Number of genres
- Various actors: Leo, Christian Bale, Matt Damon, Brad Pitt, Adam Sandler
- Various directors: Christopher Nolan, Quentin Tarantino, Clint Eastwood

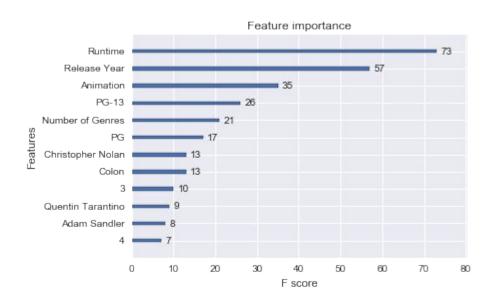
Positive effect Insignificant Negative effect

(Assuming  $\alpha = 0.05$ )

#### **Results Redux**

#### XGBoost $R^2$ score = 0.306





#### **Conclusion**

- Best features were runtime and release year
- Animations and G movies tend to be rated higher
- Engineered features improved the model
- Certain actors and directors have an impact on ratings
- Other possible features:
  - Facebook likes or tweets for movie, actors, directors
  - Interaction effects between certain actors and directors.