An Investigation into How Movie Ratings Vary Following a Movie's Release

TEAM 11 | CITADEL DATA OPEN WEST COAST REGIONAL

Summary of Insights

> Users tend to rate movies more negatively the older a movie is

> Movie features are weak indicators of the variability of movie ratings over time

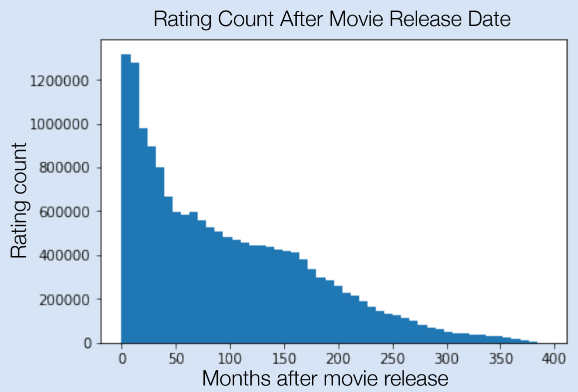
> Movie features become more accurate predictors of variability within a longer timeframe

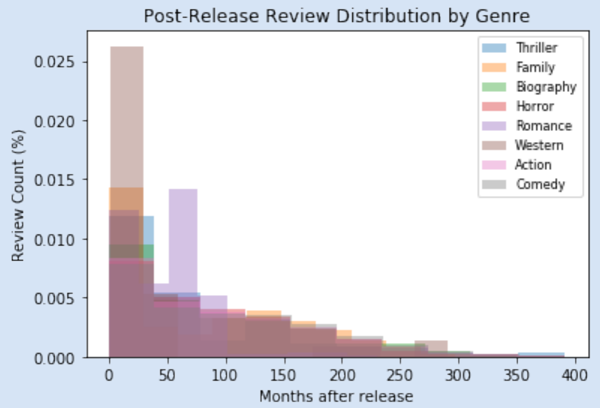
BACKGROUND

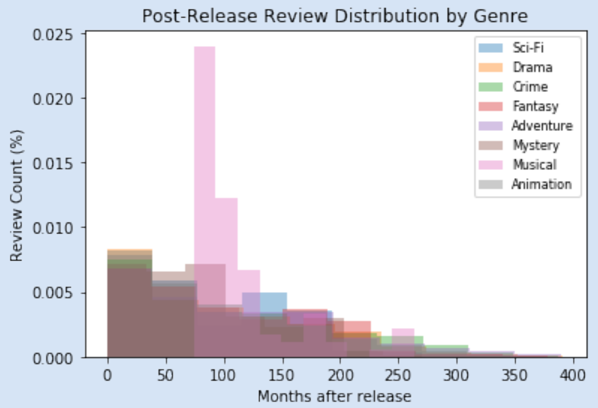
Consumers read product ratings and reviews frequently to make informed consumption decisions. As the film industry enters a Second Golden Age with the emergence of streaming giants, movie ratings are playing an increasingly prominent role in consumer choice. However, as these alternative platforms offer greater viewing flexibility to viewers, their profiles and perceptions toward a specific movie diverge across time. For example, the emergence of Disney+ may mean that fans of the Marvel Cinematic Universe are more likely to catch the upcoming Black Widow movie in cinemas, whereas casual viewers may defer to its release online, thereby potentially inflating early ratings of the movie. How might we better understand the evolution of consumers' perception of a movie following its release? Do temporal differences in consumer perception of movies vary across genres? Through understanding these differences, can we predict which movies may behave like hidden gems and grow on consumers over time, and which experiences an initial hype before fading out?

Motivation

While one would presume most consumers tend to watch movies within a year or two after its release, we found that a bulk of consumers actually continue watching movies many years after (right). These distributions also seem to vary across genres (bottom).







DATA

Features for ~60,000 Movies
Industry metadata such as genre, budget, profit margin, runtime, year released

~28,000,000 User Rating Data from MovieLens
Unique user ratings for movies with timestamp

1,128 "Genome Tags" for ~13,000 Movies
Each tag-movie pair has a relevance score based on user feedback

MODEL 1: HOW DO MONTHLY AVERAGE RATINGS DEPEND ON TIME AFTER RELEASE AND CONSUMER PROFILE?

> MODEL

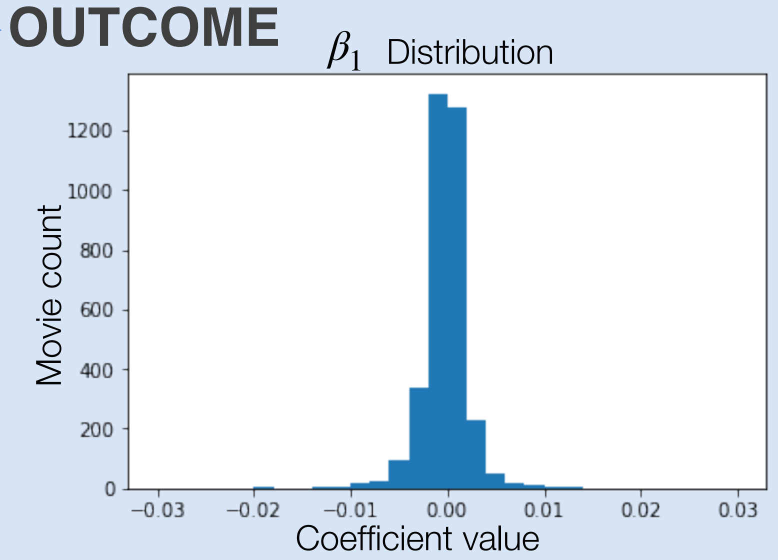
We ran a multilinear regression model for movies released during and after 1996 using the following equation.

$$y_t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon_i$$

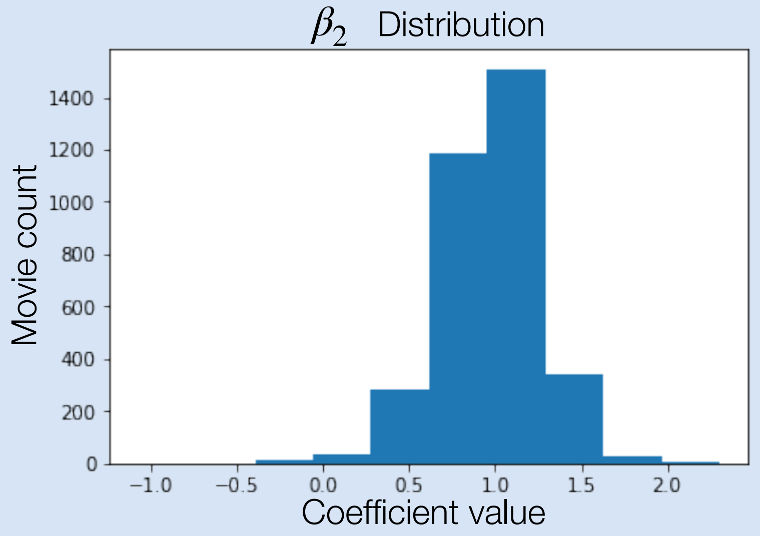
- y_t monthly mean rating of a specific movie
- x_1 number of months since the movie was first rated
- x_2 mean user rating (across all movies rated by each specific user) for all users who rated the movie in the given month

In short, we are using time elapsed and overall user rating behavior (predictors) to predict a movie's monthly ratings.

> OUTCOME



For the impact of time elapsed since movie release, there is an almost even split on the direction of this impact, with a slightly negative skew, suggesting that monthly ratings decrease slightly over time. This distribution also suggests that impact may vary across movies.



For the impact of user rating profile, the coefficient is generally positive, suggesting that the rating of most movies are in line with people's expectations. We can also see that there is an uneven distribution near 1.0, suggests

> DISCUSSION

Both of our predictors have high statistical significance across our movies dataset, with the user profile predictor having a much higher significance.

One interesting observation came in the even distribution in the polarity of elapsed time predictor. Should we be able to classify which movies grow on consumers over time, we can potentially advise streaming platforms on investing in movie streaming rights. We attempt to create such a model in the next section using an artificial neural network.

MODEL 2: DO MOVIE FEATURES DETERMINE THEIR RATING TRENDS OVER TIME?

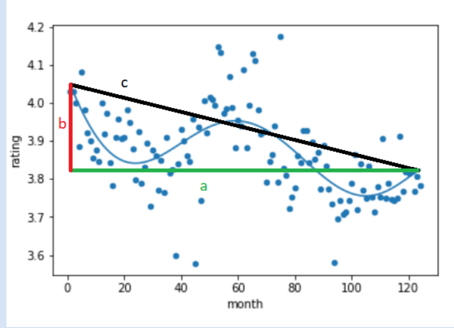
> MODEL

Based on the insights from the first model, we decided to further investigate the impact of time elapsed on monthly movie ratings, emphasizing the movie features as a predictor for the monthly rating trends over time.

We selected two particular characteristics in evaluating rating trends over time:

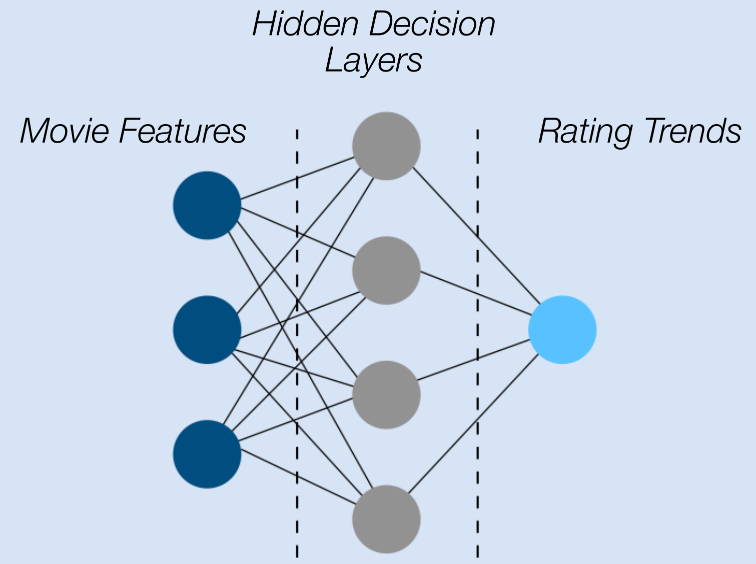
> Total variance in ratings over time

> Net rating change (magnitude and direction) over a specific time period



> E.g. This is a movie with high variability (comparing curved blue line and black straight line) and negative net rating change (red line).

Using the various features for our movies, we ran a neural network in an attempt to predict the rating trends based on movie features.



Simplified illustration of our artificial neural network, which we use to predict monthly rating trends using movie features

> OUTCOME

We ran two neural networks; one to predict rating variance and another to predict net rating change. We found that our models were weak predictors of both rating variance and net rating change. When we ran our model on our data for a time frame of 4 months after a movie's release, it was able to predict rating variance around, on average, one standard deviation away from the movie's true rating variance. We saw similar results on our net rating change model. We did find though, that our rating variation model became significantly more predictive as we increased the time frame considered following a movie's release.

> DISCUSSION

Our input dataset, which included 100+ features about movie metadata and tags, predicted the variation and change in a movie's rating over time within one standard deviation. Importantly, our models became significantly more predictive as the time frame increased following a movie's release. Though seemingly inaccurate, the models in fact highlight two important conclusions. First, they indicate that features other than the metadata must be analyzed. Increased information about the movie's contents (e.g. transcripts) and about the budget (e.g. marketing), will enable a better prediction.

Second, our model fits better for the longer timeframe. This suggests that we can potentially further develop a model which relates movie features to their long-term variability. These results can then be taken into consideration by movie recommender systems to improve user satisfaction and retention. For movie producers, such a model can advise on movie features that decrease rating variability over time — a much needed trait in a movie to secure funding in a volatile industry.