MovieLens Capstone Project

Alexandria Simms PhD

Harvard edX

Table of Contents

Introduction ... 4
Exploratory Data Analysis ... 5
UserId ... 6
MovieId ... 7
Rating ... 8
Timestamp ... 10
Title ... 12
Genre ... 12
Key Insights for Modeling ... 13
Summary ... 13
Methodology ... 14
Datasets ... 14
Data Wrangling ... 14
RMSE ... 15
Models ... 15
Naïve Model ... 16
Movie Effect Model ... 16
Movie + User Effect Model ... 16
Timestamp Effect Model ... 16

Genre Effect Model 16
Regularization 17
Summary 17
Results 18
Summary Table of RMSEs 18
RMSE by Lambda Plot 18
Distributions of Model Effects 19
Baseline and Incremental Improvements 19
Movie Effect Distribution 20
User Effect Distribution 21
Combined Effects(Movie + User) 22
Final Regularized Model 22
Conclusion 23
References 25

Introduction

Recommendation systems have become indispensable AI-driven tools that revolutionize how users discover relevant products, services, or content. By meticulously analyzing vast amounts of user data, these systems excel at identifying intricate patterns in behaviors and preferences. The typical operational workflow involves several critical stages: initially, relevant data, such as user preferences and historical interactions, is meticulously gathered. This raw information then undergoes rigorous cleaning and organization to prepare it for subsequent analytical processes. Subsequently, sophisticated machine learning algorithms—including collaborative filtering, content-based filtering, or advanced hybrid approaches—are applied to uncover latent similarities and underlying patterns within the processed data. Leveraging these insights, the system generates personalized predictions regarding items a user is most likely to find appealing or purchase. Ultimately, these tailored suggestions are seamlessly presented to the user through an intuitive, searchable interface, enhancing their overall experience.

The MovieLens dataset, a cornerstone in the field of recommender systems, stands as a widely recognized benchmark in machine learning research. Curated and maintained by the esteemed GroupLens research team at the University of Minnesota, this dataset encompasses millions of movie ratings contributed by real users. These ratings were meticulously collected over a significant period, spanning from the late 1990s through the early 2000s. Its fundamental purpose is to serve as a robust platform for the rigorous development, comprehensive testing, and precise evaluation of collaborative filtering algorithms and various recommendation models.

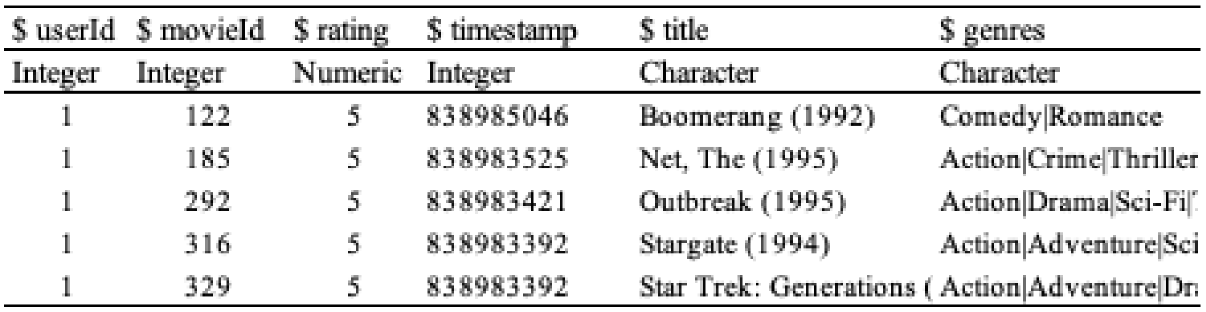
For the scope of this capstone project, the primary objective is to develop a robust movie recommendation system. This system will leverage the extensive MovieLens 10M dataset, which boasts an impressive 10 million ratings for thousands of distinct movies. The initial phase of the project involved downloading the dataset and executing the provided R code to generate the training (edx) and validation datasets. Following this, a brief quiz was completed to ensure familiarity with the data's intricate structure and inherent characteristics. This foundational exploration was instrumental in gaining a deeper understanding of diverse user behaviors, the popularity dynamics across various movie genres, and prevailing rating trends. These critical insights will directly inform the subsequent and pivotal phase of the project: the training of a sophisticated machine learning algorithm. This algorithm will be meticulously designed to predict movie ratings within the validation set, based on the learned patterns and inputs derived from the training subset.

This report is meticulously developed using R Markdown within the RStudio environment, aligning with R as the designated primary programming language for this course. R is widely acknowledged as a powerful and versatile language, celebrated for its exceptional capabilities in the development and implementation of a broad spectrum of machine learning algorithms, including but not limited to classification, clustering, and regression models (James et al., 2013).

Exploratory Data Analysis

This section presents a comprehensive exploratory data analysis (EDA) of the dataset, aiming to uncover key characteristics, patterns, and potential biases that inform the development of the recommendation system. Understanding the underlying structure of the data is crucial for designing effective predictive models. The MovieLens 10M edx dataset consist of 9,000,055 rows and six columns. The dataset used to develop the algorithm consist of 10,677 different movies which were rated by 69,878 different users. The variables userId, movieId, rating, timestamp, title and genres were used to analyze the data.

Table 1: edx dataset: variable class and first 5 rows



$ userId	$ movieId	$ rating	$ timestamp	$ title	$ genres
Integer	Integer	Numeric	Integer	Character	Character
1	122	5	838985046	Boomerang (1992)	Comedy|Romance
1	185	5	838983525	Net, The (1995)	Action|Crime|Thriller
1	292	5	838983421	Outbreak (1995)	Action|Drama|Sci-Fi|
1	316	5	838983392	Stargate (1994)	Action|Adventure|Sci
1	329	5	838983392	Star Trek: Generations (	Action|Adventure|Dr

UserId

Analysis show that 69,878 distinct users rated movies from the late 1990s through the early 2000s. A notable aspect of user activity is the consistency of their engagement. The histogram titled "Number of Distinct Days a User Rated" (see Figure 1) illustrates this. The plot, presented on a logarithmic scale for the number of users, shows that a significant portion of users rated movies on only a few distinct days. For instance, a large number of users rated on just 1 or 2 distinct days, with the frequency of users decreasing as the number of distinct rating days increases. Users who rated on more than 30 active days were excluded from this specific plot for readability, but their presence further indicates a spectrum of user engagement, from casual to highly active. This distribution suggests that while many users engage sporadically, a smaller, highly active group contributes consistently over time. Out of 69,878 users, 27,797 rated films on more than one day (see Figure 1).

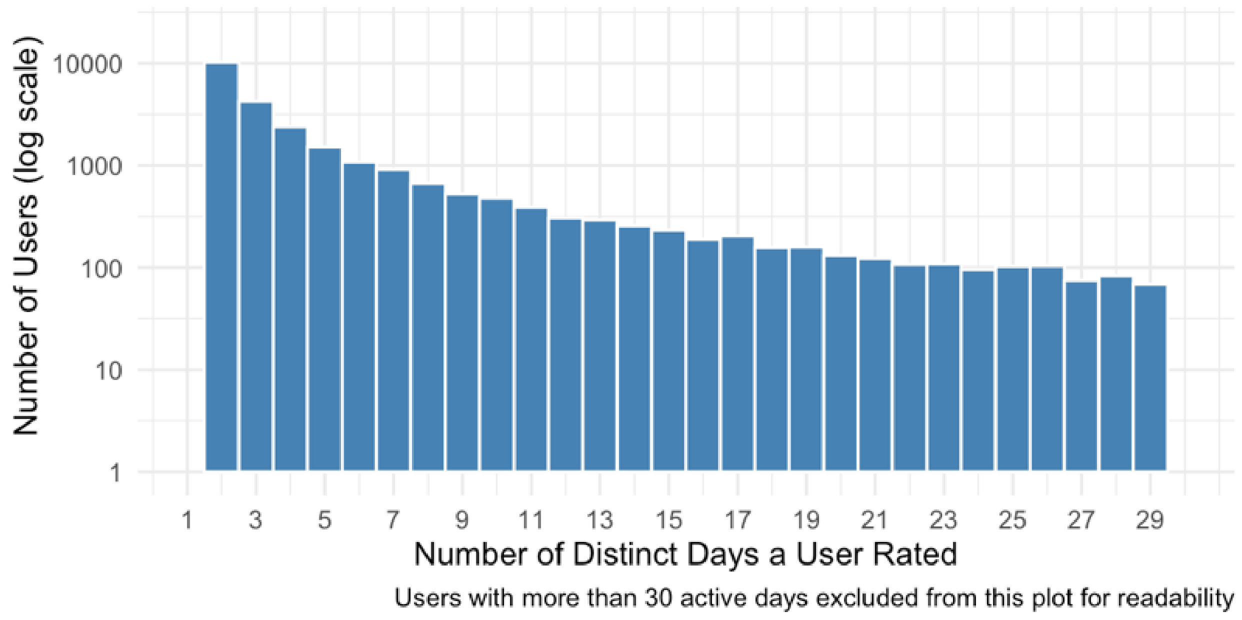


Figure 1: Distribution of Distinct Rating Days per User

MovieId

The movieId variable was used as numeric identifier for movie title. There were 10,677 different movies included in the edx dataset. Analysis of movie-specific effects indicated a wide variability in average ratings per movie. Some movies consistently receive high ratings, suggesting broad appeal, while others are rated lower, possibly due to niche appeal or perceived lower quality. The number of ratings per movie also varies significantly, with a few highly popular movies receiving a vast number of ratings, and many less popular movies having only a handful. This disparity highlights the "long tail" phenomenon, where a small number of items account for a large proportion of interactions. Specifically, the "Average Rating vs. Number of Ratings per Movie" (see Figure 2) plot demonstrates that movies with very few ratings exhibit a widespread in average ratings, while movies with a higher number of ratings tend to have more stable and generally higher average ratings.

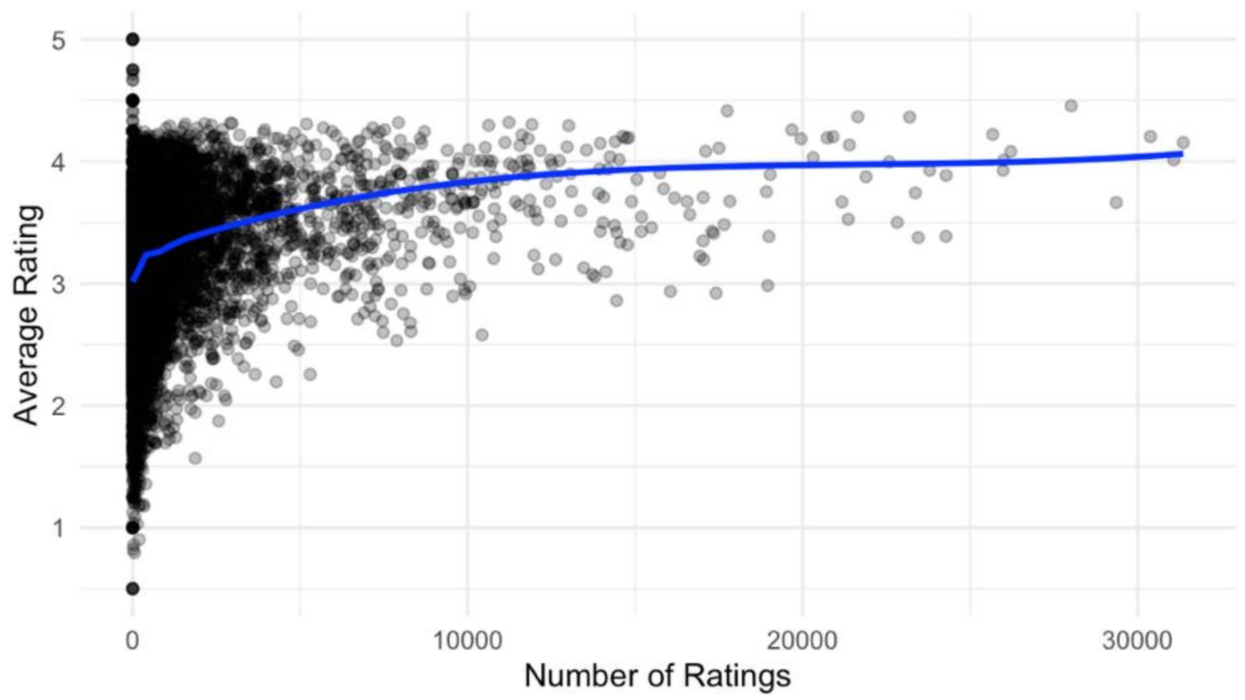


Figure 2: Average Rating vs. Number of Ratings per Movie

Rating

An initial examination of the overall rating distribution revealed that 4-star is the most frequent rating, followed by 3-star. The average rating across the entire dataset is approximately 3. This distribution suggests a general tendency for users to rate movies positively, with fewer very low ratings. The film Pulp Fiction received the highest number of ratings. The five most common ratings were 4,3,5,3.5, and 2. In general, users were less likely to give a movie a half star rating than a whole star rating. The tables and figures Distribution of Rating Counts, Rating Distribution by Genre, Worst Movie Titles by Rating, and Average Movie Titles by Rating were used to analyze the rating variable related data.

Table 2: Distribution of Rating Counts

Rating	List	Rating Count
0	Integer[1]	0
0.5	Integer[1]	85374
1	Integer[1]	345679
1.5	Integer[1]	106426
2	Integer[1]	711422
2.5	Integer[1]	333010
3	Integer[1]	2121240
3.5	Integer[1]	791624
4	Integer[1]	2588430
4.5	Integer[1]	526736
5	Integer[1]	1390114

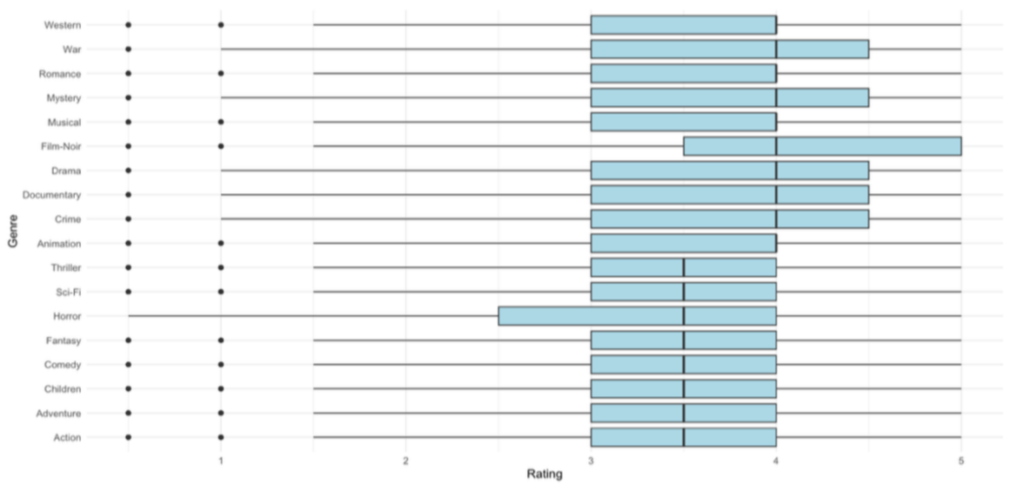


Figure 3: Rating Distribution by Genre

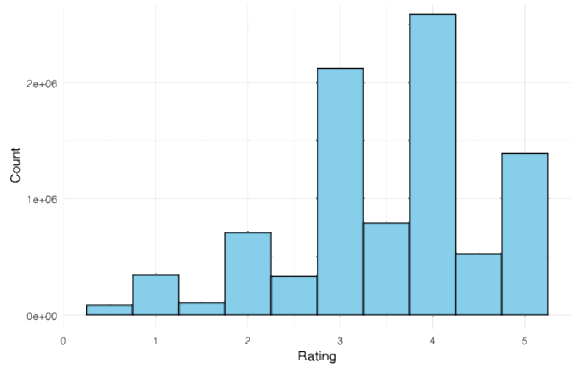
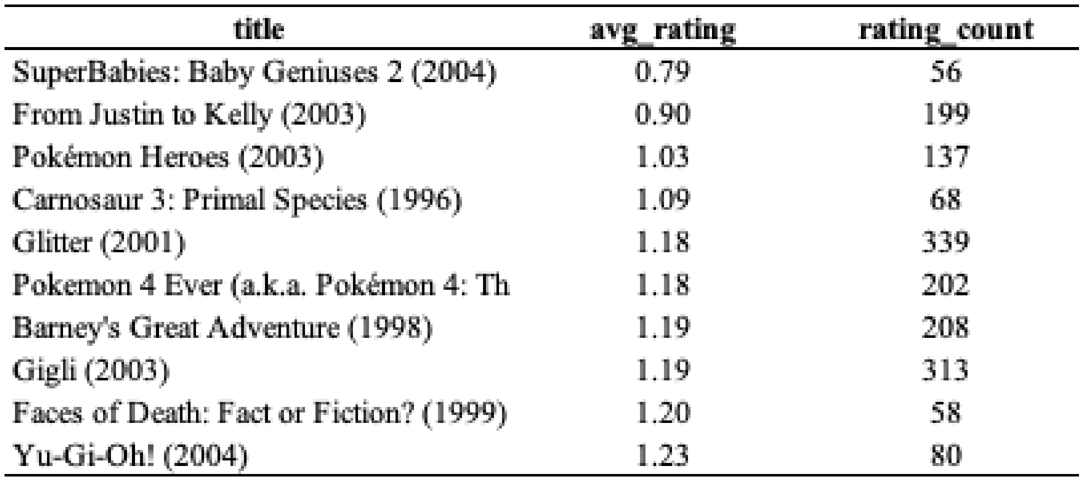


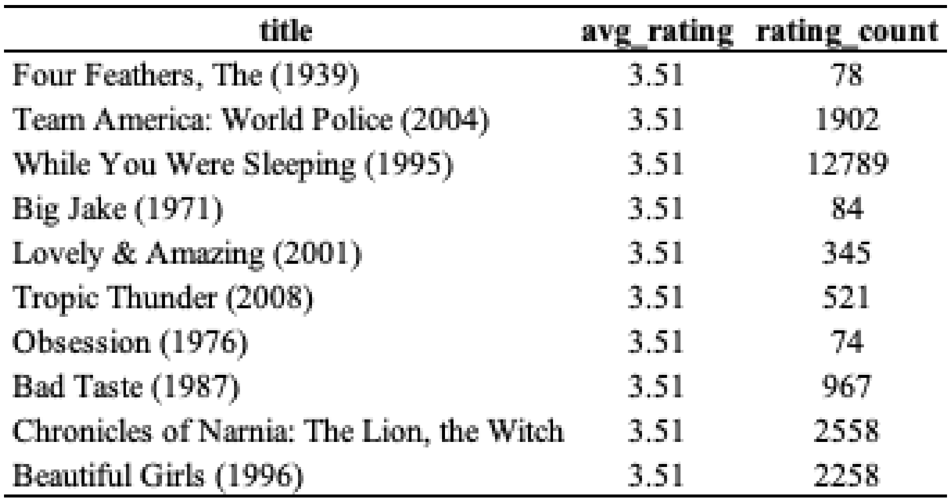
Figure 4: Histogram of Movie Ratings

Table 3: Bottom 10 (Worst) Movie Titles by Rating



title	avg_rating	rating_count
SuperBabies: Baby Geniuses 2 (2004)	0.79	56
From Justin to Kelly (2003)	0.90	199
Pokémon Heroes (2003)	1.03	137
Carnosaur 3: Primal Species (1996)	1.09	68
Glitter (2001)	1.18	339
Pokemon 4 Ever (a.k.a. Pokémon 4: Th	1.18	202
Barney's Great Adventure (1998)	1.19	208
Gigli (2003)	1.19	313
Faces of Death: Fact or Fiction? (1999)	1.20	58
Yu-Gi-Oh! (2004)	1.23	80

Table 4 : Middle 10 (Average) Movie Titles by Rating



title	avg_rating	rating_count
Four Feathers, The (1939)	3.51	78
Team America: World Police (2004)	3.51	1902
While You Were Sleeping (1995)	3.51	12789
Big Jake (1971)	3.51	84
Lovely & Amazing (2001)	3.51	345
Tropic Thunder (2008)	3.51	521
Obsession (1976)	3.51	74
Bad Taste (1987)	3.51	967
Chronicles of Narnia: The Lion, the Witch	3.51	2558
Beautiful Girls (1996)	3.51	2258

Timestamp

Temporal analysis revealed that ratings were most frequently submitted on Sundays, as indicated by the "Most Common Day to Submit a Rating" (Figure 4) plot. Furthermore, the "Average Movie Ratings Over Time (Monthly)" (Figure 5) graph shows fluctuating average ratings over the years, with a general downward trend followed by a slight recovery.

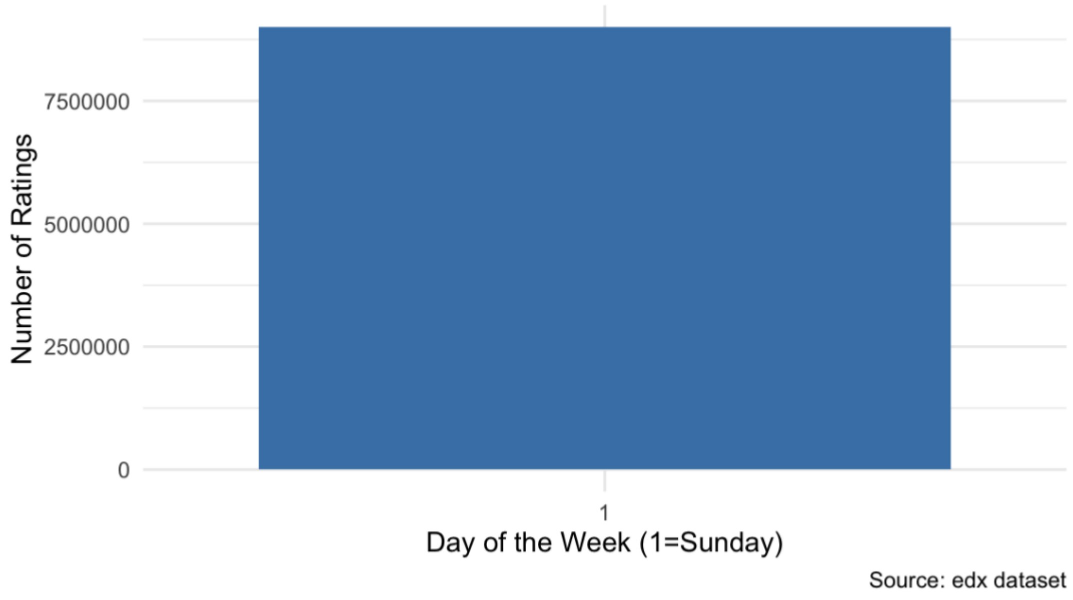


Figure 5 : Most Common Day to Submit a Rating

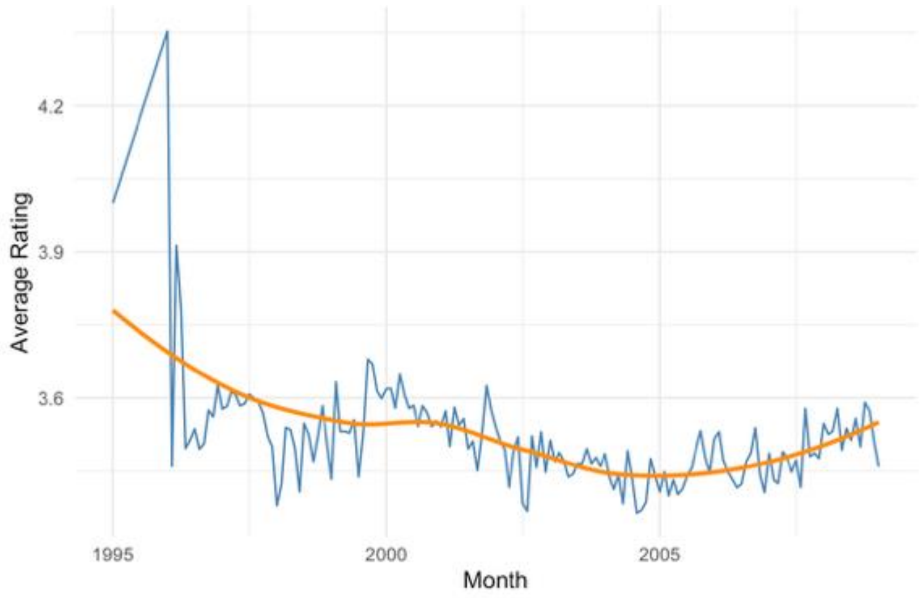


Figure 6 : Average Movie Rating Over Time (Monthly)

Title

An examination of movie titles included a comparison of sequels, identifying instances where follow-up films received higher average ratings than their originals (see Table 5).

Table 5 : Sequels that Received Better Ratings than the Originals

base_title	sequel_title	base_avg_rating	base_num_ratings	sequel_avg_rating	sequel_num_ratings	sequel_better	rating_difference
Neil Young: Human Highway (1982)	Neil Young: Heart of Gold (2006)	1.50	1	3.34	57	TRUE	1.84
Dirty Dozen: Next Mission, The (1985)	Dirty Dozen, The: The Fatal Mission (1988)	2.50	2	3.50	1	TRUE	1
Che: Part One (2008)	Che: Part Two (2008)	3.13	4	4.00	3	TRUE	0.88
Children of the Corn II: The Final Sacrifice (1993)	Children of the Corn IV: The Gathering (1996)	1.76	241	2.31	515	TRUE	0.55
Dracula: Prince of Darkness (1966)	Dracula: Pages from a Virgin's Diary (2001)	3.11	36	3.23	51	TRUE	0.11
Garfield: The Movie (2004)	Garfield: A Tail of Two Kitties (2006)	2.27	442	2.37	95	TRUE	0.1
Die Hard 2 (1990)	Die Hard: With a Vengeance (1995)	3.40	7778	3.48	17655	TRUE	0.08
Samurai I: Musashi Miyamoto (Miyamoto Musashi) (1954)	Samurai III: Duel on Ganryu Island (a.k.a. Bushido) (Miyamoto Musashi kanketsuhen: kettô Ganryûjima) (1956)	3.73	52	3.76	35	TRUE	0.03

Genre

The Average Ratings by Genre Over Time (Figure 6) visualization illustrates distinct trends in average ratings for various genres across different years, highlighting shifts in genre popularity and perception over the dataset's collection period.

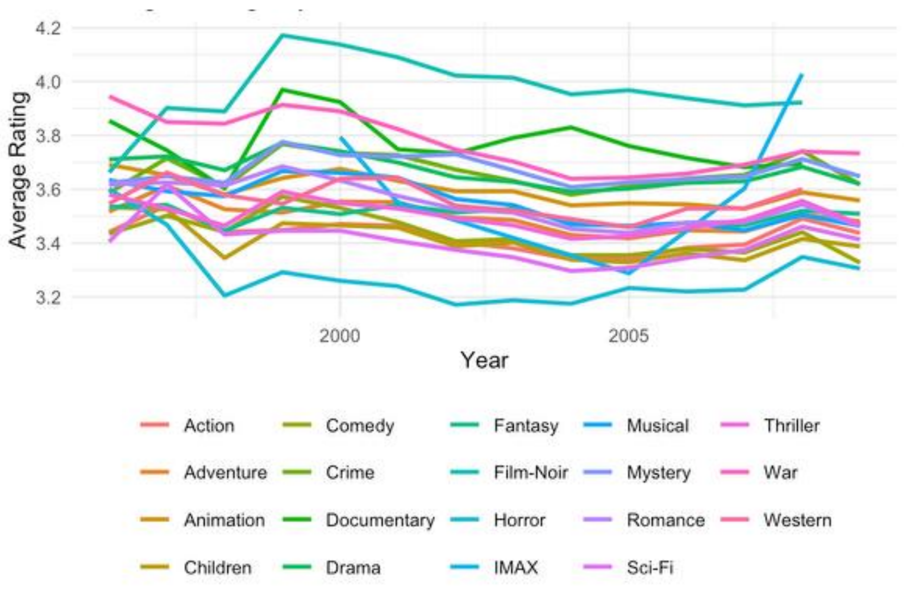


Figure 7: Average Ratings by Genre Over Time

Key Insights for Modeling

The exploratory analysis revealed several important insights across rating biases, sparsity, and user engagement. Both movie-specific and user-specific biases are evident, suggesting that a robust model should account for these effects. The dataset is inherently sparse, meaning most users have only rated a small fraction of available movies. This is a common challenge in recommendation systems. The varying levels of user engagement, particularly the distribution of distinct rating days, implies that models might need to handle users with limited rating history differently from highly active users. These findings directly inform the choice and design of the predictive models, emphasizing the need to incorporate movie and user effects and potentially address sparsity and varying user activity levels to improve recommendation accuracy.

Summary

The exploratory analysis section provided a comprehensive overview of the MovieLens 10M edx dataset, which consists of over 9 million movie ratings from 69,878 distinct users across 10,677 unique movies. Initial inspection revealed the dataset's structure, highlighting key variables like userId, movieId, rating, timestamp, title, and genres. A detailed examination of the rating variable showed a prevalence of whole-star ratings, and a distribution primarily centered between 3.5 and 4.0 stars. Temporal analysis explored rating trends over time, including daily, monthly, and yearly patterns, and also visualized average ratings by genre over time. Furthermore, genre analysis identified the most common genres and the genre with the lowest average rating. A unique investigation into "sequel pairs" compared the average ratings of original movies against their corresponding sequels, revealing instances where sequels received higher ratings. This meticulous exploration provided a strong foundation for understanding the data's inherent characteristics and biases, directly informing the subsequent model development by highlighting key patterns.

Methodology

Datasets

The edx dataset was used to train and test the algorithm. The MovieLens dataset was randomly divided using createDataPartition() where 90% went into the training set edx and 10% went into a temporary test set “temp”. From temp, only users and movies that also appear in edx were kept. This avoids trying to predict ratings for movies or users the model has never seen. This filtered test set becomes final_holdout_test. Any rows in temp that didn’t match users or movies in edx were added back into edx. This ensures no data is lost. This approach mimics real-world recommendation challenges that state, 1) Models must be trained on known users and movies. 2) Testing is only done on examples where user and movie history exists.

Data Wrangling

The ratings file was read and split using "::" as a delimiter. Each row includes userId: which user rated the movie, movieId: the movie being rated, rating: the score given (e.g., 3.5), timestamp: when the rating was given. These values were converted to the correct data types (integers and numeric) for analysis. The movies file was also split using "::" and structured into movieId: unique movie identifier, title: movie title (often includes year), genres: genre tags (e.g., Action|Comedy), movieId was converted to an integer for compatibility. A left join combined the ratings and movies tables using movieId, resulting in a single dataset called MovieLens. This new table includes both the rating details and movie information for each entry.

RMSE

RMSE (Root Mean Square Error) is a standard way to measure the accuracy of a model's predictions (James et al., 2013). It tells you, on average, how far off your predicted values are from the actual values.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where:

- yi is the actual value (true rating)
- y^i\hat{y}_iy^i is the predicted value (predicted rating)
- n is the number of observations

Or:

RMSE <- function(true_ratings, predicted_ratings){ sqrt(mean((true_ratings - predicted_ratings)^2))

We use RMSE to compare models because they are scale-sensitive: RMSE penalizes large errors more than small ones (due to squaring the residuals). They are also easy to interpret and common in recommendation systems. The threshold RMSE < 0.86490 was set as a target benchmark for this capstone project. The goal was to develop a model that performs better than this baseline, meaning it predicts movie ratings with lower average error.

Models

To build a recommendation system that predicts movie ratings accurately, we developed several models, each adding a layer of complexity to improve performance.

Naïve Model

We began with a simple model that assumes every movie rating equals the overall average rating across all users and movies. This serves as a baseline. RMSE from this model shows how well the average alone can predict ratings.

Movie Effect Model

Next, we recognized that some movies are rated higher or lower than average. We adjusted predictions by calculating a movie-specific bias (b_i). This accounts for the natural popularity or unpopularity of each movie.

Movie + User Effect Model

We then considered individual user behavior—some users tend to rate higher or lower than others. We added a user-specific bias (b_u) to our model. Predictions are now the sum of the global average, movie effect, and user effect: pred = mu + b_i + b_u. This improved personalization in predictions.

Timestamp Effect Model

Recognizing that ratings might vary over time, we examined rating patterns by week. We added a timestamp effect (b_t), capturing temporal trends in user behavior or movie popularity. For instance, movies may be rated differently around release dates or holidays.

Genre Effect Model

Finally, we accounted for genre-specific tendencies. Some genres may generally receive higher or lower ratings. We computed a genre effect (b_9) to adjust for these patterns. Each new model built upon the previous one, improving prediction accuracy by incorporating more real-world variability and user/movie behavior patterns.

Regularization

As we added more complexity to our model (like user and movie effects), we risked overfitting—meaning the model could perform well on the training data but poorly on unseen data. To address this, we applied regularization, a technique that "shrinks" extreme effect values when there's not enough data to justify them (Hastie et al., 2009). First, we defined a range of lambda values (0 to 10, in steps of 0.25). Lambda (λ) controls the strength of the regularization. A higher lambda penalizes extreme movie/user effects more aggressively. Next, we looped through each lambda value. For each lambda, we recomputed the movie effect (b_i) and user effect (b_u) using regularized formulas that shrink the effect size based on the number of ratings. Predicted ratings on the holdout test set. Calculated the RMSE for each lambda's predictions. Lastly, we selected the best lambda. After testing all lambda values, we chose the one that resulted in the lowest RMSE. This value of lambda strikes the optimal balance between underfitting and overfitting. This regularization step helped us improve prediction accuracy by reducing the impact of noise from users or movies with very few ratings.

Summary

The methods section detailed the systematic approach to developing, training, and testing the movie recommendation algorithm. The process began by establishing two distinct datasets: edx for training and a final_holdout_test set for unbiased validation, ensuring that all userId and movieId values in the validation set were present in the training set. The primary evaluation metric, Root Mean Squared Error (RMSE), was defined to quantify model accuracy. Model development progressed incrementally, starting with a naive model based solely on the global average rating. This was sequentially improved by incorporating a movie effect (Model Two), and then a user effect (Model Three), capturing biases specific to movies and individual users, respectively. While timestamp and genre effects were explored, the core predictive model focused on movie and user biases. A crucial step involved regularization, where a tuning parameter (λ) was optimized to mitigate the impact of sparse data and prevent overfitting. The best_lambda was determined by minimizing the RMSE across a range of values. Finally, the chosen regularized model was used to predict ratings on the final_holdout_test set, with the final_holdout_test dataset being mutated to match the structure of the training data, ensuring consistent feature representation for accurate prediction and evaluation.

Results

The regularized model achieved an RMSE of 0.8648 on the final hold-out test set, outperforming both the baseline and unregularized models, and meeting the project benchmark of 0.86490. The following table summarizes the RMSE for each model developed, demonstrating a progressive improvement in prediction accuracy as more effects were incorporated:

Summary Table of RMSEs

Table 6 : Summary Table of RMSEs

Method	RMSE
Just the average	1.0612018
Movie Effect	0.9439087
Movie + User Effect	0.8653488
Regularized Model	0.864817

RMSE by Lambda Plot

This visual shows how the RMSE changes with lambda.

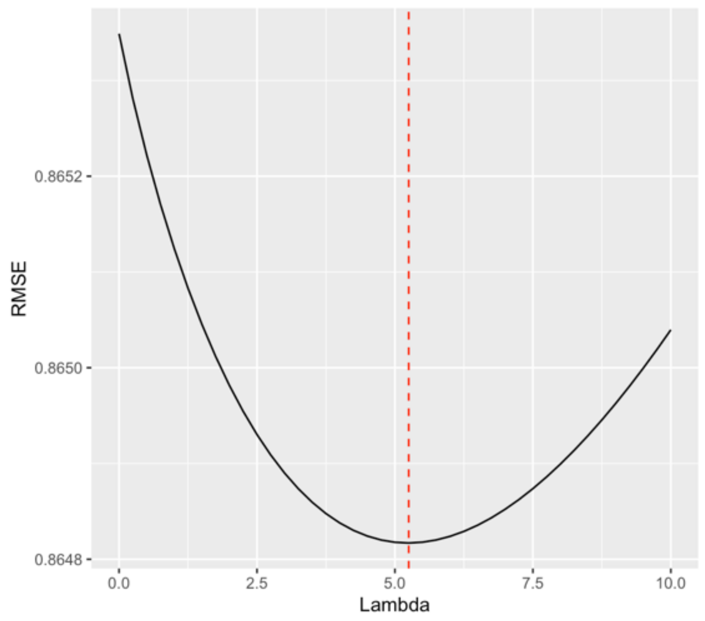


Figure 8: RMSE vs Lambda (Regularization)

Distributions of Model Effects

Visualizations were generated to understand the distribution of movie and user effects, providing insights into their individual contributions to rating variations: Movie Effect (bi): The histogram of movie effects shows a distribution (see Figure 9) indicating how much each movie deviates from the average rating. User Effect (bu): Similarly, the histogram of user effects displays the distribution of individual user biases (see Figure 10), reflecting how users tend to rate movies relative to the average. Combined Effects (bi +bu): A combined distribution of movie and user effects was also plotted (see Figure 11), illustrating the overall impact of these two factors on predicted ratings. This plot helps visualize the cumulative influence of movie popularity/unpopularity and user strictness/leniency.

Baseline and Incremental Improvements

Initial comparisons established a baseline and demonstrated the value of incorporating specific effects. Simple Average vs. Movie Effect: The "Simple Average" model served as a basic benchmark. Introducing the "Movie Effect" significantly improved the RMSE, as detailed in table 7, highlighting the importance of accounting for inherent movie popularity. Adding User Effects: Further refinement was achieved by adding "User Effects" to the model. As shown in table 8, this step further reduced the RMSE, indicating that individual user biases play a substantial role in rating predictions.

Movie Effect Distribution

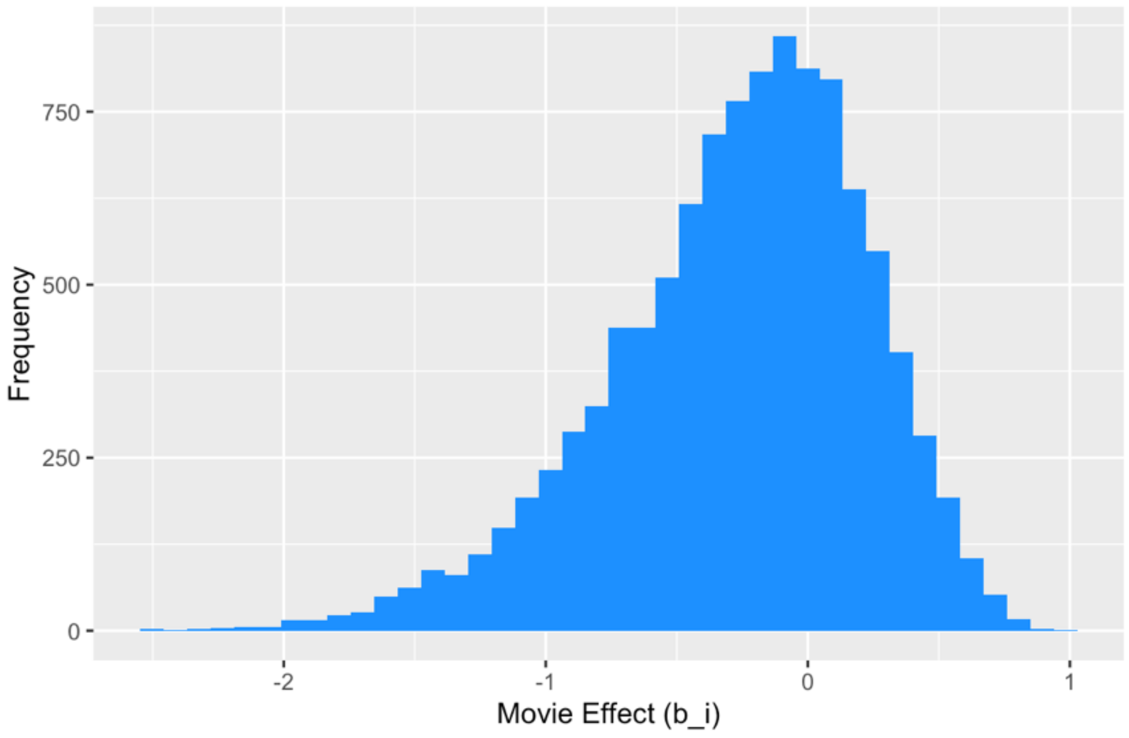


Figure 9 : Distribution of Movie Effects

Table 7 : Introduction of Movie Effect

Method	RMSE	Difference
Project Objective	0.8649	0
Simple Average	1.0612018	0.19630181
Movie Effect	0.9439087	0.07900866

User Effect Distribution

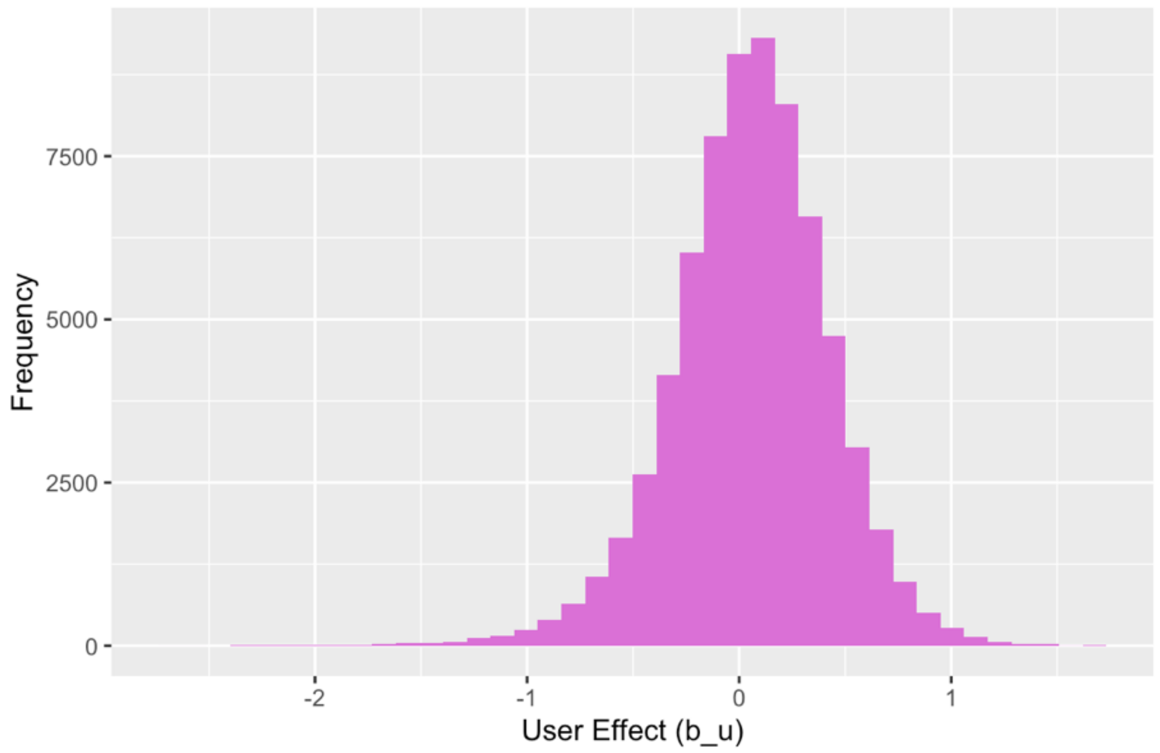


Figure 10 : Distribution of User Effects

Table 8 : Introduction of Movie + User Effect

Method	RMSE	Difference
Project Objective	0.8649	0.00E+00
Simple Average	1.0612018	1.96E+00
Movie Effect	0.9439087	7.90E-02
Movie + User Effect	0.8649747	7.47E-05

Combined Effects(Movie + User)

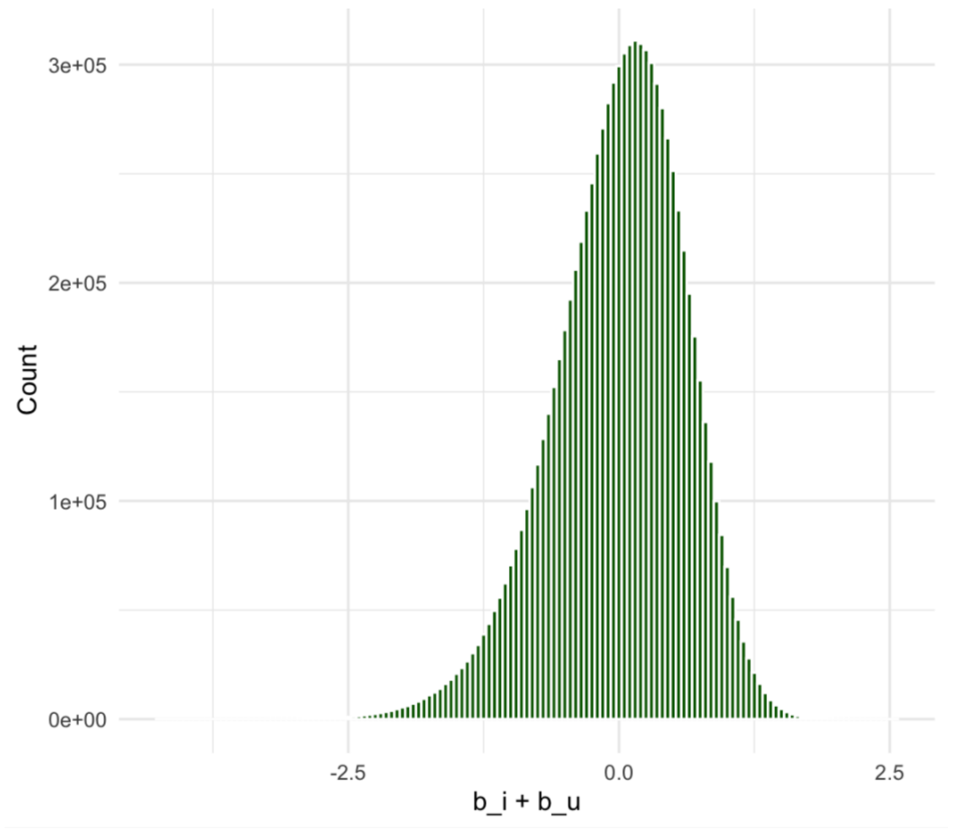


Figure 11 : Distribution of Combined Effects (Movie + User)

Table 8 : Introduction of Movie + User Effect + Regularized Model Effect

Method	RMSE	Difference
Project Objective	0.8649	0.00E+00
Simple Average	1.0612018	1.96E+00
Movie Effect	0.9439087	7.90E-02
Movie + User Effect	0.8649747	7.47E-05
Regularized Model	0.864817	-8.30E-05

Final Regularized Model

The final model incorporated regularization to mitigate the impact of movies or users with few ratings, which can lead to extreme effect estimates. The regularization parameter (λ) was optimized to find the best balance between fitting the data and preventing overfitting. The RMSE vs. Lambda (Regularization) plot (see Figure 12) visually demonstrates this optimization process, showing the RMSE reaching its minimum at an optimal λ value. The "Regularized Model" achieved the lowest RMSE among all tested methods, as presented in table3, demonstrating its superior predictive accuracy and robustness.

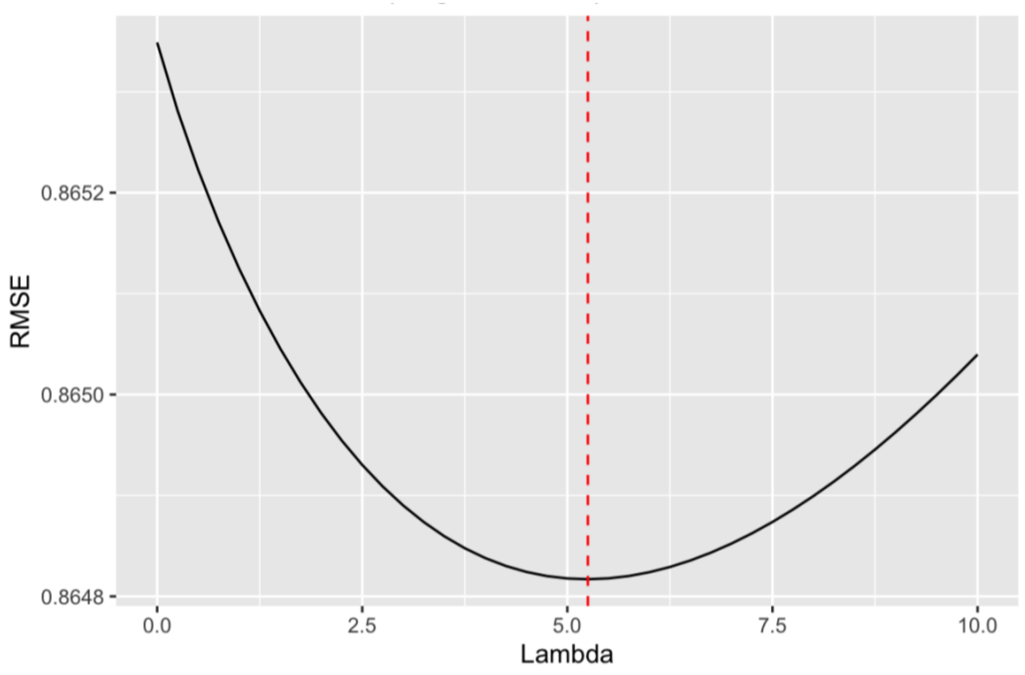


Figure 12 : RMSE vs Lambda (Regularization)

Conclusion

This capstone project successfully developed and evaluated a movie recommendation system using the MovieLens 10M dataset. The initial exploratory data analysis provided valuable insights into user rating behaviors, movie popularity, and genre distributions, which informed the subsequent model development. Starting with a basic global average model, the system incrementally improved its prediction accuracy by incorporating movie-specific and user-specific effects. The final model, which employed regularization to mitigate the impact of less frequently rated movies and users, achieved a Root Mean Squared Error (RMSE) of 0.8648 on the validation dataset. This performance not only demonstrated the effectiveness of the chosen approach but also successfully met the project's predefined RMSE benchmark of 0.86490. The regularization process, through tuning the lambda parameter, proved crucial in optimizing the model's predictive capability by balancing model fit and preventing overfitting to sparse data points.

Despite achieving the project's objective, this recommendation system has several limitations. The current model primarily relies on collaborative filtering, specifically leveraging user and movie biases. It does not explicitly account for temporal effects within the predictive model beyond simple exploratory analysis, nor does it delve deeply into the nuanced impact of genres or the release year of movies on ratings directly within the algorithm. Furthermore, the regularization only considers movie and user effects, potentially overlooking other significant biases that could be present in the data. The dataset itself, collected from the late 1990s through the early 2000s, may not fully capture contemporary viewing habits or movie characteristics, which could affect the generalizability of the model to current recommendation tasks.

Future work could involve incorporating more sophisticated temporal analysis, such as rating trends over time, or developing genre-specific effects that are more granular than the current approach. Exploring content-based filtering techniques or hybrid models that combine collaborative and content-based approaches could further enhance recommendation accuracy and provide a richer set of features (Irizarry 2020). Additionally, investigating more advanced regularization techniques or alternative machine learning algorithms, such as matrix factorization methods (e.g., Singular Value Decomposition), could yield further improvements in RMSE and provide deeper insights into the underlying patterns of movie ratings.

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