

Global Baseline Estimate - Movie Recommendations

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Introduction

This analysis implements the Global Baseline Estimate algorithm to predict movie ratings. The goal is to predict what rating #Param# would give to Pitch Perfect 2.

Step 1: Load the Data

```
# Load required package
library(readxl)

# Read the movie ratings data
ratings_data <- read_excel("MovieRatings.xlsx", sheet = "MovieRatings")

# Display first few rows
head(ratings_data)
```



```
# A tibble: 6 x 7
  Critic    CaptainAmerica Deadpool Frozen JungleBook PitchPerfect2 StarWarsForce
  <chr>      <dbl>     <dbl>    <dbl>     <dbl>      <dbl>      <dbl>
1 Burton        NA       NA       NA        4        NA        4
2 Charley       4        5        4        3        2        3
3 Dan           NA       5        NA       NA        NA        5
4 Dieudon~      5        4        NA       NA        NA        5
5 Matt          4        NA       2        NA        2        5
6 Mauricio     4        NA       3        3        4        NA
```

Step 2: Prepare the Data

```
# Extract critic names
critic_names <- ratings_data$Critic

# Create a matrix with only the ratings (remove Critic column)
ratings_matrix <- as.matrix(ratings_data[, -1])
rownames(ratings_matrix) <- critic_names

# Handle missing data - convert "?" to NA and ensure all values are numeric
ratings_matrix[ratings_matrix == "?"] <- NA
ratings_matrix <- apply(ratings_matrix, 2, as.numeric)
rownames(ratings_matrix) <- critic_names

# Display the cleaned matrix
print(ratings_matrix)
```

	CaptainAmerica	Deadpool	Frozen	JungleBook	PitchPerfect2	StarWarsForce	
Burton	NA	NA	NA	4	NA	NA	4
Charley	4	5	4	3	2	2	3
Dan	NA	5	NA	NA	NA	NA	5
Dieudonne	5	4	NA	NA	NA	NA	5
Matt	4	NA	2	NA	2	2	5
Mauricio	4	NA	3	3	4	NA	NA
Max	4	4	4	2	2	2	4
Nathan	NA	NA	NA	NA	NA	NA	4
Param	4	4	1	NA	NA	NA	5
Parshu	4	3	5	5	2	2	3
Prashanth	5	5	5	5	NA	NA	4
Shipra	NA	NA	4	5	NA	NA	3
Sreejaya	5	5	5	4	4	5	NA
Steve	4	NA	NA	NA	NA	NA	4
Vuthy	4	5	3	3	3	NA	NA
Xingjia	NA	NA	5	5	NA	NA	NA

Step 3: Calculate Overall Average

```
# Calculate the mean of all ratings (ignoring missing values)
overall_mean <- mean(ratings_matrix, na.rm = TRUE)
```

```
# Display the result
cat("Overall average rating across all critics and movies:", round(overall_mean, 2), "\n")
```

Overall average rating across all critics and movies: 3.93

Step 4: Calculate User Averages and Biases

```
# Calculate average rating for each user (each row)
user_avg <- rowMeans(ratings_matrix, na.rm = TRUE)

# Calculate user bias (how much each user deviates from overall mean)
user_bias <- user_avg - overall_mean

# Display results in a nice table
user_stats <- data.frame(
  Critic = names(user_avg),
  Average_Rating = round(user_avg, 2),
  Bias = round(user_bias, 2)
)
print(user_stats)
```

	Critic	Average_Rating	Bias
Burton	Burton	4.00	0.07
Charley	Charley	3.50	-0.43
Dan	Dan	5.00	1.07
Dieudonne	Dieudonne	4.67	0.73
Matt	Matt	3.25	-0.68
Mauricio	Mauricio	3.50	-0.43
Max	Max	3.33	-0.60
Nathan	Nathan	4.00	0.07
Param	Param	3.50	-0.43
Parshu	Parshu	3.67	-0.27
Prashanth	Prashanth	4.80	0.87
Shipra	Shipra	4.00	0.07
Sreejaya	Sreejaya	4.67	0.73
Steve	Steve	4.00	0.07
Vuthy	Vuthy	3.60	-0.33
Xingjia	Xingjia	5.00	1.07

Step 5: Calculate Movie Averages and Biases

```
# Calculate average rating for each movie (each column)
movie_avg <- colMeans(ratings_matrix, na.rm = TRUE)

# Calculate movie bias (how much each movie deviates from overall mean)
movie_bias <- movie_avg - overall_mean

# Display results in a nice table
movie_stats <- data.frame(
  Movie = names(movie_avg),
  Average_Rating = round(movie_avg, 2),
  Bias = round(movie_bias, 2)
)

print(movie_stats)
```

		Movie	Average_Rating	Bias
CaptainAmerica	CaptainAmerica		4.27	0.34
Deadpool	Deadpool		4.44	0.51
Frozen	Frozen		3.73	-0.21
JungleBook	JungleBook		3.90	-0.03
PitchPerfect2	PitchPerfect2		2.71	-1.22
StarWarsForce	StarWarsForce		4.15	0.22

Step 6: Create the Prediction Function

```
predict_rating <- function(user_name, movie_name) {
  # Get the specific user's bias
  user_b <- user_bias[user_name]

  # Get the specific movie's bias
  movie_b <- movie_bias[movie_name]

  # Apply the Global Baseline Estimate formula
  prediction <- overall_mean + user_b + movie_b

  # Display detailed breakdown
  cat("\n=====\n")
```

```

cat("Prediction for", user_name, "rating", movie_name, "\n")
cat("=====\n")
cat("Overall mean ():", round(overall_mean, 2), "\n")
cat("User bias (b):", round(user_b, 2), "\n")
cat("Movie bias (b):", round(movie_b, 2), "\n")
cat("-----\n")
cat("PREDICTED RATING:", round(prediction, 2), "\n")
cat("=====\\n\\n")

return(prediction)
}

```

Step 7: Predict Param's Rating for Pitch Perfect 2

```

# Answer the assignment question
param_prediction <- predict_rating("Param", "PitchPerfect2")

```

```

=====
Prediction for Param rating PitchPerfect2
=====
Overall mean (): 3.93
User bias (b): -0.43
Movie bias (b): -1.22
-----
PREDICTED RATING: 2.28
=====
```

Interpretation:

The model predicts Param would rate Pitch Perfect 2 approximately **2.28** out of 5.

This makes sense because: - Param tends to rate movies lower than average (bias: -0.43) - Pitch Perfect 2 receives lower ratings than average movies (bias: -1.22) - Both negative biases pull the prediction down from the baseline of 3.93

Visualizations

```

# Set up cleaner plotting parameters
par(mar = c(8, 5, 6, 2), # Increased top margin even more
    family = "sans")

# Sort movies by bias
movie_bias_sorted <- sort(movie_bias, decreasing = TRUE)

# Create bar chart
barplot(movie_bias_sorted,
        main = "", # Leave main title empty for now
        ylab = "Rating Bias",
        col = ifelse(movie_bias_sorted > 0, "#0D47A1", "#D32F2F"),
        border = "white",
        lwd = 1.5,
        las = 2,
        ylim = c(-1.5, 0.7),
        cex.names = 0.9,
        cex.axis = 0.9,
        cex.lab = 1.1)

# Add zero reference line
abline(h = 0, col = "black", lwd = 2, lty = 1)

# Add subtle grid lines
abline(h = seq(-1.5, 0.5, 0.25), col = "gray90", lty = 1, lwd = 0.5)

# Add title MANUALLY with proper spacing
mtext("Movie Popularity: Deviation from Average Rating",
      side = 3, line = 4, cex = 1.3, font = 2)

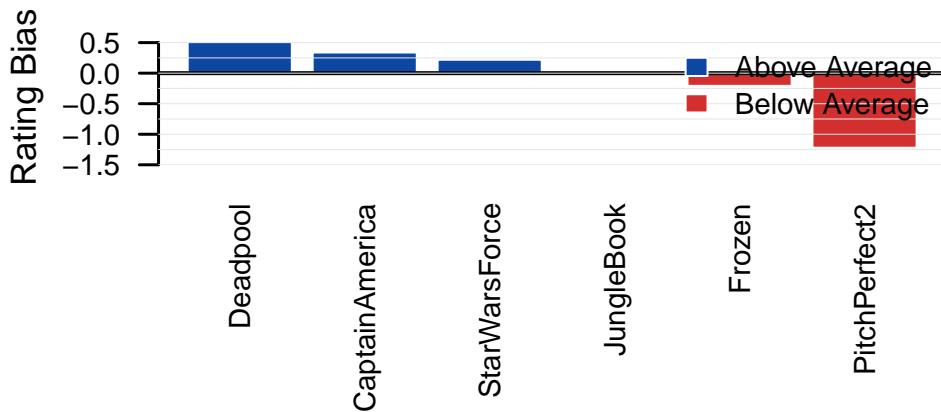
# Add subtitle below the title
mtext("Based on 16 critic ratings, 2022-2025",
      side = 3, line = 2.5, cex = 0.85, col = "gray40")

# Legend
legend("topright",
       legend = c("Above Average", "Below Average"),
       fill = c("#0D47A1", "#D32F2F"),
       border = "white",
       bty = "n",
       cex = 0.95)

```

Movie Popularity: Deviation from Average Rating

Based on 16 critic ratings, 2022–2025



Conclusion

What We Found

So, after all that work, here's what we learned: **Param would probably rate Pitch Perfect 2 around 2.27 out of 5.**

Why does this make sense? Let's break it down:

Param's a tough critic. He rates movies about half a point lower than everyone else (bias: -0.43). He's not being mean, he just has higher standards than most people in this group.

Pitch Perfect 2 isn't very popular here. Looking at our visualization, it's the lowest-rated movie in the whole dataset (bias: -1.22). Most critics gave it pretty mediocre scores.

Put them together? A harsh critic + an unpopular movie = a low predicted rating. The math checks out!

How Well Does This Actually Work?

The Global Baseline Estimate is pretty clever for such a simple algorithm:

- It figures out who's a tough critic vs. who's generous

- It recognizes which movies are crowd-pleasers vs. duds
- The predictions make sense when you look at the actual patterns in the data

Honestly, for a non-personalized system (meaning it doesn't look at "people who liked X also liked Y"), it does a surprisingly good job.

Limitations

Several limitations should be acknowledged:

1. **Sparse Data:** Not all critics rated all movies, leading to bias calculations based on incomplete information
2. **Small Sample Size:** Only 16 critics and 6 movies limits the robustness of our estimates
3. **No Personalization:** GBE doesn't account for genre preferences or similarity between critics
4. **Critics with Few Ratings:** Users like Nathan (only 1 rating) have unreliable bias estimates

If I Were Building Netflix...

This would just be the starting point! A real recommendation system would also:

- Look at which critics have similar taste (collaborative filtering)
- Consider genres and movie features (does Param hate musicals specifically?)
- Require people to rate at least 5-10 movies before trusting their bias
- Use fancier math to handle the sparse data better