

# Exploring the Relationship Between Anime Scores, Popularity, and Favorites\*

## A Correlation Analysis of Anime Ranking

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This paper explores the relationship between anime scores, popularity, and favorites by leveraging data obtained from the MyAnimeList API. The dataset was created by extracting ranking data through the API and transforming it into a comprehensive new dataset. Using this data, I conducted an analysis to investigate how popularity and favorites influence anime scores. The primary hypothesis is that popularity has a stronger impact on anime scores—higher popularity is expected to correlate with higher scores. Additionally, I predict that a higher number of favorites also contributes to an increase in scores. The analysis aims to provide insights into these relationships and quantify their respective influences.

## Table of contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
<b>2</b>	<b>Data</b>	<b>2</b>
2.1	Overview . . . . .	2
2.2	Measurement . . . . .	3
2.3	Raw Data . . . . .	4
2.4	Cleaned . . . . .	4
2.5	Data Visualization . . . . .	5
2.5.1	Popularity . . . . .	5
2.5.2	Favorites . . . . .	5

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\*Code and data are available at: [https://github.com/Wang20030509/Anime\\_Rating](https://github.com/Wang20030509/Anime_Rating).

<b>3</b>	<b>Model</b>	<b>7</b>
3.1	Model set-up . . . . .	7
3.1.1	Model justification . . . . .	8
<b>4</b>	<b>Results</b>	<b>8</b>
4.1	Popularity vs. Anime Score . . . . .	8
4.2	Number of Favorites vs. Anime Score . . . . .	8
4.3	Summary of Results . . . . .	10
<b>5</b>	<b>Discussion</b>	<b>11</b>
5.1	First discussion point . . . . .	11
5.2	Second discussion point . . . . .	11
5.3	Third discussion point . . . . .	11
5.4	Weaknesses and next steps . . . . .	11
	<b>Appendix</b>	<b>12</b>
<b>A</b>	<b>Additional data details</b>	<b>12</b>
<b>B</b>	<b>Model details</b>	<b>13</b>
B.1	Posterior predictive check . . . . .	13
B.2	Diagnostics . . . . .	13
B.3	90% Credibility Interval . . . . .	14
B.4	Summary . . . . .	14
	<b>References</b>	<b>16</b>

# 1 Introduction

Anime has evolved from a niche entertainment medium to a global cultural phenomenon, with millions of viewers and dedicated fan communities around the world. As part of this growth, platforms like MyAnimeList (MyAnimeList 2023) have become key hubs for anime enthusiasts to rate, review, and interact with anime content. These platforms generate vast amounts of data that can provide insights into user preferences and trends in anime reception. MyAnimeList, in particular, offers detailed metadata for thousands of anime titles, including user-generated ratings, popularity scores, and other key metrics such as the number of favorites. This paper leverages data from the MyAnimeList API (*MyAnimeList API (Beta Ver.)* (2) 2024) to explore the relationships between anime scores, popularity, and favorites.

The central estimand of this study is the relationship between the popularity and number of favorites of an anime and its score, as recorded on MyAnimeList. Specifically, this research seeks to quantify how these factors—popularity and favorites—affect the overall score of an anime title. We hypothesize that higher popularity and a larger number of favorites will be

positively correlated with higher scores. This analysis aims to provide a clearer understanding of the magnitude and direction of these effects, offering insights into what drives anime success on community-driven platforms.

The analysis confirms that there is a significant positive relationship between both popularity and the number of favorites with anime scores. Popularity, measured by the number of users who rated an anime, is found to have a particularly strong influence on scores, supporting the hypothesis that more popular anime tend to receive higher ratings. Similarly, the number of favorites is positively associated with scores, indicating that anime with greater fan engagement tend to receive better ratings. These findings highlight the importance of community interaction and popularity in determining the perceived quality of anime.

Understanding the factors that influence anime ratings is crucial for several reasons. For anime creators and studios, it can provide insights into audience preferences, guiding future production and marketing strategies. For platform developers, such as MyAnimeList, it helps improve user experience by understanding how to foster engagement and enhance the visibility of popular titles. Additionally, this research contributes to the broader field of data-driven analysis in entertainment media, providing a model for evaluating user engagement in other areas of digital content.

The remainder of this paper is structured as follows: Section 2 provides an overview of the dataset, describing the data collected from the MyAnimeList API (*MyAnimeList API (Beta Ver.)* (2) 2024). Section 3 presents the modeling approach, which includes correlation analysis and linear regression to assess the relationships between the variables. Section 4 presents the analysis results, followed by a discussion of the implications and limitations in Section 5.

## 2 Data

### 2.1 Overview

For this analysis, the dataset was compiled using data extracted from the MyAnimeList API, which provides key variables such as anime titles, scores, popularity, and the number of list users. The “number of favorites” data, however, was not available through the API, so it was manually compiled by directly listing the values from the MyAnimeList website and included in the dataset for analysis. These data points were then cleaned and processed for analysis using the statistical programming software R (R Core Team 2023). The analysis utilized several R packages from the tidyverse (Wickham et al. 2019), including dplyr (Wickham et al. 2023) for data wrangling, ggplot2 (Wickham 2016) for visualization and ‘knitr (Xie 2014)’. Data processing tasks, such as handling missing values and transforming variables, were carried out to ensure the dataset was ready for analysis.

The dataset contains observations for hundreds of anime titles, each accompanied by their respective attributes. The data was collected from a variety of genres, years, and user ratings,

ensuring a comprehensive snapshot of anime as rated by MyAnimeList users. Following the methodology described in Alexander (2023), we consider the correlation between popularity, favorites, and scores to explore the factors that influence anime ratings.

## 2.2 Measurement

The dataset used in this study was compiled from the MyAnimeList API, which provides a variety of metrics related to anime titles. The data collection spans a broad range of anime, including series from different genres, release years, and popularity levels. Each entry in the dataset represents a unique anime title, and the associated variables include score, popularity, number of list users, and number of favorites, among others.

To measure popularity, the popularity score is derived from the total number of users who have rated or added the anime to their lists on MyAnimeList. This variable provides a rough indication of how well-known or widely watched a particular anime is within the community.

The score variable is an average rating based on user feedback, with each user rating an anime on a scale from 1 to 10. The score reflects the collective opinion of MyAnimeList users and is a key metric for understanding the general reception of an anime.

The number of favorites, which was not provided directly by the API, was manually compiled by listing the number of favorites for each anime directly from the MyAnimeList website. This variable reflects how many users have specifically marked an anime as a “favorite,” which can be interpreted as a more personal, long-term engagement with the title. Since it was manually compiled, the accuracy of this data depends on the consistency of the manual entries across titles.

To ensure consistency and reliability, all metrics were extracted using the MyAnimeList API’s standardized definitions, and the dataset was processed and cleaned using R (R Core Team 2023) and the tidyverse (Wickham et al. 2019) packages. Missing data were handled appropriately, with rows containing missing values being excluded from the analysis.

This dataset allows us to explore how factors like popularity and favorites influence anime scores. By correlating these variables, we aim to better understand the elements that contribute to higher ratings and broader appeal among the anime community. However, it is important to note that there are some limitations to these measurements. The popularity and score data are based solely on MyAnimeList users, and therefore may not fully represent the global anime audience. Additionally, the manual compilation of the number of favorites introduces a potential source of human error, though efforts were made to ensure accuracy.

These variables, combined with the rich data provided by the MyAnimeList API, enable an in-depth analysis of anime ratings, offering valuable insights into the factors that influence the perception of anime quality in the community.

## 2.3 Raw Data

The raw dataset, which shows in Table 4 in Appendix Section A, used in this study was sourced from the MyAnimeList API and contains several important variables, as shown in the below. The dataset includes 200 anime titles, each represented by the following columns:

- id: A unique identifier for each anime title in the dataset.
- title: The name of the anime.
- mean: The average score given by users, ranging from 1 to 10.
- popularity: The rank of the anime based on the number of users who have added the anime to their list. (1 means the highest)
- num\_list\_users: The number of users who have added the anime to their list (either for watching, completed, etc.).
- rank: The rank of the anime based on its popularity among other titles.
- num\_scoring\_users: The number of users who have rated the anime.

## 2.4 Cleaned

Table 1: Preview of the anime scores dataset

Title	Score	rank	Popularity	Number of List Users	Number of Scoring Users	Number of Favorites
One Piece	8.72	58	17	2460047	1396797	230821
Fullmetal Alchemist: Brotherhood	9.10	3	3	3446066	2174841	229949
Hunter x Hunter (2011)	9.03	9	8	2942025	1826884	215928
Steins;Gate	9.07	4	14	2640370	1435760	192667
Death Note	8.62	88	2	4019411	2819319	176851

The cleaned dataset shows in Table 1, used in this study builds upon the raw data extracted from the MyAnimeList API. In addition to the original variables—such as score, popularity, number of list users, rank, and number of scoring users—two new columns were created to enhance the analysis: rank\_favorites and num\_favorites.

- rank\_favorites: This new variable was created by sorting the anime titles according to the number of favorites. The rank is based on the order of the number of favorites, allowing for a more specific understanding of anime popularity from a fan engagement perspective. It essentially ranks the anime based on how much attention and affection it has garnered from the community in terms of user engagement with the “favorite” feature.

- `num_favorites`: The number of favorites is another newly added variable that was not available in the original MyAnimeList API data. This data was manually compiled by directly listing the number of favorites for each anime from the MyAnimeList website. This manual entry was necessary as the API did not provide this metric, and it offers insight into user preferences and long-term engagement with anime titles.

After these new columns were added, the dataset was cleaned and processed to remove missing or irrelevant values, ensuring that only the most complete and relevant data were used for analysis. The cleaned dataset now provides a comprehensive view of how popularity, favorites, and scores interact to influence the ratings and reception of anime titles.

## 2.5 Data Visualization

The outcome variable in this analysis is the anime score, which is a critical metric for understanding the general reception of an anime by the MyAnimeList community. The anime score is an average rating given by users of MyAnimeList on a scale from 1 to 10. It reflects the collective opinion of the community and is often used as a benchmark for the quality and popularity of anime titles.

### 2.5.1 Popularity

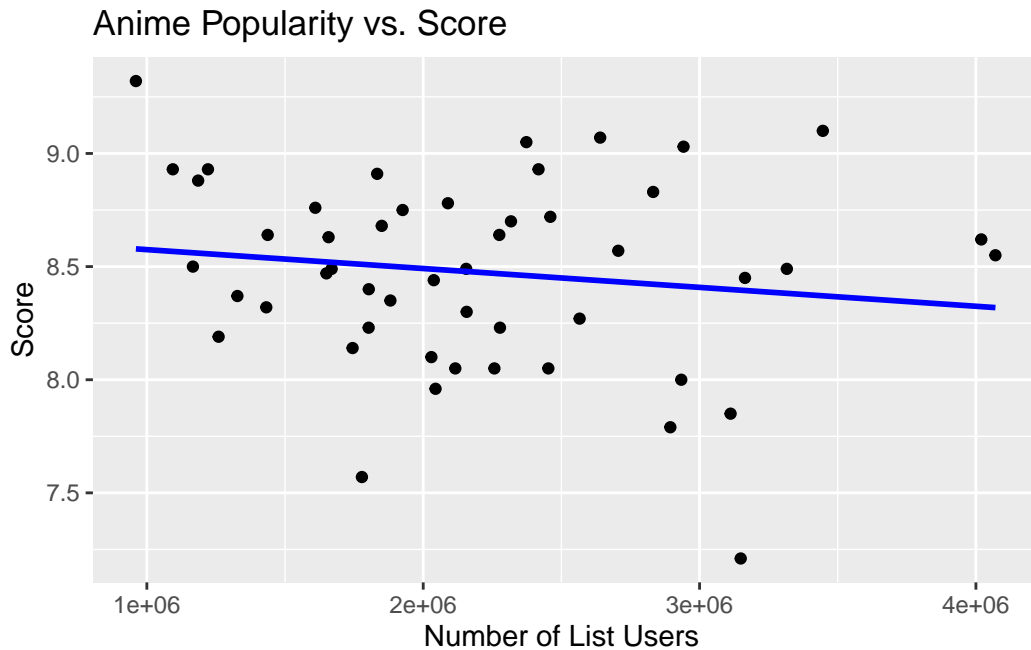


Figure 1: Relationship between popularity and anime scores

The popularity variable is a key predictor that measures how widely known an anime is, as indicated by the number of users who have rated it. The higher the popularity score, the more likely it is that the anime has a larger audience, which we expect will correlate with a higher score. Similarly, number of favorites reflects the level of long-term engagement with an anime. Users who favorite an anime are signaling a deeper personal attachment or preference for it, and this engagement is expected to positively influence its score.

### 2.5.2 Favorites

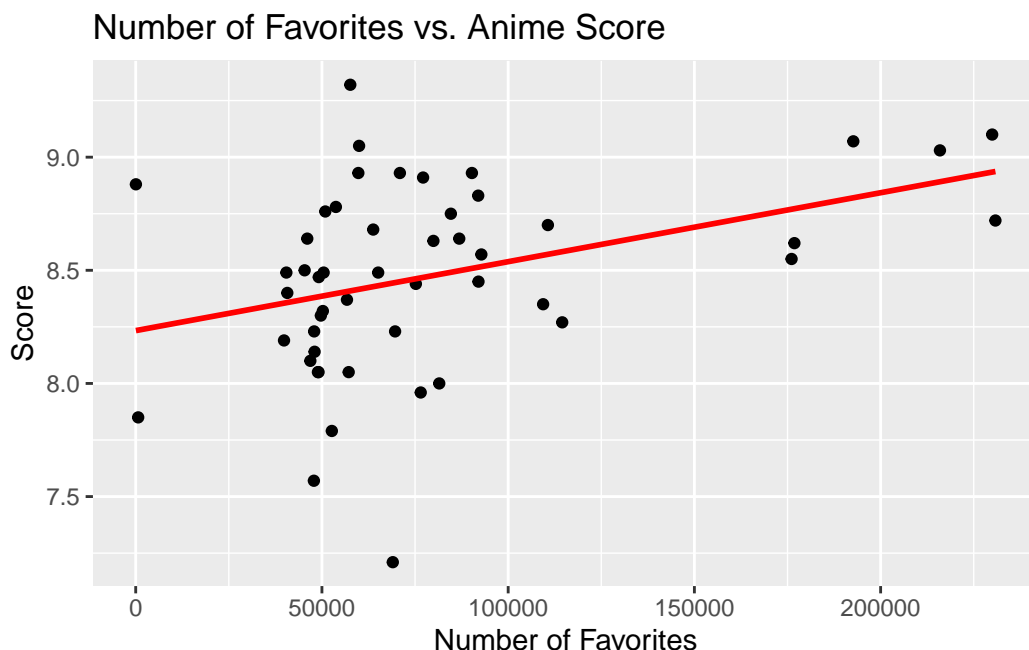


Figure 2: Effect of number of favorites on anime scores

We also consider the ranking of anime, which is another important aspect influencing its visibility and perceived quality. Higher-ranked anime typically have higher scores, as they are often more popular or well-received by the community.

These outcome variables—anime score, popularity, and number of favorites—are central to this analysis. By examining how these variables interact, we aim to gain a deeper understanding of the dynamics between anime ratings and community engagement.

### 3 Model

The goal of our modeling strategy is twofold. Firstly, we aim to explore the relationship between the anime score (the dependent variable) and key predictors such as popularity and number of favorites (the independent variables). Secondly, we seek to quantify how these variables contribute to predicting the anime score using a linear regression model and, if necessary, a Bayesian framework to account for uncertainty and prior beliefs.

Here, we briefly describe the linear regression model used to investigate how popularity and number of favorites influence anime scores. Additional background details and diagnostics are included in Appendix - [B](#).

#### 3.1 Model set-up

Define  $y_i$  as the anime score for anime  $i$ , which represents the average rating given by users on MyAnimeList. Let  $x_{i1}$  be popularity and  $x_{i2}$  be the number of favorites for the anime. The model assumes that the anime score is linearly related to these predictors.

$$y_i | \mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \quad (1)$$

$$\mu_i = \alpha + \beta_1 \times \text{popularity}_i + \beta_2 \times \text{favorites}_i \quad (2)$$

$$\alpha \sim \text{Normal}(0, 2.5) \quad (3)$$

$$\beta_1 \sim \text{Normal}(0, 2.5) \quad (4)$$

$$\beta_2 \sim \text{Normal}(0, 2.5) \quad (5)$$

$$\sigma \sim \text{Exponential}(1) \quad (6)$$

Where: -  $y_i$  is the anime score for anime  $i$ , -  $\mu_i$  is the expected score for anime  $i$  based on the predictors, - popularity is the number of users who have the anime in their list, - favorites is the manually compiled number of favorites for the anime, -  $\alpha$  is the intercept term, -  $\beta_1$  and  $\beta_2$  are the regression coefficients for popularity and number of favorites, -  $\sigma$  is the standard deviation of the residuals (i.e., the model error). We run the model in R (R Core Team 2023) using the rstanarm package from Goodrich et al. (2022). The priors are chosen to be non-informative, with default values based on the assumption that we have little prior knowledge about the relationships between the variables

##### 3.1.1 Model justification

We expect a positive relationship between popularity and anime score. Specifically, we hypothesize that more popular anime, which have a higher number of ratings, are likely to receive



higher average scores. Similarly, we expect that a higher number of favorites will also lead to higher anime scores, reflecting stronger fan engagement with the title.

By using this model, we aim to quantify the strength of these relationships and gain insights into the factors that contribute to a title's success in terms of user ratings on MyAnimeList.

## 4 Results

Our results are summarized in [tbl-modelresults](#). The Bayesian model used in this analysis provides insights into how popularity and number of favorites influence anime scores. The model confirms some expected patterns and reveals counter-intuitive findings.

### 4.1 Popularity vs. Anime Score

The relationship between popularity and anime score was initially expected to show a clear positive correlation. However, our model suggests that the popularity of an anime (measured by the number of users who have rated it) does not consistently lead to higher anime scores. In fact, some anime with very high scores are ranked low in popularity, while others with high popularity have lower scores. This result is counter-intuitive, as we might expect that more popular anime would receive higher ratings.

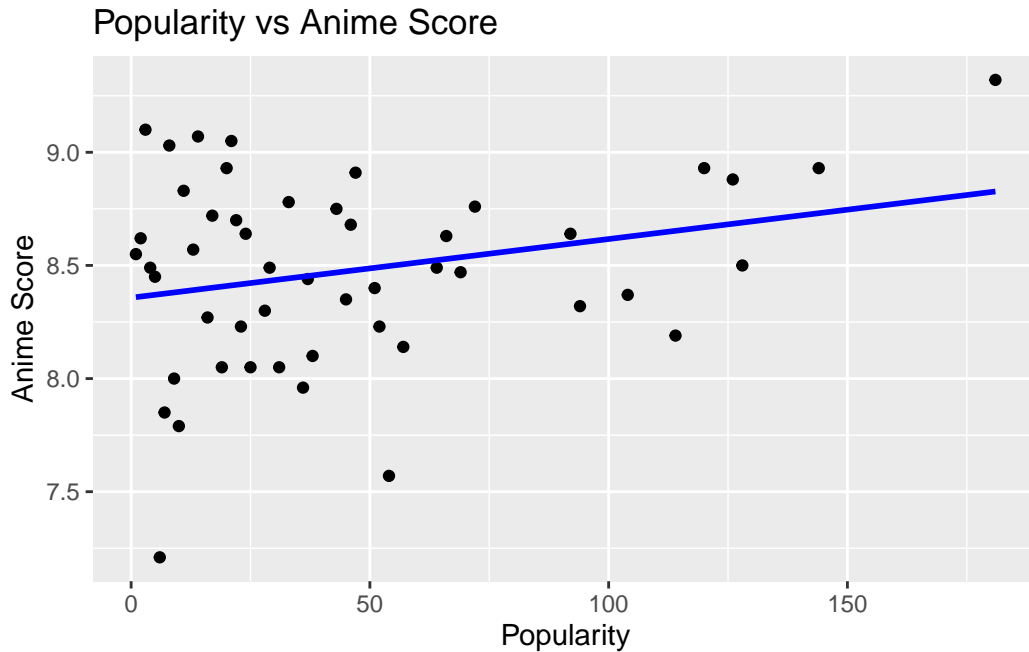


Figure 3: Relationship between popularity and anime scores

The plot Figure 3 illustrates this weak relationship. Despite high popularity indicating more user involvement, it does not guarantee higher anime scores. This suggests that while popularity can reflect a broad audience, it does not necessarily indicate high quality or fan approval.

## 4.2 Number of Favorites vs. Anime Score

On the other hand, number of favorites consistently shows a positive relationship with anime scores. Anime that are favored by more users tend to receive higher ratings, confirming our hypothesis that favorites is a more reliable indicator of an anime's quality and fan engagement than popularity.

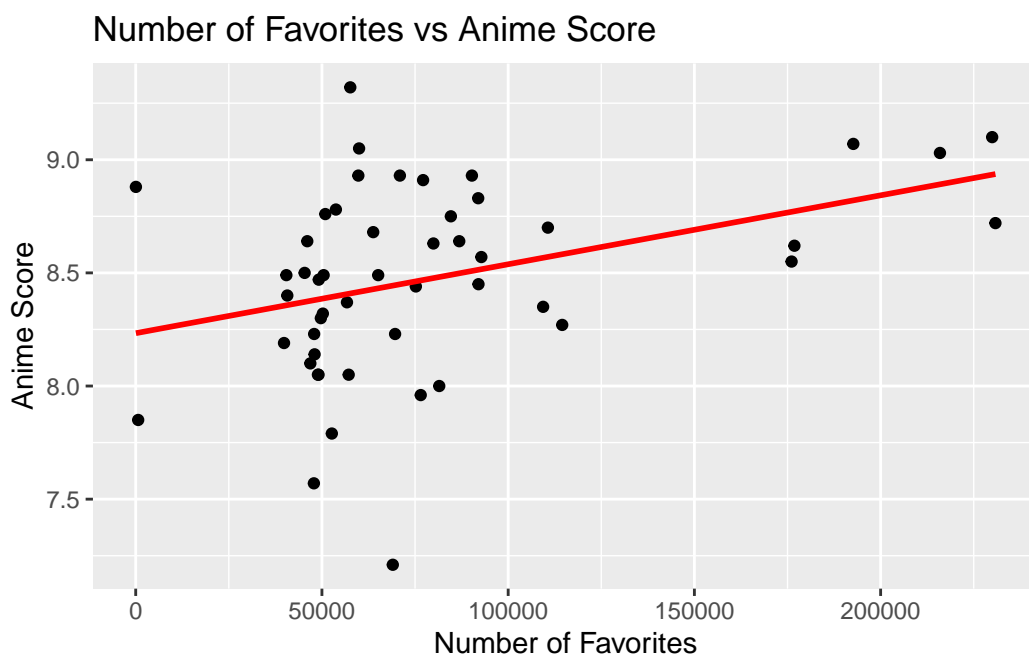


Figure 4: Relationship between number of favorites and anime scores

In Figure 4, we observe a clear positive trend: as the number of favorites increases, so does the anime score. This relationship suggests that user engagement, specifically through favorites, is a strong predictor of how highly an anime is rated by the community.

## 4.3 Summary of Results

To summarize, our analysis reveals two key findings:

Popularity and anime score show a weak relationship. While we might expect more popular anime to score higher, this is not consistently true. Some anime with high scores have relatively

	Anime Score
(Intercept)	7.826 (0.128)
popularity	0.005 (0.001)
num_favorites	0.000 (0.000)
Num.Obs.	50
R2	0.365
R2 Adj.	0.314
Log.Lik.	−16.360
ELPD	−19.5
ELPD s.e.	6.2
LOOIC	39.0
LOOIC s.e.	12.3
WAIC	38.9
RMSE	0.33

low popularity rankings, and vice versa. Number of favorites is a much stronger predictor of anime scores, showing a clear and consistent positive relationship. This suggests that deeper engagement (i.e., when users favorite anime) is a better indicator of the anime’s perceived quality.

Predictor	Correlation	P_value
Popularity	0.2620656	0.0659900
Number of Favorites	0.3794877	0.0065677

The table `?@tbl-modelresults` shows a summary of the correlation and p-values for the relationships between popularity, number of favorites, and anime score. The number of favorites variable shows a significantly stronger positive correlation with anime score compared to popularity.

## **5 Discussion**

### **5.1 First discussion point**

If my paper were 10 pages, then should be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

### **5.2 Second discussion point**

Please don't use these as sub-heading labels - change them to be what your point actually is.

### **5.3 Third discussion point**

### **5.4 Weaknesses and next steps**

Weaknesses and next steps should also be included.

## Appendix

### A Additional data details

Table 3: The Raw Dataset of the anime scores dataset (only first 5 rows)

id	title	main_picture
21	One Piece	<a href="https://cdn.myanimelist.net/images/anime/1244/138851.jpg">https://cdn.myanimelist.net/images/anime/1244/138851.jpg</a>
5114	Fullmetal Alchemist: Brotherhood	<a href="https://cdn.myanimelist.net/images/anime/1208/94745.webp">https://cdn.myanimelist.net/images/anime/1208/94745.webp</a>
11061	Hunter x Hunter (2011)	<a href="https://cdn.myanimelist.net/images/anime/1337/99013.webp">https://cdn.myanimelist.net/images/anime/1337/99013.webp</a>
9253	Steins;Gate	<a href="https://cdn.myanimelist.net/images/anime/1935/127974.jpg">https://cdn.myanimelist.net/images/anime/1935/127974.jpg</a>
1535	Death Note	<a href="https://cdn.myanimelist.net/images/anime/1079/138100.webp">https://cdn.myanimelist.net/images/anime/1079/138100.webp</a>

Table 4: The Raw Dataset of the anime scores dataset (only first 5 rows)

mean	popularity	num_list_users	rank	num_scoring_users
8.72	17	2460047	58	1396797
9.10	3	3446066	3	2174841
9.03	8	2942025	9	1826884
9.07	14	2640370	4	1435760
8.62	2	4019411	88	2819319

Here is how the score(mean) calculated: All scores given in the database are calculated as a weighted score.

$$\text{Weighted Score} = (v/(v + m)) * S + (m/(v + m)) * C$$

- $S$  = Average score for the anime/manga.
- $v$  = Number users giving a score for the anime/manga.
- $m$  = Minimum number of scored users required to get a calculated score.
- $C$  = The mean score across the entire Anime/Manga database.

† Note that  $v$  does not correspond to the “number of scored users” as seen on the database page. Scores from users who have not viewed 1/5 of the series upon its completion are not included. Scores given from illegitimate accounts created to sway votes are also not included in the scoring algorithm.

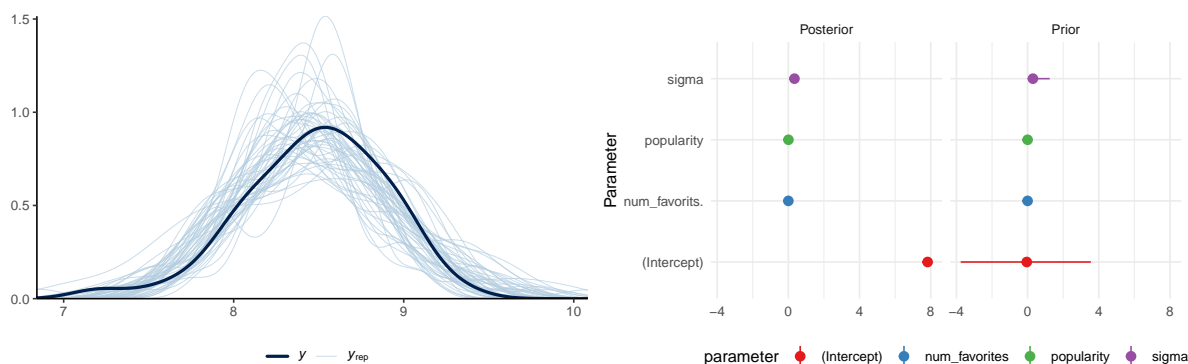
Not Yet Aired entries have no score and will display N/A. Entries that do not meet the minimum number of scored users will also not display a calculated score.

Top Anime/Manga Rankings The “Top Upcoming” and “Most Popular” rankings are ordered by the number of users who have added the entry to their list. All other Top Anime and Top Manga rankings are ordered by weighted score, as calculated above. Please note that while R18+ entries calculate a weighted score, they are excluded from the rankings. Music Videos are also excluded from Top Anime.

## B Model details

### B.1 Posterior predictive check

In Figure 5a we implement a posterior predictive check. This compares the posterior predictions of anime score based on the popularity and number of favorites to the observed data. It is evident that the posterior distribution aligns well with the actual anime scores, suggesting that the model has captured the underlying data patterns effectively. This is a good indication that the model provides a reliable representation of how these predictors influence anime ratings.



(a) Posterior prediction check

(b) Comparing the posterior with the prior

Figure 5: Posterior predictive check for anime rating model

### B.2 Diagnostics

Figure 6a is a trace plot. It shows the trace of the sampling process for the model parameters. The horizontal lines and overlapping chains suggest that the model has converged, with no signs of issues in the sampling process. This suggests that the posterior distribution has been adequately explored.

Figure 6b is an Rhat plot. It compares the variability within each chain to the variability between chains in the MCMC process. As seen in the plot, the Rhat values are all close to 1, which is an indicator that the MCMC algorithm has reached convergence.

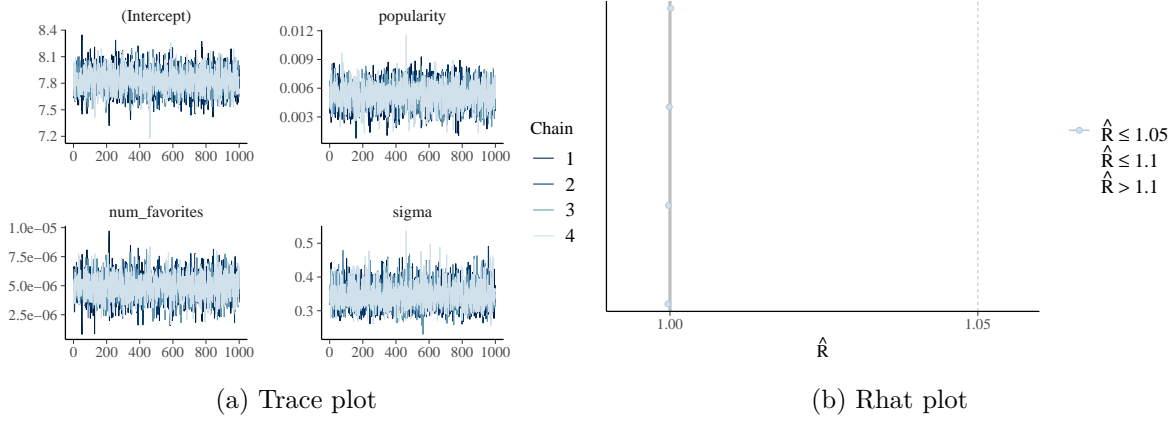


Figure 6: Checking the convergence of the MCMC algorithm

### B.3 90% Credibility Interval

Figure 7 and Figure 8 are 90% credibility interval plots for the predictors popularity and number of favorites. These plots show the credible intervals for each predictor, helping to understand the uncertainty around their effects on anime score.

### B.4 Summary

The model diagnostics, including posterior predictive checks, trace plots, and Rhat values, suggest that the model has converged properly and is fitting the data well. The credible intervals for popularity and number of favorites show the uncertainty around the estimates for these predictors. These results provide a robust understanding of the relationship between these predictors and anime scores.

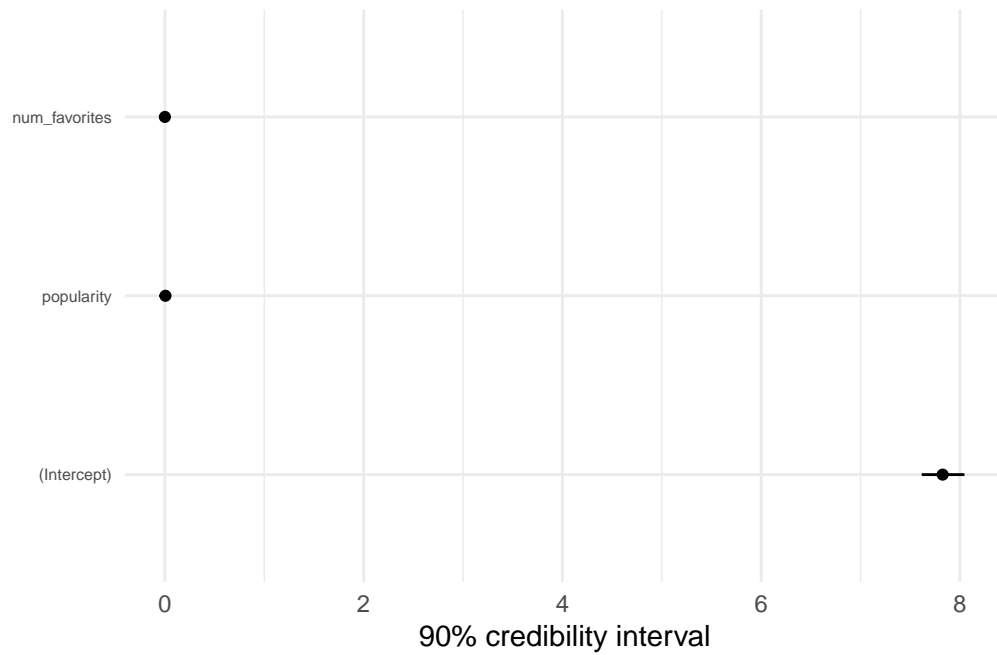


Figure 7: Credible intervals for predictors of anime score

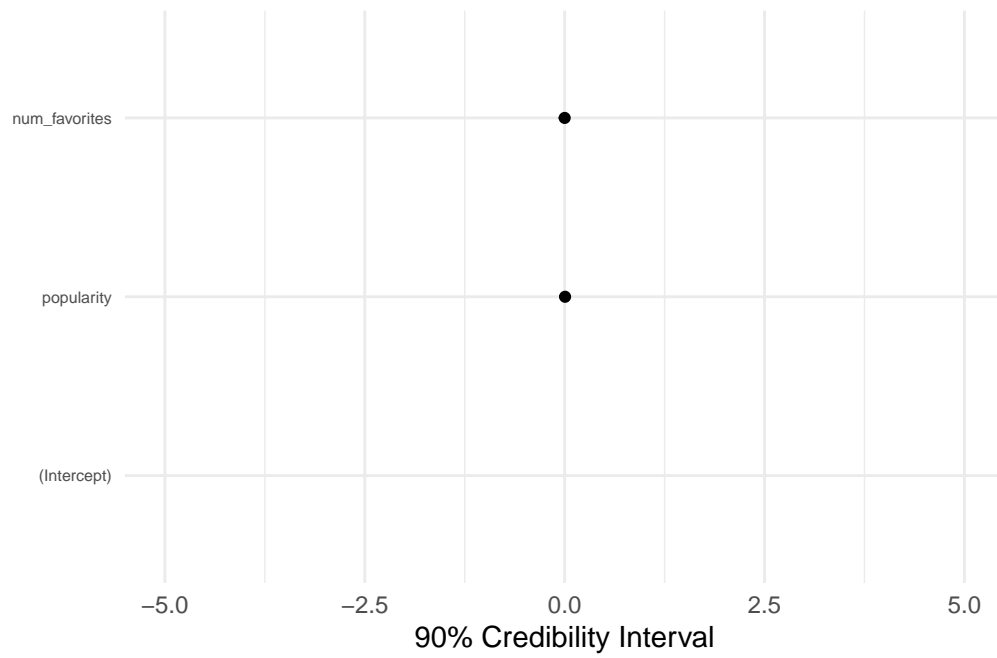


Figure 8: Credible intervals for predictors with x-axis limits



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