Predicting which anime are animazing through quantitative analysis*

People are more likely to rate great anime, regardless of age

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This paper examines the top 10000 anime on MyAnimeList (MAL) by user score to understand the tendencies of highly rated anime. Using data provided by the MAL API, we discovered that the fraction of users that rate an anime to the total users that have engaged with the anime is a large indicator of user score. Our multiple linear regression model predicts the user score of an anime based on scoring fraction, date, and popularity and may indicate highly rated anime that have not yet gotten adequate exposure based on difference between the predicted and actual scores. This concept of scoring fraction is applicable to media forms beyond anime and may serve as the basis for recommendation algorithms.

Can I add keywords under abstract somehow? keywords: anime, regression, MyAnimeList

1 Introduction (longer)

Anime refers to animation originating from Japan. (I want to introduce what anime is better). In 2021, half of Netflix's 222 million subscribers watched some anime on the platform and viewership saw an increase of 20% in the total hours over the previous year (Brzeski 2022). Anime is not much different compared to other forms of media, however anime and animation in general is still often regarded by many as 'childish', despite plenty of anime covering serious topics(Fiirgaard 2023).

MyAnimeList, herein referred to as MAL, is one of the largest and most popular anime databases and communities online. Users are able to keep track of anime they have watched or plan to watch, as well as rate and find similar anime. MAL is similar to IMDb in terms of functionality.

*Code and data are available at: https://github.com/varygx/AnimeAnalysis

The estimand of interest is the effect of

We conduct an analysis on the ratings of anime on MAL. Specifically we contrast

The subsequent sections follow a structured format. Section 2 outlines the source and variables of interest for our analysis. Section 3 details the construction and methodology of the statistical models used. Section 4 presents the key findings of our analysis, while Section 5 critically reviews the content, addresses the implications of the results, acknowledges model limitations, and suggests potential research directions.

2 Data

The data in this paper is sourced from the MAL API (*MyAnimeList API (Beta Ver.) (2)* 2024) and was gathered on April 12, 2024. The rankings of anime in the database are updated twice a day so the data gathered can be assumed to be up to date. Data analysis is performed in R (R Core Team 2023) with help from the following libraries: `tidyverse` (Wickham et al. 2019), `arrow` (Richardson et al. 2024), `rstanarm` (Goodrich et al. 2022), `modelsummary` (Arel-Bundock 2022), `testthat` (Wickham 2011), `here` (Müller 2020), `knitr` (Xie 2023), `kableExtra` (Zhu 2021), `dotenv` (Csárdi 2021), and `httr2` (Wickham 2023).

2.1 Measurement

In order to rate anime and add them to a list users must register an account on the MAL website. Each account can add an anime to their list once by choosing 1 of 5 statuses: watching, completed, on-hold, dropped, and plan to watch. It is also possible to remove an anime from the list if it was added by mistake. Every user that has an anime on their list is counted as a member of that anime, which is how the popularity rank is calculated. The user can also give a score to an anime, regardless of status, which is an integer from 1 to 10. The score of an anime on MAL is a weighted score calculated via the following:

$$\text{Weighted Score} = \left(\frac{v}{v+m}\right) \cdot S + \left(\frac{m}{v+m}\right) \cdot C$$

where:

Weighted Score is the calculated score for the anime/manga.

v is the number of users who have given a score for the anime/manga.

m is the minimum number of scored users required to get a calculated score.

S is the average score given by users to the anime/manga.

C is the mean score across the entire anime/manga database.

Table 1: Sample of Anime

id	title	rank	start_date	studio	mean	popularity	num_list_users	num_scoring_users	adventure	drama	fraction	days_since_start
52991	Sousou no Frieren	1	2023-09-29	Madhouse	9.39	295	681005	344608	1	1	0.5060286	196
5114	Fullmetal Alchemist: Brotherhood	2	2009-04-05	Bones	9.09	3	3333671	2113588	1	1	0.6340122	5486
9253	Steins;Gate	3	2011-04-06	White Fox	9.07	13	2555269	1395401	0	1	0.5460877	4755
26017	Backkom Specials	9998	NA	RG Animation Studios	5.90	15675	537	224	0	0	0.4171322	NA
38341	Bai Niao	9999	2017-06-13	RG Animation Studios	5.90	14471	737	233	0	0	0.3161465	2495
31965	Balala Xiao Mo Xian: Qiji Wubu	10000	2013-04-19	Alpha Animation	5.90	12966	1128	291	0	0	0.2579787	4011

This equation requires a minimum number of scores to ensure a fair sample size, takes into account popularity, and normalizes the score compared to the mean score in the database. Note that for a sufficiently large number of scoring users the weighted score will be close to the actual mean score. In addition, MAL verifies whether the user has viewed 1/5 of the series upon completion and excludes scores by illegitimate accounts that try to sway votes. How this is done is not detailed. Due to the personal nature of these lists we assume that each user and list is associated with exactly one individual.

2.2 Top 10000 Ranked Anime

The MAL API is capable of fetching up to 500 anime based on ranking at a time for a given offset. Table 1 shows a small subset of the data gathered. Relatively little cleaning was required as the API allows one to specify what fields should be returned. The genre was returned as a list of strings which was turned into a multi-hot encoding for data processing. MAL has 74 listed genres and themes, so only 2 genre columns are displayed here for readability. The fraction column was calculated as the fraction of num_scoring_users to num_list_users, this is the fraction of users that gave a score to the anime. The days_since_start column was calculated as the integer day difference between the start date of the anime and the date the dataset was gathered.

(maybe move this to discussion) Three fields of interest were unable to be retrieved without an API call for a specific id, namely related anime, recommendations, and statistics regarding the exact numbers of member status. When attempting to get this data, rate limiting was encountered at roughly 250 calls per 10 minutes, with no clear way to raise the API call limit. Due to this the relationships between anime could not investigated thoroughly.

2.2.1 Score Distribution

From the right skewed distribution of Figure 1, we observe that it is difficult for an anime to become top rated. This makes sense in the context of any subject that is reviewed as it requires a large group of people to consistently find greatness with no glaring flaws. It is also sensible that the mean score of the top 10000 anime is closer to 7 than to 5. Scores are inherently a subjective opinion and may take into account enjoyability, as well as how 'good' the piece of work is. Many people could enjoy a bad show even despite having many flaws. This matches the description MAL gives to each score number, where 1 is appalling, 5 is average, 7 is good,

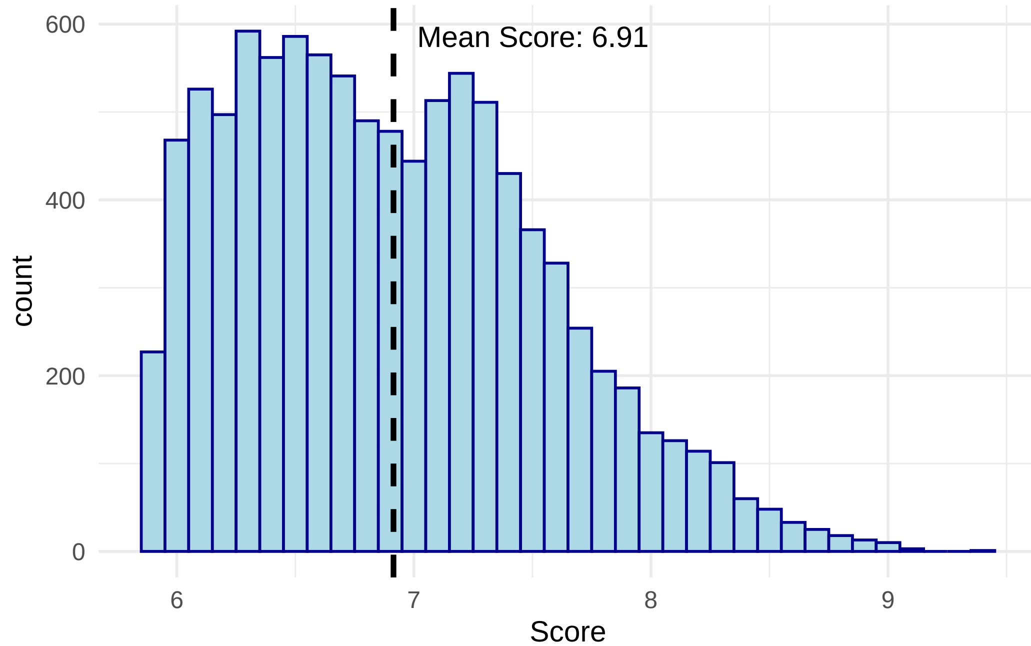


Figure 1: Distribution of Scores of Top 10000 Anime

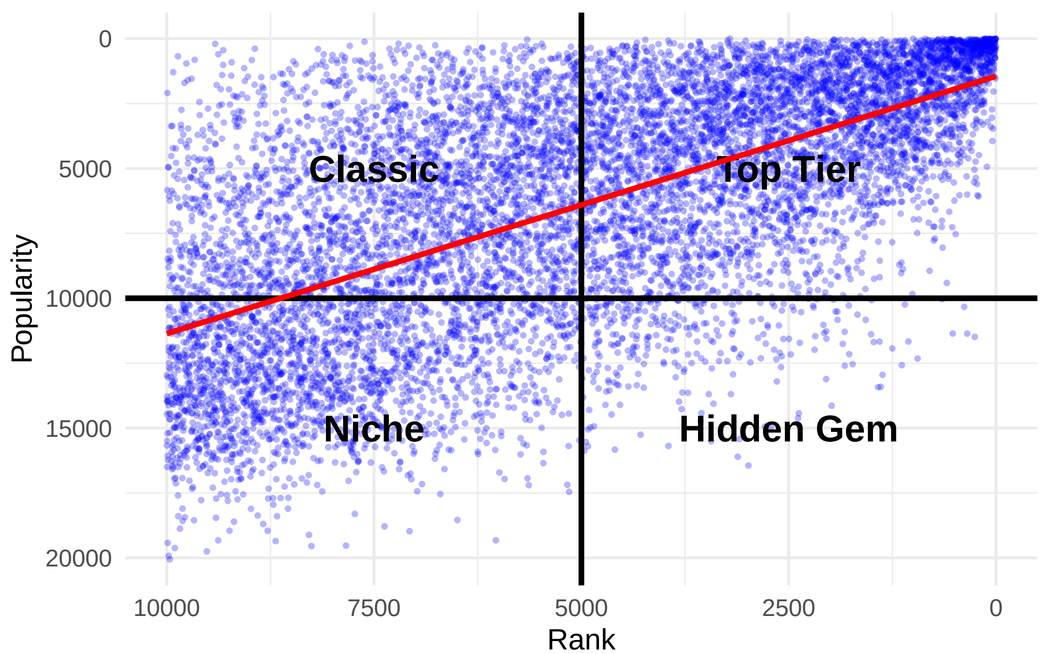
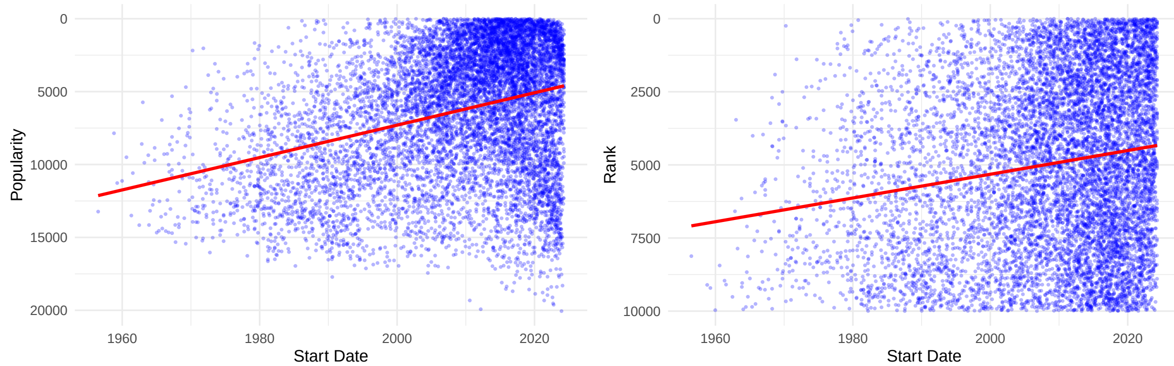


Figure 2: Rank vs Popularity for Top 10000 Anime

and 10 is a masterpiece. Seven is often seen as the borderline of acceptable in many contexts (objective source here maybe?).

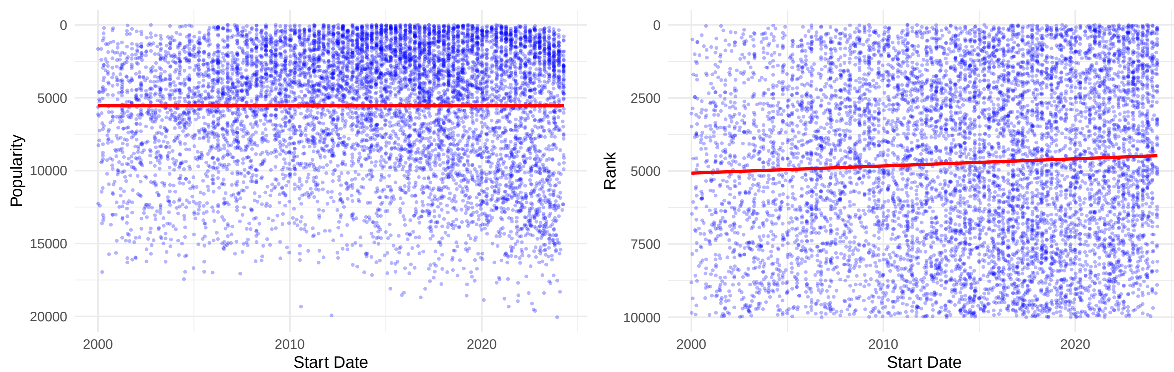
2.2.2 Rank and Popularity

If scoring is subjective how much of a relationship is there between rating and popularity? From Figure 2 we see there is a moderately strong positive linear correlation between rank and popularity. This is also a sensible conclusion as a highly rated anime is more likely to attract new viewers.



(a) Popularity plot (b) Rank plot

Figure 3: Correlation to Date



(a) Popularity plot (b) Rank plot

Figure 4: Correlation to Modern Dates

2.2.3 Correlation to Date

It may seem like the date an anime airs can be a factor for popularity as older anime could have longer exposure over time or newer anime has more coverage but this does not seem to be the case. Figure 3a shows people are less likely to watch very old anime and Figure 4a suggests date is generally irrelevant to popularity but modern anime does have more viewership compared to older anime by the density of the points.

We observe a weaker relationship between date and rating in Figure 3b which suggests viewers are still appreciative of older works. As the amount of anime produced has increased in modern times, Figure 4b suggests that for every 'good' anime there is a 'bad' anime to match it.

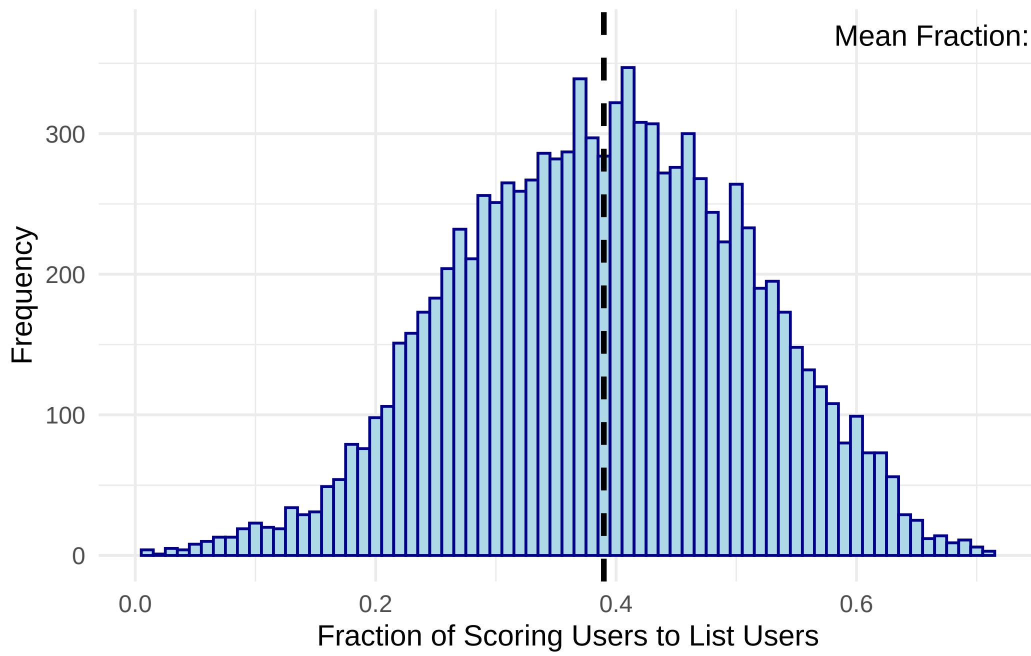
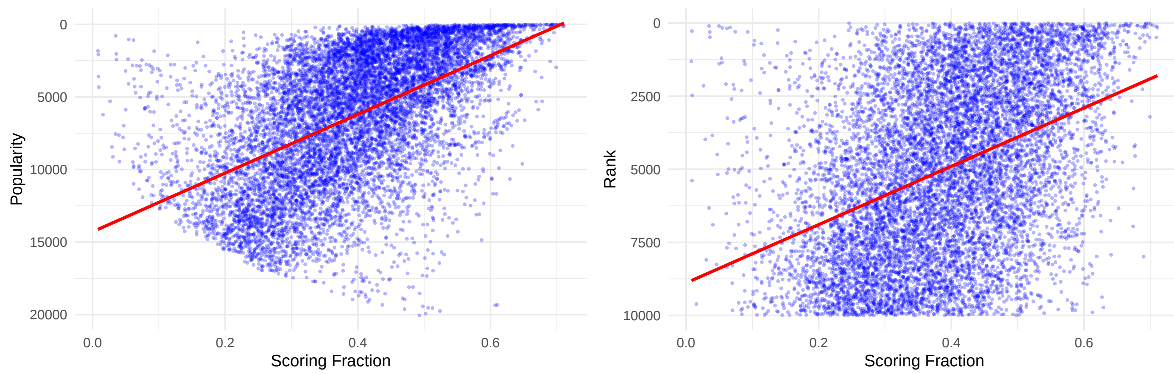


Figure 5: Distribution of Scoring Fraction of Top 10000 Anime

2.2.4 Scoring Fraction

On average, 39% of users end up rating an anime on their list according to Figure 5. There is a strong positive correlation between scoring fraction and popularity as seen in Figure 6a, which is sensible as fans of an anime or any media in general are likely express their opinion on that particular media. Surprisingly in Figure 6b there is a positive correlation between scoring fraction and rank. One might expect a normal distribution as people are more likely to voice their opinion on a particularly good or bad piece of work but not so much for average ones. Instead we see a linear relationship between scoring fraction and rank.



(a) Popularity plot

(b) Rank plot

Figure 6: Correlation to Scoring Fraction

3 Model

Here we briefly describe the Bayesian analysis model used to investigate the user score of anime on MAL. Background details and diagnostics are included in Appendix B.

3.1 Model Set-up

From the preliminary analysis conducted in Section 2, we build a multiple linear regression model to predict the rating of an anime based on quantitative statistics. Define y_i as the user score of the anime i. Then fraction_i is the fraction of users who have rated the anime i to members of the anime i, popularity_i is the total members of anime i, and startDate_i is the number of days from the start date of anime i to the current date.

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \beta_0 + \beta_1 \times \text{fraction} + \beta_2 \times \text{popularity} + \beta_3 \times \text{startDate} && (2)\\
\beta_0 &\sim \text{Normal}(0, 1.6) && (3)\\
\beta_1 &\sim \text{Normal}(0, 13) && (4)\\
\beta_2 &\sim \text{Normal}(0, 3.6 \times 10^{-4}) && (5)\\
\beta_3 &\sim \text{Normal}(0, 6.3 \times 10^{-6}) && (6)\\
\sigma &\sim \text{Exponential}(1.6) && (7)
\end{aligned}
$$

We run the model in R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm` which are Normal distributions and apply autoscaling for better results.

3.1.1 Model Justification

We expect a positive relationship between the score of the anime and scoring fraction as seen in Section 2.2.4. This is likely to be the most important factor in our model. We expect a very minor to no relationship between the score of the anime and the start date of an anime as seen in Section 2.2.3. As such this coefficient is expected to be close to zero. Finally, we expect a minor positive relationship between the score of an anime and its popularity as seen in Section 2.2.2. This coefficient will likely be close to zero and smaller than start date, as an anime can have millions of members, but should be a better indicator than start date.

4 Results

Our results are summarized in Table 2. Our model observes a score intercept of 6.02, which means when an anime has been out for 0 days, has 0 members and thus 0 scoring fraction, it will likely have a user score of 6.34. This is slightly nonsensical as an anime had to have a positive scoring fraction and the minimum amount of scoring users to be ranked within the top 10000. When considering only the mean scoring fraction in Section 2.2.4 of 0.39, our model predicts a user score of $6.34 + 1.55 \times 0.39 = 6.94$, which is close to the mean user score of 6.91 seen in Section 2.2.1. The start date coefficient is extremely small indicating the date of an anime has no impact on its score. For a 10 year old anime the model expects the score to decrease by $-1.605 \times 10^{-5} \times (10 \times 365) = -0.06$, which can be considered a neglible amount. Finally, for every 1 million members of an anime, its score increases by $7.77 \times 10^{-7} \times 10^{6} = 0.78$.

Table 3 shows the predictions of our model compared to the actual scores of the top 5 and bottom 5 anime in the dataset. Some observations that should be noted are:

1. The score intercept is higher than the score of lower ranked anime
2. The model is harsh on highly ranked anime that are not yet popular

5 Discussion

5.1 First discussion point

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

Table 2: Explanatory models of score based on scoring fraction, popularity, and start date

	(1)
(Intercept)	6.335
	(2.097×10^{-2})
fraction	1.546
	(4.927×10^{-2})
days_since_start	-1.605×10^{-5}
	(1.273×10^{-6})
num_list_users	7.776×10^{-7}
	(2.354×10^{-8})
Num.Obs.	9821
R2	0.276
R2 Adj.	0.275
Log.Lik.	−7976.899
ELPD	−7982.1
ELPD s.e.	69.0
LOOIC	15 964.2
LOOIC s.e.	138.0
WAIC	15 964.1
RMSE	0.55

Table 3: Comparing predictions of model to actual scores

title	rank	popularity	num_list_users	fraction	start_date	days_since_start	mean	predicted
Sousou no Frieren	1	295	681005	0.5060286	2023-09-29	196	9.39	7.643911
Fullmetal Alchemist: Brotherhood	2	3	3333671	0.6340122	2009-04-05	5486	9.09	9.819708
Steins;Gate	3	13	2555269	0.5460877	2011-04-06	4755	9.07	9.090175
Gintama°	4	341	628518	0.3982623	2015-04-08	3292	9.06	7.386770
Shingeki no Kyojin Season 3 Part 2	5	21	2265274	0.6973669	2019-04-29	1810	9.05	9.145847
Zou no Inai Doubutsuen	9995	16500	452	0.2831858	1982-03-20	15364	5.90	6.526666
Akai Koudan Zillion Recaps	9996	13984	854	0.2177986	1987-07-21	13415	5.90	6.457157
Atagoal wa Neko no Mori	9997	13785	897	0.2441472	2006-10-14	6390	5.90	6.610686
Bai Niao	9999	14471	737	0.3161465	2017-06-13	2495	5.90	6.784406
Balala Xiao Mo Xian: Qiji Wubu	10000	12966	1128	0.2579787	2013-04-19	4011	5.90	6.670436

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

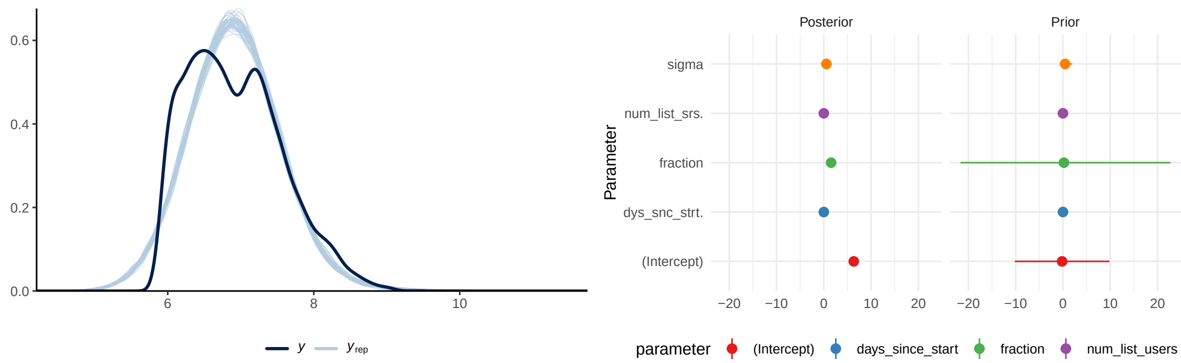
A Additional data details

B Model details

B.1 Posterior predictive check

In Figure 7a we implement a posterior predictive check. This shows...

In Figure 7b we compare the posterior with the prior. This shows...



(a) Posterior prediction check

(b) Comparing the posterior with the prior

Figure 7: Examining how the model fits, and is affected by, the data

B.2 Diagnostics

Maybe don't keep this

?@fig-stanareyouokay-1 is a trace plot. It shows... This suggests...

?@fig-stanareyouokay-2 is a Rhat plot. It shows... This suggests...

Checking the convergence of the MCMC algorithm

Figure 8: **?(caption)**

C Datasheet

Link to datasheet in repo here

D R package

TODO: create package

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