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# Understanding Book Popularity on Goodreads

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## Abstract

Goodreads has launched the Readers Choice Awards since 2009 where users are able to nominate/vote books of their choice, released in the given year. In this work, we question if the number of votes that a book would receive (aka the popularity of the book) can be predicted based on the characteristics of various entities on Goodreads. We are successful in predicting the popularity of the books with high prediction accuracy (correlation coefficient  $\sim 0.61$ ) and low RMSE ( $\sim 1.25$ ). User engagement and author's prestige are found to be crucial factors for book popularity.

## Author Keywords

book popularity; Goodreads; prediction

## ACM Classification Keywords

H.4.m [Information Systems Applications]: Miscellaneous;  
J.4 [Computer Applications]: [Social and Behavioral Sciences]; K.4.2 [Computers And Society]: [Social Issues]

## Introduction

Popularity/success of a book is important not only for the authors but also for the publishers, the professional book reviewers and the book selling platforms like Amazon, eBay etc. The initial popularity of books can have a significant impact how the eventual sales would be [5]. Understanding book popularity is a difficult task even for an expert working

**Related Work**

Predicting popularity of content on social media has been widely researched. Most of these studies focus on popularity prediction of various Twitter specific entities. Extensively studied among these being the hashtags. Tsur and Rappoport [7] studied popularity of hashtags based on content features of tweets only. Ma et al. in [4] proposed a framework for predicting popularity of newly emerging hashtags. Kong et al. [2] studied the burstiness (sudden rise in hashtag usage and quick fall thereafter) of hashtag on a temporal scale. Maity et al. [6] studied various factors affecting the popularity of hashtag compounds (two or more hashtags merging together). In a recent work by Maity et al. [5], the authors have studied how book reading behavior on Goodreads can determine Amazon Best Sellers.

in the publication industries. Some of the eventual award winners and best sellers have gone through one or multiple rejections before being finally accepted by a certain publisher. There are potentially many influencing factors that can impact popularity of a book. Broadly these factors can be categorized into (i) intrinsic and (ii) extrinsic factors. Intrinsic factors correspond to the content and the quality of the book like how interesting the book is, how engaging the story line is, novelty, style of writing etc. However, these quality factors of the books are very different for different genres. For example, a successful thriller requires a credible story-line, complex twists and plots, escalating stakes and tension whereas a popular romantic novel demands demonstration of strong and healthy relationship, sexual tension, happy and optimistic endings etc. A great mystery novel involves secrets, misdirection of clues, a relatable protagonist etc. [1]. Therefore, finding common grounds is difficult for quantification of the quality aspects for different genres. On the other hand, extrinsic factors include the readers' reading behaviors, social contexts, reviews by the critics etc. which are relatively easier to obtain. In this paper, we shall consider the readers' reading, reviewing characteristics for the books, engagement activities, authors' prestige etc. to understand book popularity in Goodreads. Specifically, we are interested in predicting book votes as a popularity metric.

Goodreads is a community-driven social cataloging site which has grown exponentially into one of the most popular social book reading and recommendation sites. Goodreads provides various opportunities like quizzes, trivia apart from social book reading so as to engage their users. Goodreads Readers Choice Award is such an attempt. This was first launched in 2009. From then on, Goodreads users can take part in deciding the recipients of this award by nominating as well as by voting for their nominations. There

are 20 categories like Fiction, Thrillers, Fantasy, Romance etc. of awards and in each category 15 official nominations are made. In the first round of voting, users can nominate books to be included in the awards as write-in candidates; five in each category get added to the group of official nominees, making the total 20 in each category. Using APIs and automated crawls, we gathered all the books' data prior to the start of the voting phase. In table 1, we show all the award categories.

**Present work:** In this study, we aim to determine the salient factors from various Goodreads entities that contribute to the popularity of books in terms of the number of votes they receive. Towards this objective, we have considered collective user engagement behavior and show that this is an important aspect to understand book popularity alongside author's prestige. The user engagements toward books characterized by the rating/review behavior, shelve characterization and organization - a very unique utility that the Goodreads platform provides to its users, are important determinant. Further, we observe that author's prestige features like – the avg. rating of an author, the number of awards received by an author of a book etc. are crucial to the book popularity.

**Table 1:** Award Categories

Fiction	History & Biography
Mystery & Thriller	Science & Technology
Historical Fiction	Food & Cookbooks
Fantasy	Graphic Novels & Comics
Romance	Poetry
Science Fiction	Debut Goodreads Author
Horror	Young Adult Fiction
Humor	Young Adult Fantasy
NonFiction	Middle Grade & Children's
Memoir & Autobiography	Picture Books

**Discriminative features:**

We use *RELIEFF* feature selection algorithm [3] to rank the attributes. In table 2, we show the rank of the features in terms of their discriminative power for prediction. The rank order clearly indicates the dominance of the user engagement features, however author's rating seems to be the most discriminative feature. In the top 10, three of the author features find place. Among engagement features, shelf diversity, no. of books in 'read' or 'currently-reading' shelf are the important factors for popularity prediction. This suggest that Goodreads' user engagement is crucial factor for popularity prediction. Among author features, apart from rating of the author, other prestige features of the authors like no. of awards received, no. of rating received, no. of best sellers act as prominent popularity prediction features.

**Factors behind Book Popularity:**

In this section, we try to understand various factors driving book popularity. We consider two major types of factors: User engagement towards books - these includes various user engagement characteristics toward books like rating, reviewing, organizing in shelves etc.

Author characteristics - these factors are related to the prestige of an author of a nominated book. Subsequently we shall use them as features to our prediction model.

**User Engagement:**

These factors are extracted from various characteristic properties of Goodreads' user engagement toward books which we have already studied earlier.

- Average rating of the book given by the users.
- Number of ratings given by the users.
- Number of 4-star ratings given to the book.
- Number of 5-star ratings given to the book.
- User rating entropy of the book.
- Number of reviews received by the users.
- Review Sentiments - We take only 30 reviews of the books and use NLTK sentiment analysis tool<sup>1</sup> to find sentiment of the reviews. We then take the avg. positive sentiment score, negative sentiment score, neutral sentiment score and standard deviation of these sentiment scores as features to our model. In total, we have six set of features here.
- Number of genres of the book.
- Number of different user shelves the book is present in.
- Shelf diversity of the book - Similar to rating entropy,

we calculate shelf diversity. Formally, shelf diversity (ShelveDiv) is defined as follows:

$$ShelveDiv(b) = - \sum_{j \in shelveset} s_j \times \log(s_j)$$

where  $s_j$  is the probability that the book belongs to the  $j^{th}$  user shelf in the set of user bookshelves.

- Number of users who have added the book in 'currently reading' or 'read' shelves.
- Number of users who have added the book in 'to read' shelves.

**Author Characteristics:**

These factors are extracted from various characteristic properties (mostly prestige) of the authors of the nominated book.

- Number of books written by the author of the book.
- Average rating of the author of the book.
- Number of ratings received by the author of the book.
- Number of reviews received by the author of the book.
- Number of distinct awards received by the author.
- Number of 'best seller' books of the author.
- Follower count of the author.
- Number of common shelves among the authors' books.
- Number of unique shelves among the authors' shelves.

**Table 2:** Top 10 predictive features.

Rank	Features
1	Avg. rating of the author
2	Shelve Diversity
3	No. of users who have added the book in 'currently reading' or 'read' shelves
4	No. of awards received by the author
5	No. of different shelves the book is present in
6	No. of users who have added the book in 'to-read' shelves
7	Rating Entropy of the book
8	No. of reviews received by the book
9	No. of 5-star ratings received by the book
10	No. of ratings received by the author

<sup>1</sup><http://text-processing.com/demo/sentiment/>

**Table 3:** Prediction results for the highly voted books

	Corr. Coeff. ( $r$ )	RMSE
top 100	0.66	2.72
top 50	0.63	1.56
top 20	0.75	1.15
top 10	0.68	1.04
top 5	0.7	1.17
top 3	0.83	2.2

**Table 4:** Prediction results for the Award category specific prediction

Category	$r$	RMSE
Fiction	0.76	0.83
Mystery & Thriller	0.69	1.08
Historical Fiction	0.84	1.15
Fantasy	0.82	0.89
Romance	0.49	1.63
Science Fiction	0.67	1.19
Horror	0.73	1.11
Humor	0.7	1.25
NonFiction	0.7	1.33
Memoir & Autobiography	0.48	1.18
History & Biography	0.66	1.08
Science & Technology	0.41	1.3
Food & Cookbooks	0.61	1.77
Graphic Novels & Comics	0.39	1.39
Poetry	0.52	1.59
Debut Goodreads Author	0.87	0.82
Young Adult Fiction	0.8	0.86
Young Adult Fantasy	0.79	1.46
Middle Grade & Children's	0.61	1.2
Picture Books	0.66	1.38

## Prediction Framework

We shall now use the above user engagement and author characteristics as features for our prediction model.

We consider 400 books from all the 20 award categories of Goodreads Choice Award in 2015 for our prediction task. We perform a 10-fold cross-validation on the data sample. We use Support Vector Regression (SVR) for the prediction. For evaluating how good the prediction is, we use Pearson correlation coefficient ( $r$ ) and root mean square error (RMSE). We achieve high correlation coefficient ( $\sim 0.61$ ) and low root mean square error ( $\sim 1.25$ ). We observe that user engagement feature type is the strongest feature type contributing to correlation coefficient of 0.59 with RMSE value of 1.29 whereas with only author features, we achieve corr. coeff. of 0.44 and RMSE value of 1.41.

### *Predicting the votes of the highly voted books:*

Apart from overall prediction of the votes for the book nominations, we also investigate how our model performs in predicting the votes of the highly voted books. In specific, we ask if the features are able to suitably discriminate these books and if the predictions for them are better or worse than the overall prediction. We observe that our prediction model can very well predict the highly voted books' vote and the correlation coefficient is always higher than the overall case (see table 3). For predicting the votes of the top 3 most voted books, our model achieves a very high correlation coefficient of 0.83 (although the RMSE value goes a bit higher).

### *Award category specific prediction:*

We further categorize the books into the Award categories to investigate whether such categorization helps in improving the prediction accuracy. For prediction of votes of the books in each category, we train the prediction model on all the books except for the books belonging to that category.

The set of books in this category acts as a test set for the prediction task. In table 4, we show the results of the prediction. In most of the categories, we observe significant improvement in prediction accuracy from the case with no categorization. We also observe that in some award categories, prediction accuracies fall e.g., Romance, Science & Technology, Memoir & Autobiography, Graphic Novels & Comics etc.

## Conclusions and Implications

In summary, we propose a framework for predicting popularity (no. of votes) of books. Our proposed model achieves a high correlation coefficient  $\sim 0.61$  with low RMSE ( $\sim 1.25$ ). We observe that the user engagement features are the most discriminative ones compared to the others. Our prediction framework can predict votes of the highly voted books with higher accuracy than the above base case. The stratification of the books into award categories further enhances the prediction accuracies for most of the categories significantly.

Our research has important implications. It shows that initial rating, reviewing, user engagement features obtained from collective Goodreads user behavior along with authors' prestige can efficiently determine popularity of books. Our proposed system can early predict book popularity using these above features which can be easily obtainable. This early prediction can be effective in several ways - (i) act as guide for recommending appropriate books to the new users joining Goodreads and, (ii) help the book selling platforms like Amazon, eBay by forecasting early the eventual fate of a book/group of books/genre so that these platforms are able to launch proper and focused advertisements/promotional campaigns to boost up the sales.

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