

Scalable Neighbor-based Online Textbook Recommendation Application

Kunaal Ahuja, Naman Arora, Abhishek Patria, Sai Abhishek Pidaparthi, Samadipa Saha

Introduction

We have built a book recommendation system (**SNOTRA**) using publicly accessible data (Goodreads API).

There are two ways it is done today, **content based** filtering and **collaborative** filtering.

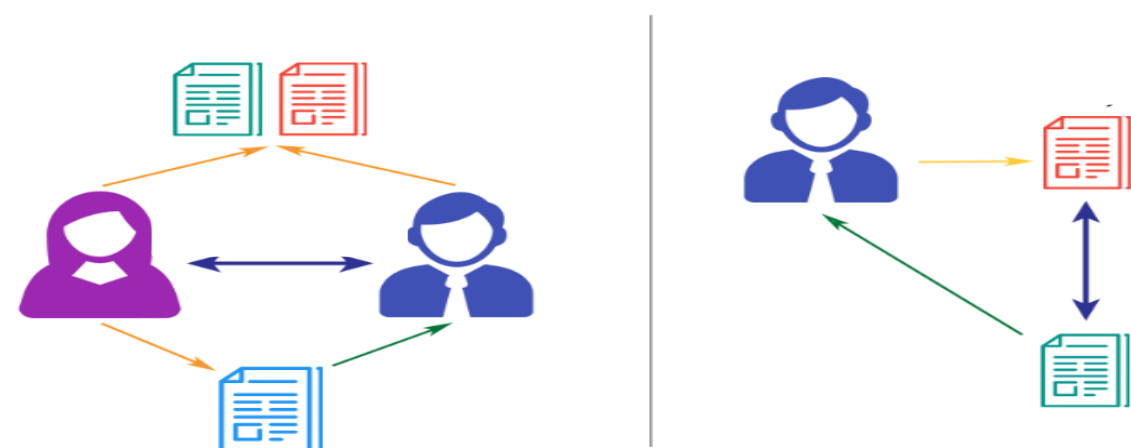


Figure 1: Collaborative (left) vs Content-Based (right) Filtering

We are integrating both the techniques to create a **hybrid** recommendation system to provide a better **personalized recommendation** to the user.

Approach

Collaborative Filtering

We performed user-to-user K-nearest neighbor collaborative filtering using cosine similarity on all the books.

We find the approximate rating that the user 'u' might give an unrated book 'i'. The formula is given below:

$$\hat{r}_{ui} = \mu_u + \sigma_u \frac{\sum_{v \in N_k^i(u)} \text{sim}(u, v) \cdot (r_{vi} - \mu_v) / \sigma_v}{\sum_{v \in N_k^i(u)} \text{sim}(u, v)}$$

We measured the accuracy of our model using RMSE metric.

Content Based Filtering

In this approach, we are recommending subset of those books to the users, which are similar to the user's reviewed books in the past.

To calculate similarity between 2 books, we use the book descriptions for both the books and pre-process the texts (removing any numbers and special characters, converting all text to lower case, removing stop words and lemmatizing the remaining words).

Then, we evaluate bag-of-words representation of the books and calculate cosine similarity to create similarity matrix for all books.

Hybrid Approach

We recommend the top books to the user as the **intersection** of books by the above methods which would give us the best of both worlds. In addition, we would give unique recommendations individually from the 2 approaches.

Visualization

Existing user

We use the hybrid model to find the recommended books for a user and display the top 5 books using D3. We show the name of the book, image of the cover, author, genre and the average rating of the book. The image of the cover is clickable and takes it to actual Goodreads page of the book on its website.



Figure 2: A snapshot of book recommendations for an existing user

New user

We ask a new user to rate 10 random books on the scale of 1 to 5 suggesting how likely he is to read these books. Based on his ratings, we are able to deploy our hybrid algorithm and give him the best set of recommendations.

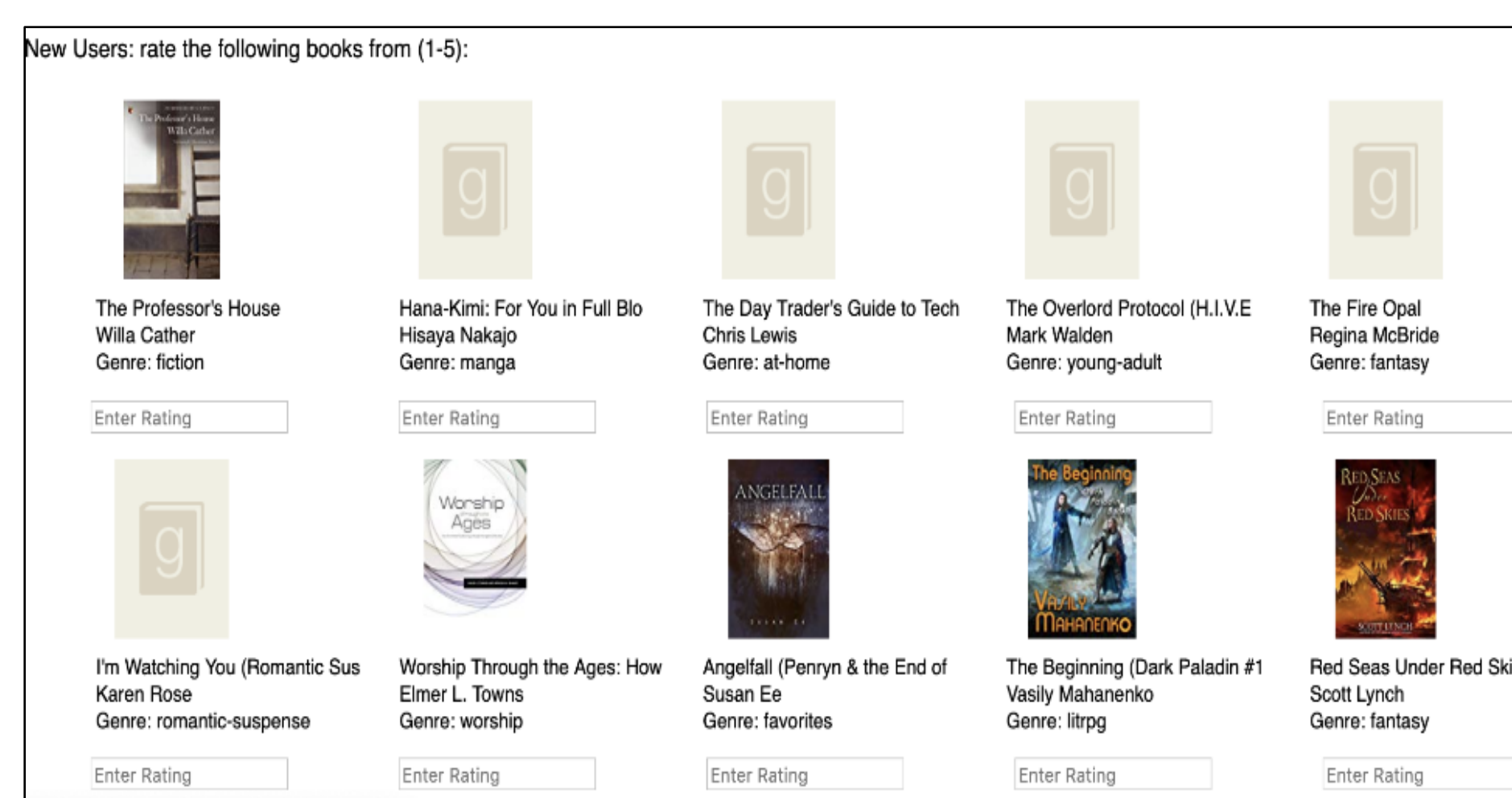


Figure 3: A snapshot of books need to be rated by a new user

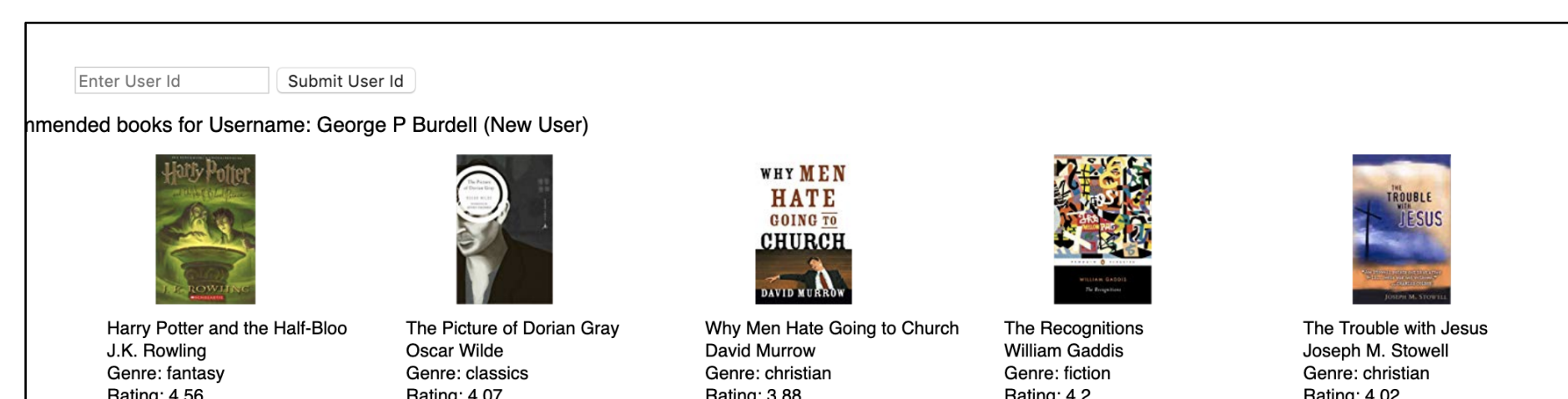


Figure 4: A snapshot of book recommendations for a new user

Neighbor based graph

Another key visualization in our project is a force layout neighbor-based graph, which is also incorporated using D3. This graph shows a user's top 2 similar users along with top 5 rated books for the user as well as both the similar users.

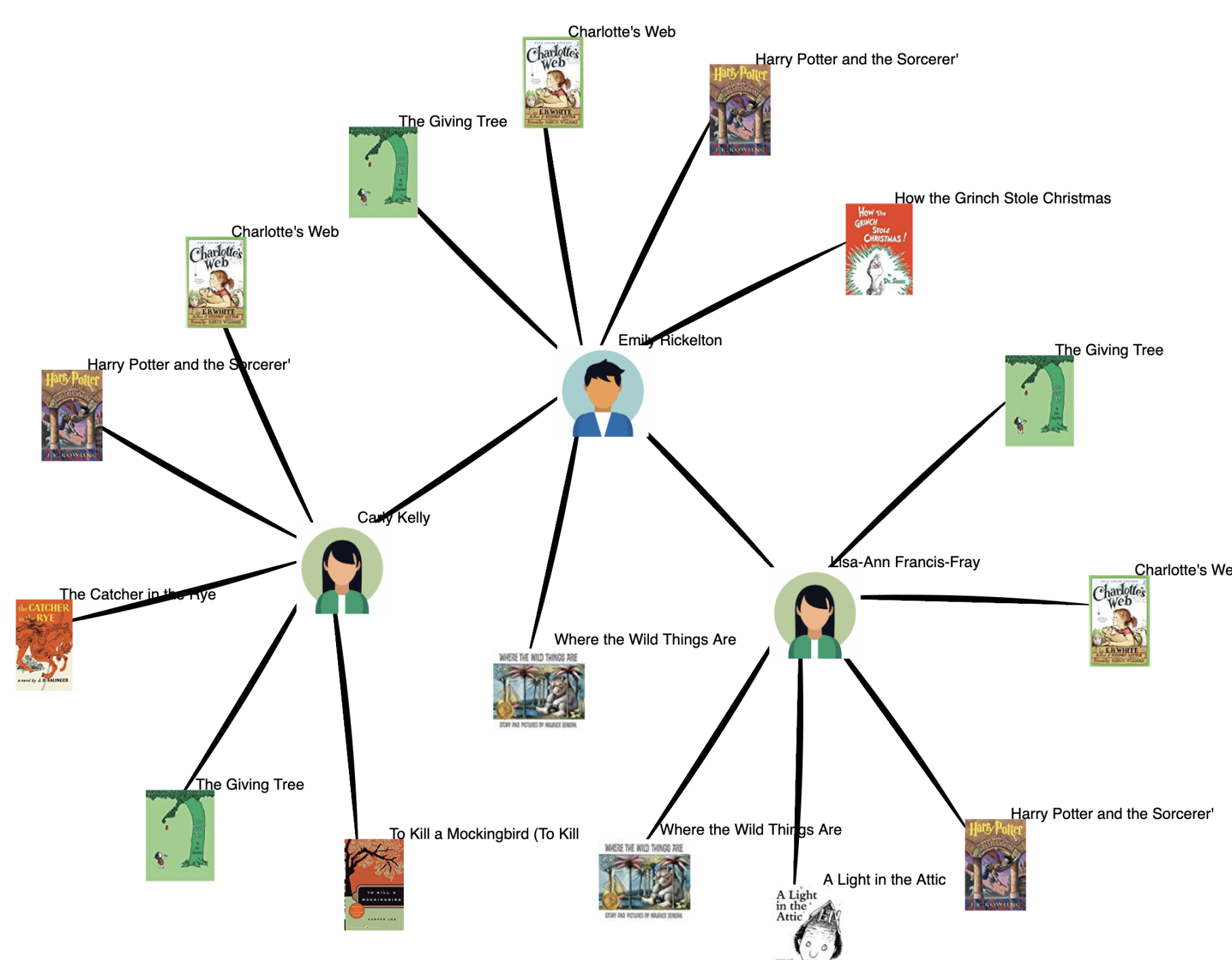
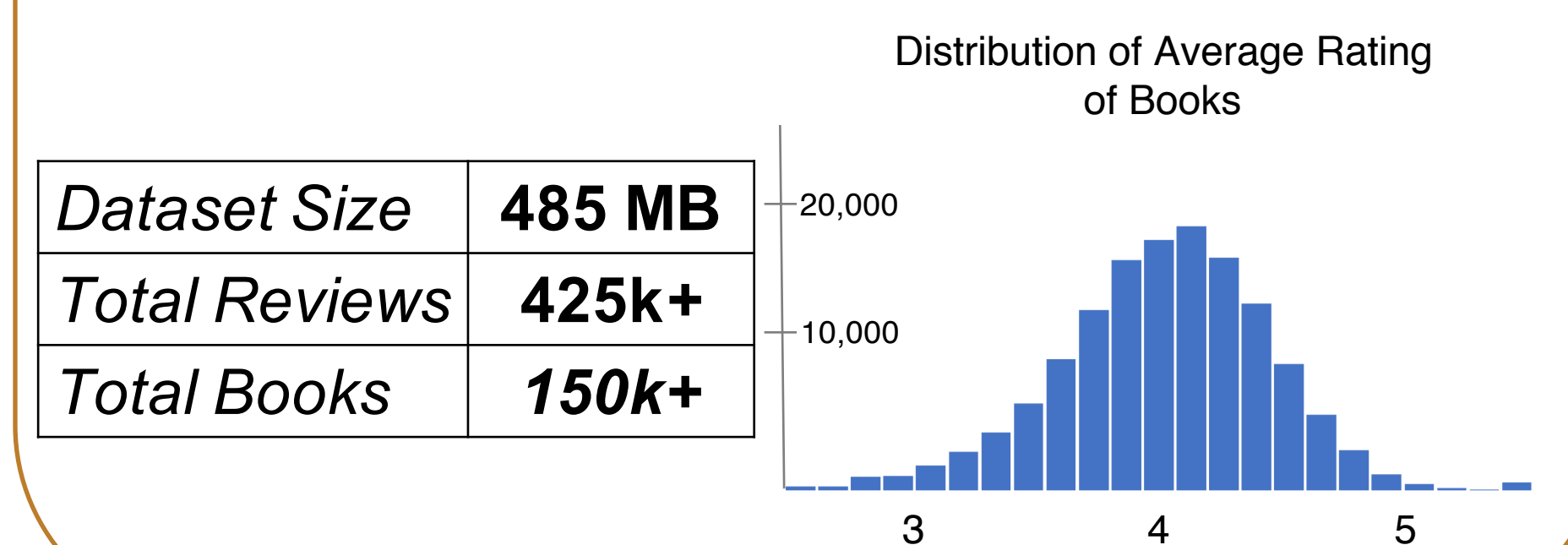


Figure 5: A snapshot of force layout neighbor based graph

Data

goodreads

Used **Goodreads** API to fetch all the data. Randomly selected users from a set of all Goodreads users and fetched their corresponding ratings of all the books they reviewed.



Experiments and Results

Collaborative Filtering

For collaborative filtering, we experimented with various KNN models: KNN basic, KNN with means and KNN baseline being among them. We also tried two approaches of similarity, cosine and Pearson similarity respectively. **KNN baseline** model with cosine similarity emerged as the best model.

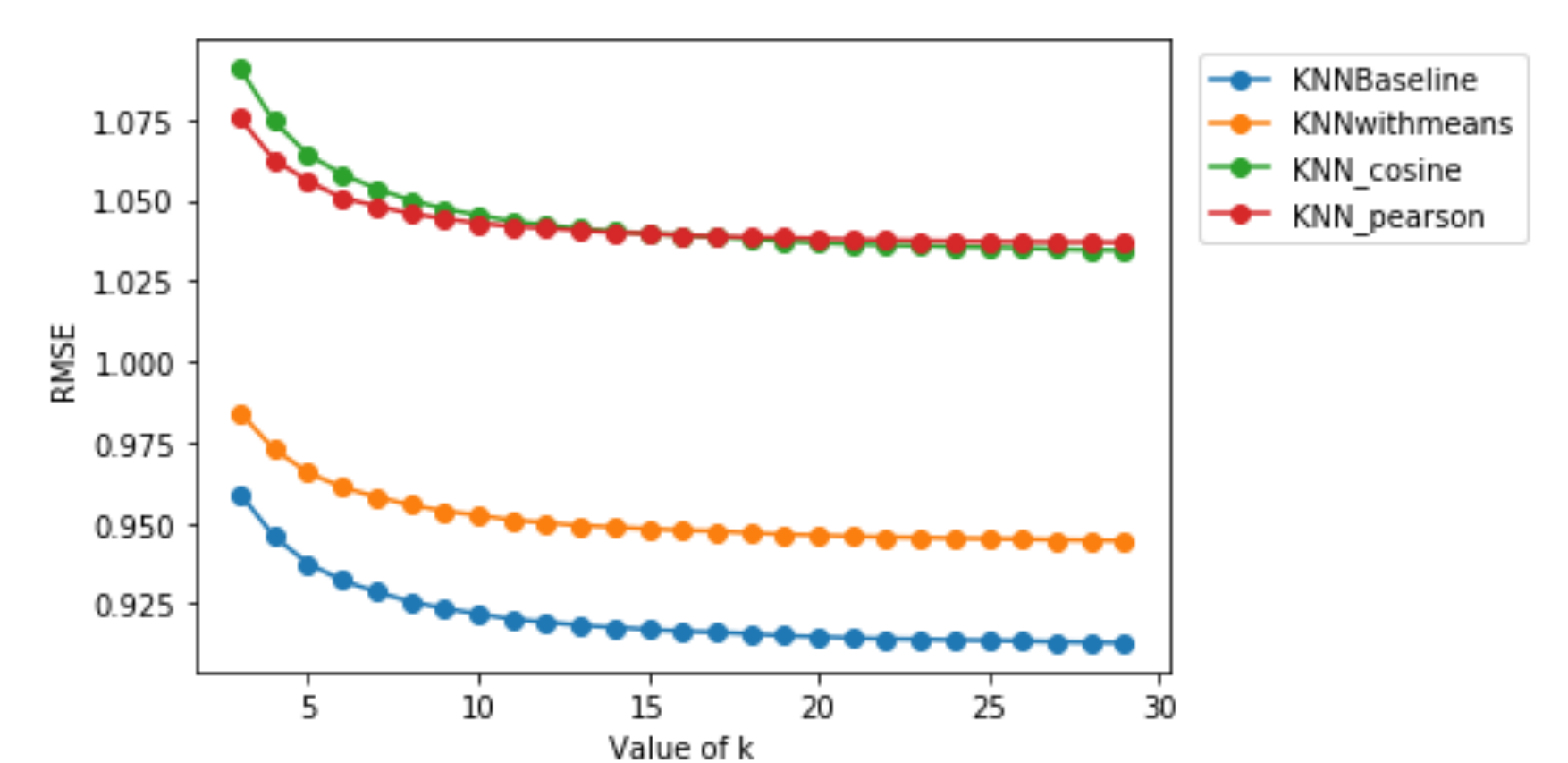


Figure 6: RMSE vs k for user-based collaborative filtering algorithm

User Survey

We conducted two user surveys with sample size 52. One for a basic collaborative filtering model and one for a hybrid model to see if there is any improvement in the recommendations.

32 out of 52 users like the recommendations of hybrid model compared to only 10 users who like the basic collaborative filtering model.

We performed t-test to compare the mean of the current ratings with that of the previous ratings, the p-value is very low suggesting means of the two ratings are statistically different.

t = 4.4908, df = 100.39, p-value = 1.899e-05
 H_0 : True difference in means is equal to 0
 H_A : True difference in means is not equal to 0
 95% confidence interval: (0.44, 1.13)

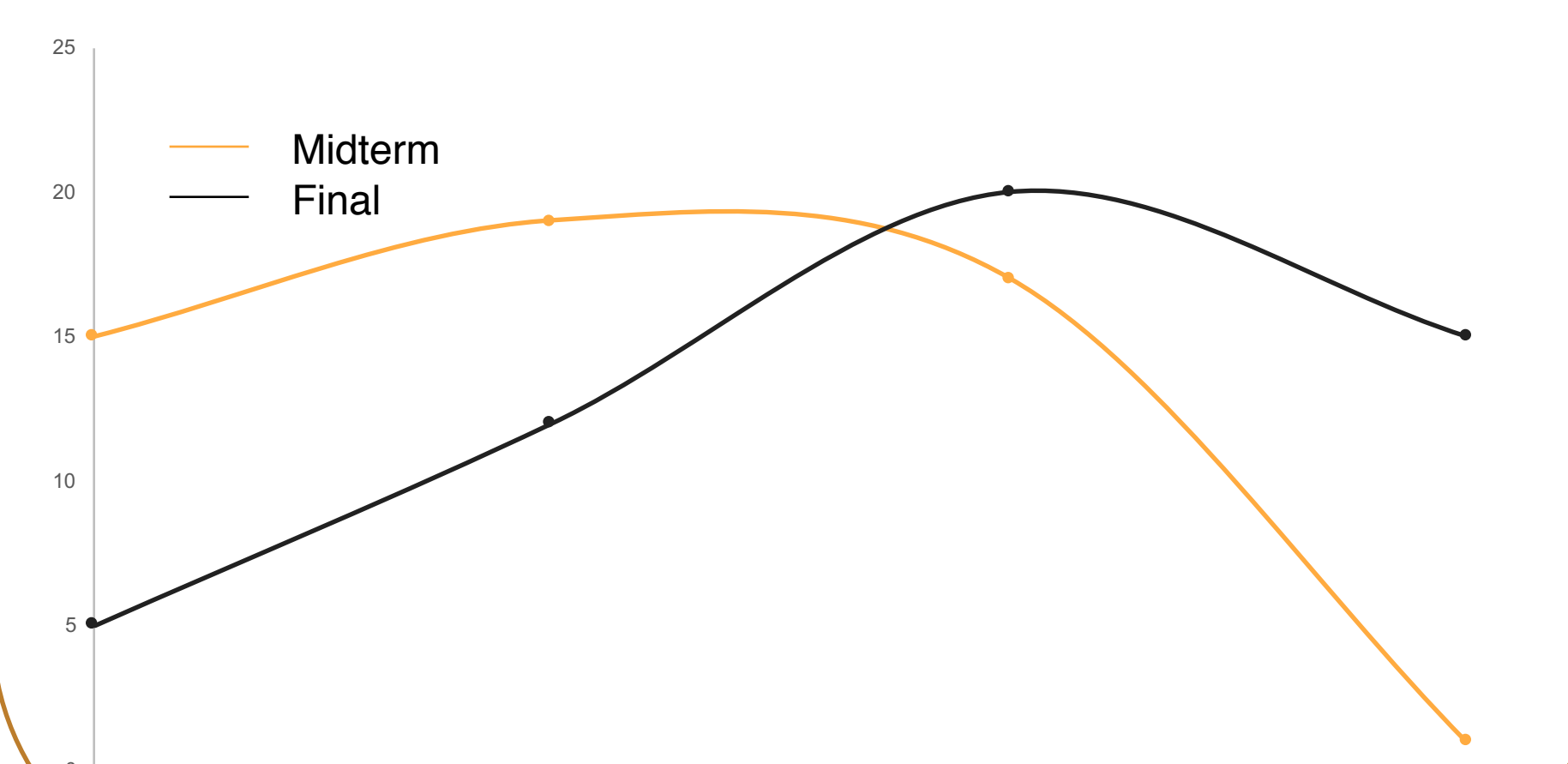


Figure 7: Midterm vs Final Survey Results (Ratings distribution)