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A Book Recommendation System Considering Contents and Emotions of User Interests

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***Abstract*— Although the benefits of reading are widely recognized, many people seldom read even though they often claim to have interest in reading. Since conventional book recommendation systems require keywords or a browsing history related to books that reflect user interests, users who rarely read struggle to obtain satisfactory results. In this study, we propose a book recommendation system that enables both users who read habitually and those who rarely read to easily get results that reflect their interests with their own content of interest as queries. Our proposed method identifies recommended books based on the similarity of the vectors of contents and emotions, contained in tweets about the content of user interests and book reviews. In this study's experiments, we confirmed the effectiveness of our proposed method.**

Keywords—book recommendation, sentiment analysis, Twitter

I. Introduction

Many studies show the benefits of reading. Research on book recommendation systems [1] has identified such benefits as increased life satisfaction, improved empathy and social support skills, and better social communication. A study on the relationship between reading and health [2] concluded that people, who read more than 3.5 hours a week, have a 23% lower risk of death than non-readers. According to a survey by the Agency for Cultural Affairs, Government of Japan [3], of almost 3,600, 47.3% answered that they did not read a book a month. On the other hand, 60.4% answered "strongly agree" or "agree" to the question "Do you want to read more?" This result suggests that many people are interested in reading, even though they do not actually read very much. Perhaps one explanation is that those who rarely read struggle to get book recommendation results that reflect their interests.

In previous book recommendation systems, the suggested books are generally determined based on keywords and browsing history related to books. Unfortunately, non-readers might not get satisfactory recommendation results because they lack keywords or adequate browsing histories that reflect their own interests.

In this study, we propose a book recommendation system that simply obtains recommendation results that reflect the interests of both users who have regular reading habits and those users who seldom read. In our system, the content of the interest of users is wielded as a query, and book recommendations are based on the similarity of contents and emotions in the reviews of others from various social media sources.

II. Related work

The following algorithms are commonly used in recommender systems: content-based filtering (CB), collaborative filtering (CF), and hybrid systems that combine these two.

Content-based filtering determines items to be recommended using the characteristics of book genres and reviews. Many studies have investigated accurate book recommendations with CB, improving performance through iterative machine learning and user evaluations of recommendation results based on book titles and themes [4] and suggesting books based on the similarity of such elements as subjects and covers [5]. However, CB suffers from a bias toward items with similar contents and the inability to provide valuable recommendations when it lacks sufficient information. Collaborative filtering determines which items to recommend by estimating the appropriateness of unevaluated items with the behavioral histories of users. Various studies have addressed book recommendation systems with CF, including proposing similar items based on such behavior history as purchases and evaluations [6], modeling preferences based on user access logs and making recommendations based on other similar users [7], and combining CF systems on each of the book and author characteristics [8]. One drawback of the CF approach is that it cannot provide valuable recommendations when sufficient data are unavailable, such as new items or new users. Therefore, many studies on hybrid systems have combined CB and CF to complement their respective shortcomings [9, 10, 11].

Some investigations of recommender systems improve the accuracy of their suggestions by considering the emotions that items illicit in users. A study on movie recommendations [12] addressed both a film's characteristics and the emotions contained in reviews and summaries to determine suggestions and consistently improved recommendation accuracy by considering the emotions evoked by movies. In book recommendation studies, several studies improved the accuracy

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of book retrieval and recommendation by focusing on the emotional words in book reviews [13, 14].

Our study differs from previous studies using CB considering the emotions evoked by books in readers and can easily be used even by non-readers based on query contents comprised of their own interests.

III. Method

An overview of our proposed method is shown in Fig. 1. Book recommendations are determined by the calculated scores of each book based on the similarity of the contents and the sentiment between a tweet set on the content in which a user has interest and a review set about the book.

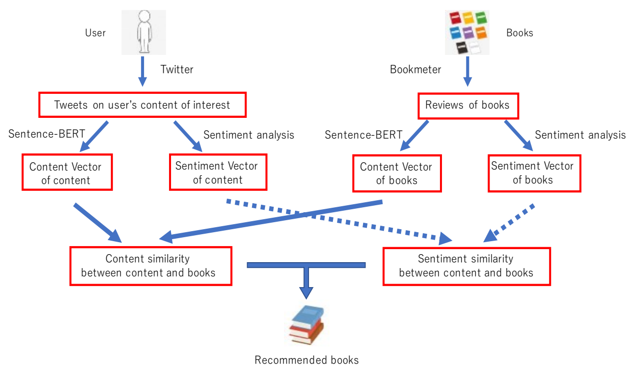

Fig. 1. Overview of proposed method.

A. Getting Book Reviews and Tweets

Reviews on books were acquired using Bookmeter, one of the largest book review sites in Japan. To calculate a book's content and sentiment vectors from a set of book reviews, the acquired reviews must include its contents and emotions. Therefore, reviews with fewer than 120 characters, half of Bookmeter's character limit, were excluded. Books with fewer than 200 reviews were also excluded to prevent bias caused by an insufficient number.

We acquired tweets on content a user is interested in using Twitter API. To calculate the content and sentiment vectors from a set of tweets, the acquired reviews must include its contents and emotions. Therefore, tweets with fewer than 70 characters, half of Twitter's character limit, were excluded from the acquired tweets. In addition, content with fewer than 100 tweets was excluded to prevent bias caused by an insufficient number.

B. Content Similarity

The content vector of each book and content were determined by averaging all the vectors of that content or book calculated by Sentence-BERT, which represented documents as a 768-dimensional vector. We used Japanese pre-trained Sentence-BERT model, which was published by Isamu Sonobe from NS Solutions Corporation. Its evaluation showed the highest performance using the 5-nearest neighbors algorithm in a study that compared the Sentence-BERT performance with six other Sentence-BERT models based on existing Japanese BERT models [15].

We calculated the content similarity between the content users are interested in and the book by the cosine similarity of the content vectors of both.

C. Sentiment Similarity

Each book and the content's sentiment vectors were determined by averaging all the vectors whose content or book were calculated with ML-Ask, which represented the documents as a 10-dimensional sentiment vector that consisted of joy, anger, sadness, fear, shame, fondness, dislike, excitement, relief, and surprise.

As shown in Table 1, for the *King Gnu* (a popular Japanese rock band) query, the emotions of "joy" and "excitement" were strong due to the effect of songs like *boy* that encouraged listeners to be brave and face their problems. For query about *Joker* (a dark movie in 2019), "dislike" was very strong, and "joy" was very weak due to not only a movie contents itself but also a stabbing incident in Japan that the killer stated that he admired the *Joker*. *Bump of Chicken* is a popular Japanese rock band whose songs often include emotions of nostalgia and sentimental. For this query, "sadness" and "fondness" were strong, and "dislike" was low due to the effect of such songs as *Nanairo* and *Acacia*, which remind listeners of nostalgia and convey a positive message about overcoming a painful past. The results in Table 1 show that the sentiment vectors using ML-Ask reflected the emotions and impressions given by the query content.

The sentiment similarity between the user content of interest and books was calculated by the cosine similarity of each sentiment vector.

TABLE I. EXAMPLES OF SENTIMENT VECTORS OF USER CONTENT OF INTEREST

	King Gnu	Joker	Bump of Chicken
Joy	2.67	0.54	2.02
Anger	-0.72	-0.42	-1.06
Sadness	0.19	-0.13	0.94
Fear	-0.58	-0.62	-1.06
Shame	-0.86	-0.91	-0.86
Fondness	0.19	0.44	1.10
Dislike	0.19	2.68	0.01
Excitement	0.33	-0.42	0.11
Relief	-0.77	-0.52	-0.65
Surprise	-0.63	-0.62	-0.55

D. Score between User Content of Interest and Each Book

We define score $S(c,b_i)$ between the user content of interest c and each book b_i as follows:

$$S(c,b_i) = \alpha \cdot content\_sim(c,b_i) + (1-\alpha) \cdot sentiment\_sim(c,b_i), \quad (1)$$

where α is a variable between 0 to 1, $content\_sim(c,b_i)$ is a cosine similarity between the content vectors of c and b_i, and $sentiment(c,b_i)$ is a cosine similarity between the sentiment vectors of c and b_i.

IV. PRELIMINARY EXPERIMENT

We conducted a preliminary experiment order to determine parameter α in (1). In this experiment, 10 university students aged 21-22 rated each book on a scale of one to five concerning the following statement: "The item recommended to me matches my interests."

In the preliminary experiment results (Fig. 2), $\alpha = 0$ was the evaluation for the result with just the sentiment vector using ML-Ask, and $\alpha = 1$ is the evaluation for the result with just the content vector using Sentence-BERT. The proposed method performance was always better than only using sentiment analysis by ML-Ask and the distributed representation by Sentence-BERT, and the proposed method showed its highest performance at $\alpha = 0.4$. For this reason, we decided $\alpha = 0.4$ in (1).

Table 2 shows examples of the results of the proposed method and previous book recommendation systems. When the query was *King Gnu*, the first, second, and fourth books (*Haikyu!!* Series, which contained elements such as effort and commitment to one's dreams) reflected a song called *boy*, whose theme was courage and the power of assertion. The fifth book, which emphasized affection for friends/family and human connections, reflected the query represented by a song named *Itizu*, which evokes in listeners a pure, single-minded love. The third book, which focused on the musical genius of characters with a wide range of musical expressions, reflected many different musical genres like *King Gnu*. Thus, Table 2 shows that our proposed method recommended books based on a query's content and the emotions and impressions evoked in users.

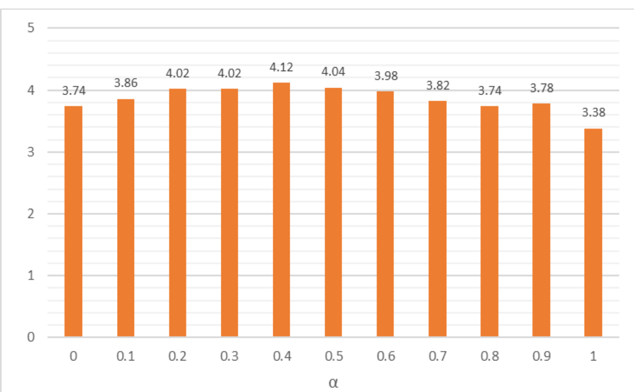

Fig. 2. Results of preliminary experiment.

V. EXPERIMENTS

Previous book recommendation systems fail to provide satisfactory results when the user's content of interest is employed as queries. For example, Table 2 shows the results with the previous systems when *King Gnu* was used as a query. The results with the proposed method addressed the band's contents, their music, and the emotions and impression evoked in users. Since the Amazon and Bookmeter results only recommended music scores of their songs and weekly and music magazines that they are on the cover, evaluating the performance of the proposed method by comparing it with the results of previous systems with the same query was complicated. Therefore, we evaluated its performance by comparing it with the results of a previous system that used books as queries that reflected user interests. As a previous book recommendation system, we used an Amazon recommendation called "Popular products inspired by this item."

TABLE II. RECOMMENDATION RESULTS WITH *KING GNU* QUERY

Proposed method	Amazon (1/12/2022)	Bookmeter (1/12/2022)
Haikyu!! Vol. 36	Band score piece BP2395 *Itizu*	PIA MUSIC COMPLEX(PMC) Vol.16
Haikyu!! Vol. 37	Piano piece for easy playing PPE52 *Sakayume*	PIA MUSIC COMPLEX(PMC) Vol.17
Honeybees and Distant Thunder	Piano piece for easy playing PPE51 *Itizu*	Piano Piece PP1697 *Sanmon Syousetsu*
Haikyu!! Vol. 33	Piano piece PP1836 *Sakayume*	SWITCH Vol.39 No.2
March comes in like a *lion Vol.* 14	Piano piece PP1835 *Itizu*	AERA 2020-2/3 issue

A. Experiment Setup

We experimentally evaluated the proposed and comparison methods with 11 university students aged 21-22. The dataset for the proposed method consisted of 233,822 reviews of 2,633 books obtained from Bookmeter's monthly book rankings from January 2013 to October 2021 in the following four categories: hardcovers, paperbacks, comics, and light novels. In the proposed method's evaluation experiment, we evaluated the top five books determined by each user's content of interest as a query. We also evaluated the top five books of Amazon's recommendations that were determined using each user's books of interest as a query.

We evaluated the performance of each method by revising the ResQue questionnaire [16], which is a widely used evaluation framework for recommender systems. Table 3 lists the evaluation items and questions. Concerning the questionnaire items, excluding UI-related and redundant items, six items (Q1~Q3, Q6~Q8) came from ResQue, and we added two items (Q4, Q5) to the performance evaluation of the proposed method.

Concerning the evaluation items, Q1~Q5 are 5-point ratings for each recommended item, and Q6~Q8 are 5-point ratings for the method based on all the recommended items.

B. Results and Discussion

The experiment's results (Fig. 3) shows that the proposed method outperformed the comparison method in every items except Diversity (Q6). Intention (Q3), Content reflection (Q4), Sentiment reflection (Q5), and Satisfaction (Q8) were significantly superior to the comparison method.

For evaluations of the proposed method, here are examples of some responses from participants: "I felt that the recommendation was made based on emotions and elements that are difficult to verbalize as keywords" and "It accurately found books that were related to my interests." Both comments suggest that the results using the proposed method reflect the content of users' interest and each book as well as the emotions and impressions invoked them.

We also obtained several complaints from users that "Books in the same series appeared in the results" for the proposed method's Diversity, which was the only evaluation item that was lower than the performance of the comparison method. This result can probably be attributed to the fact that book reviews and reviewers tend to be similar in the same series.

Each evaluation item, including Diversity, was improved by considering such book elements as title and author when deciding which books to recommend.

TABLE III. EVALUATION ITEMS AND EACH QUESTION

	Item	Question
Q1	Accuracy	The item recommended to me matches my interests.
Q2	Novelty	The item recommended to me is novel.
Q3	Intention	I would read the item recommended, given the opportunity.
Q4	Content reflection	The item recommended to me reflects the query's content.
Q5	Sentiment reflection	The item recommended to me reflects my query's impression.
Q6	Diversity	The items recommended to me are diverse.
Q7	Usefulness	The recommender helped me find the ideal item
Q8	Satisfaction	I am satisfied with this recommender.

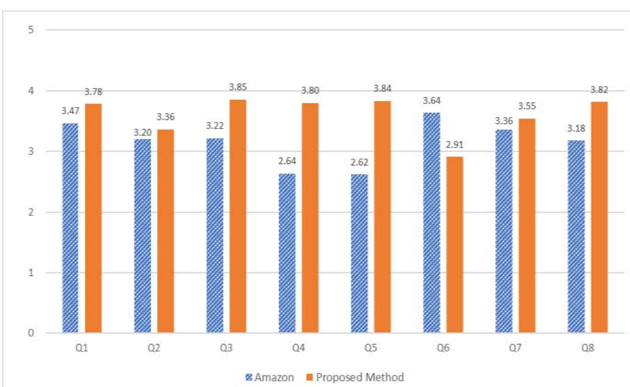

Fig. 3. Experiment results.

VI. CONCLUSIONS

We developed a book recommendation system whose results reflect the interests of both readers and non-readers. We proposed a method that identified recommended books based on the similarity between the contents and emotions that are included in the content of the users' interest and books. We experimentally confirmed our proposed method's effectiveness by comparing its results with Amazon's recommendation results.

In the future, we will improve the usability of our proposed method by reviewing it and the conditions of getting tweets related to user content of interest to increase its flexibility.

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