Embedding-based Neural Network Models for Book Recommendation in University Libraries

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Abstract. Recommendation systems have been widely used in various commercial applications for predicting the rating a user may give to an item. To encourage students to read more books, personalized book recommendation systems are of great interest in university libraries. Because university libraries do not ask students to rate books that they borrowed, book reviews and ratings are not available. Without book ratings, implementing personalized book recommendation systems in libraries is a challenging problem. In this study, we propose a library book recommendation system that uses embedding based neural network models. The system uses book metadata and user information as input features and deep learning models were used to create embeddings of the features. A multi-class classification model and a multi-label classification model were trained and soft voting was used to integrate the final outcomes. The performance of the models was evaluated by 72 university students and the multi-class classification model received 3.4 average points whereas the multi-label classification model scored 3.0 average points in the 5-Point Likert Scale.

Keywords: recommendation system · book recommendation · deep neural networks · university libraries

1 Introduction

University libraries keep many books to serve students with various reading interests. Although this broadened the range of book choices for students, it became even difficult for them to choose books that they may like to read. This also imposes burden to librarians for book recommendation and they became less confident about recommending books to students. Capturing the characteristics of the students is a key of book recommendation service and this requires us to implement personalized book recommendation systems that rely on big library

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data and advanced machine learning methods. To our knowledge, many libraries still rely on the manual labor of librarians to recommend books, which may be less effective and efficient[2,7,8].

Some university libraries have implemented personalized book recommendation systems that incorporate the book rating component. As an example, Seoul National University implemented a system called 'S-Curation' that recommend books to its users based on their borrowed records and keywords that they previously used to search for books. The system requires students to rate the recommended books based on their preference and the rating data are utilized to recommend further books to them. Although asking students to rate each of the recommended books is an effective way of improving system's performance, this requires significant amount of user involvement. This kind of system may not be practical in most university libraries because it largely depends on users' active involvement and may require a considerable time to collect enough user feedbacks as to provide reliable service. Therefore, personalized book recommendation systems without the rating component may be a more practical option that is affordable and easy to be adopted by many university libraries.

In this paper, we propose personalized book recommendation models that only utilize book metadata and user data. By applying embedding-based deep learning methods to the data, we aim to implement effective models that perform well when rating data are not available. This paper is divided into the following parts. In the Related Work, we discuss various recommendation systems followed by Methods, where we propose embedding-based neural network models. In the Results, we evaluate the proposed methods and lastly, we conclude and discuss our future work.

2 Related Works

Recommendation systems have been studied with various methods such as collaborative filtering, hybrid filtering, machine learning, and deep learning. Collaborative filtering is a method that recommends items to users by collecting their preferences through ratings[3,6]. Hybrid filtering is a combination of collaborative filtering and content-based filtering, which reflects both the characteristics of the books and the users[4,12]. Similarity based machine learning approaches[13] and embedding-based deep learning have been applied in recommendation systems as well[9,10].

Studies of recommendation systems for libraries have also used the abovementioned methods. Fu et al. proposed a book recommendation system through user-based collaborative filtering methods. They concentrated on the concept that university library users have diverse interests depending on what they learn during the semester. They utilized users' borrowed records, users' information, and book metadata, and suggested that local recommendations, which considers the students' department shows better performance than global recommendation[3]. Liu et al. employed SVD++, model-based collaborative filtering, to develop a university library book recommendation system. As it is challenging for libraries to achieve ratings from users, they used the book loan duration as the rating value[6]. By utilizing hybrid filtering, Tian et al. designed a personalized book recommendation system for university students based on the users' borrowing records, users' information, and book metadata. They showed the hybrid filtering method's superiority among individual collaborative filtering and content-based filtering[12]. Tsuji et al. applied SVM for book recommendations. Their models input utilized several similarity values made from borrowed records, book titles, and categories of the books[13]. Rahutomo et al. proposed an embedding model to produce book recommendations using content filtering. They generated embeddings from the books' original attributes namely book title, author, publisher, and demographic information of the students of Binus University and trained these embeddings through deep learning[10]. Covington et al. suggested an embedding model for the recommendation system of a large video corpus. They conducted a two-stage neural network model using the user's video search history, demographical information and the video's embeddings. This method outperformed the previous matrix factorization approaches that were used at Youtube[9].

As previously mentioned, rating-based models require extensive user responses. Although these user feedbacks play an important role in recommendation models, most university libraries do not have them. On the other hand, recommendation models that do not depend on ratings are a better option that is easy to adopt and thus practical. The key to this kind of models is the effective utilization and representation of book and user data. Therefore, we aim to use embedding methods for the representation of library data and propose embedding-based recommendation models.

3 Data and Methods

3.1 Data

We acquired the data of book borrowing history from the Sungkyunkwan University (SKKU) library. The data are about all the undergraduate students' book borrowing history from 2015 to 2019 that includes 34,335 students, 206,089 books, which cover the entire types of genre, and 662,402 loan records. The following data preprocessing and feature selection were used. First, from the downloaded book list, we removed items such as cds or dvds, the encyclopedia and theses. Likewise, we excluded books that had been designated for specific purpose and being recommended to all the students since these books do not necessarily reflect individuals' reading preferences. For the concern of information privacy, all the students were anonymized and only their affiliation at the college level and book borrowing history data were used. Book metadata such as *publish year, pages, genre, title,* and *book cover image* were used. The following Table 1 describes the features we utilized for analysis.

Table 1. List of Features

Feature	Description
Book Title	book's title
Book Genre	book's genre
Book Cover	book's cover image
Book Year	book's publish date
Book Page	book's number of pages
User Affiliation	student's associated college

3.2 Methods

Book recommendation models were implemented in two different ways by adopting different output values as the outcomes. The first model is a multi-class prediction model that predicts the last book a user borrowed and thus recommends one book to the user while the second model is a multi-label prediction model that predicts multiple books to the user. In the first model, for each user, we select 85 books (i.e., median value) and use the first 84 books as input and predict the last (i.e., the 85th) book. For example, if a student borrowed 100 books, the first 85 books would be selected and the reaming 15 books would be disposed. The second model, on the other hand, uses a maximum of 84 books as input and predict the remaining book. For example, if a student borrowed 100 books, the first 84 books would be used as input, and the remaining 16 books would be used as outcomes. We implemented two deep learning models that share the same model architecture but have different output layers. The following Fig. 1 displays the proposed model architecture.

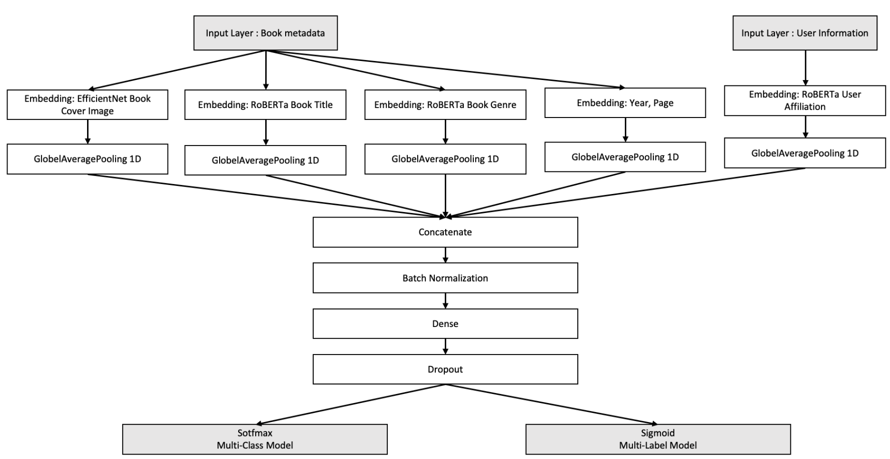


Fig. 1. The Proposed Model Architecture for Multi-class and Multi-label Model

The embeddings of the borrowed books and student's information pass through average-pooling layers and concatenated into a vector. This vector consists of the entire information of the inputs. The embeddings of books include the publish year, page, cover image, genre, and title of the books that were loaned and the student's school. The concatenated vector goes through the batch normalization layers, dropout layers, and dense layers with *relu* or *tanh* activation in sequence. In terms of the output layer, the multi-class classification's output layer uses the *softmax* activation while the multi-label classification's output layer uses the *sigmoid* activation. In turn, they predict a value and multiple values, respectively.

Embeddings lie at the heart of the proposed methods. Embeddings allow sparse data to increase the density of the data by projecting it into a vector space with a relatively lower dimension, making it more efficient[14]. For this reason, we implemented embeddings to compile the diverse types of data. Three of the embedding layers were constructed using XLM-RoBERTa(Cross-Lingual Robustly Optimized BERT pretraining approach). This includes the title of the book, the genre of the book, and the school of the student. Particularly because the titles of the books included Korean, English, and Chinese, we used XLM-RoBERTa to formulate the embeddings, which is a transformer-based multilingual masked language model that is pre-trained on a text in 100 languages that include the abovementioned languages mentioned[1]. The fourth embedding layer was constructed with the cover images of each book. We utilized EfficientNet to construct the image embeddings. Through feature extraction by the pretrained EfficientNet, which applies a compound scaling method that considers three scaling methods in balance: depth scaling, width scaling, and resolution scaling, we were able to create meaningful embedding values[11]. The last layer was a combination of the numerical values. This layer contained three versions of the books publish year and pages respectively, including the square, root, and original value. Lastly, all of these embeddings were normalized by a MinMaxScaler to coordinate the range of the data.

4 Results

4.1 Model Implementation

As the multi-class prediction model's output layer uses the softmax activation, each student is assigned with only one of the 206089 books. The multi-label prediction model uses the sigmoid activation, where each student is assigned with multiple books. These models were evaluated by accuracy. To improve models' performance, we trained multiple models by fine-tuning hyperparameters such as the learning rate, the momentum, and the optimizer. After fine-tuning the models, we constructed an ensemble model with soft voting. The following Table 2 shows the accuracy for the final models built through soft voting.

As shown in Table 2, the multi-class prediction model performed better than the multi-label prediction model. The former model's training objective concentrated on one candidate value, whereas the latter model's training focus is

Table 2. Accuracy for the Final Models

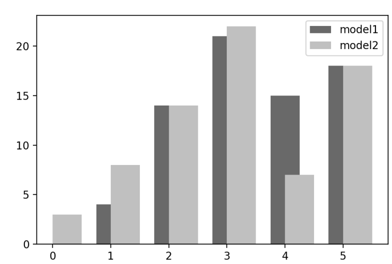
	multi-class model	multi-label model
accuracy	0.998	0.546

distracted to several candidate values, making it more challenging to predict outcomes.

4.2 User-Centered Evaluation

We recruited 72 SKKU undergraduate students to evaluate the two models. For equivalent comparison, each model selected five books with high classification probabilities, resulting in a total of ten books recommendation to each student. The students were asked to evaluate the performance of the models by rate each of the ten recommended books using a 5-point Likert scale. Each model's five ratings given by a user were averaged and treated as the final score that the user give to the model. The multi-class classification model got a higher satisfaction rating than the multi-label classification model. The multi-class model scored 3.4 average points ($sd = 1.21$) out of 5 points while the latter, the multi-label model, received 3.0 average points ($sd = 1.46$) out of 5 points. The distribution of the scores is shown in Figure 2.

Fig. 2. Distribution of the User Evaluation Score



Interviews were also conducted with the evaluation, where some students responded that they had high reliability with the models because they received recommendations of books they had borrowed from outside the school library. Other students responded that the list of the recommended books exactly matched their preference as it contained books they personally owned. Whilst most responses are positive, limitations of the models were also pointed out. Some students mentioned that the recommendations reflect their fields of study well but are not good at capturing their everyday reading patterns. This feedback is plausible as we did not use personal information of individuals for privacy reasons. By making use of more individual-level data, recommendations may be more tailored to each individual.

5 Conclusions and Future work

This study employs deep neural network techniques to propose book recommendation models using book metadata and user data while the rating data is not available. Two types of models: the multi-class classification model and the multi-label classification model were proposed and evaluated by university students. The multi-class classification model performed better than the multi-label classification model (i.e., 3.4 vs. 3.0 in the 5-Point Likert Scale). While most recommendation systems rely on users' ratings on items, the proposed models do not rely on users' book ratings given that ratings are generally not available in the university libraries. Therefore, the proposed model may have higher feasibility in the real-world setting.

For the future work, we plan to improve the models using more borrowing records from an extended period of time. In addition, we plan to add a filtering option for students to narrow down the recommendations based on their specific information needs and cluster books based on their similarities. We believe these approaches would increase user's experience and satisfaction.

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