J Inf Process Syst,
http://dx.doi.org/10.3745/JIPS

ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

The Method for Generating Recommended Candidates through Prediction of Multi-Criteria Ratings using CNN-BiLSTM

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Abstract

To improve the accuracy of the recommendation system, research on a multi-criteria recommendation system has been conducted, but it is very complicated to extract preferred features of users and items from data. To this end, subjective indicators, which indicate a user's priorities for personalized recommendations should be derived. In this paper, we propose a method for generating recommendation candidates by predicting multi-criteria ratings from reviews and using them to derive user's priorities. Using a deep learning model based on Convolutional Neural Network(CNN)-Bidirectional Long Short-Term Memory(BiLSTM), multi-criteria prediction ratings are derived from reviews. These ratings are then aggregated to form a linear regression model to predict the overall rating. This model not only predicts the overall rating, but also uses the training weights from the layers of the model as the user's priority. Based on this, a new score matrix for recommendation is derived by calculating the similarity between the user and the item according to the criteria, and an item suitable for the user is proposed. The experiment was conducted by collecting the actual 'TripAdvisor' dataset. For performance evaluation, it was compared with a general recommendation system based on Singular Value Decomposition, and it was confirmed that the performance was high.

Keywords

Recommendation System, Multi-Criteria recommendation system, Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM)

1. Introduction

Recommendation systems have already been actively applied, and the datasets used in the research related to them have changed as user data accumulation has become easier due to the activation of smart devices. In previous recommendation systems, recommendations were based on a user's item rating, and content-based, collaborative, and hybrid collaborative filtering methods were mainly used [1, 2, 3]. Content-based filtering is a method in which a user recommends another item with properties similar to the corresponding item when a user prefers a specific item, and collaborative filtering is a method in which other users prefer items that are similar to the user's preference information. The hybrid method overcomes the shortcomings of the other recommendation systems by combining several of them.

Manuscript received Month 06, 20XX; accepted Month 06, 20XX.
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Recently, research on various types of recommendation systems has been developed to increase the accuracy of personalized recommendation prediction by linking more types of data to users or items. Recommendations can be obtained by acquiring additional information to understand the user's preferences, such as the user's post-purchase reviews, social relationships through SNS, and behavior log until purchase [4, 5]. These methods help predict the user's preferences, but it is difficult to understand the user's purchasing decision factors. To this end, research is being conducted on a multi-criteria recommendation system that integrates ratings according to attributes of an item into one rating [6, 7]. Since it can reflect the priority of each user's item decision, it can provide higher prediction accuracy than the traditional recommendation systems using a single rating [6, 8].

Multi-criteria recommendation systems generally require a lot of rating input from the user, which can be cumbersome for the user. In addition, the rating is a numerical value that summarizes the satisfaction of the user, and cannot explain the reason for the user's evaluation. To compensate for this, studies using explicit data such as ratings and implicit data such as reviews are increasing, and show higher prediction accuracy [9, 10, 11].

It is possible to improve the problem of not reflecting the noise or detailed characteristics of data generated by evaluating only with explicit data. However, even if implicit data is used, the user's purchasing decision factor is not necessarily included in the data. Since reviews are evaluations of purchases of products, it is possible to see the frequent words of the reviews and confirm the sentimental evaluation of the items, but the priority criteria are not.

This paper proposes a method for generating new recommendation candidates by grasping user purchase decision factors using reviews in a multi-criteria recommendation system. It predicts ratings by multi-criteria for reviews and predicts user purchase decision priority. Through deep learning from the user's reviews, ratings by multi-criteria are inferred, and in addition to these results, learning weights about the effects of multi-criteria ratings on the overall rating are extracted. This result becomes the user's purchasing decision factor and reflects this to derive the final rating for the user and item. The result is rating scores that are optimized for tendencies of users purchasing items.

The composition of this paper is as follows: Section 2 describes the research on the multi-criteria recommendation system and rating prediction from review data. Section 3 describes an overview of the new recommendation candidate methods proposed in this paper, and Section 4 describes in detail each model of this recommendation system. Section 5 compares and analyzes the existing research based on the suggestions presented in them. Finally, Section 6 presents conclusions and suggestions for future studies.

2. Related works

2.1 Multi-criteria recommendation system

Multi-criteria recommendation systems have been studied extensively in the field of recommendation, and they are a method used to deal with uncertainty in the decision-making process. The difference between the existing single-criteria rating system and the multi-criteria rating system is that the latter has more information about the user or item [12]. Since the overall rating does not know why the user-selected such a rating, it is possible to supplement the difficulty of knowing the exact user preference from the overall rating by adding a rating for multi-criteria [8]. Where R is the overall possible rating and c is the number of multi-criteria, the overall rating R is composed of ratings, as shown in (1) for the user-item rating in multi-criteria recommendation systems [12].

$$R: Users \times Items \rightarrow R_0 + R_1 + \cdots + R_c \tag{1}$$

The previous multi-criteria recommendation related works mainly proceed through the process of defining criteria and calculating ratings through data statistics or data mining [13]. Although the validity of criteria has been shown through past studies, recently, the process of automatically extracting ratings with real-time performance has been required, because the data have become larger and both implicit data and explicit data have been used together. Alotaibi [10] proposed an improved recommendation method using multi-criteria ratings employing social networks as implicit data. Ebadi et al. [9] proposed a highly accurate hotel recommendation system, implemented in various layers. Using a multi-aspect rating system and benefitting from large-scale data of different types, the recommendation system suggests hotels that are personalized and tailored for the given user.

Although the accuracy of recommendations has increased due to the use of implicit data, the direction of research is changing due to the nature of the recently collected data, which requires a change to the learning base. Nour et al. [14] proposed a novel deep multi-criteria collaborative filtering model for recommendation systems and effectively predicted the criteria rating and overall rating based on deep learning. Mohammed et al. [15] proposed a neural network approach for improving the accuracy of multi-criteria recommendation systems. Compared to single-criteria rating systems, it was confirmed that the performance was much improved.

However, studies conducted to date are not sufficient to extract complex features between users and items according to multi-criteria. In particular, predicting a user's rating for multi-criteria indicates a user's preference for items by multi-criteria, but a supplementary method is needed because it is not a priority that the user thinks. Therefore, this study added a part that extracts the features of the user's priority.

2.2 Prediction of rating using review data

To improve the accuracy of recommendation systems, not only explicit data but also implicit data are being used. Users' intentions or sentiments can be extracted using text data, such as product review data, SNS data, audio data, and video data. Among these, review data are the most implicit data that are most frequently used in the recommendation field. Review data are used in recommendation systems to re-adjust ratings or make new predictions using sentiment analysis.

In particular, many studies have been conducted to improve the accuracy of recommendations by grasping the intentions or sentiments of users by linking the ratings with reviews [16]. Among them, when proceeding based on sentiment, text mining based on Natural Language Processing (NLP) has been used. The methods of determining the polarity are Point-wise Mutual Information (PMI) and Semantic Orientation from PMI(SO-PMI), and the polarity can be determined using a preset set of positive and negative words. De Albornoz et al. [17] conducted a study evaluating the overall sensitivity of the product by extracting the product characteristics from the review contents and assigning weights to each product feature. In Zhang et al. [18], through the sentiment analysis of user reviews, product features and user opinions were extracted and personalized recommendations were made according to the users' interests and product features.

However, most of the existing studies have limitations that cannot be overcome by grasping the context of the overall review content. To improve this, a neural network-based sentiment analysis method has been proposed. As various types of deep learning-based sentiment analysis are performed, a hybrid method has recently been proposed to suit the characteristics of data, because the result of combining several techniques in a hybrid format is better than that of using one technique [19]. In particular, there are many combinations of Convolutional Neural Network (CNN), which can automatically extract features from data, and Long Short-Term Memory (LSTM), which can grasp data according to the overall time sequence. Based on a movie review, Park et al. [20] confirmed that the performance of a model using CNN-LSTM in combination with the traditional single learning technique (CNN, LSTM) was the highest. Yenter et al. [21] described a novel approach to sentiment analysis using a combined kernel from multiple branches of CNN with LSTM layers. Wang et al. [22] further proposed the deep neural network (DNN) architecture based on CNN-LSTM-attention by adding more attention and confirmed that it showed better performance compared to those in previous studies. An et al. [23] proposed a system that enables custom recommendations for tourist spots through CNN-LSTM-based sentiment analysis for reviews and classification of seasons and weather. In recent years, studies using bidirectional learning using both previous and future data are being conducted [24]. Based on previous research, this paper proceeds with a multi-criteria rating prediction based on CNN-BiLSTM.

3. System overview

This paper is about the method of generating recommendation candidates based on user priority in multi-criteria recommendation systems. The goal is to predict the ratings by criteria for items through reviews and to obtain the weights by grasping user-defined criteria priorities. Finally, multi-criteria recommendation systems based on the proposed candidate generation method is to improve the satisfaction of personalized recommendation by calculating the new rating. It is significant in that it reflects different priorities for the multi-criteria of sophisticated users.

The proposed multi-criteria recommendation system proceeds as shown in Fig. 1. The data used are reviews and ratings that the user has made for the items, and pre-processing such as stopword processing and unification of the verb tense is in progress.

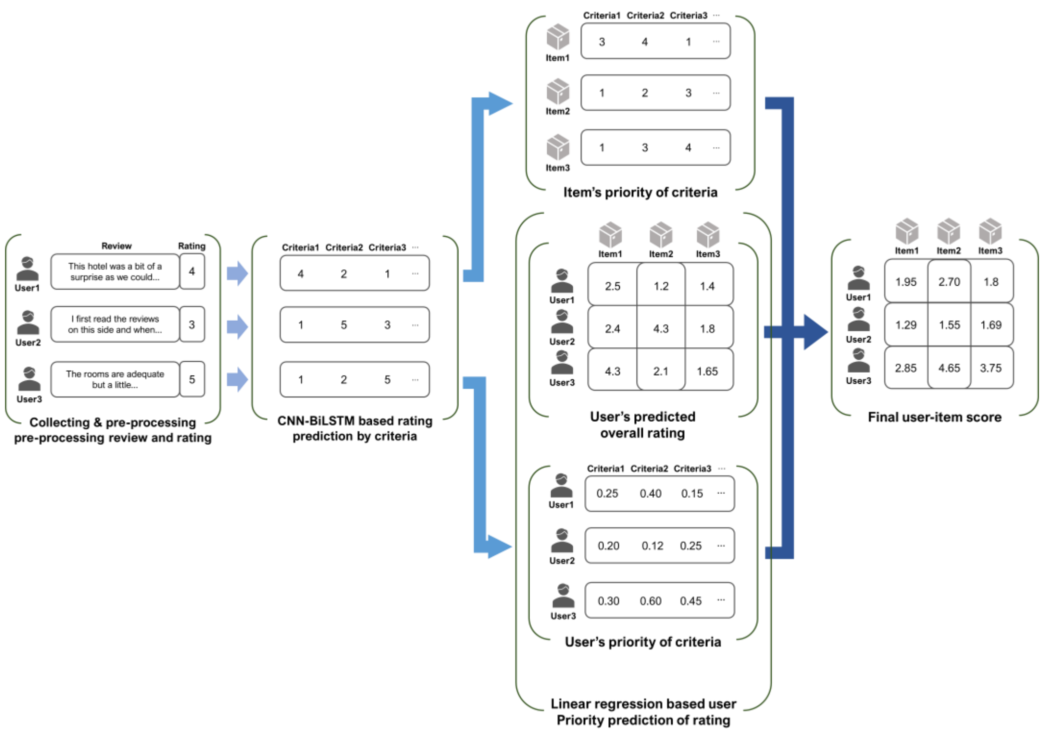

Fig. 1. System overview.

To generate a candidate for the recommendation, it can be subdivided into two main steps. First, it is a process of deriving a rating for criteria of review through context identification and using it to derive the priority of items and users. The item priority is derived by synthesizing the predicted rating for each review by item. The user priority is derived by extracting weights in the process of deriving the overall rating from the ratings for each criterion predicted through linear regression. The two processes are combined to predict a new score for each user-specific item. In the last, the top-N recommendation list is provided to the user from the recommendation item candidates created by the previous process.

This paper focuses on the proposed process for generating candidates. In section 4, the detailed process is divided into CNN-BiLSTM based multi-criteria rating prediction, linear regression-based user priority prediction, and prediction of the overall rating.

4. Method of recommended item candidate generation

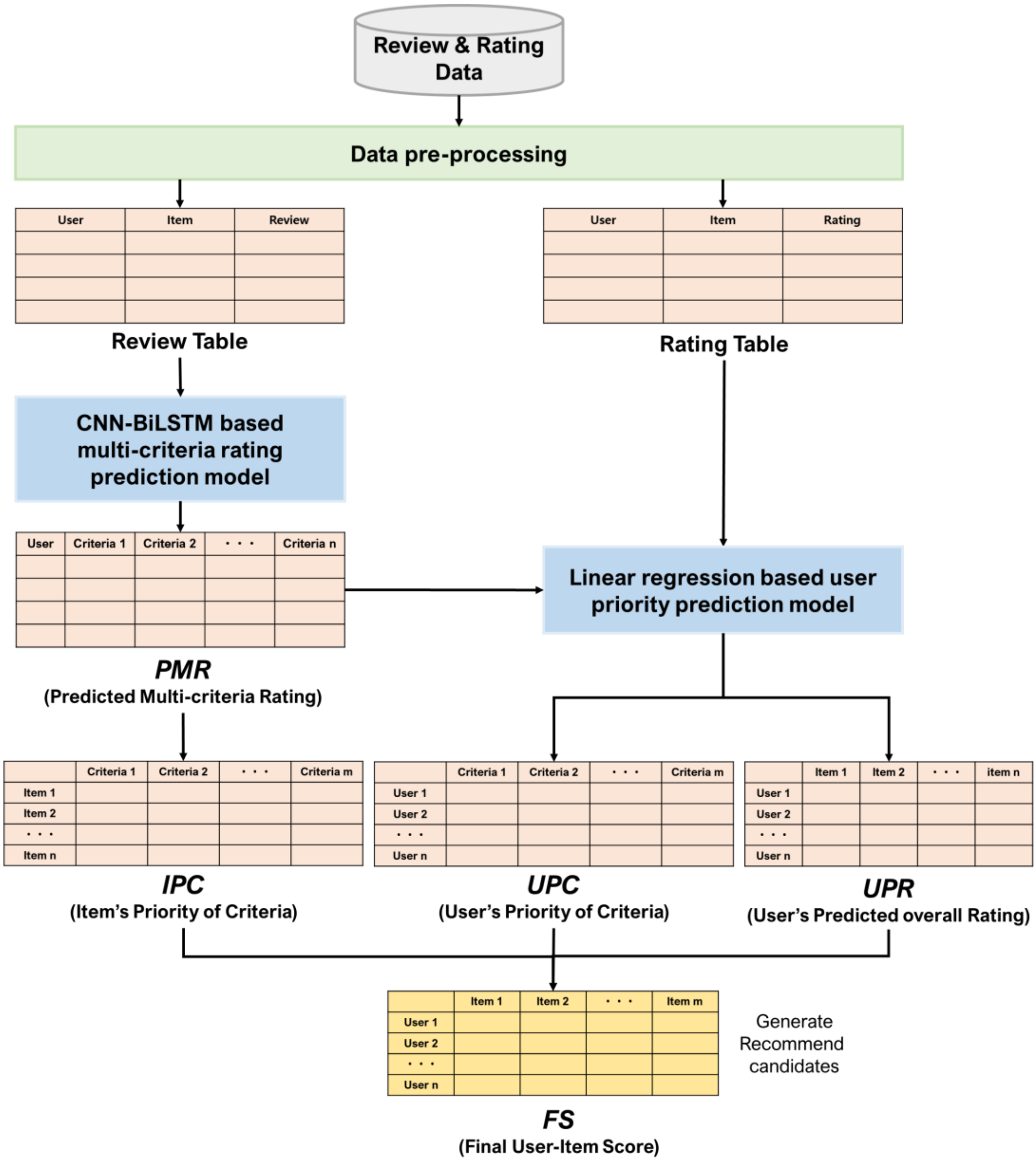

Fig. 2. Process of recommended item candidate generation.

The process of the recommended item candidate generation is shown in Fig. 2. Based on the user's reviews, the multi-criteria ratings are predicted, and then the overall rating is predicted again by synthesizing all ratings. For this, it consists of a CNN-BiLSTM based prediction model and a linear regression-based user priority prediction model.

First, a review table and rating table between the user and item are obtained through the pre-processing process of raw data. Through the CNN-BiLSTM model, a Predicted Multi-criteria Rating table (PMR) is obtained from the review data. PMR becomes the input value of the linear regression-based model along with the rating table, and through this model, the User's Priority of Criteria (UPC) and the user's predicted overall rating (UPR) are obtained. The Item's Priority of Criteria (IPC) is an average value calculated by grouping each item from PMR, and it means the item's priority of criteria. Finally, by integrating all of the UPC, UPR, and IPC, a Final user-item Score (FS) is derived for generating a recommendation candidate for the user.

4.1 CNN-BiLSTM based multi-criteria rating prediction

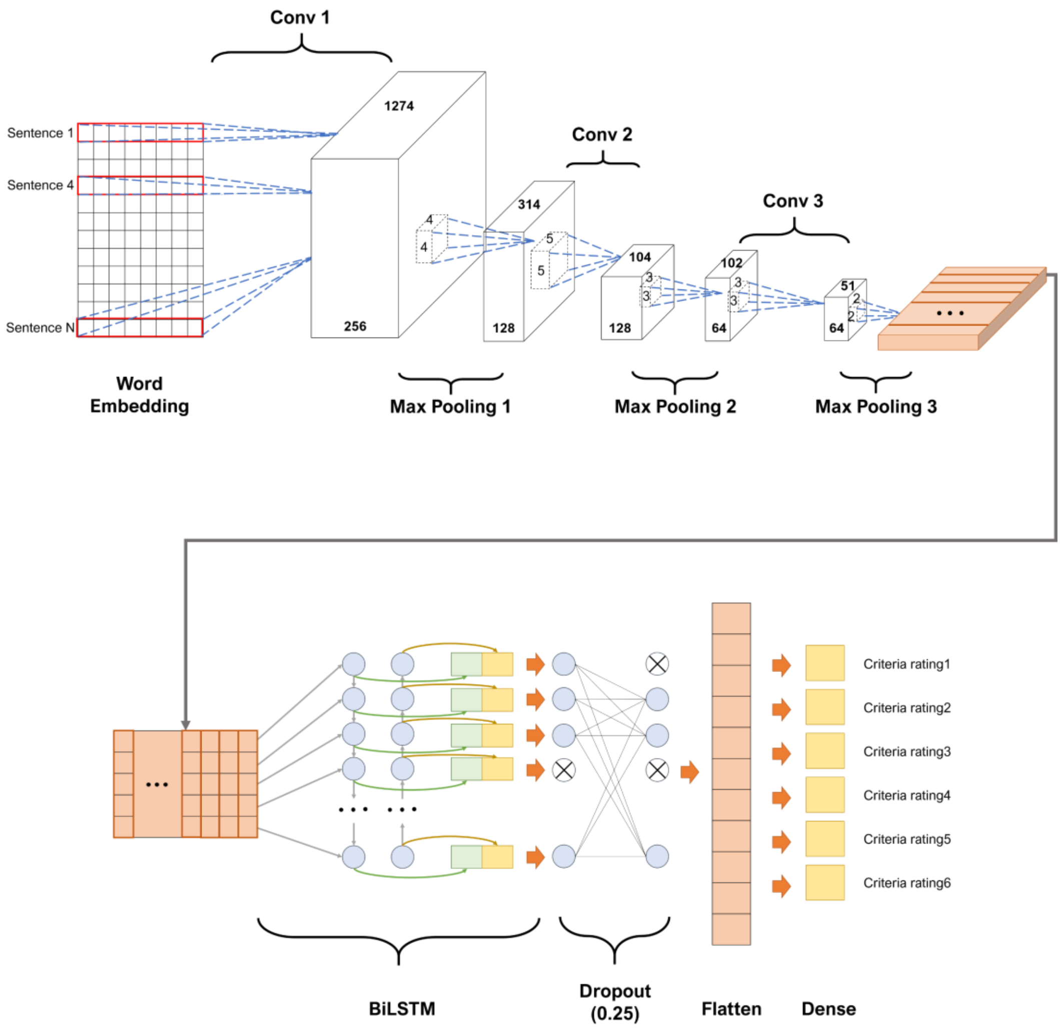

Fig. 3. Process of CNN-BiLSTM model for multi-criteria rating prediction.

The process of the CNN-BiLSTM model for multi-criteria rating prediction is shown in Fig. 3. Using the review data that the user has left on the item, supervised learning is performed based on a rating for each criterion. Through this, the prediction model, CNN-BiLSTM is used to derive prediction scores for criteria for evaluation data.

The CNN layer of this model applies three 1-dimensional convolutional layers to extract the features. The first convolution layer sets the output size as 256, the size of the kernel as 7, and the size of the max-pooling as 4. The second convolution layer sets the output size as 128, the size of the kernel as 5, and the size of the max-pooling as 3. The last convolution layer sets the output size as 64, the size of the kernel as 3, and the size of the max-pooling as 2. For the next layer of CNN, apply the BiLSTM layer that improves the accuracy by predicting the words and modeling the sequence vector. After the BiLSTM layer, the dropout layer is performed. The dropout layer is deep and when multiple networks exist, there is a problem in learning because it requires a lot of operation and a lot of time. To solve this problem, we used the dropout layer to randomly turn off the node and reduce the chance of the problem. Finally, to derive the IPC matrix's each criteria's predicted rating score, RMSprop was used as the sigmoid activation function and optimization function.

Through these processes, PMR is generated by predicting the score for criteria corresponding to the review data of each item. In PMR, grouped based on the Item ID of the Review Table to derive the average score of the predicted rating and construct the IPC.

4.2 Linear regression-based user priority prediction

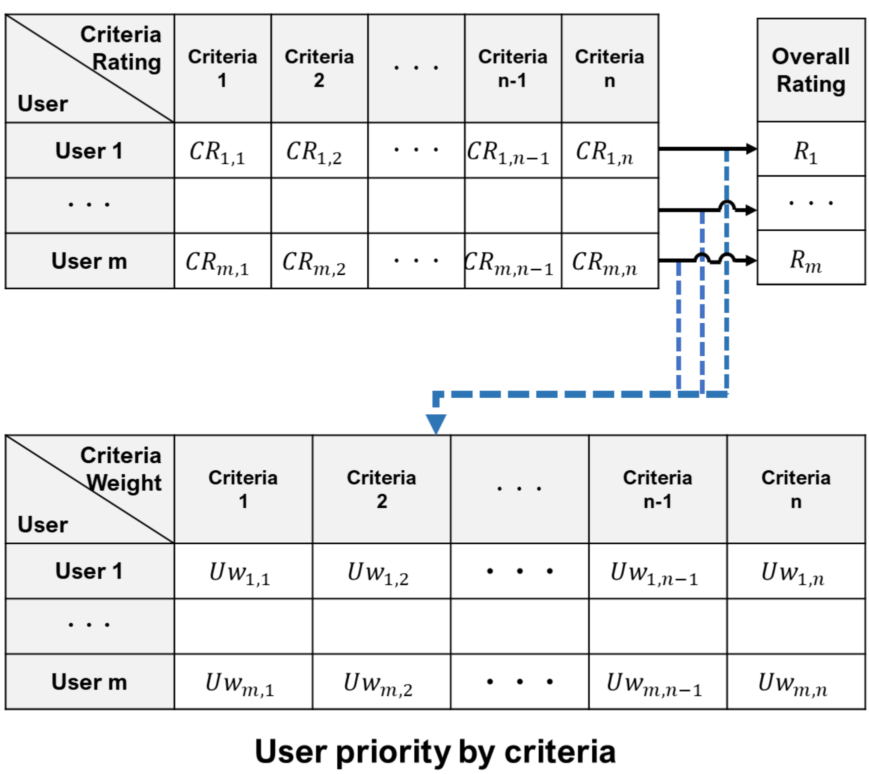

Fig. 4. Process of user priority prediction based on linear regression.

$$R_m = \sum_{n,m=1}^{n,m} CR_{m,n} Uw_{m,n} \tag{2}$$

To derive the priority that users consider important among multi-criteria, this paper uses a linear regression model consisting of one layer. if *m* is the number of users and *n* is the number of criteria, it predicts the overall rating R_m with criteria rating $CR_{m,n}$ for the criteria extracted from the previous CNN-BiLSTM model as shown in Equation (2). And it also derives the final weight $Uw_{m,n}$ for criteria generated in this process.

This model consists of only an input and an output layer and performs supervised learning. The sigmoid activation function is used in the learning method as a learning model for each user to derive the overall rating using *CR*. The sigmoid activation function is used in the output layer and serves to normalize the overall rating from learning in the input layer to a value between 0 and 1. In addition, Adam, which combines the advantages of Adagrad and RMSProp, is used as an optimizer, and it is known to perform a stable descent for optimization even when the gradient increases. Mean Squared Error(MSE) was used as the loss function, and it is excellent in numerical prediction as a method of knowing the part showing the features of the error through the method of squaring the distance difference. The dropout layer was not used in this model because it is a process for deriving weights *Uw* through a linear regression model. When learning is completed, a matrix UPC representing the user's priorities is constructed with the learning weights extracted from the layer as shown in Fig. 4, and the UPR, which is the overall rating matrix predicted by the learning result, is constructed.

4.3 Prediction of overall rating

In the previous process, IPC, UPC, and UPR matrix were derived based on the rating for each user and item. In this process, the derived matrices are aggregated to derive a Final user-item Score(FS) between users and items. First, to derive the FS, it checks whether the user has a rating for the item. This rating has the highest accuracy and reliability because it is the score the user actually rated for an item.

Next, in the case of not having a rating because it is not a previously purchased item, the similarity between users is obtained with UPR. This is calculated based on cosine, and the closer the value for the item prioritized for each criterion is, the closer it is to 1. With this, the rating of the item that the user has not experienced is replaced with the average value of the rating of a similar upper user.

Finally, for the rating of an item that cannot be obtained by the previous two methods, the similarity between the items is obtained with IPC. It is calculated based on cosine as previously obtained for the user similarity, and the closer the item's rating for each criterion is, the closer it is to 1. The rating is applied to the FS for items most similar to the items previously purchased by the user.

The final FS matrix is derived by synthesizing the above methods, and based on this, the item with the top rating to the user is recommended.

5. Experiment

5.1 Collected data

The experiment was conducted using review data on ‘TripAdvisor’ provided by Wang et al [25]. The criteria are clearly divided compared to other datasets, and are suitable because they provide ratings for criteria. The description of the entire dataset is shown in Table 1, about 12 years of data were collected from April 2002 to September 2012.

Table 1. Description of the dataset in the experiment

Type	Value
Period	12 year
Number of criteria	6
Number of reviews	1,325,447

The total number of criteria provided by 'TripAdvisor' is 8, which is the same as service, cleanliness, rooms, value, sleep quality, business service, check-in / front desk. However, in the case of business service, check-in / front desk, it was excluded because it had a missing value of 90 percent or more. As shown in Table 2, 6 criteria-specific ratings and overall ratings reflecting them were collected. Service is the user's rating for hotel services, cleanliness is the user's rating for hotel cleanliness, rooms is the user's rating for hotel rooms, location is the user's rating for hotel location, value is the user's rating for hotel prices, and sleep quality means the user's rating for the quality of sleep in a hotel.

Since the proposed model performs personalized learning, it is required to retain a minimum of individual training data, so filtering was performed only when the user left at least 13 or more reviews. At this time, among these data, there were many public IDs that many people could access, so they were identified and removed.

Table 2. Description of multi-criteria ratings in the experiment

Criteria	Description
Service	User's rating for hotel services
Cleanliness	User's rating for hotel cleanliness
Rooms	User's rating for hotel rooms
Value	User's rating for hotel prices
Sleep Quality	User's rating for the quality of sleep in a hotel
Location	User's rating for hotel location
Overall	User's overall rating for hotels

5.2 Environment

The model proposed in this paper is designed and implemented using TensorFlow and Keras. The detailed experiment environment is shown in Table 3 below.

Table 3. Experiment Environment

Type	Contents
CPU	Intel® core™ i9-9900K
GPU	Nvidia TITAN RTX
RAM	128GB
Python	3.7.8
TensorFlow	1.14.0
Keras	2.2.5

5.3 Experiment Result

To evaluate the performance of the proposed recommendation service, the proposed model is set to M1 and the comparison model, SVD-based matrix decomposition method, is set to M2. The SVD-based matrix factorization method is a method of predicting an item that has not been evaluated through matrix factorization based on the user's evaluation of the item.

In the performance evaluation, after dividing the data into 70% of the training data and 30% of the test data based on time, the training was conducted, and then the predicted recommendation list and the actual stay in the 30% data were checked. Precision, recall, and F-measure values were calculated based on Table 4. The precision is the ratio of the hotel stayed by the user among the hotels predicted as in equation (3), and recall is the ratio predicted from the hotel stayed by the user as in equation (4). Calculate f-measure as in equation (5) based on precision and recall.

Table 4. Descriptions of symbols

Actual' Predicted	Predicted	Not Predicted
Stay	a	b
Not Stay	c	d

$$Precision = \frac{a}{a+c} \tag{3}$$

$$Recall = \frac{a}{a+b} \tag{4}$$

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

When the number of recommendations is from 1 to 300, precision, recall, and f-measure values were calculated, and the results are shown in Fig. 5. Although M2 showed high performance in some parts depending on the number of recommendations, the proposed model M1 generally shows high performance. Table 5 is a table comparing the average values of precision, recall, and f-measure when the number of recommendations is from 1 to 300. Compared to the comparative model, M2, about 32.4% in the precision, about 24.5% in the recall, and 32.6% in the f-measure showed higher results.

The general recommendation model uses only explicit data, rating, whereas the proposed model is a model that suggests recommendations only with reviews, which are implicit data. Therefore, this study is meaningful in that it predicted the multi-criteria rating from reviews to grasp the user's priority, and predicted the recommendation to show better performance than the existing recommendation model.

Table 5. An average result of performance comparison

Method	Precision	Recall	F-measure
M1 : Supposed System	0.0102	0.6171	0.0191
M2 : SVD-based matrix factorization	0.0077	0.4957	0.0144

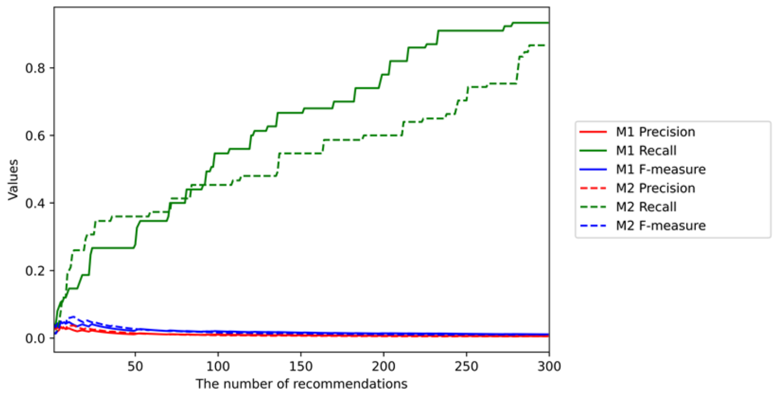

Fig. 5. Result of performance evaluation between SVD-based matrix factorization model and supposed system.

6. Conclusions

In this paper, we propose a method of generating a new recommendation candidate for users through a learning model that predicts multiple criteria rating and overall rating from reviews. Through this, it is possible to grasp the criteria that the user considers important with the review data written by the user, and provide a personalized recommendation by assigning it as a weight.

CNN-BiLSTM was used to predict the user's rating for each criterion through word embedding in the user review data, and the overall rating was predicted through a linear regression model. In this process, the weight is extracted from the layer and determined as the user's priority. The priority of an item is an average value obtained by grouping the rating for each criterion by item, and a recommendation candidate is generated by synthesizing the predicted overall rating of the user's item. For the experiment, the proposed method was applied to the user's hotel recommendation using the ‘TripAdvisor’ dataset. As a result of the experiment, it was confirmed that the performance was high on average.

This paper is meaningful in that the recommendation system uses explicit data for implicit data. In general, a recommendation system can be the best offer for such a system. This is because in most cases there is no rating for each detailed multiple criteria.

However, since most of the publicly disclosed data exclude personal information (gender, age, preference, etc.) due to information protection issues, there was a limit to subdividing users' priorities as the data used in this paper. It can also cause cold-start issues due to a lack of data when not reviewed by the user. We need other information from the user to compensate. To improve these limitations in the future, we will improve the accuracy of personal recommendations through linkage with other relevant data.

Acknowledgement

This research is supported by Ministry of Culture, Sports and Tourism (MCST) and Korea Creative Content Agency (KOCCA) in the Culture Technology (CT) Research & Development Program 2019(R2018020083).

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