ISSN 2288-4866 (Print)
ISSN 2288-4882 (Online)
https://www.jiisonline.org
J Intell Inform Syst 2023 December: 29(4): 31~49 http://dx.doi.org/10.13088/jiis.2023.29.4.031

Developing a deep learning-based recommendation model using online reviews for predicting consumer preferences: Evidence from the restaurant industry

Dongeon Kim
Department of Big Data Analytics, Graduate School, Kyung Hee University
(ponben@khu.ac.kr)

Dongsoo Jang
Department of Big Data Analytics, Graduate School, Kyung Hee University
(zsdf21@khu.ac.kr)

Jinzhe Yan
College of Business, Gachon University
(yanjz@gachon.ac.kr)

Jiaen Li
College of Business, Kwangwoon University
(jiaenlee@kw.ac.kr)

With the growth of the food-catering industry, consumer preferences and the number of dine-in restaurants are gradually increasing. Thus, personalized recommendation services are required to select a restaurant suitable for consumer preferences. Previous studies have used questionnaires and star-rating approaches, which do not effectively depict consumer preferences. Online reviews are the most essential sources of information in this regard. However, previous studies have aggregated online reviews into long documents, and traditional machine-learning methods have been applied to these to extract semantic representations; however, such approaches fail to consider the surrounding word or context. Therefore, this study proposes a novel review textual-based restaurant recommendation model (RT-RRM) that uses deep learning to effectively extract consumer preferences from online reviews. The proposed model concatenates consumer-restaurant interactions with the extracted high-level semantic representations and predicts consumer preferences accurately and effectively. Experiments on real-world datasets show that the proposed model exhibits excellent recommendation performance compared with several baseline models.

Keywords : restaurant recommender system; online review; deep learning; CNN-LSTM; text mining

Received : September 14, 2023 Revised : November 1, 2023 Accepted : November 17, 2023
Publication Type : Regular Track Corresponding Author : Jiaen Li

1. Introduction

With the recent development of information and communication technology, e-commerce websites have been providing detailed information and various options for purchase decision-making (Esmaeili et al., 2020). With a growing variety of options, consumers can face an overload problem (Idrissi & Zellou, 2020), requiring a considerable time to choose a restaurant that suits their preferences. Consumers typically search for information on multiple sources to make purchasing decisions about products and services (Nemade et al., 2017). Previous studies have reported that consumers do not purchase tourism products or services online for reasons such as lack of personalization recommendation services and high information-search cost. Personalized recommendation services support consumers in making effective purchasing decisions based on their preferences (Bobadilla et al., 2013; Nemade et al., 2017). Such personalized services allow consumers to select the best option (Lu et al., 2015). Selecting a restaurant suitable for consumer preferences is one of the purposes of personalized recommendation services (Esmaeili et al., 2020). As the food-catering industry grows, consumer preferences and the number of dine-in restaurants also increase. Consumer visits to dine-in restaurants require considering various options, such as employee services, parking facilities, choice of food, and ambience (Horng & Hsu, 2020; Loureiro et al., 2013). However, existing recommendation approaches have limitations in terms of effectively extracting consumer preferences. The widely used questionnaire (Miao et al., 2016) and star rating approach (Mahadi et al., 2018) do not dynamically extract consumer preferences.

With the rapid development of social media and Web 2.0 (Li et al., 2014), online reviews have become essential sources of information for making purchase decisions (Hlee et al., 2019; Lee et al., 2017). Saumya et al. (2020) found that 88% of consumers consider online reviews in the purchasing decision-making process. Consumer preferences can be extracted by cleaning online reviews and analyzing sentiments in this context. Therefore, natural language processing (NLP) techniques have been applied to extract consumer preferences inherent in online reviews (Abdi et al., 2019; Salehan & Kim, 2016). Many scholars support that sentiment analysis is an effective method for extracting consumer sentiment from online reviews (Salehan & Kim, 2016; Yang et al., 2020; Yoo et al., 2018). Additionally, consumers use several different words to combine sentences to express their opinions about a particular product or service. Therefore, the semantic representation approach is the most effective method for extracting consumer preferences from online reviews.

However, previous studies do not effectively use semantic representations of online reviews. Many studies have aggregated online reviews into long documents, and the topic model and term frequency-inverse document frequency (TF-IDF) method have been applied to online reviews to extract semantic representations (Hegde et al., 2018). The extracted representation feature is then combined with traditional collaborative filtering (CF) models or directly fed into regression models to predict consumer preferences. Although these approaches have improved recommendation performance, the surrounding word or context, when extracting semantic representations, is insufficiently considered. Furthermore, as online reviews continue to grow, previous approaches are limited in terms of scalability.

This study proposes a novel review text-based restaurant recommendation model (RT-RRM) that uses deep learning to effectively extract consumer preferences from online reviews. The RT-RRM model can integrate the latent factors of ratings and textual information and effectively learn the interactions between consumers and restaurants. To this end, this study first applied a convolutional neural network (CNN) and long short-term memory (LSTM) to extract consumer preferences through the semantic representation of online reviews. Online reviews are essential information sources that contain detailed consumer preference information (Li et al., 2021). As the traditional approach ignores sentence context and semantic representations, there are limitations in capturing consumer preferences (Kim et al., 2016). Especially, CNN can extract high-level semantic representations using convolutional operations in a sentence context (Onan, 2021). Second, we apply an advanced deep neural network to extract complex, nonlinear interaction representations between consumers and restaurants. This study most effectively extracted nonlinear interactions by applying multilayer perceptron (MLP), which showed excellent performance in several existing studies (He & Chua, 2017; Li et al., 2021). Finally, the proposed model learns a complex nonlinear relationship between extracted high-level interaction representations and semantic representations captured from online reviews. Based on this information, the proposed recommendation algorithm recommends the best restaurant suitable for consumer preferences. This study evaluated the performance of the proposed RT-RRM model using a dataset from Yelp.com. The experimental results demonstrate that the proposed RT-RRM model can provide highly accurate recommendations to consumers. The contributions of this study are as follows.

- An RT-RRM was proposed that concatenates consumer-restaurant interactions with the extracted high-level semantic representation in online reviews using deep learning mechanisms to predict consumer preferences accurately.
- Because the proposed model does not adopt a review aggregation approach, it may provide better recommendation accuracy and model scalability.
- Experiments on real-world datasets show that the proposed model exhibits excellent recommendation performance compared to several baseline models.

The remainder of this paper is organized as follows: Section 2 describes related studies on restaurant recommender systems; the proposed methodology is described in Section 3; Section 4 describes the datasets, evaluation metrics, and the experimental settings; Section 5 presents experimental results and discussion; finally, Section 6 presents conclusions and future work.

2. Related Work

Previously, best-seller methods that recommended items to users based on sales were used. However, best-seller methods did not consider individual user preferences. Therefore, many studies have proposed CF methods to improve user experience and better reflect user preference by using individual user information such as user history, ratings, and clicks (Goldberg et al., 1992). CF methods are roughly divided into memory- and model-based CF methods (Jain et al., 2020; Lima et al., 2020).

Memory-based CF methods are further divided into user- and item-based CF methods (Yue et al., 2021). The user-based CF methods recommend items to users using similarity (e.g., inner-product and Pearson correlation coefficient) between target users and the neighborhoods of target users (Resnick et al., 1994). Item-based CF methods recommend items to users by considering the similarity between target items and the neighborhoods of target items (Sarwar et al., 2001). Yu et al. (2004) proposed a probabilistic method for memory-based CF (PMCF) to reduce computational cost. They demonstrated that the proposed PMCF methods effectively improve accuracy compared to existing CF methods based on two real-world datasets. Gao et al. (2011) proposed item-based CF methods that incorporated user-weight, -rank, and item similarities to improve the recommendation; the proposed methods improved the recommendation performance compared to typical item-based CF methods. Koohi and Kiani (2016) proposed user-based CF methods using fuzzy C-means techniques to improve the recommendation performance; the proposed method outperformed existing CF methods.

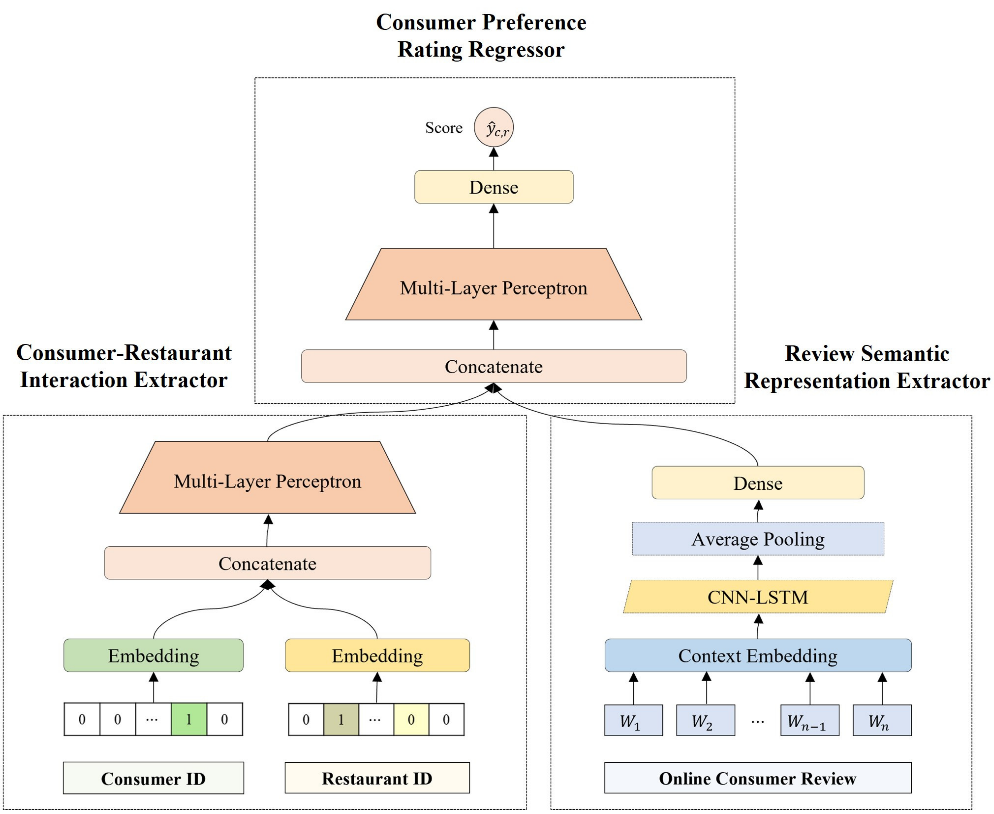
Although memory-based CF methods demonstrate good performance, there are certain limitations: 1) Sparsity problems, which occur because of limited user behaviors (Nilashi et al., 2018). Specifically, it is caused by many items that users have not purchased compared to the items that they have purchased; 2) Scalability problems, which occur because of the rapid increase in the number of items sold on websites (Das et al., 2007; Singh, 2020). To mitigate these problems, many studies have proposed model-based CF methods (Koren et al., 2009). The most notable example is the matrix factorization (MF) methods (Koren et al., 2009). MF methods project user and item embedding by using a linear function, such as an inner product, into a low-dimensional latent space to reduce computation cost (Chen & Peng, 2018). However, MF methods encounter problems when non-linear interactions between users and items exist. Therefore, recent studies have attempted to combine model-based CF and deep neural networks (DNN) methods to effectively reflect non-linear interactions (He et al., 2017). He et al. (2017) proposed a neural collaborative filtering (NCF) method that replaces the inner product with a non-linear activation function to consider complex interactions between users and items. Xue et al. (2017) proposed a novel framework called deep matrix factorization (DMF) to improve recommendation performance using explicit feedback (i.e., ratings) and implicit feedback (i.e., purchase history). He and Chua (2017) proposed a neural factorization machine (NFM) by combining the linearity of MF methods and nonlinearity of DNN methods; the proposed NFM method outperforms existing methods by a maximum of 7.3%.

Such studies demonstrate superior recommendation performance by considering only structured information, such as ratings, clicks, and purchase history, and not unstructured information. However, restaurants have unstructured information, such as consumer reviews; thus, recommendation performance may be affected if the aforementioned techniques are applied. Therefore, recent studies have utilized restaurant review information to improve recommendation performance. Yu et al. (2017) proposed machine learning-based methods such as support vector machines (SVM) based on the bag of words (BoWs). Asani et al. (2021) proposed context-based restaurant recommender systems using static information as well as unstructured information, such as consumer reviews. Chhipa et al. (2022) proposed recipe recommender systems to help users make fast decisions in complex information using TF-IDF and cosine similarity. However, such studies have difficulty extracting consumer preferences in reviews owing to the use of conventional NLP techniques, such as TF-IDF and BoWs, that do not consider contextual information in reviews.

In this study, we propose a novel framework RT-RRM that uses static information as well as unstructured information by combining the MLP and convolutional neural network long-short term memory (CNN-LSTM) methods.

3. Methodology

This study proposes a novel framework RT-RRM that can be divided into consumer-restaurant interaction extractors, review semantic representation extractors,



〈Figure 1〉 Schematic framework of the proposed RT-RRM method.

and consumer preference rating regressors: first, the consumer-restaurant interaction extractor learns the interaction between consumers and restaurants through each identification (ID); second, the semantic representation extractor learns semantic representations included in online consumer reviews based on CNN-LSTM methods; finally, the consumer preference rating regressor predicts consumer ratings of restaurants by concatenating the step outputs. Figure 1 shows a schematic of the framework of the proposed method.

3.1. Consumer-Restaurant Interaction Extractor

This extractor uses the consumer and restaurant IDs as input data to learn the interaction between consumers and restaurants. Accordingly, following Equation (1), ID information was transformed into a dense embedding vector:

$$e_c = W_c^{\top} x_c, \quad e_r = W_c^{\top} x_r, \tag{1}$$

where $x_c \in \mathbb{R}^N, x_r \in \mathbb{R}^M$ indicate the consumer and restaurant IDs, respectively. $e_c \in \mathbb{R}^d$ and $e_r \in \mathbb{R}^d$ indicate the consumer and restaurant embedding vectors, respectively. d indicates the number of embedding vector dimensions. $W_c \in \mathbb{R}^{N\times d}$ and $W_r \in \mathbb{R}^{M\times d}$ indicate the trainable weight matrices, where N indicates the number of consumers, M indicates the number of restaurants.

Next, following Equation (2), we adopted the MLP method, which uses embedding vectors that concatenate consumer and restaurant embedding vectors as input data:

$$\begin{gathered} h_1^I = \begin{bmatrix} e_c \\ e_r \end{bmatrix}; \\ h_2^I = a_2(W_2 h_1^I + b_2), \\ \cdots \\ h_L^I = a_L(W_L h_{L-1}^I + b_L), \end{gathered} \tag{2}$$

where W_l, b_l, and a_l indicate the trainable weight matrix, bias vector, and activation function, respectively. h_l^I indicates l-th layer's hidden embedding vector for the interaction extractor.

3.2. Review Semantic Representation Extractor

This extractor extracts interactions between consumers and restaurants to learn latent semantic representations in online consumer reviews based on CNN-LSTM methods. CNN-LSTM is one of the methods that demonstrate performance in a variety of fields, such as NLP (Hassan & Mahmood, 2018). We defined reviews as $R_{c,r} = \{w_1, w_2, \cdots, w_n\}$: $R_{u,i}$ indicates that consumer c has written reviews of restaurant r, where n is a word in the review sentence. CNN-LSTM methods consist of CNN and LSTM. If we use reviews as input of CNN-LSTM methods, the review to embedding vector $t_n \in \mathbb{R}^d$ must be transformed. d indicates the dimension of the review embedding vector. Thereafter, following Equation (3), we applied a convolution operation:

$$c_j = a\left(t_n * K_j + b_j\right), \tag{3}$$

where $*$ denotes the convolutional operator. $K_j \in \mathbb{R}^{k \times m}$ and b_j denote the filter kernel and the bias vector, respectively. $k \times m$ denotes the kernel size of the CNN method. a denotes an activation function, such as rectified linear units or sigmoid function. Subsequently, following Equation (4), we used an average-pooling operation to capture the semantic representation and mitigate the noise effect:

$$o_j = \text{average}\left(\left[c_1, c_2, \cdots, c_{(l-t+1)}\right]\right) \text{ and}$$
$$x_c = [o_1, o_2, \cdots, o_n], \tag{4}$$

where o_j indicates the output after the permutation-invariant function (i.e., average pooling). Although this study adopted average pooling, any permutation-invariant function, such as max-pooling and mean-pooling, may be used. x_c indicates the set of final embedding vector o_j.

Following Equation (5), we then broadly used LSTM in the NLP field. LSTM has been proposed to mitigate the vanishing gradient problem and long-term dependency problem of existing methods, such as conventional recurrent neural networks (RNN) (Sak et al., 2014):

$$i_t^R = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1}^R + b_{hi})$$
$$f_t^R = \sigma\left(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}\right)$$
$$g_t^R = \tanh\left(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1}^R + b_{hg}\right) \tag{5}$$
$$o_t^R = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1}^R + b_{ho})$$
$$c_t^R = f_t \odot c_{t-1}^R + i_t^R \odot g_t^R$$
$$h_t^R = o_t^R \odot \tanh(c_t^R)$$

where i_t^R, f_t^R, g_t^R, o_t^R, c_t^R, and h_t^R indicate the input gate, forget gate, cell gate, output gate, cell state, and hidden state at time t, respectively. b_* and W_* indicate the bias vector and trainable weight metrics, respectively. $\odot$ denotes element-wise product.

3.3. Consumer Preference Rating Regressor

Following Equation (6), this regressor predicts a consumer's rating for a restaurant by concatenating the interaction extractor outputs h_L^I, and the representation extractor outputs h_t^R:

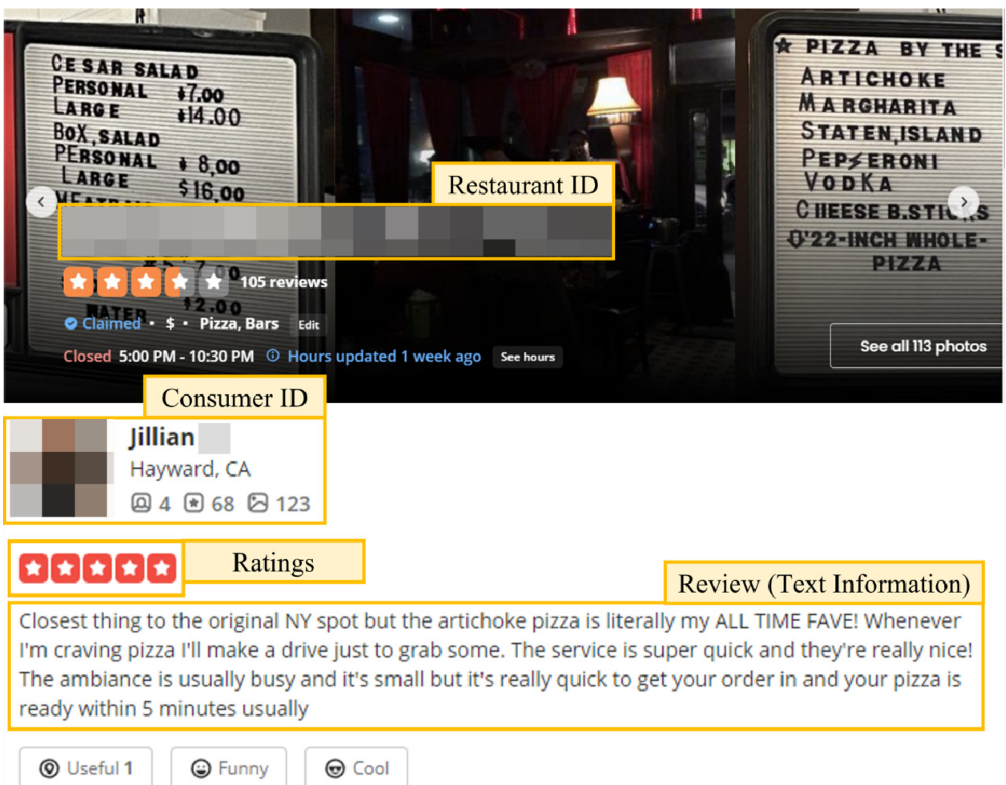
$$h_1 = \begin{bmatrix} h_L^I \\ h_t^R \end{bmatrix}$$
$$h_2 = a_2(W_2 h_1 + b_2) \tag{6}$$
$$\cdots$$
$$\hat{y}_{c,r} = a_L(W_L h_{L-1} + b_L)$$

where h_l indicates l-th layer's hidden embedding vector of the rating regressor to predict restaurant consumer ratings. $\hat{y}_{c,r}$ indicates the ratings of consumer c for restaurant r. a_*, W_*, and b_* indicate the activation function, trainable weight metrics, and bias vectors of the l-th layers, respectively.

4. Experimental Settings

4.1. Datasets

This study used a broad dataset provided by Yelp.com (https://www.yelp.com) to evaluate the performance of the proposed RT-RRM method. The Yelp.com dataset consists of over one million ratings (ranging from 1 to 5) on the Yelp website. Additionally, this study used dataset from all regions officially provided by Yelp.com (https://www.yelp.com/dataset), and filtered consumers who wrote at least 20 reviews (Hazrati & Ricci, 2022; He & Chua, 2017). Referring to the previous study, we have preprocessed the dataset to train models. First, we filtered blank and special characters (such as at sign, tilde, asterisk, etc). Second, review text was converted to lowercase and tokenized. Finally, we remove stop words such as the, an, a, etc. Consequently, this study used the Yelp.com dataset, which contains 1,206,587 reviews from 25,369 consumers for 46,613 restaurants. Subsequently, to optimize restaurant recommendations, we adopted a cross-validation strategy, which has been avoided in many studies. Specifically, the overall dataset randomly selected 80% of each user to constitute the training set and used the remaining as the testing set. Subsequently, 10% of this was randomly selected as the validation set to tune the proposed method and evaluate the recommendation performance from the training set. An example of the Yelp.com dataset is shown in Figure 2.



〈Figure 2〉 Example of a review on Yelp.com platform.

4.2. Evaluation Metric

In this paper, we proposed RT-RRM methods to predict restaurant consumer ratings using online consumer reviews as textual information. Therefore, following Equation (7), we adopted prevalent rating regression metrics, such as the root mean squared error (RMSE) and mean absolute error (MAE) (Chai & Draxler, 2014).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{c,r} - \hat{y}_{c,r}\right|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{c,r} - \hat{y}_{c,r}\right)^2}\ , \tag{7}$$

where $y_{c,r}$ indicate the ground truth ratings. $\hat{y}_{c,r}$ indicate the ratings predicted by the model. MAE is used to measure the ratings predicted by the model for consumer c and restaurant r and is widely used for the evaluation of recommender systems in various rating prediction studies (Chen et al., 2016; Zhang et al., 2021). RMSE is a variation of MAE that emphasizes larger errors as compared to MAE using a square operation.

4.3. Baseline Model

To confirm the effectiveness of our proposed method, we compared it with various recommender systems:

- **MF** (Koren et al., 2009): conventional matrix factorization (MF) estimates consumer preference using the inner product of the consumer latent vector and restaurant latent vector. Thus, it can alleviate the sparsity and scalability problems.
- **NCF** (He et al., 2017): neural collaborative filtering (NCF) method overcomes the limitations of the MF method. Specifically, it effectively captures non-linear interactions between consumers and restaurants because it adopts MLP and non-linear activation functions such as ReLU and sigmoid functions.
- **NeuMF** (He et al., 2017): neural matrix factorization (NeuMF) combines the linear operation of MF and the non-linear operation of NCF Thus, NeuMF precisely extracts interactions between consumers and restaurants.
- **UCAM** (Unger et al., 2020): unstructured context-aware model (UCAM) incorporates consumer and restaurant IDs and unstructured information, such as consumer reviews. In contrast to the aforementioned methods, UCAM can effectively capture consumer preferences using a CNN.

4.4. Parameters Settings

All the models were initialized using the Xavier initialization method (Glorot & Bengio, 2010). We adopted the Adam optimizer (Kingma & Ba, 2015) to optimize the model with a mini-batch. Then, the best parameters of the batch sizes were set as 32, 64, 128, 256, and 512, and the best parameters of the learning rate were set as 0.01, 0.05, 0.001, and 0.005. To verify the robustness of the experiment, we repeated the experiment five times and reported the mean of the five experimental results (Al-Shamri, 2016). The embedding size of the CNN was set to

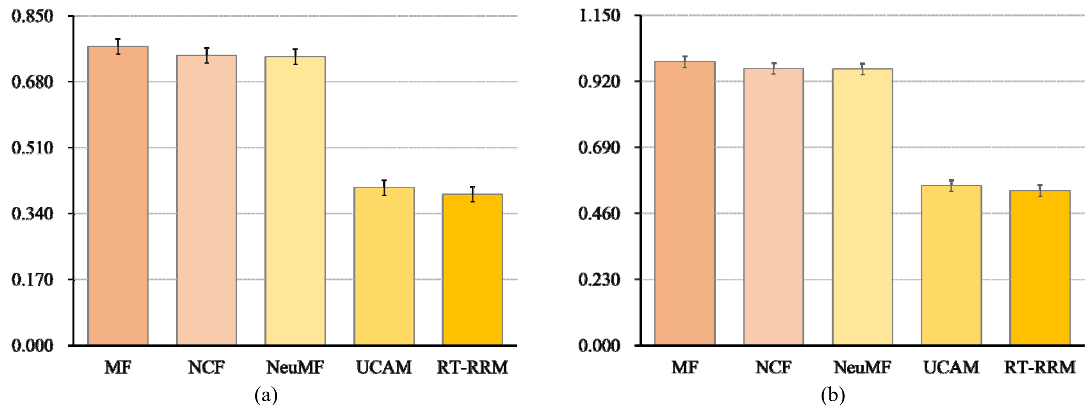
100, 200, 300, 400, and 500, and the kernel size was set to 5. Finally, the embedding size of the LSTM was set to 100, 150, 200, 250, and 300. More details are shown in Section 5.3 (i.e., Effect of hyperparameters on performance). Following a previous study, we used early stopping for model training when the validation loss was not reduced for three epochs (Jin et al., 2020). We implemented our methods based on TensorFlow and Keras software. All experiments and results of the system were carried out using an Intel Core i9-9900F CPU, 128GB of memory, and a GeForce RTX 3080 Ti GPU.

5. Experimental Result

5.1. Performance Comparison with Baselines

To verify the recommendation performance of the proposed method, we compared widely used SOTA methods such as MF, NCF, NeuMF, and UCAM in the field of recommender systems. The experimental results are shown in Figure 3. In all cases, our method outperformed existing recommender systems on real-world datasets. Specifically, RT-RRM method was 49.42% (MF), 47.86% (NCF), 47.58% (NeuMF), and 4.18% (UCAM) better than the existing methods in terms of MAE; and 45.45% (MF), 44.09% (NCF), 43.97% (NeuMF), and 3.06% (UCAM) better than existing methods in terms of RMSE. Based on these experimental results, we conclude the following:

- The NCF model has shown a better performance than the widely used MF model in many studies. These results can address data sparsity issues because the NCF models transform consumer and restaurant information into dense embedding vectors. It also learns the nonlinear interactions between consumers and restaurants, effectively capturing the complex relationships between them.
- The NeuMF models show superiority over the NCF and MF models. This indicates that learning about the interaction between consumers and restaurants in a nonlinear and linear manner can better predict consumer preferences.
- The recommendation performance of the UCAM method is better than that of conventional methods, such as MF, NCF, and NeuMF. These results indicate that traditional recommendation methods are ineffective at predicting preferences because they use star ratings as the only source of information. Additionally, such results indicate that using online consumer reviews as auxiliary information improves the recommendation performance.
- The recommendation performance of our method (RT-RRM) was superior in all cases. Indicating that the CNN-LSTM method can effectively extract textual information in online reviews better than the CNN method because it considers sequential information in online reviews. These results confirm that the proposed RT-RRM method can effectively predict consumer preferences because it



〈Figure 3〉 Performance comparison with baselines MAE and RMSE. (a) Performance comparison among recommender systems based on MAE metrics; (b) Performance comparison among recommender systems based on RMSE metrics.

considers reviews as textual information to capture complex consumer preferences.

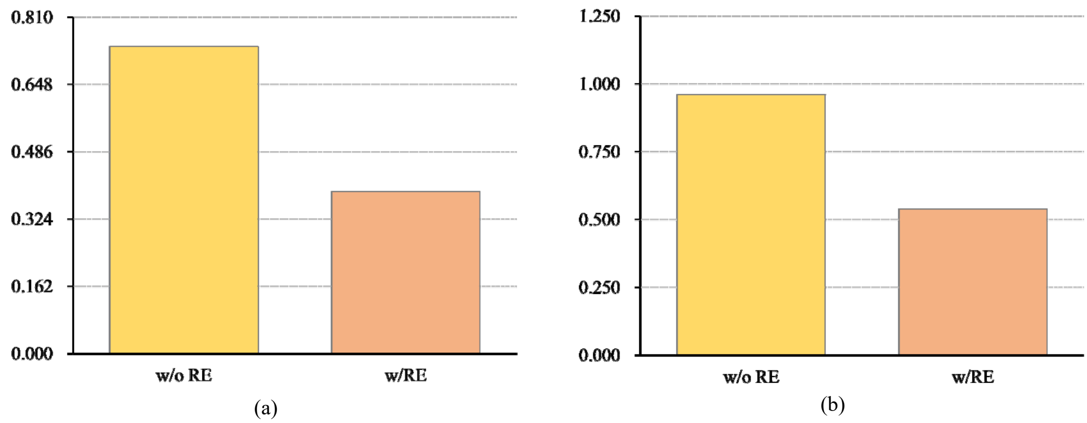
5.2. Ablation Study

To measure the effect of the representation extractor, we constructed two models: without representation extractor (w/o RE) and with representation extractor (w/RE). As shown in Figure 4, for w/o RE (i.e., not considering textual information), performance degradation is observed. The experimental results show that the use of textual information improves the model performance. Specifically, w/RE outperforms w/o RE method by 47.23% based on MAE metrics. Additionally, the w/RE outperforms w/o RE method by 43.85% based on RMSE metrics. Therefore, using textual information means improving recommendation performance because it considers various types of information on consumer preferences, including online consumer reviews.

We conducted an ablation study to demonstrate the representation extractor layer's effects. According to the ablation study experiment results, recommendation performance can be improved if online consumer reviews are used. Whereas if not using consumer reviews, recommendation performance has degraded rather than using consumer reviews. Based on the results, we concluded that online consumer reviews are significant in capturing consumer preferences.

5.3. Effect of Hyperparameters on Performance

To investigate the importance of various hyperparameters, we varied the hyperparameters that consist of the number of layers and embedding size. We first experimented with the number of MLP layers in the rating regressor, followed by the embedding sizes of consumers and restaurants. Tables 1 and 2 report the performance of the proposed method (MAE and RMSE) with different numbers of MLP layers for the rating regressor and embedding sizes. l indicates that the number of



〈Figure 4〉 Performance comparison w/o RE and with RE. (a) Performance comparison between w/o RE and with RE based on MAE metrics; (b) Performance comparison between w/o RE and with RE based on RMSE metrics.

hidden MLP layers. Initially, performance improves upon increasing the number of MLP layers. However, when the number of MLP layers is larger than three (i.e., l=4), the recommendation performance degrades owing to gradient vanishing or explosion. The embedding-size results show that the recommendation performance improves as the embedding size increases. This means that the scalability problem can be alleviated when the embedding size is small; however, the recommendation performance of the model degrades when the embedding size is large.

〈Table 1〉 RT-RRM performance (MAE) with different number of MLP layers (rating regressor).

Embedding Sizes	$l=1$	$l=2$	$l=3$	$l=4$
4	0.404	0.398	0.396	0.408
8	0.397	0.395	0.394	0.400
16	0.395	0.393	0.390	0.399
32	0.391	0.389	0.387	0.392

〈Table 2〉 RT-RRM performance (RMSE) with different number of MLP layers (rating regressor).

Embedding Sizes	$l=1$	$l=2$	$l=3$	$l=4$
4	0.552	0.546	0.546	0.560
8	0.546	0.546	0.544	0.554
16	0.542	0.541	0.539	0.544
32	0.539	0.539	0.537	0.540

Finally, we experimented with the embedding size of the CNN and LSTM to confirm the effect of each method embedding size. As listed in Table 3, we first experimented with the embedding size of the CNN method. The proposed method exhibited the best performance when the CNN embedding size was 300. These results suggest that a small embedding size may not effectively extract contextual information from online consumer reviews, whereas a large embedding size causes performance degradation because the embedding vectors of consumers and restaurants become extremely sparse. As shown in Table 4, we then experimented with the embedding size of the LSTM method. The proposed method exhibited the best performance when the LSTM embedding size was 200. These results suggest that a small embedding size may not capture the representation between consumers and restaurants, whereas a large embedding size may cause performance degradation.

〈Table 3〉 RT-RRM performance with different number of CNN embedding size after fixing LSTM embedding size.

Embedding Sizes	100	200	300	400	500
MAE	0.402	0.398	0.390	0.394	0.394
RMSE	0.549	0.546	0.540	0.541	0.543

〈Table 4〉 RT-RRM performance with different number of LSTM embedding size after fixing CNN embedding size.

Embedding Sizes	100	150	200	250	300
MAE	0.394	0.390	0.390	0.397	0.398
RMSE	0.545	0.542	0.540	0.545	0.546

6. Conclusion and Future Work

This study proposes a novel recommendation method to address the limitations of previous studies using online reviews. Importantly, this study used individual reviews instead of aggregated reviews to improve recommendation accuracy and scalability. To achieve this, we applied CNN-LSTM to extract high-level semantic representations of online reviews. Additionally, this study applied the MLP model to extract the interaction features between consumers and restaurants. Finally, this study concatenates the interactions between consumers and restaurants and semantic representations from online reviews to predict consumer preferences. Extensive experiments on real-world datasets showed that the proposed model exhibits superior recommendation performance compared to several baseline models.

The main implications of this study are as follows. First, this study extracted consumer preference information from online reviews and applied it to the recommender system to confirm the enhancement performance. Previous studies measured consumer preference information using star ratings or sentiment score information. However, extracting detailed consumer preference information from online reviews is challenging. This study used CNN and LSTM to extract context and semantic representations in the review. It confirmed the enhancement of the recommendation performance, implying that the context and semantic representations of online reviews reflect consumers' preferences. Thus, this study contributes to the hospitality and tourism literature by proposing an integrated approach to extracting consumer preferences from online reviews and building a recommendation model. Third, this study has significant methodological value in that it proposed various recommendation models (including the proposed model and benchmark) to estimate consumer preference scores in the restaurant industry. Most previous recommendation tasks used traditional CF and survey approaches to estimate consumer preference scores. Additionally, the latent factor vectors of consumers and restaurants are extracted to predict consumer preference scores. However, such an approach is challenging to capture between consumer-restaurant interactions; additionally, it cannot consider the various types of textual information for restaurants. Thus, this study combines various textual information with a feature fusion approach and confirms the enhanced recommendation performance. Third, this study proposed a novel restaurant recommendation methodology combining online reviews. The proposed methodology uses online restaurant reviews, so it can be applied to an online platform to build a more accurate recommender system. Thus, platform administrators can use the current methodology to identify features embedded in online reviews affecting personalized recommendation services and develop an excellent model. This study found that features embedded in review text have an essential effect on recommendation performance, suggesting that online reviews affect consumer purchase decisions. The results of this study suggest that restaurant practitioners should effectively manage online reviews regarding restaurants.

Future work will seek to build a knowledge graph that extracts contextual representations of various aspects of online reviews and combines them with interactions between consumers and restaurants. Building a knowledge graph can effectively extract the contextual representation of online reviews better than various NLP methods such as BoWs, TF-IDF, CNN, and CNN-LSTM. Furthermore, a graph-based recommendation model can be constructed by applying a graph convolutional network (GCN) to develop a more accurate recommendation methodology.

Reference

Abdi, A., Shamsuddin, S. M., Hasan, S., & Piran, J. (2019). Deep learning-based sentiment classification of evaluative text based on Multi-feature fusion. *Information Processing & Management*, *56*(4), 1245-1259.

Al-Shamri, M. Y. H. (2016). User profiling approaches for demographic recommender systems. *Knowledge-based systems*, *100*, 175-187.

Asani, E., Vahdat-Nejad, H., & Sadri, J. (2021). Restaurant recommender system based on sentiment analysis. *Machine Learning with Applications*, *6*, 100114.

Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. *Knowledge-based systems*, *46*, 109-132.

Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geoscientific model development*, *7*(3), 1247-1250.

Chen, H., Li, Z., & Hu, W. (2016). An improved collaborative recommendation algorithm based on optimized user similarity. *The Journal of Supercomputing*, *72*, 2565-2578.

Chen, S., & Peng, Y. (2018). Matrix factorization for recommendation with explicit and implicit feedback. *Knowledge-based systems*, *158*, 109-117.

Chhipa, S., Berwal, V., Hirapure, T., & Banerjee, S. (2022). Recipe Recommendation System Using TF-IDF. ITM Web of Conferences,

Das, A. S., Datar, M., Garg, A., & Rajaram, S. (2007). Google news personalization: scalable online collaborative filtering. Proceedings of the 16th international conference on World Wide Web, Esmaeili, L., Mardani, S., Golpayegani, S. A. H., & Madar, Z. Z. (2020). A novel tourism recommender system in the context of social commerce. *Expert Systems with Applications*, *149*, 113301.

Gao, M., Wu, Z., & Jiang, F. (2011). Userrank for item-based collaborative filtering recommendation. *Information Processing Letters*, *111*(9), 440-446.

Glorot, X., & Bengio, Y. (2010). Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*. JMLR Workshop and Conference Proceedings, 249-256.

Goldberg, D., Nichols, D., Oki, B. M., & Terry, D. (1992). Using collaborative filtering to weave an information tapestry. *Communications of the ACM*, *35*(12), 61-70.

Hassan, A., & Mahmood, A. (2018). Convolutional recurrent deep learning model for sentence classification. *IEEE Access*, *6*, 13949-13957.

Hazrati, N., & Ricci, F. (2022). Recommender systems effect on the evolution of users' choices distribution. *Information Processing & Management*, *59*(1), 102766.

He, X., & Chua, T. S. (2017). Neural factorization machines for sparse predictive analytics. In *Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval*, 355-364.

He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017, April). Neural collaborative filtering. In *Proceedings of the 26th international conference on world wide web*, 173-182.

Hegde, S. B., Satyappanavar, S., & Setty, S. (2018). Sentiment based food classification for restaurant business. In *2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, 1455-1462.

Hlee, S., Lee, J., Yang, S. B., & Koo, C. (2019). The moderating effect of restaurant type on hedonic versus utilitarian review evaluations. *International Journal of Hospitality Management*, *77*, 195-206.

Horng, J. S., & Hsu, H. (2020). A holistic aesthetic experience model: Creating a harmonious dining environment to increase customers' perceived pleasure. *Journal of Hospitality and Tourism Management*, *45*, 520-534.

Idrissi, N., & Zellou, A. (2020). A systematic literature review of sparsity issues in recommender systems. *Social Network Analysis and Mining*, *10*(1), 1-23.

Jain, A., Nagar, S., Singh, P. K., & Dhar, J. (2020). EMUCF: Enhanced multistage user-based collaborative filtering through non-linear similarity for recommendation systems. *Expert Systems with Applications*, *161*, 113724.

Jin, B., Gao, C., He, X., Jin, D., & Li, Y. (2020, July). Multi-behavior recommendation with graph convolutional networks. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 659-668.

Kim, D., Park, C., Oh, J., Lee, S., & Yu, H. (2016). Convolutional matrix factorization for document context-aware recommendation. In *Proceedings of the 10th ACM conference on recommender systems*, 233-240.

Kingma, D. P., & Ba, J. (2015). Adam: A Method for Stochastic Optimization. *arXiv preprint arXiv:1412.6980*.

Koohi, H., & Kiani, K. (2016). User based collaborative filtering using fuzzy C-means. *Measurement*, *91*, 134-139.

Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. *Computer*, *42*(8), 30-37.

Lee, M., Jeong, M., & Lee, J. (2017). Roles of negative emotions in customers' perceived helpfulness of hotel reviews on a user-generated review website: A text mining approach. *International Journal of Contemporary Hospitality Management, 29*(2), 762-783.

Li, Q., Li, X., Lee, B., & Kim, J. (2021). A Hybrid CNN-Based Review Helpfulness Filtering Model for Improving E-Commerce Recommendation Service. *Applied Sciences*, *11*(18), 8613. https://www.mdpi.com/2076-3417/11/18/8613

Li, X., Wang, M., & Liang, T.-P. (2014). A multi-theoretical kernel-based approach to social network-based recommendation. *Decision Support Systems*, *65*, 95-104.

Lima, G. R., Mello, C. E., Lyra, A., & Zimbrao, G. (2020). Applying landmarks to enhance memory-based collaborative filtering. *Information Sciences*, *513*, 412-428.

Loureiro, S. M. C., Almeida, M., & Rita, P. (2013). The effect of atmospheric cues and involvement on pleasure and relaxation: The spa hotel context. *International Journal of Hospitality Management*, *35*, 35-43.

Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: a survey. *Decision Support Systems*, *74*, 12-32.

Mahadi, M., Zainuddin, N., Shah, N., Naziron, N. A., & Rum, S. (2018). E-halal restaurant recommender system using collaborative filtering algorithm. *Journal of Advanced Research in Computing and Applications*, *12*(1), 22-34.

Miao, X., Gao, Y., Chen, G., Cui, H., Guo, C., & Pan, W. (2016). SI2P: A restaurant recommendation system using preference queries over incomplete information. *Proceedings of the VLDB Endowment*, *9*(13), 1509-1512.

Nemade, G., Deshmane, R., Thakare, P., Patil, M., & Thombre, V. (2017). Smart tourism recommender system. *International Research Journal of Engineering and Technology (IRJET)*, *4*(11), 601-603.

Nilashi, M., Ibrahim, O., & Bagherifard, K. (2018). A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques. *Expert Systems with Applications*, *92*, 507-520.

Onan, A. (2021). Sentiment analysis on product reviews based on weighted word embeddings and deep neural networks. *Concurrency and Computation: Practice and Experience*, *33*(23), e5909.

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., & Riedl, J. (1994, October). Grouplens: An open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM conference on Computer supported cooperative work*, 175-186.

Sak, H., Senior, A., & Beaufays, F. (2014). Long short-term memory based recurrent neural network architectures for large vocabulary speech recognition. *arXiv preprint arXiv:1402.1128*.

Salehan, M., & Kim, D. J. (2016). Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. *Decision Support Systems*, *81*, 30-40.

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001, April). Item-based collaborative filtering recommendation algorithms. In *Proceedings* *of the 10th international conference on World Wide Web*, 285-295.

Saumya, S., Singh, J. P., & Dwivedi, Y. K. (2020). Predicting the helpfulness score of online reviews using convolutional neural network. *Soft Computing*, *24*(15), 10989-11005.

Singh, M. (2020). Scalability and sparsity issues in recommender datasets: a survey. *Knowledge and Information Systems*, *62*(1), 1-43.

Unger, M., Tuzhilin, A., & Livne, A. (2020). Context-aware recommendations based on deep learning frameworks. *ACM Transactions on Management Information Systems (TMIS)*, *11*(2), 1-15.

Xue, H. J., Dai, X., Zhang, J., Huang, S., & Chen, J. (2017). Deep matrix factorization models for recommender systems. In *IJCAI, 17*, 3203-3209.

Yang, S., Yao, J., & Qazi, A. (2020). Does the review deserve more helpfulness when its title resembles the content? Locating helpful reviews by text mining. *Information Processing & Management*, *57*(2), 102179.

Yoo, S., Song, J., & Jeong, O. (2018). Social media contents based sentiment analysis and prediction system. *Expert Systems with Applications*, *105*, 102-111.

Yu, B., Zhou, J., Zhang, Y., & Cao, Y. (2017). Identifying restaurant features via sentiment analysis on yelp reviews. *arXiv preprint arXiv: 1709.08698*.

Yu, K., Schwaighofer, A., Tresp, V., Xu, X., & Kriegel, H.-P. (2004). Probabilistic memory-based collaborative filtering. *IEEE Transactions on Knowledge and Data Engineering*, *16*(1), 56-69.

Yue, W., Wang, Z., Liu, W., Tian, B., Lauria, S., & Liu, X. (2021). An optimally weighted user-and item-based collaborative filtering approach to predicting baseline data for Friedreich's Ataxia patients. *Neurocomputing*, *419*, 287-294.

Zhang, H., Ganchev, I., Nikolov, N. S., Ji, Z., & O'Droma, M. (2021). FeatureMF: an item feature enriched matrix factorization model for item recommendation. *IEEE Access*, *9*, 65266-65276.

국문요약

딥러닝 기반 온라인 리뷰를 활용한 추천 모델 개발: 레스토랑 산업을 중심으로

김동언* · 장동수* · 엄금철** · 이가은***

레스토랑 산업의 성장과 함께 레스토랑 오프라인 매장 수는 점차 증가하지만, 소비자는 자신의 선호도에 적합한 레스토랑을 선택하는 데 어려움을 경험하고 있다. 따라서 소비자의 선호도에 맞는 레스토랑을 추천하는 개인화된 추천 서비스의 필요성이 대두하고 있다. 기존 연구에서는 설문조사 및 평점 정보를 활용하여 소비자 선호도를 조사했으나, 이는 소비자의 구체적인 선호도를 효과적으로 반영하는데 어려움이 존재한다. 이러한 배경하에 온라인 리뷰는 방문 동기, 음식 평가 등 레스토랑에 대한 소비자 구체적인 선호도를 효과적으로 반영하기 때문에 필수적인 정보이다. 한편, 일부 연구에서는 리뷰 텍스트에 전통적인 기계학습 기법을 적용하여 소비자의 선호도를 측정하였다. 그러나 이러한 접근 방식은 주변 단어나 맥락을 고려하지 못하는 한계점이 존재한다. 따라서 본 연구는 딥러닝을 효과적으로 활용하여 온라인 리뷰에서 소비자의 선호도를 정교하게 추출하는 리뷰 텍스트 기반 레스토랑 추천 모델을 제안한다. 본 연구에서 제안된 모델은 추출된 높은 수준의 의미론적 표현과 소비자-레스토랑 상호작용을 연결하여 소비자의 선호도를 정확하고 효과적으로 예측한다. 실험 결과에 따르면 본 연구에서 제안된 추천 모델은 기존 연구에서 제안된 여러 모델에 비해 우수한 추천 성능을 보이는 것으로 나타났다.

주제어 : 레스토랑 추천 시스템, 온라인 리뷰, 딥러닝, CNN-LSTM, 텍스트 마이닝

논문접수일 : 2023년 9월 14일 논문수정일 : 2023년 11월 1일 게재확정일 : 2023년 11월 17일
원고유형 : Regular Track 교신저자 : 이가은

* 경희대학교 대학원 빅데이터응용학과
** 가천대학교 경영대학 경영학과
*** 교신저자: 이가은
광운대학교 경영대학 국제통상학부
서울특별시 노원구 광운로 21
Tel: + 82-2-940-5569, E-mail: jiaenlee@kwangwoon.ac.kr

저 자 소 개

Dongeon Kim

Dongeon Kim obtained his M.S. in Engineering from Kyung Hee University, and his B.S. and B.A. in Mathematics and Economics from Myongji University. His current research interests focus on recommender systems, natural language processing, graph neural networks, and deep learning.

Dongsoo Jang

Dongsoo Jang is a master student at the Department of Big Data Analytics, Kyung Hee University. He obtained his B.S. in Economics from Pusan University. His current research interests focus on personalized service, natural language processing, and deep learning.

Jinzhe Yan

Jinzhe Yan is an Assistant Professor at the College of Business, Gachon University. He received a Ph.D. in Marketing at Sungkyunkwan University. His research area primarily focuses on structure modeling, text mining, digital marketing, big data marketing, marketing strategies, and consumer decision-making.

Jiaen Li

Jiaen Li is an Assistant Professor in the Division of International Trade at Kwang Woon University. She received a Ph.D. in international economics from Kyung Hee University. Her research interests include the global value chain, foreign direct investment, big data analysis, text mining, and personalized recommendation services.