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User-to-User Matching Services through Prediction of Mutual Satisfaction Based on Deep Neural Network

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Abstract

With the development of the sharing economy, existing recommender services are changing from user–item recommendations to user–user recommendations. The most important consideration is that all users should have the best possible satisfaction. To achieve this outcome, the matching service adds information between users and items necessary for the existing recommender service and information between users, so higher-level data mining is required. To this end, this paper proposes a user-to-user matching service (UTU-MS) employing the prediction of mutual satisfaction based on learning. Users were divided into consumers and suppliers, and the properties considered for recommendations were set by filtering and weighting. Based on this process, we implemented a convolutional neural network (CNN)–deep neural network (DNN)-based model that can predict each supplier's satisfaction from the consumer perspective and each consumer's satisfaction from the supplier perspective. After deriving the final mutual satisfaction using the predicted satisfaction, a top recommendation list is recommended to all users. The proposed model was applied to match guests with hosts using Airbnb data, which is a representative sharing economy platform. The proposed model is meaningful in that it has been optimized for the sharing economy and recommendations that reflect user-specific priorities.

1. Introduction

Recommender systems have already been widely applied in daily life and various recommender applications have been developed. In particular, as mobile devices have become popular, the real-time accumulation of user data has become easier and recommender systems have been developed based on big data [1-3]. Thus, personalized recommender services have become more intelligent [4-8].

Most general recommender systems use user–item recommender systems such as content-based filtering, collaborative filtering, and hybrid collaborative filtering [9-12]. However, with the development of shared economy-based businesses (Airbnb, Uber Taxi, etc.), new systems are starting to differ from existing recommender services.

Currently, consumers may still appear to be recommended specific items; however, when purchasing an item, consumers can now start considering their supplier. In other words, the presence of suppliers has

begun to be integrated into items, and the supplier–consumer relationship has become important. Rather than simply purchasing items, suppliers and consumers choose each other; thus, beyond item recommendations to consumers, mutual recommendations suitable for consumers and suppliers are required.

However, consumer-oriented recommender service research has primarily focused on the consumers' item selection rather than suppliers. These services are unidirectional in their recommendations of items to consumers and recommendations are made with consumer- and item-related information. For mutual recommendation, information about the supplier is added to the data, which increases the data and the calculations become more complicated. However, this step is very important in the sharing economy platform because it can increase satisfaction for all users.

Mutual recommendations of consumers and suppliers first require an understanding of each user's situation and preferences. For example, the consumer data for Airbnb can include the location, date, and number of people that wish to stay, and the supplier data can include the consumer's number of nights. As such, the characteristics desired by the consumer from the supplier differ from those desired by the supplier from the consumer, so modeling the overall situation is difficult.

In this paper, we propose a matching service that predicts mutual satisfaction between users. Here, "users" refers both to consumers who purchase items and suppliers who provide items, and consumers and suppliers are matched together. To this end, we derive the required property variables from the perspective of consumers and suppliers; based on these variables, the satisfaction from each user is derived using two deep neural network (DNN) models. Finally, we propose matching to users by calculating the mutual satisfaction between consumers and suppliers.

This paper is organized as follows: Section 2 discusses existing studies, Section 3 describes our proposed method and Section 4 describes the process used to generate mutual satisfaction. Section 5 analyzes existing research and compares it with our proposed method. Finally, Section 6 presents conclusions and future research.


2. Related Works

Recommender services are largely divided into collaborative filtering and content-based filtering. Among them, collaborative filtering is a method of recommending items to other users with similar preferences. Content-based filtering is a method for determining and recommending items that a user may prefer with similar characteristics to previously preferred items. Since collaborative filtering is a good algorithm in that it produces a variety of results rather than the same result, it has been used as a basis in many studies [13,14]. Memory-based collaborative filtering is commonly used and is divided into user-based filtering, which recommends items with high similarity to other users, and item-based filtering, which recommends items with high similarity to recommended items. Various studies have predicted and recommended preferences by calculating similarity using various data types such as social relations and location [15-17].

However, as data grows in size and complexity, a larger amount of computation is required and systems have changed to neural network-based recommendations—convolutional neural network (CNN), recurrent neural network (RNN), etc. [18]. Unlike existing recommender services, the accurate prediction of preferences is possible through efficient weighted learning between users, and various studies are being conducted in this field. Fu et al. [7] proposed a new collaborative filtering model based on deep learning

that can predict ratings by learning low-dimensional embeddings for both users and items and by using multi-view feedforward neural networks. Liu et al. [8] proposed a recommendation DNN framework based on deep reinforcement learning. Unlike previous studies, this study confirms that the recommendation performance is improved by explicitly modeling dynamic user–item interactions based on reinforcement learning. Most previous studies suggest recommendations between learning-based user–items according to the data's features.

Research on matching services for user–user recommendations has also been ongoing. Xia et al. [19] proposed a partner recommender system for online dating sites based on the similarity between users' messages and attractiveness, and Kacchi and Deorankar [20] proposed a friend recommender system based on users' lifestyles in social network services (SNS). Most of these matching recommender services only differ in terms of users' inclination and are equal without distinguishing user roles. Therefore, there is no difference in what feature factors should be considered for each user.

However, the latest trend is the sharing economy, which differs from the previous business. The sharing economy refers to economic activities in which items are rented to various users rather than owned. Various sharing economy platforms such as Airbnb, Uber Taxi, and Zipcar are being used worldwide [21]. One characteristic of these platforms is that users' roles are generally divided into consumers and suppliers. Since items are limited due to the nature of "sharing," various suppliers may exist for one item or similar items. In the existing recommender service, as shown in Fig. 1(a), consumers simply selected and were recommended items. In the recommender service based on the shared economy, shown in Fig. 1(b), consumers are recommended both items and suppliers, which becomes a factor in consumers' purchasing decisions. In addition, if many consumers make purchase requests, suppliers can choose their consumer.
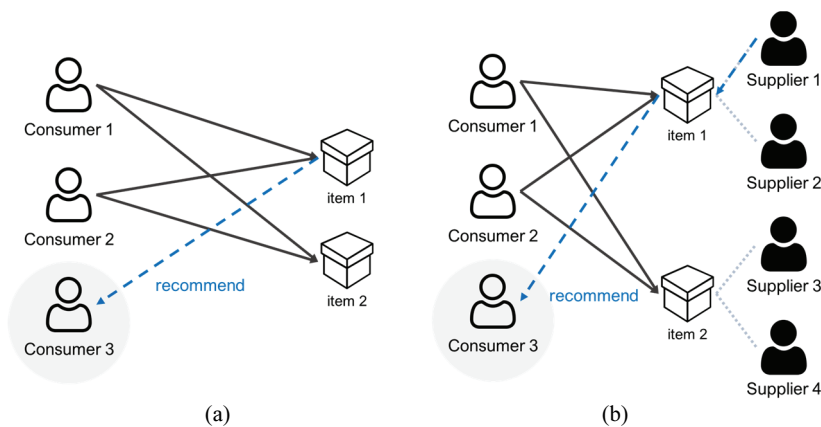
Fig. 1. (a) Existing recommender service and (b) Shared economy-based recommender service.

Most research in this area has focused on consumers and suppliers among various multi-stakeholders [22], and various aspects such as multi-stakeholder pattern analysis and recommendation algorithms are in progress [23,24]. However, there is a lack of research on consumer–supplier matching services suitable for consumption trends in the "shared economy" [25]. To this end, this paper proposes a user matching-related study suitable for consumption trends in the sharing economy. At this time, we propose a matching recommendation method based on deep learning because information about suppliers is added to grow the dataset.

3. User-to-User Matching Service

In this paper, we propose a user-to-user matching service (UTU-MS) that can be used in a sharing economy. At this time, various multi-stakeholders may exist depending on the shared economic platform, but this paper only distinguishes consumers who want to purchase items and suppliers who provide such items.

One important consideration when matching consumers to suppliers is that they have disparate recommendation priorities. Therefore, it is necessary to consider each group's recommendation priorities separately. To this end, in this paper, we derive the properties preferred by each group and predict the satisfaction of suppliers from the consumer's perspective and the satisfaction of consumers from the supplier's perspective. Then, we propose a UTU-MS that satisfies both groups and derives mutual satisfaction by combining the two preferences. As shown in Fig. 2, the process includes setting user-specific properties, predicting user-specific satisfaction, and deriving mutual satisfaction.
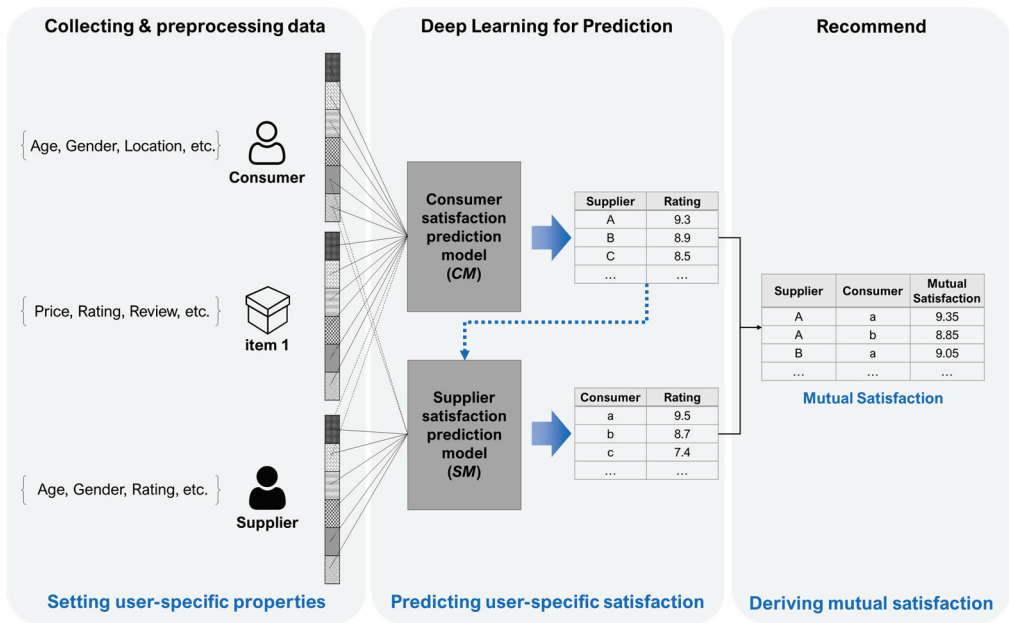

Fig. 2. UTU-MS process.

First, setting user-specific properties is a process that involves selecting necessary data for consumers, suppliers, and items to extract satisfaction as well as collecting and preprocessing these groups according to each data. During this process, property selection is performed for each data to select only necessary data. The next step involves predicting satisfaction based on the collected data. This process consists of two deep neural network models. One is a model (CM) that predicts consumer satisfaction with suppliers, and the other (SM) predicts supplier satisfaction with consumers. Since the supplier does not need to predict satisfaction for all consumers, the SM performs satisfaction prediction only for consumers with high purchasing probability according to the prediction results derived from the CM. Mutual satisfaction is derived using the user-specific satisfaction predicted by the CM and SM, and, finally, a top recommendation list based on this process is generated and proposed to the user.

4. UTU-MS Process

4.1 The Artificial Image Dataset Experiments

Before extracting mutual satisfaction, each user has different priorities (consumer, supplier), so it is necessary to set properties for deriving mutual satisfaction. Therefore, it is necessary to understand the purchasing process from the point of view of consumers and suppliers.

Assume that Consumer 1 and Consumer 2 want to purchase Item 1, as shown in Fig. 3. The existing recommender service would result in both consumers choosing Item 1, but the model proposed in this paper adds a process that selects a supplier to sell Item 1 since it is a recommender service model based on the sharing economy. Using Airbnb as an example, when a consumer is looking for accommodation in Area A, Item 1 could be an accommodation location in Area A, and the suppliers are those who provide accommodation in Area A. In addition, Item 1 may be subject to specific conditions such as accommodation for more than four people in the A area. The item setting may vary depending on the platform to which it is applied. After selecting Item 1, which is an accommodation in Area A, the consumer selects a supplier that provides Item 1 that satisfies their priorities. This selection may be performed based on the ratings of users who chose different accommodations or the style of the host.
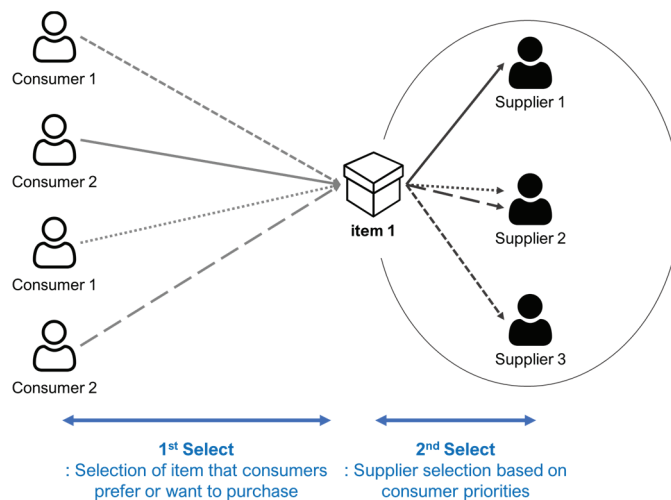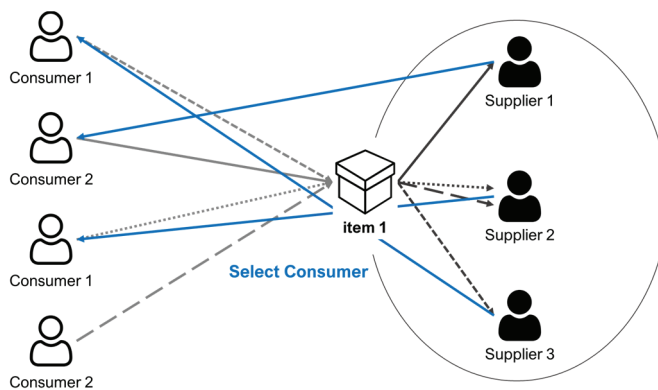

Fig. 3. Consumers' purchasing procedure.

On the other hand, since the item to be sold is already determined from the supplier's point of view, it is not necessary to select the item; in that case, a selection is made from among consumers who wish to purchase the item provided. In general, as in the case of Supplier 1 and Supplier 3 in Fig. 4, most consumers are selected without any special evaluation or condition. However, since items are limited in the shared economy, the consumer may be selected, as in the case of Supplier 2, or rejected if they are rude, depending on the platform.

The derivation of properties is set separately because each user has a different priority. There are two properties: a filtering property and a weighting property. The filtering property improves the recommendation speed by removing an item if it is not purchased by the user or when it is not a condition, and the weighting property is input into the learning model as a priority for each user and is used when extracting

mutual satisfaction. The consumer's weighting property may include the consumer's preference information and evaluation information about the product and the supplier; the supplier's weighting property may include the customer's suitability or intention to purchase the product.

In the case of the first model, which predicts consumer satisfaction with a supplier, the properties may include consumer information (personal information, location, purchase history, etc.) and item preference information (rating, etc.) as in the existing recommender system model. In this study, the supplier's information is added to these properties. In the second model for predicting supplier satisfaction with consumers, since items from the supplier's perspective are already determined, only the information about consumers and suppliers is obtained. For the collected data, the numeric type is expressed as a value between 0 and 1 using min-max scaling for efficient learning, and the categorical type is converted using label encoding.

**Fig. 4.** Suppliers' purchasing procedure.

4.2 Prediction of User-Specific Satisfaction

To predict the satisfaction level for each user, we constructed the consumer satisfaction prediction model (*CM*) and the supplier satisfaction prediction model (*SM*), both of which proceed with hybrid learning based on the CNN and DNN. This process extracts features from data input using the CNN, and then user satisfaction is predicted using the DNN.

Before predicting satisfaction using a model, information in the input layer is input in relation to an item to which a user-specific filtering property is applied. In the case of the *CM*, the item information and the supplier information related to the item are obtained for items that satisfy the condition that the consumer wants to fulfill by making a purchase. In the case of the *SM*, based on the consumer satisfaction prediction result, information regarding the top consumer is produced. This process can reduce unnecessary calculations.

The input data is transferred to the embedding layer. Since categorical variables are high-dimensional, mapping to low-dimensional space is necessary. In particular, since information about items includes rating and categorical variables regarding various aspects, embedding is performed because the data is larger than that used for other models. Next, the primary feature map is output by a convolution operation on metadata such as the consumer preference information, item information, and host information. Then, Global max pooling is used to translate to the lower dimension. After that, all embedding vectors are concatenated, and the weight of each node is corrected using a fully connected layer that predicts

satisfaction. At this time, the rectified linear unit (ReLU) activation function is used for every layer of the hidden layer up to this point. The overfitting problem is solved using the dropout layer, which is located before the output layer, and the output layer derives the expected satisfaction using a sigmoid activation function that outputs a value between 0 and 1 that predicts satisfaction. The *CM* and *SM* models are similar, but because the input data are different, the number of hidden layers in both was adjusted as shown in Fig. 5(a) and 5(b).

(a)

(b)
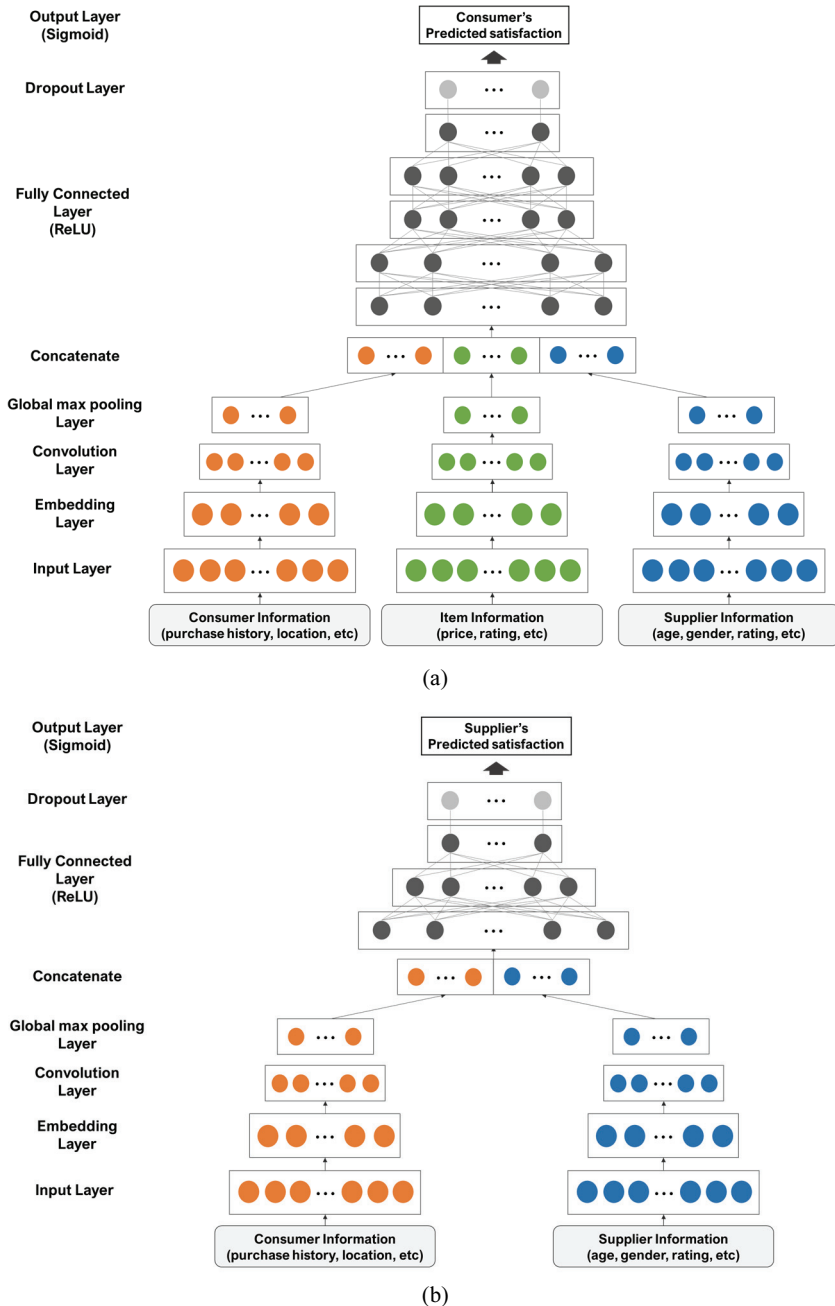
Fig. 5. (a) Consumer and (b) supplier satisfaction prediction models.

4.3 Mutual Satisfaction Derivation

Mutual satisfaction is the satisfaction of both the consumer and the supplier. The key here is to consider the differences between the two users. Regarding mutual satisfaction, higher user satisfaction indicates better matching, but if the satisfaction of either user is low, the matching is not suitable. For example, as shown in Fig. 6, mutual satisfaction can be viewed by comparing three situations. In these three situations, the satisfaction of both the consumer and the supplier is equal to 8 on average. In the case of Fig. 6(a), the consumer is more satisfied than the supplier. In the case of Fig. 6(b), the supplier is more satisfied than the consumer. In the case of Fig. 6(c), the average of the consumer and the supplier is equal to 8. First, a smaller difference between the satisfaction of the consumer and the supplier indicates better satisfaction of the consumer and the supplier. Therefore, cases (a), (b), and (c), (c) should have the highest mutual satisfaction result. Next, when comparing (a) and (c), the satisfaction difference is the same. This equality does not mean that mutual satisfaction is the same because, as mentioned in Section 3.1, suppliers have fewer opportunities to make choices than consumers, and therefore, in this case, it is their first choice. For this reason, the consumer's satisfaction is given slightly more priority.

$\therefore Average_{a,b} = 8, \ MS_{a,b} = 7.5$

Consumer a
(Predicted satisfaction : 10)

Supplier b
(Predicted satisfaction : 6)

(a)

$\therefore Average_{a,b} = 8, \ MS_{a,b} = 7$

Consumer a
(Predicted satisfaction : 6)

Supplier b
(Predicted satisfaction : 10)

(b)

$\therefore Average_{a,b} = 8, \ MS_{a,b} = 8$

Consumer a
(Predicted satisfaction : 8)

Supplier b
(Predicted satisfaction : 8)

(c)
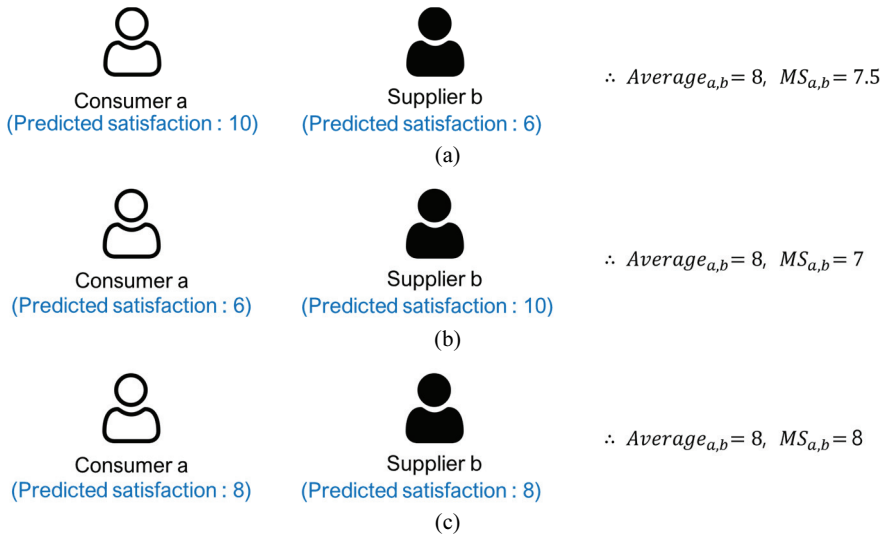
Fig. 6. Results of the mutual satisfaction calculation according to the conditions. (a) If the consumer's satisfaction is greater. (b) If the supplier's satisfaction is greater. (c) If the consumer's satisfaction and the supplier's satisfaction are the same.

Considering this factor, the mutual satisfaction ($MS_{a, \ b}$) is derived by comparing the magnitude of the satisfaction score of both "consumer a" and the satisfaction score of "supplier b," as shown in Eqs. (1) and (2). Before this calculation, the DNN model extracts the value of "consumer a" from consumers' satisfaction (CS) and the value of "supplier b" from suppliers' satisfaction (SS). Mutual satisfaction is calculated by subtracting the variance from the sum of the two values and dividing by 2. This process reflects the difference between the two values using a variance that is the deviation from the mean. A greater difference between the two values indicates lower mutual satisfaction because one of the two users may be unsatisfied.

Finally, the mutual satisfaction is derived in the form of a consumer-supplier matrix as shown in Fig. 7. Based on this calculation, whenever the satisfaction of the consumer or supplier is predicted, it is

updated with the predicted value. The recommended list is sorted in the order of the highest score for the user and generated by providing the appropriate number K of the supplier and the consumer.

$$MS_{a,\,b} = \frac{(CS_a + SS_b) - \frac{1}{2}\sqrt{\left(\frac{CS_a - SS_b}{2}\right)^2}}{2} \quad (CS_a - SS_b \geq 0) \tag{1}$$

$$MS_{a,\,b} = \frac{(CS_a + SS_b) - \sqrt{\left(\frac{CS_a - SS_b}{2}\right)^2}}{2} \quad (CS_a - SS_b < 0) \tag{2}$$
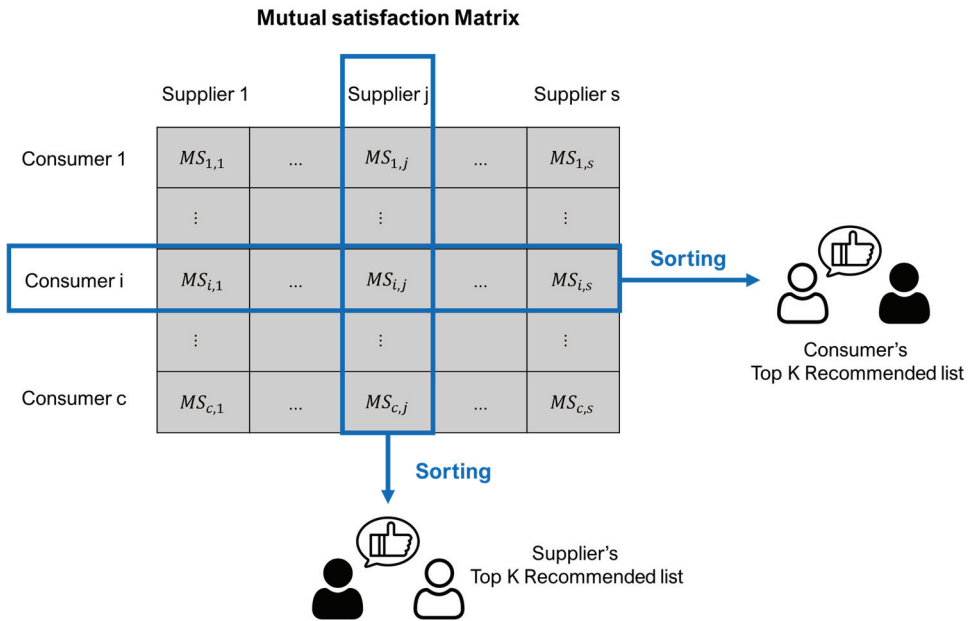
Fig. 7. Recommendation process using derived mutual satisfaction matrix.

5. Experiment

5.1 Experimental Environment

The experiment was implemented using Python-based TensorFlow and Keras; Table 1 shows the experimental environment presented in this paper.

Table 1. Experimental environment

Type	Value
CPU	Intel Core i7-8700K
GPU	GeForce GTX 1080
RAM	32 GB
Python	3.6
TensorFlow	1.13.1
Keras	2.2.4

5.2 Dataset

To apply the matching service model proposed in this paper, we collected Airbnb data in New York from July 2019 to January 2020 from InsideAirbnb. It was judged whether or not to use accommodation based on a review written by the user, and only users who used Airbnb over four times were filtered. As a result, the experiment was conducted with 67,045 reviews as shown in Table 2.

Table 2. Dataset information

Details	Value
Period	July 2019 to January 2020
Area	New York
Number of rooms	17,978
Number of hosts	14,182
Number of guests	11,732
Number of reviews	67,045

5.3 User-Specific Property Settings

The filtering and weighting property set to derive mutual satisfaction are listed in Table 3. The filtering properties are for Airbnb accommodation information and are set as typical room type and region. In addition, the consumer recommended list, which is the result from the *CM*, is delivered and set as a filtering property in the *SM*.

Table 3. User-specific property settings for the dataset

Property	Model	Data type	Element
Filtering	All	Item	Room type, Region
	SM	Consumer	The consumer recommended list
Weighting	*CM*	Consumer	Location, Preferred price
		Item	Location, Price, Room type, Number of beds, Rating
		Supplier	Location, Super host or not, Identity verified or not
	SM	Consumer	The probability of writing a review, Location
		Supplier	Consumer location

The weighting properties are separate in the *CM* and *SM*. In the *CM*, since the consumer information cannot include data such as gender or age for information protection, it was set to location and preferred price. Item information was set by location, price, room type, number of beds, and rating. The supplier information was set to the location of accommodation, super host or not, and identity verified or not. In the *SM*, since a supplier desires many reviews on his page, the weighting property sets the probability of writing a review and location among consumer information. At this time, the probability of writing a review is calculated by taking the average of the consumer's review history. Additionally, among the weighting properties, the supplier's information is set to the location.

5.4 Experimental Results

The experiment compared the UTU-MS proposed in this paper with the matrix factorization (MF) model, which is based on support value decomposition (SVD) and is frequently used in existing recom-

mendation systems. To confirm the mutual recommendation performance, the experiment was conducted using four different configurations:

   C1: only the CM model of the UTU-MS,

   C2: UTU-MS,

   C3: the MF model for unidirectional recommendation, and

   C4: the MF model for mutual recommendation.

The model's input data are properties specified in Section 5.3. Since Airbnb data does not provide information about ratings given by the guest, this information was obtained by setting the output data (i.e., on whether or not the actual guest selected the accommodation). For model training, the training data comprised 70% and the test data 30%. In addition, the model's learning rate was 0.001, and 100 learning epochs were conducted. The performance evaluation involved calculating the precision and recall based on Table 4, thereby calculating the F-measure value. Precision is the percentage at which the consumer stays at the predicted hosts' accommodation. Recall is the percentage of how many consumers were recommended specific accommodation that they then visited, which is calculated using Eqs. (3)–(5).

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

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

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

Table 4. Descriptions of symbols

Actual predicted	Predicted	Not predicted
Stay	a	b
Not stay	c	d

Table 5 shows the results of evaluating the experimental performance of the proposed model. It is the average of the results of the experiments in terms of the number of recommended users for precision, recall and F-measure. Fig. 8 shows the F-measure of each model for the number of recommended users. It was confirmed that the methods C2 and C4, which carried out mutual satisfaction predictions, were slightly more dominant. In other words, it was shown that the F-measure value improved when using the recommendation model that calculates mutual satisfaction. In addition, when comparing the performance evaluation of C2 and C4, it was confirmed that the performance of C2 is approximately 13% higher. Through this experiment, it can be confirmed that the recommendation based on the prediction of user mutual satisfaction is meaningful, and the suitability of the UTU-MS model proposed in this paper was confirmed.

Table 5. Average of the results of experimental performance

Method	Precision	Recall	F-measure
C1	0.130	0.211	0.143
C2	0.131	0.229	0.156
C3	0.094	0.134	0.103
C4	0.129	0.174	0.138
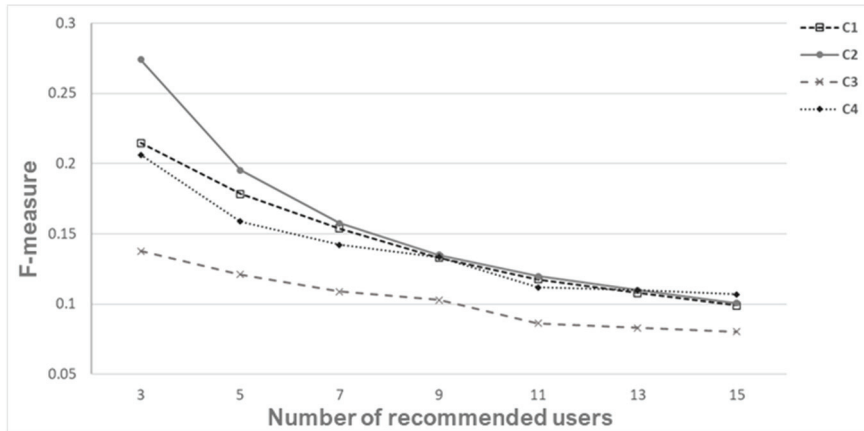
Fig. 8. F-measure for each model according to the number of recommended users.

6. Conclusion

In this paper, a UTU-MS for use in a business platform based on a shared economy was proposed; in this context, the users are both consumers and suppliers. This classification suggests matching of the consumer to the supplier, unlike user–item recommendations in existing recommendation services. To this end, the priorities of consumers and suppliers were identified, and filtering and weighting properties were derived. Using the CNN-DNN-based learning model, satisfaction predictions from the consumer's and supplier's perspectives were synthesized, and mutual satisfaction was derived to make recommendations. We conducted experiments using Airbnb data and confirmed better performance than the user–item recommendation method.

The proposed model can be said to be an optimized model for the sharing economy and is meaningful in that it is a recommendation that reflects the priorities of each user. However, since the prediction is performed using two models, it has a limitation in terms of learning speed. In future studies, we intend to study ways to improve the speed and increase the accuracy of recommendations to apply it to various sharing-based platforms.

Acknowledgement

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