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A MinMax Item-based Method for Multi-Criteria Recommendation Systems

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Abstract

One of the common challenges in multi-criteria recommendation systems is dealing with data normalization. The challenge occurs since criteria can have diverse rating ranges and user rating behaviors are dissimilar. Previous studies on data normalization showed the supremacy of the Decoupling technique in the user-based multi-criteria recommendation system and the MinMax technique in the multi-criteria decision-making system as well as in data mining. A study also showed that the performance of Decoupling is improved in the item-based method than in the user-based. However, no study has been conducted to investigate the performance of MinMax compared to Decoupling in the item-based multi-criteria recommendation system. This study aims to combine the MinMax normalization technique and the item-based modeling approach in a multi-criteria recommendation system. The proposed method is named the MinMax Item-based method (MIB). We conducted a series of experiments using the Yelp Hotel multi-criteria rating dataset to perform a sensitivity analysis of MIB. The best settings are then used to benchmark MIB MIB towards DCMItem, i.e., a method that combines the Decoupling normalization technique and item-based multi-criteria modeling approach. The comparison results show the outperformance of MIB towards DCMItem by 2.30% in Precision and 2.00% in NDCG. Therefore, we can conclude that MixMax is able to improve the performance of the item-based multi-criteria recommendation system better than Decoupling.

Keywords: Decoupling; item-based; MinMax; multi-criteria recommendation system

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1. Introduction

The multi-criteria recommendation system is a system that lets its users rate each item based on several aspects or criteria [1, 2]. Thus, such as system generates a list of recommendations based on a recommendation model that considers those multiple judgments. We can implement a multi-criteria recommendation system for various domains, such as movies [3], tourism attractions [4], hotels [5], and university courses [6].

One of the common challenges in multi-criteria recommendation systems is dealing with data normalization. A usual reason for this is the diverse rating ranges amongst criteria since each criterion has a different rating range. Another reason is that users have different rating behaviors, i.e., some users were kind when giving ratings while the others were the opposite. Therefore, when developing the recommendation model, it is necessary to implement a normalization technique that aims to eliminate the dominance of ratings on certain criteria or given by specific users.

The study in this paper is motivated by three discoveries of preceding research. First, the Decoupling normalization technique outperforms the no-normalization and Z-Score techniques in the user-based multi-criteria recommendation system [7]. Second, the performance of the Decoupling technique in the item-based modeling approach is better than that of the user-based [8]. Third, the MinMax technique outperforms others – where Decoupling was included in the study – when implemented in multi-criteria decision-making systems [9] and data mining [10]. All of those discoveries raise a research question, i.e., whether MinMax can improve the performance of the item-based multi-criteria recommendation system better than Decoupling.

This paper proposes a method that combines the MinMax normalization technique and the item-based modeling approach for the multi-criteria recommendation systems, then labels it as MinMax Item-based (MIB). To answer the research question, we compare the performance of MIB to a method that combines the Decoupling normalization technique and the item-based modeling approach, i.e., DMCItem.

The remains of this paper are organized as the following. Section II presents the previous research closely related to the work conducted in this study, i.e., the implementation of the normalization technique in multi-criteria-based systems. Section III details the development of the proposed method that combines the MinMax normalization technique and the item-based modeling approach for the multi-criteria recommendation systems. Section IV describes the experimental setup used for the empirical analysis, including the dataset, evaluation method, evaluation metric, and benchmarking method. Section V presents the experiment results and the comprehensive discussion. Finally, Section VI summarizes and concludes the findings of this paper; and states the possible future work.

2. Related Work

Researchers have been investigating the impact of various normalization techniques in multi-criteria-based systems. In recommendation systems, Bilge and Yargıç [7] conducted a study to analyze the performance of three normalization techniques in the user-based modeling approach: no-normalization, Z-score, and Decoupling. The experiment results revealed that the user-based modeling approach performs the best when combined with the Decoupling technique. While in decision-making systems, Vafaei, et al. [9] compared the performances of MinMax, Max, Sum, Vector, Logarithmic, and Fuzzification normalization techniques for selecting suppliers in the collaborative networks. Their empirical analysis showed that the MinMax and Fuzzification are the best techniques.

Following the study of [7], Ifada, et al. [8] investigated the impact of the Decoupling technique when implemented in user- and item-based modeling approaches. Experiment results on the Yelp multi-criteria dataset showed that Decoupling performs better in the item-based multi-criteria recommendation system than that in the user-based. This paper proposes a method that combines the MinMax normalization technique and the item-based modeling approach for multi-criteria recommendation systems. It then compares its performance to its counterpart proposed in [8].

3. Proposed Method

Our proposed method combines the MinMax normalization technique and the item-based modeling approach for multi-criteria recommendation systems, labeled as MinMax Item-based (MIB). MIB generates an item recommendation list for a target user by learning from the rating histories of the target user and other users towards items based on multiple criteria. Assume that the system has a set of p users denoted as $U = \{u_1, u_2, \dots, u_p\}$, a set of q items denoted as $I = \{i_1, i_2, \dots, i_q\}$, and a set of k criteria denoted as $C = \{c_1, c_2, \dots, c_k\}$. The multi-criteria rating histories, which hold the ternary relationships between users, items, and criteria, are represented as $R \in \mathbb{R}^{p \times q \times k}$ where r_{uic} indicates the rating specified by user u to item i based on criterion c. From the rating histories, we can as well form U_i that denotes the set of users who have rated item i.

The development of consists of four main stages: (1) Multi-criteria MinMax normalization, (2) Multi-criteria item-based similarity, (3) Multi-criteria item-based rating prediction, and (4) Multi-criteria Top-N recommendation. Fig. 1 presents the proposed MIB algorithm for the multi-criteria recommendation systems.

ALGORITHM:
MinMax Item-based method (MIB) for the Multi-Criteria Recommendation System

INPUT:
Multi-criteria rating data; New range of rating $RatingNewRange = [NewMin, NewMax]$; Size of item neighborhood h; Weighted Scoring of Criteria W;

PROCESS:
1. Get U and p from the multi-criteria rating data
2. Get I and q from the multi-criteria rating data
3. Get C and k from the multi-criteria rating data
4. Represent the multi-criteria rating data as $R \in \mathbb{R}^{p \times q \times k}$ where r_{uic} is the rating specified by user u to item i based on criterion c
5. Get U_i that lists the users who rated item i

/* Stage 1: Multi-criteria MinMax Normalization */
6. Calculate minimum rating Min_u according to Equation (2)
7. Calculate maximum rating Max_u according to Equation (3)
8. Calculate $\Delta Range_u$ according to Equation (4)
9. Calculate $\Delta NewRange$ according to Equation (5)
10. Generate the MinMax normalization rating matrix $M \in \mathbb{R}^{p \times q \times k}$ where m_{uic} is calculated according to Equation (1)

/* Stage 2: Multi-criteria Item-based Similarity */
11. Calculate $\hat{\mu}_{uc}$ as the mean of the MinMax normalization rating $M \in \mathbb{R}^{p \times q \times k}$ of user u based on criterion c
12. According to Equation (6), calculate the item based per criterion similarity $\acute{S}(i,j)_c$ thus $\acute{S} \in \mathbb{R}^{q \times q \times k}$
13. According to Equation (7), aggregate $\acute{S} \in \mathbb{R}^{q \times q \times k}$ to get the item-based overall similarity $\hat{S}(i,j)$ such that $\hat{S} \in \mathbb{R}^{q \times q}$

/* Stage 3: Multi-criteria Item-based Rating Prediction */
14. Determine the target user $u \in U$
15. Get I_u that lists items that have been rated by target user u
16. Get target items $\hat{I}_u$ according to Equation (8)
17. Generate $Y_u(i)$ as the list of item neighborhoods of $\hat{I}_u$, such that $|Y_u(i)| \leq h$
18. For each $i \in \hat{I}_u$, calculate the item-based per criterion rating prediction $\acute{r}_{uic}$ according to Equation (9)
19. According to Equation (10), aggregate $\acute{r}_{ui*}$ to get the item-based overall rating prediction $\hat{r}_{ui}$

/* Stage 4: Multi-criteria Top-N Recommendation */
20. Generate $Top_u(N)$ for a target user u, according to Equation (11)

OUTPUT:
$Top_u(N)$ as the Top-N recommendation for the target user u

Fig. 1. Algorithm of MinMax Item-based method (MIB) for the multi-criteria recommendation systems

3.1. Multi-criteria MinMax Normalization

This stage transforms the (original) multi-criteria rating r_{uic} into a new multi-criteria rating m_{uic} by implementing the MinMax normalization technique. The MinMax normalization maps r_{uic} to m_{uic} by considering the original range as well as the new range of ratings. Assume that the original rating range of user u is $[Min_u, Max_u]$ and the new range of ratings is set as $[NewMin, NewMax]$, the transformation of r_{uic} to m_{uic} is formulated as Equation (1).

$$m_{uic} = \frac{r_{uic} - Min_u}{\Delta Range_u} \Delta NewRange + NewMin \quad (1)$$

where

$$Min_u = \min_{i \in I, c \in C} r_{uic} \quad (2)$$

$$Max_u = \max_{i \in I, c \in C} r_{uic} \quad (3)$$

$$\Delta Range_u = Max_u - Min_u \quad (4)$$

$$\Delta NewRange = NewMax - NewMin \quad (5)$$

3.2. Multi-criteria Item-based Similarity

This stage calculates the similarity between items based on the MinMax normalization rating matrix $M \in \mathbb{R}^{p \times q \times k}$. Given the multi-criteria rating, the calculation of the item-based similarity must follow the two-phase computations, i.e., the per criterion and the overall criteria similarities. The per c criterion similarity between item i and j is formulated as Equation (6).

$$\acute{S}(i,j)_c = \frac{\sum_{u \in U_i \cap U_j} (m_{uic} - \hat{\mu}_{uc}) \cdot (m_{ujc} - \hat{\mu}_{uc})}{\sqrt{\sum_{u \in U_i \cap U_j} (m_{uic} - \hat{\mu}_{uc})^2} \cdot \sqrt{\sum_{u \in U_i \cap U_j} (m_{ujc} - \hat{\mu}_{uc})^2}} \quad (6)$$

where $\hat{\mu}_{uc}$ is the mean of the MinMax normalization rating of user u based on criterion c.

The overall criteria similarity is derived by aggregating the multiple similarities $\acute{S}(i,j)_c$, where $c \in C$, as a single similarity $\hat{S}(i,j)$. In this paper, we implement the worst-case scenario, following the approach in [7], that the lowest $\acute{S}(i,j)_c$ is used to represent the overall criteria similarity. The calculation of the overall criteria similarity is formulated as Equation (7).

$$\hat{S}(i,j) = \min_{c \in C} \acute{S}(i,j)_c \quad (7)$$

3.3. Multi-criteria Item-based Rating Prediction

In this stage, we calculate the rating prediction of each target item $i \in \hat{I}_u$, i.e., items that have not been previously rated by a target user u. The target items $\hat{I}_u$ can be formulated as Equation (8).

$$\hat{I}_u = I - I_u \quad (8)$$

where I_u is the set of items rated by user u such that $I_u \cap \hat{I}_u = \emptyset$.

Given the multi-criteria rating, the calculation of the item-based rating prediction must follow the two-phase computations, i.e., the per criterion and the overall criteria rating predictions. The per c criterion rating prediction of target item i by target user u is formulated as Equation (9).

$$\acute{r}_{uic} = \frac{\sum_{j \in Y_u(i)} \hat{S}(i,j) \ . \ (m_{uic} - \hat{\mu}_{uc})}{\sum_{j \in Y_u(i)} |\hat{S}(i,j)|} \quad (9)$$

where $Y_u(i)$ is the set of h items rated by the target user u that have similarities with item i, such that $|Y_u(i)| \leq h$. In the rest of this paper, we define h as the size of the item neighborhood.

The overall criteria rating prediction is derived by aggregating the multiple rating predictions of $\acute{r}_{uic}$, where $c \in C$, as a single rating prediction $\hat{r}_{ui}$. This paper implements the weighted scoring scheme [11], following the approach in [8]. The overall rating prediction is computed by assigning a relative weight to each rating prediction of each criterion. The overall criteria rating prediction is formulated as Equation (10).

$$\hat{r}_{ui} = \sum_{c \in C} \acute{r}_{uic} \cdot w_c \tag{10}$$

where $\sum_{c \in C} w_c = 1$ and $|W| = |C|$.

3.4. Multi-criteria Top-N Recommendation

The multi-criteria Top-N recommendation is the stage where we determine the $Top_u(N)$ as the Top-N item recommendations listed for the target user u. In this case, $Top_u(N)$ contains up to N target items that have N highest overall criteria rating predictions. The multi-criteria Top-N recommendation is formulated as Equation (11).

$$Top_u(N) = \underset{i \in \hat{I}_u}{\overset{N}{argmax}}\, \hat{r}_{ui} \tag{11}$$

4. Experiment Setup

4.1. Dataset

We evaluate the performance of our proposed MIB by using the Yelp dataset (https://www.kaggle.com/yelp-dataset/yelp-dataset/version/6/), which contains the ratings of Hotels based on four criteria. Following the approach in [8], we only use the rating data of users who have rated at least three hotels. Table 1 displays the details of the Yelp dataset used in this paper.

Table 1. Details of the Yelp dataset used in the experiments

Description	Detail
Number of users	2,595
Number of items/hotels	5,209
Number of ratings	25,000
Criteria and the rating ranges	Criteria #1: “Overall”, range [1, 5] Criteria #2: “Useful”, range [0, 110] Criteria #3: “Funny”, range [0, 59] Criteria #4: “Cool”, range [0, 103]

4.2. Evaluation Method and Metric

We implement the 5-fold cross-validation evaluation method, i.e., each fold randomly contains 80% of training data and 20% of test data. The former is used to build the recommendation model, i.e., for generating $Top_u(N)$ for each target user u; while the latter is used as the recommendation ground-truth G_u of each target user u. In this case, the target users are those listed in the test data, and the evaluation process is to compare the list in $Top_u(N)$ to those in G_u. The per target user performance scores are calculated based on the Precision and Normalized Discounted Cumulative Gain (NDCG) metrics formulated as Equation (12) and (13), respectively.

$$Precision_u(N) = 100 \cdot \frac{|Top_u(N) \cap G_u|}{N} \tag{12}$$

$$NDCG_u(N) = \frac{DCG_u(N)}{IDCG(N)} \tag{13}$$

where

$$DCG_u(N) = \sum_{x=1}^{N} \frac{1}{log_2(1+x)} \cdot \mathbb{I}(Top_u(x) \in G_u) \tag{14}$$

$$IDCG(N) = \sum_{x=1}^{N} \frac{1}{log_2(1+x)} \tag{15}$$

where $\mathbb{I}(\cdot)$ is a conditional function to return 1 when the condition is true or 0 otherwise.

4.3. Benchmarking

For benchmarking, the performances of MIB are compared to those of DMCItem [8]. DMCItem is a multi-criteria recommendation system method that combines the Decoupling normalization technique and the item-based modeling approach.

5. Results and Discussion

5.1. Sensitivity of MIB

This section aims to investigate the best setting of each parameter of MIB to achieve the best performance of MIB. As shown in Fig. 1, MIB depends on the set of three parameters: the new range of rating $[NewMin, NewMax]$, size of item neighborhood h, and weighted scoring of criteria W.

5.1.1. New Range of Rating $RatingNewRange = [NewMin, NewMax]$

From Table 1, we can observe that the criteria in the Yelp dataset have diverse (original) rating ranges. However, we can also notice that the rating range of the "Overall" criterion is a proper subset of those of the other three criteria. For this reason, the study of MIB sensitivity towards the new range of rating $[NewMin, NewMax]$ is conducted by comparing the performances of MIB when implemented on various new rating ranges that are defined as within the original rating range of the "Overall" criterion. In other words, $NewMin$ is always equal to the 1 while $NewMax$ is either less or equal to 5. Hence, the variations of $RatingNewRange = \{[1,2], [1,3], [1,4], [1,5]\}$.

Fig. 2 shows the sensitivity of MIB towards the variation of new rating ranges, in which the Precision and NDCG metrics results show the same pattern. We can notice that the performances of MIB are linear to the increase of $NewMax$ until $NewMax = 4$, and then declines afterwards. These results indicate that scaling down the original range of rating to the new range of rating can increase the performance of MIB. Based on this finding, MIB is set to use $RatingNewRange = [1,4]$ for the purpose of performance benchmarking.

5.1.2. Size of Item Neighborhood h

The study of MIB sensitivity towards the size of item neighborhood h is conducted by comparing the performances of MIB when implemented on various h that are defined by following the procedure in [8]. Hence, a variation of $h = \{5,10,20,30,40,50\}$.

Fig. 3 shows the sensitivity of MIB towards the variation of h, in which the results in terms of Precision and NDCG show similar behavior. We can observe that MIB performs the best at the lowest h and tends to deteriorate at larger h. These results suggest that a small amount of h is sufficient for MIB. Based on this finding, MIB is set to use $h = 5$ for performance benchmarking.

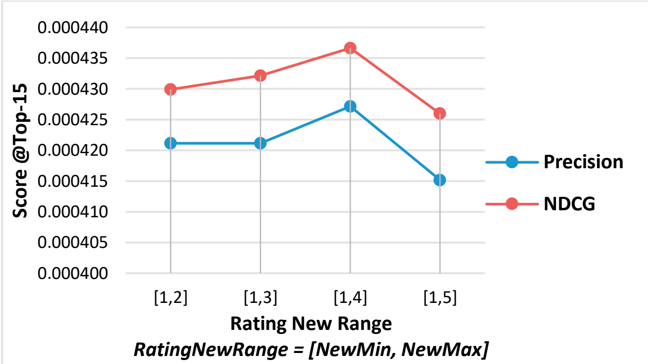

Fig. 2. MIB sensitivity towards rating new range $RatingNewRange = [NewMin, NewMax]$

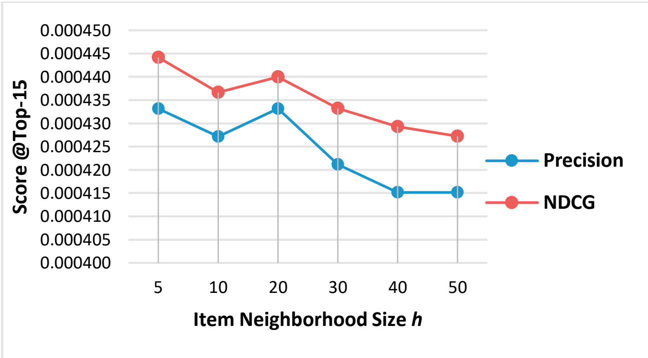

Fig. 3. MIB sensitivity towards item neighborhood size h

5.1.3. Weighted Scoring of Criteria W

The study of MIB sensitivity towards the weighted scoring of criteria W is conducted by comparing the performances of MIB when implemented on various W that are defined by following those in [8]. Table 2 shows the details of the variation of W used in this paper.

Fig. 4 shows the sensitivity of MIB towards the variation of W. We can observe that MIB performs the best when $W = WS1$ in terms of Precision and $W = WS5$ in terms of NDCG. Considering that NDCG is more sensitive than Precision towards the ranking of the items in the list of recommendations, we choose to use the results of NDCG to determine the best W for MIB. Hence, MIB performs the best when $W = WS5$, which means that the ratings of the "Cool" criterion most influence the recommendation quality. Based on this finding, MIB is set to use $W = WS5$ for the purpose of performance benchmarking.

Table 2. Variation of criteria weighted scoring W

Label	W				Description
	w_1	w_2	w_3	w_4	
WS1	0.25	0.25	0.25	0.25	Equal weight of all criteria
WS2	0.40	0.20	0.20	0.20	Criterion #1 is the most important
WS3	0.20	0.40	0.20	0.20	Criterion #2 is the most important
WS4	0.20	0.20	0.40	0.20	Criterion #3 is the most important
WS5	0.20	0.20	0.20	0.40	Criterion #4 is the most important

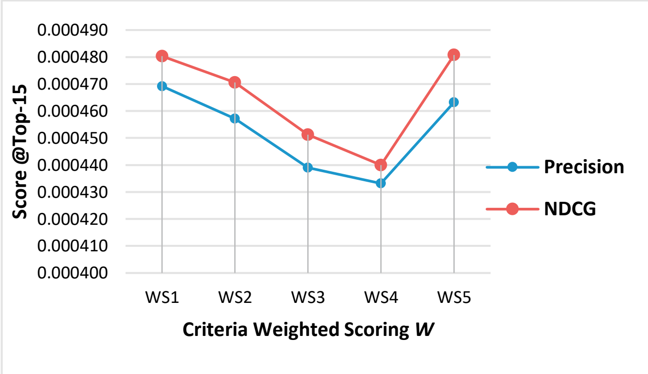

Fig. 4. MIB sensitivity towards criteria weighted scoring W

5.2. Performance Benchmarking

The purpose of performance benchmarking is to compare the performance of the MinMax normalization technique to that of the Decoupling in the item-based multi-criteria recommendation system. In other words, this comparison aims to prove whether MinMax can outperform Decoupling. We compare the performance of our proposed MIB to DMCItem [8], where the setting of MIB follows the results of the previous section (Section V.A), i.e., $RatingNewRange = [1,4]$, $h = 5$, and $W = WS5$. Meanwhile, the setting of parameters of DMCItem follows those in [8], i.e., $h = 50$ and $W = WS5$.

Fig. 5 and Fig. 6, respectively, show the comparison results of MIB and DMCItem in terms of Precision and NDCG. Notice that MIB performs better than DMCItem on both metrics. In this case, we can state that MinMax outperforms Decoupling in the item-based multi-criteria recommendation system. To further detail the exact increase of the MIB towards DMCItem from Top-1 to Top-20, we list the performance results in a tabular form (Table 3). The percentage increase of MIB towards DMCItem is formulated as Equation (16).

$$\%Increase = \frac{MIB - DMCItem}{DMCItem} \times 100\% \tag{16}$$

From Table 3, we can notice that the average percentage increase of MIB towards DMCItem is 2.30% in terms of Precision and 2.00% in terms of NDCG. These comparable numbers between the Precision and NDCG indicate that the increase of MIB towards DMCItem is relatively stable on both metrics.

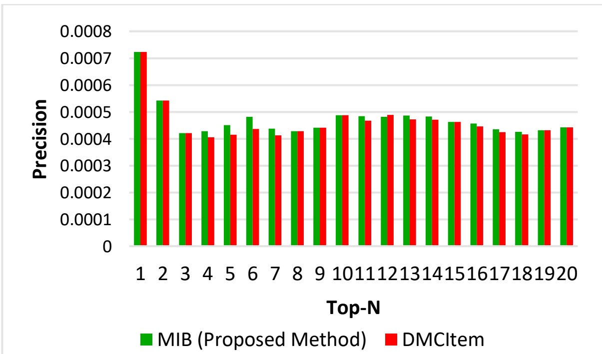

Fig. 5. Performance comparison in terms of Precision

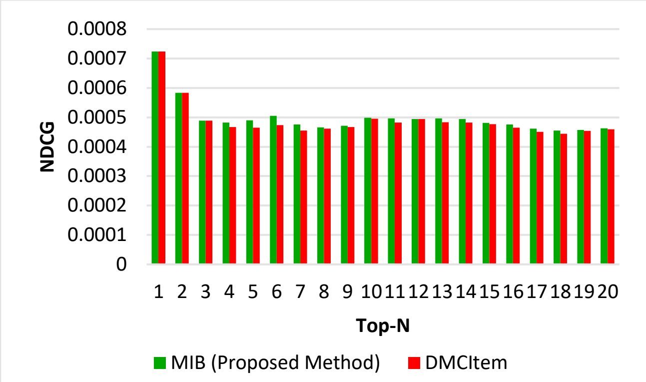

Fig. 6. Performance comparison in terms of NDCG

Table 3. Percentage of increase of *MIB* towards *DMCItem* in terms of Precision and NDCG

Top-N	Precision			NDCG		
	DMCItem	MIB	%Increase	DMCItem	MIB	%Increase
1	0.00072346	0.00072346	0.00%	0.00072346	0.00072346	0.00%
2	0.00054204	0.00054204	0.00%	0.00058309	0.00058309	0.00%
3	0.00042123	0.00042123	0.00%	0.00048842	0.00048842	0.00%
4	0.00040615	0.00042870	5.55%	0.00046698	0.00048215	3.25%
5	0.00041514	0.00045112	8.67%	0.00046490	0.00048984	5.37%
6	0.00043608	0.00048119	10.35%	0.00047308	0.00050512	6.77%
7	0.00041231	0.00043825	6.29%	0.00045444	0.00047538	4.61%
8	0.00042853	0.00042853	0.00%	0.00046143	0.00046621	1.04%
9	0.00044109	0.00044102	-0.02%	0.00046711	0.00047150	0.94%
10	0.00048731	0.00048727	-0.01%	0.00049485	0.00049899	0.84%
11	0.00046762	0.00048400	3.50%	0.00048189	0.00049623	2.98%
12	0.00048889	0.00048130	-1.55%	0.00049468	0.00049386	-0.16%
13	0.00047211	0.00048596	2.93%	0.00048370	0.00049622	2.59%
14	0.00047058	0.00048347	2.74%	0.00048219	0.00049416	2.48%
15	0.00046324	0.00046324	0.00%	0.00047700	0.00048076	0.79%
16	0.00044564	0.00045694	2.54%	0.00046516	0.00047602	2.33%
17	0.00042472	0.00043535	2.50%	0.00045099	0.00046143	2.31%
18	0.00041610	0.00042618	2.42%	0.00044449	0.00045459	2.27%
19	0.00043219	0.00043220	0.00%	0.00045391	0.00045751	0.79%
20	0.00044214	0.00044211	-0.01%	0.00045965	0.00046310	0.75%
AVG			2.30%			2.00%

6. Conclusion and Future Work

We have presented our proposed method's development and empirical analysis, i.e., MinMax Item-based method (MIB) for the multi-criteria recommendation system. As its name would suggest, MIB is a multi-criteria recommendation method that combines the MinMax normalization technique and the item-based modeling approach.

Using the Yelp Hotel Multi-criteria rating dataset, we conducted the sensitivity analysis of MIB towards its parameter settings and the performance benchmarking of MIB towards DMCItem [8]. Recall that DMCItem is the counterpart of MIB that implements the Decoupling normalization technique. The sensitivity analysis results showed that MIB achieves its best performance when its parameters are set as $RatingNewRange = [1,4]$, $h = 5$, and $W = WS5$. Meanwhile, the performance benchmarking results showed that MIB outperforms DMCItem respectively by 2.30% and 2.00% in terms of Precision and NDCG. In this case, MixMax improves the performance of the item-based multi-criteria recommendation system compared to Decoupling.

For future work, we plan to study the impact of combining the normalization technique and the fusion of the user-based and item-based modeling approaches.

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