A User-based Normalization Multi-Criteria Rating Approach for Hotel Recommendation System

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ABSTRACT

This paper develops a method that implements a proposed user-based normalization multi-criteria rating approach for the hotel recommendation system. The inspirations come from two main reasons. First, data normalization is a common problem in the multi-criteria based recommendation system. It occurs since users have diverse tendencies when giving ratings and that each criterion might have a varied range of ratings. Second, a previous study showed the superiority of the Decoupling technique for solving the normalization problem in a user-based multi-criteria recommendation system. In the meantime, researchers of non-recommendation systems showed that the MinMax technique dominates others – the Decoupling technique was not used in the study. These two facts raise a research question on whether MinMax could also outperform Decoupling when implemented on a user-based multi-criteria recommendation system. Therefore, in this paper, we propose implementing the MinMax normalization technique on a user-based multi-criteria recommendation approach and then comparing the performance to that of the Decoupling. Through series of experiments using the Yelp Hotel Dataset, we confirm that the MinMax technique can significantly improve the quality of a user-based multi-criteria hotel recommendation system better than the Decoupling. That is, the performance of MinMax is more than two times higher than Decoupling.

CCS CONCEPTS

• **Information systems** → Information retrieval; Retrieval tasks and goals; Recommender systems;

KEYWORDS

decoupling, hotel recommendation system, MinMax, multi-criteria rating, normalization technique, user-based approach

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1 INTRODUCTION

Hotel satisfaction can impact the satisfaction of tourists [4, 5, 10] recommendation system is a system that helps its users, i.e., tourists, by providing a list of hotels that might suit their preferences. A multi-criteria hotel recommendation system is a system that allows users to rate hotels based on multiple criteria, e.g., users can rate hotels based on the "service", "hospitality", and "facility" criteria. Meanwhile, a user-based multi-criteria hotel recommendation system is a system that assumes that the ratting pattern of other users influences the target users' preferences towards hotels as items [1]. For this reason, a user-based approach implements the user-to-user similarity rating concept for generating the list of recommendations.

One common problem in the multi-criteria based recommendation system is data normalization. Users have diverse tendencies when giving ratings, e.g., generous, moderate, or stingy users. Additionally, the range of rating of each criterion might also be different, e.g., the range of rating of "service", "hospitality", and "facility" criteria are respectively [1,5],[1,10], and [1,20]. In this case, implementing a normalization technique in the recommendation system is advantageous for avoiding the dominance of per-user or per-criterion ratings.

The motivation of this paper comes from the fact that a previous study has shown the superiority of the Decoupling technique for solving the normalization problem in a user-based multi-criteria recommendation system [3]. On the other hand, researchers of the multiple-criteria decision-making systems [13] and data mining [11] showed the dominancy of the MinMax normalization technique. However, the Decoupling technique was not included in the studies. These discoveries raise a question on whether MinMax could also outperform Decoupling when implemented on the user-based multi-criteria recommendation system.

This paper proposes to implement the MinMax technique in a user-based multi-criteria hotel recommendation system. The experiments are conducted using the Yelp Hotel Dataset, and the results are then compared to those of the Decoupling.

2 RELATED WORK

Researchers of recommendation systems have implemented various techniques to solve the normalization problem, i.e., Decoupling [3, 7, 8], Gaussian [7, 8], Mean [9], Variance [9, 12], and Z-Score [3]. The Decoupling technique appeals as it has been shown to outperform the Gaussian in the single-criterion based system [7, 8] and Z-Score in the multi-criteria based system [3]. Meanwhile, researchers of multi-criteria decision-making systems [13] showed the superiority of the MinMax technique in comparison to Max, Vector, Sum, Logarithmic, and Fuzzification. Another research in data mining [11] showed that MinMax performs better than Z-Score and Decimal Scaling.

Following the approach in [3], we conduct a comparison study towards implementing the MinMax and Decoupling normalization techniques on a user-based multi-criteria approach, specifically for a hotel recommendation system. The main discussion of our paper focuses on the implementation of the MinMax technique, while the Decoupling technique is used for benchmarking.

3 USER-BASED NORMALIZATION MULTI-CRITERIA RATING APPROACH

The task of a hotel recommendation system is to generate a list of Top-N hotel recommendations that the target users have not rated. We propose to solve it by combining a normalization technique and a user-based multi-criteria recommendation approach. The implementation consists of three phases: (1) multi-criteria rating normalization, (2) multi-criteria user-based similarity, and (3) multi-criteria user-based rating prediction. Let's assume that we have a set of p users $U = \{u_1, u_2, u_3, ..., u_p\}$, a set of q hotels $I = \{i_1, i_2, i_3, ..., i_q\}$, and a set of k criteria $C = \{c_1, c_2, c_3, ..., c_k\}$. The hotel multi-criteria rating data is presented as a multi-criteria rating matrix $R \in \mathbb{R}^{pxqxk}$ where r_{uic} indicates the rating of hotel i given by user u based on criterion c.

3.1 Multi-criteria Rating Normalization

The process of rating normalization is transforming the rating data into another range of scales to reveal the latent relationship [3]. In this paper, we implement the MinMax normalization technique that has been shown to outperform other techniques.

The MinMax normalization is a technique that implements a linear mapping towards the initial data. The mapping of a hotel multi-criteria rating data r_{uic}, which has the initial range of $[Min_u, Max_u]$, into m_{uic} that has a new specified range of $[NewMin, NewMax]$ is formulated as Equation (1).

$$m_{uic} = \frac{r_{uic} - Min_u}{Max_u - Min_u}(NewMax - NewMin) + NewMin \quad (1)$$

where

$$Min_u = \min(r_{u**}) \quad (2)$$

$$Max_u = \max(r_{u**}) \quad (3)$$

ALGORITHM 1 shows the complete algorithm of the MinMax multi-criteria rating normalization.

Algorithm 1: MinMax Multi-Criteria Rating Normalization

```
Input  : Multi-criteria rating matrix R ∈ ℝ^{pxqxk}; New
         minimum value NewMin ; New maximum value
         NewMax
for each u ∈ U do
    Min_u ← min(r_{u**})
    Max_u ← max(r_{u**})
    for each i ∈ I do
        for each c ∈ C do
            compute m_{uic} according to Equation (1)
        end
    end
end
Output : MinMax normalization multi-criteria rating matrix
         M ∈ ℝ^{pxqxk}
```

Toy example of MinMax multi-criteria rating normalization: Table 1 shows an example of a hotel multi-criteria rating matrix $R \in \mathbb{R}^{4x3x3}$ where $U = \{u_1, u_2, u_3, u_4\}$, $I = \{i_1, i_2, i_3\}$, and $C = \{c_1, c_2, c_3\}$. Table 2 shows the Min_u and Max_u calculated based on Table 1. Assume that we specified $NewMin = 1$ and $NewMax = 2$, we can generate the MinMax normalization hotel multi-criteria rating matrix $M \in \mathbb{R}^{4\times3\times3}$, as presented in Table 3, by implementing ALGORITHM 1.

3.2 Multi-criteria User-based Similarity

The similarity between user u and v per criterion c can be calculated as Equation (4).

$$Sim(u,v)_c = \frac{\sum_{i \in I_u \cap I_v} (m_{uic} - \mu_{uc})(m_{vic} - \mu_{vc})}{\sqrt{\sum_{i \in I_u \cap I_v} (m_{uic} - \mu_{uc})^2}\sqrt{\sum_{i \in I_u \cap I_v} (m_{vic} - \mu_{vc})^2}} \quad (4)$$

where I_u and I_v are respectively the sets of hotels previously rated by user u and v . While m_{uic} and m_{vic} are respectively the MinMax normalization multi-criteria rating of user u and v towards hotel i based on criterion c. Whereas μ_{uc} and μ_{vc} are respectively the average of the MinMax normalization multi-criteria rating of user u and v based on criterion c.

Given the multi-criteria user-based similarities, the next step is to determine the aggregation of the multiple values. In this paper, we conduct the aggregation by implementing the worst-case similarity technique that has been shown to perform better than the average [3]. In this case, we select the minimum value amongst the multi-criteria similarities and then use it to represent the user-based similarity. ALGORITHM 2 shows the complete algorithm of the multi-criteria user-based similarity.

Table 1: Example of multi-criteria rating matrix $R \in \mathbb{R}^{4\times3\times3}$

		Hotel								
		i_1			i_2			i_3		
		c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
User	u_1	3	5	3	3	4	5	3	4	4
	u_2	1	2	1	3	2	1	2	2	1
	u_3	3	5	4	3	3	4	4	3	3
	u_4	2	2	1	2	2	1	2	1	2

Table 2: Example of Min_u and Max_u

User	Min_u	Max_u
u_1	3	5
u_2	1	3
u_3	3	5
u_4	1	2

Algorithm 2: Multi-criteria User-based Similarity

```
Input  : MinMax multi-criteria rating matrix M ∈ ℝ^{p×q×k}
/* User-based similarity per criterion                */
for each u ∈ U do
    for each v ∈ U do
        get I_u ( note that I_u = I_v if u = v)
        for each c ∈ C do
            μ_uc ← (Σ_{i∈I_u} m_uic) / |I_u|  (note that μ_uc = μ_vc if u = v)
            compute Sim(u, v)_c according to Equation (4)
        end
    end
end
/* Aggregate user-based similarities overall
   criteria                                            */
for each u ∈ U do
    for each v ∈ U do
        S(u, v) ← min_{1≤c≤k} Sim(u, v)_c
    end
end
Output : Multi-criteria user-based similarity matrix
         S ∈ ℝ^{p×p}
```

3.3 Multi-criteria User-based Rating Prediction

The user-based rating prediction of a target user u towards hotel i per criterion c is formulated as Equation (5).

$$r'_{uic} = \mu_{uc} + \frac{\sum_{v \in T_u(i)} S(u,v)\,(m_{vic} - \mu_{vc})}{\sum_{v \in T_u(i)} |S(u,v)|} \tag{5}$$

where $T_u(i)$ is the users neighborhood of size h, i.e., the set of users who have rated hotel i and whose similarity scores towards the target user u are in the top-h list such that $|T_u(i)| \leq h$.

Given the multi-criteria predicted ratings, the next step is to determine the aggregation of the multiple values. This paper uses the Weighted Linear Sum (WLS) technique [2] that tallies the multi-criteria predicted ratings by implementing a weighted scoring scheme. In this case, we assume that $W = \{w_1, w_2, ..., w_k\}$ is the set of k criteria weighted scoring that satisfies $1 = \sum_{c \in C} w_c$ such that $|W| = |C|$. ALGORITHM 3 shows the complete algorithm of the multi-criteria user-based rating prediction.

Algorithm 3: Multi-criteria User-based Rating Prediction

```
Input  : MinMax multi-criteria rating matrix M ∈ ℝ^{p×q×k};
         Multi-criteria user-based similarity matrix
         S ∈ ℝ^{p×p}; Set of target users Û where Û ⊂ U; Set
         of target hotels Î_u where I_u ⋂ Î_u = ∅; Users
         neighborhood size h; Criteria weighted scoring W.
/* Predicted rating per criterion                      */
for each u ∈ Û do
    for each i ∈ Î_u do
        for each c ∈ C do
            calculate r'_uic according to Equation (5)
        end
    end
end
/* Aggregate predicted ratings overall criteria
   */
for each u ∈ Û do
    for each i ∈ Î_u where I_u ⋂ Î_u = ∅ do
        r̂_ui ← Σ_{c∈C} w_c . r'_uic
    end
end
Output : User-based rating prediction r̂_ui
```

Hence, the Top-N recommendations list for a target user is generated based on the ordered list of the user-based predicted ratings of the target hotels, i.e., the higher the predicted rating, the more recommended the target hotel.

Table 3: Example of MinMax normalization multi-criteria rating matrix $M \in \mathbb{R}^{4x3x3}$

		Hotel								
		i_1			i_2			i_3		
		c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
User	u_1	1.00	2.00	1.00	1.00	1.50	2.00	1.00	1.50	1.50
	u_2	1.00	1.50	1.00	2.00	1.50	1.00	1.50	1.50	1.00
	u_3	1.00	2.00	1.50	1.00	1.00	1.50	1.50	1.00	1.00
	u_4	2.00	2.00	1.00	2.00	2.00	1.00	2.00	1.00	2.00

4 EMPIRICAL ANALYSIS

We evaluate our proposed approach by conducting empirical analysis through series of experiments. Recall that our evaluated method is based on a user-based multi-criteria recommendation approach that implements a MinMax normalization technique. Therefore, it is labeled as MinMax User-based (MUB) method.

4.1 Experiment Setup

We follow the experiment setup of previous normalization multi-criteria recommendation research [6]. In this case, we use the Yelp Hotel multi-criteria rating dataset (https://www.kaggle.com/yelp-dataset/yelp-dataset/version/6/), which were rated based on four criteria: (1) "Overall" that has a rating range of [1, 5]; (2) "Useful" that has a rating range of [0, 110]; (3) "Funny" that has a rating range of [0, 59]; and (4) "Cool" that has a rating range of [0, 103]. The evaluation method is the 5-fold cross-validation, in which the dataset is randomly split into five folds of training and test sets. The former set is used for building the recommendation model, while the latter is used as the ground truth for evaluating. The evaluation metrics are Precision and Normalized Discounted Cumulative Gain (NDCG).

4.2 Results and Discussion

4.2.1 Sensitivity of New Range $[NewMin, NewMax]$. The new specified range of $[NewMin, NewMax]$ influences the performance of MUB as it is used in the MinMax multi-criteria rating normalization process shown in ALGORITHM 1. To determine the best new range, we conduct series of experiments by varying $[NewMin, NewMax] = \{[1, 2], [1, 3], [1, 4], [1, 5]\}$. The variations of the and are respectively decided by considering the highest minimum rating and the lowest maximum rating of all criteria in the Yelp Hotel Dataset.

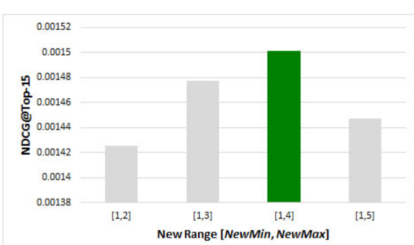

Figure 1: Sensitivity of new range $[NewMin, NewMax]$**.**

Figure 1 presents a chart that shows the impact of varying $[NewMin, NewMax]$ on the performance of MUB. We can observe that MUB performs the best when $[NewMin, NewMax] = [1, 4]$. This finding indicates that scaling down the rating range can improve the recommendation quality – yet, the new specified range should not be too low either. It is to be noted that we only show the results in terms of NDCG, as those of Precision show the same behavior.

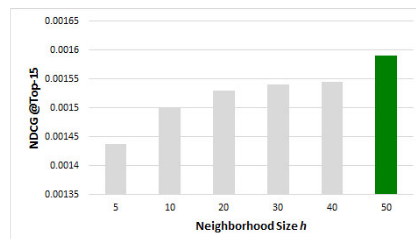

Figure 2: Sensitivity of users neighborhood size h**.**

4.2.2 Sensitivity of Users Neighborhood Size h. The users neighborhood size impacts the performance of MUB as it is used in the calculation of per criterion rating prediction as shown in ALGORITHM 3. Therefore, we conduct experiments by varying $h = \{5, 10, 20, 30, 40, 50\}$ to determine the best h, following the approach in [6].

Figure 2 presents a chart that shows the impact of varying h on the performance of MUB. We can observe that MUB is at its best when $h = 50$. This finding indicates that the more neighbors, the better the quality. Note again that we only show the NDCG results as those of Precision show the same manner.

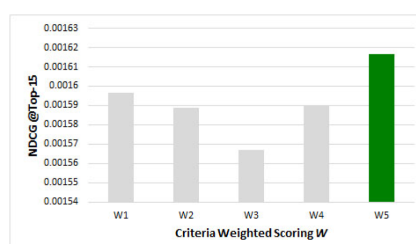

Figure 3: Sensitivity of criteria weighted scoring W**.**

4.2.3 Sensitivity of Criteria Weighted Scoring W. The criteria weighted scoring W controls the performance of MUB as it is used to aggregate the multi-criteria predicted ratings as described in ALGORITHM 3. To determine the best W, we conduct experiments by varying $W = \{W_1, W_2, W_3, W_4, W_5\}$ following the approach in [13], i.e. $W_1 = \{0.25, 0.25, 0.25, 0.25\}$, $W_2 = \{0.40, 0.20, 0.20, 0.20\}$, $W_3 = \{0.20, 0.40, 0.20, 0.20\}$, $W_4 = \{0.20, 0.20, 0.40, 0.20\}$, $W_5 = \{0.20, 0.20, 0.20, 0.40\}$.

Figure 3 displays a chart that shows the impact of varying W towards the performance of MUB. We can observe that MUB achieves its best performance when $W = \{0.20, 0.20, 0.20, 0.40\}$. In other words, "Cool" is the criterion that most influences the target users' preferences compared to other criteria. The results are shown only in terms of NDCG since those of Precision are showing the same pattern.

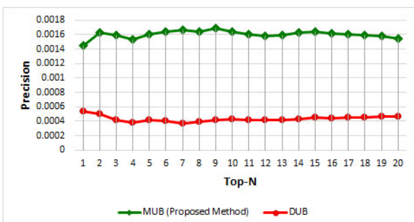

Figure 4: Comparison of performances in terms of Precision.

4.2.4 Comparison of Performance. To benchmark, we compare the performance of our proposed MUB with the related method DUB [3], i.e., a user-based multi-criteria recommendation method that implements the Decoupling normalization technique. The tuning parameters to achieve the best performance of DUB are $h = 5$ and $W = \{0.40, 0.20, 0.20, 0.20\}$.

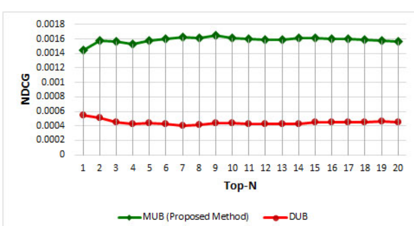

Figure 5: Comparison of performances in terms of NDCG.

Figure 4 and Figure 5 respectively show graphs that demonstrate the performance comparisons of MUB and DUB in terms of Precision and NDCG. We can easily observe that MUB significantly outperforms DUB on both metrics, i.e., the performance of MUB is more than two times higher than DUB. These findings confirm and answer our research question, i.e., the MinMax normalization technique can improve the user-based multi-criteria recommendation quality better than the Decoupling.

5 CONCLUSION

We have presented our proposed MUB method that implements the MinMax normalization technique on a user-based multi-criteria hotel recommendation system. Series of experiments are conducted by using the Yelp Hotel Dataset – which has four criteria (Overall", "Useful", "Funny", and "Cool"), Precision as well as NDCG as the evaluation metrics, and DUB [3] as the benchmarking method. Recall that DUB is a user-based multi-criteria recommendation system that implements the Decoupling technique. Our main finding confirms that the MinMax technique can significantly improve the quality of a user-based multi-criteria hotel recommendation system better than the Decoupling. That is, the performance of MUB is more than two times higher than DUB.

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REFERENCES

[1] C. C. Aggarwal. 2016. *Recommender Systems: The Textbook.* Switzerland: Springer International Publishing.
[2] J. I. Barredo and J. Bosque-Sendra. 1998. Multi-criteria evaluation methods for ordinal data in a GIS environment. *Geographical Systems* 5 (1998), 313–328.
[3] A. Bilge and A. Yargıç. 2017. Improving accuracy of multi-criteria collaborative filtering by normalizing user ratings. *Anadolu Üniversitesi Bilim Ve Teknoloji Dergisi A-Uygulamalı Bilimler ve Mühendislik* 18, 1 (2017), 225–237.
[4] K. Chen, P. Wang, and H. Y. Zhang. 2021. A novel hotel recommendation method based on personalized preferences and implicit relationships. *International Journal of Hospitality Management* 92 (2021), 102710.
[5] Á. García-Crespo, J. L. López-Cuadrado, R. Colomo-Palacios, I. González-Carrasco, and B. Ruiz-Mezcua. 2011. Sem-Fit: A semantic based expert system to provide recommendations in the tourism domain. *Expert systems with applications* 38, 10 (2011), 13310–13319.
[6] N. Ifada, N. F. D. Putri, and M. K. Sophan. 2020. Normalization based Multi-Criteria Collaborative Filtering Approach for Recommendation System. *Rekayasa* 13, 3 (2020), 234–239.
[7] R. Jin and L Si. 2004. A study of methods for normalizing user ratings in collaborative filtering. In *Proceedings of The 27th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (Sheffield, United Kingdom). 568–569.
[8] R. Jin, L. Si, C. Zhai, and J. Callan. 2003. Collaborative filtering with decoupled models for preferences and ratings. In *Proceeding of The 12th International Conference on Information and Knowledge Management* (New Orleans, Louisiana, USA). 309–316.
[9] P. Jirachanchaisiri, J. Kitsupapaisan, and S. Maneeroj. 2019. Bayesian flexible mixture model with rating conversion on multi-criteria recommender system. *International Journal of Web Information Systems* 15, 4 (2019), 402–419.
[10] M. Nilashi, O. bin Ibrahim, N. Ithnin, and N. H. Sarmin. 2015. A multi-criteria collaborative filtering recommender system for the tourism domain using Expectation Maximization (EM) and PCA–ANFIS. *Electronic Commerce Research and Applications* 14, 6 (2015), 542–562.
[11] C. Saranya and G. Manikandan. 2013. A study on normalization techniques for privacy preserving data mining. *International Journal of Engineering and Technology (IJET)* 5, 3 (2013), 2701–2704.
[12] P. Sitkrongwong, S. Maneeroj, and A. Takasu. 2019. Multi-criteria rating conversion without relation loss for recommender systems. *International Journal of Computers and Applications* (2019), 1–9.
[13] N. Vafaei, R. A. Ribeiro, L. M. Camarinha-Matos, and L. R. Valera. 2020. Normalization techniques for collaborative networks. *Kybernetes* 49, 4 (2020), 1285–1304.