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An Effective Doctor Recommendation Algorithm for Online Healthcare Platforms

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Abstract. The emergence of online healthcare platforms provides patients with convenience, but choosing the right doctor among the thousands of doctors available on these platforms has become a challenge for patients. The majority of these platforms recommend the same doctors to all patients based on a global ranking, disregarding individual patient preferences. The use of recommender systems helps to resolve this issue by assisting patients in locating doctors who meet their preferences and requirements. Particularly, Collaborative Filtering (CF) algorithms have been extensively utilized to generate personalized recommendations for a variety of applications. Despite their success, they still need to be further optimized to address both the sparsity and cold-start problems due to insufficient data. In this paper, we propose an effective doctor recommendation approach to assist patients in searching for satisfactory doctors who precisely match their preferences regardless of time and location. The proposed approach employs Multi-Criteria CF and content filtering to enhance the quality of recommendations by mitigating the impact of data sparsity and cold start challenges. Offline tests conducted on a real-world dataset show that the proposed approach is superior to state-of-the-art approaches in addressing the aforementioned issues and boosting prediction accuracy and coverage.

Key-words: Content filtering; doctor; multi-criteria collaborative filtering; medical informatics; recommender systems.

1. Introduction

Online healthcare platforms have emerged as valuable sources of patient satisfaction data, enabling patients to rate and review their interactions with healthcare professionals. These platforms serve as decision-making tools for patients seeking healthcare providers, influencing approximately one-third of users in their doctor selection decisions. RateMDs, founded in 2004, is a prominent example of such a platform, where doctors are ranked based on multiple criteria, including punctuality, staff, knowledge, and helpfulness. While these platforms provide convenience, patients face the challenge of selecting the most suitable doctor among a vast number of options. Therefore, leveraging online data to create personalized models becomes crucial in overcoming the information overload barrier and enhancing the patient experience. Recommender systems, which predict and recommend items based on user preferences, can assist patients in finding doctors who align with their preferences by analyzing patient ratings and reviews [1, 2]. In this context, there is a need to explore the effective utilization of online data to develop personalized models, addressing the challenges of doctor selection and improving the patient experience on online healthcare platforms.

Multi-criteria (MC) CF recommender systems consider multiple criteria or aspects to provide personalized and relevant recommendations by analyzing item attributes. For example, in online medical platforms, patients rate doctors based on multiple criteria such as punctuality, staff, knowledge, and helpfulness. To accurately understand users' needs and preferences, it is crucial to develop MC-based recommender systems that leverage this additional rating information for more precise and effective recommendations [3, 4]. On the other hand, content-based collaborative filtering systems recommend items based on their characteristics, assuming that users who like one item will also like similar items. By analyzing previously favored items, the system identifies comparable items and recommends them to the user [5]. While both MC-based CF and content-based filtering approaches are popular, they have limitations. MC-based CF systems face challenges with the cold-start problem for new users or items and the sparsity problem when data about specific items or users is insufficient, affecting recommendation accuracy. It is important to note that higher sparsity and the presence of cold-start items lead to decreased recommendation accuracy and coverage, as the recommendation approach becomes incapable of generating recommendations for several items because of not locating appropriate nearest neighbors due to the small proportion of user ratings to the total number of readily available items. Content-based systems may lack serendipity, recommending only similar items and limiting users' exposure to new and unexpected options [6]. To address these limitations, hybrid recommender systems that combine multiple recommendation approaches offer a solution. By leveraging the strengths of different methods, hybrid systems generate more precise and diverse recommendations, enhancing overall system performance [7].

The primary motivation for this research stems from the increasing demand for effective and personalized recommendation systems in the healthcare domain. While our previous contributions focused on recommendation algorithms for different domains such as e-commerce [8], hotels [9], restaurants [10], and general recommendations [3, 4], this study introduces a novel approach specifically designed to address the unique challenges and requirements associated with recommending doctors to patients in the healthcare domain. Furthermore, our prior works encompassed a diverse range of recommendation approaches, including user-based CF [4], item-based CF [3], hybrid user-based and item-based CF [9, 10], and hybrid trust-semantic [8] approaches. These prior studies explored different strategies to provide personalized recommendations, considering factors such as user preferences, item characteristics, users' trustworthiness, and semantic relationships. Building upon this comprehensive understanding of recommendation systems, our current research introduces a hybrid approach that combines multi-criteria CF and content filtering techniques to assist patients in finding doctors who precisely match their preferences, regardless of time and location. This combination of techniques effectively addresses the common obstacles of cold start and data sparsity encountered in online healthcare platforms, ultimately enhancing the quality of recommendations and improving prediction accuracy and coverage. Through extensive testing and evaluation, we demonstrate the superiority and effectiveness of our approach compared to our previous works. Therefore, this study contributes new insights and advancements to the field, building upon our previous works and presenting a significant leap forward in recommendation system research.

To this end, the main contributions of the study can be summarized as follows:

- Introduction of a Hybrid Multi-Criteria Content-based Collaborative Filtering (HMCCCF), which assists patients in finding doctors who align with their preferences on online healthcare platforms, regardless of time and location.

- Integration of multi-criteria CF and content filtering modules to effectively address the challenges frequently faced on online healthcare platforms, including data sparsity and the presence of cold start items. By combining these modules, our approach tackles the scarcity of user ratings and the difficulty of making recommendations for newly added doctors.

- Development of an item-based similarity metric considering distance, structural similarities, and overall reputation score. By incorporating these factors, the metric captures more nuanced relationships between doctors. This enhances the representation of item similarities, leading to more precise and relevant recommendations.

- Empirical validation of the proposed approach's efficacy in terms of predictive accuracy and coverage, surpassing baseline recommendation approaches, using a real-world healthcare patient-doctor MC dataset.

The remaining sections of this paper are laid out as follows. In Section 2, we provide a brief review of previous research in the field of doctor recommendations. The architecture of the proposed approach is shown in Section 3, and the validation results are presented in detail in Section 4. Section 5 illustrates the study's conclusion and recommendations for future study.

2. Related Work

Demands for creativity have arisen in every industry as a direct result of the rapid pace of technological development in recent years. Several studies [11] have examined the application of recommender systems in the healthcare industry. Despite the publication of various works on the use of recommender systems in the healthcare domain, very little research on doctor recommendation systems has been conducted.

A doctor recommendation method based on patient preferences and doctor performance models was proposed by Yong-Feng, Peng, Qiao and Jing-Sheng [12]. The algorithm constructs a doctor performance model using the analytic hierarchy process method and a patient preference model based on past reservation choices. This approach successfully generates doctor recommendations for patients. Sridevi and Rajeshwara Rao [13] proposed a personalized health recommender system that recommends hospitals and doctors to patients. The proposed system uses a CF-based recommendation approach that exploits patients' demographic data, the similarity between patients based on their ratings, the total number of reviews, and average ratings to generate a personalized list of top-rated hospitals or doctors for patients. Acharjee, Chanda, Nunia, Choudhury and Kumar [14] have developed a recommendation framework that can be used to locate the most qualified doctors in accordance with the needs of patients. The framework uses a decision tree for mapping symptoms to diseases and a Naive Bayes classifier for sentiment analysis on patients' reviews in order to return a list of recommended doctors. Mondal, Basu and Mukherjee [15] proposed a doctor recommendation system considering patient symptoms, doctor location, and patient trust levels. The patient–doctor relationship is modeled as a MClayer graph at the back end of the recommendation system for efficient data access as well as to model the trust factor on the basis of the underlying database. Iftikhar, Anwar and Majid [16] introduced a doctor recommendation system that identifies reliable doctors based on patient satisfaction data collected through questionnaires. Their CF-based approach incorporates patient data, satisfaction survey results, and doctor information to generate ranked doctor recommendations. In order to integrate medical data across platforms, Che, Zhao and Jin [2] proposed a framework for doctor recommendation using multi-source heterogeneous data. Their knowledge fusion model integrates medical data from various platforms, while attribute-based methods generate doctor recommendations based on individual rankings. In a similar vein, Shambour, Al-Zyoud, Hussein and Kharma [17] proposed a doctor recommender system to assist patients in finding suitable doctors by leveraging collaborative and content-based filtering methods. While this study aligns with our proposed approach, it is important to highlight that there are implementation differences, particularly in the techniques employed for calculating similarities between doctors. Using the user's existing medical conditions, Haque, Pranta and Zoha [18] proposed a content-based doctor recommendation model using rule inference and convolutional neural networks. Ju and Zhang [19] presented an online prediagnosis doctor recommendation model that incorporates ontology characteristics and disease text mining. These models consider various factors such as patient information, symptoms, diagnoses, geographical locations, and doctor expertise to generate personalized doctor recommendations.

3. The Proposed Approach

3.1. Preliminaries

Let $T = t_1, t_2, ..., t_n$ be a set of n patients, and $X = x_1, x_2, ..., x_m$ be a set of m doctors rated by patients in T. Let $c_1, c_2, ..., c_k$, be a collection of k evaluation criteria for doctor x, with each criterion representing a rated aspect of the doctor. The MC ratings of a doctor x can therefore be expressed as a vector of k criteria $r(x) = [c_1(x), c_2(x), ..., c_k(x)]^T$. According to the Multi-Attribute Utility Theory [20], the overall utility $U^t(x)$ (also known as the overall rating) of doctor x for a patient t can be represented as follows:

$$U^t(x) = \sum_{c=1}^{k} r_c^t(x) \times w_c^t(x), \quad where \sum_{c=1}^{k} w_c^t(x) = 1 \tag{1}$$

where $r_c^t(x)$ represents the rating on criteria c of doctor x by patient t, and $w_c^t(x)$ is the relevance of criterion c on doctor x by patient t, which indicates the patient's preference for criterion c.

3.2. Architecture and design

The design of the proposed approach includes three major building blocks: The Multi-Criteria CF module, the content filtering module, and the hybrid prediction module.

3.2.1. The multi-criteria collaborative filtering module

Step 1: Compute doctor-doctor MC-based CF similarity

To improve the accuracy of predictions, a novel similarity metric for Multi-Criteria CF that takes into account both distance and structural similarities is proposed. Direct doctor-doctor implicit similarity is primarily computed using doctors' ratings to determine the accuracy of a given doctor's prediction as a reliable recommender to another doctor. Doctors x and y must achieve a high implicit similarity score if, for instance, doctor x can make accurate recommendations to doctor y based on their prior evaluations from co-rated patients. Consequently, the following prediction metric is used to calculate the rating of doctor x for the active patient t using only one neighbor, namely the doctor y:

$$P_{t,x} = \overline{r}_x + (U^t(x) - \overline{r}_y) \tag{2}$$

where $\overline{r}_x$ and $\overline{r}_y$ are the average ratings of doctors x and y, respectively. $U^t(x)$ represents the overall utility/rating of patient t for doctor x.

The quasi-norm-based similarity measure demonstrates its superiority in utilizing rating values more effectively than commonly used distance-based similarity measures in the literature. Experiments utilizing diverse datasets demonstrate conclusively that the quasi-norm-based similarity measure is superior in dealing with sparse or cold-start scenarios [21]. Accordingly, the quasi-norm-based similarity measure with $p = 0.5$, is employed to calculate the implicit similarity of doctors x and y, as follows:

$$QN_{x,y} = \sum_{i \in T_{x,y}} \left(1 - \frac{|P_{i,x} - U^i(x)|^p}{((r_{max} - r_{min})/2)^p}\right) \tag{3}$$

where $T_{x,y}$ is the set of patients who have rated both doctors x and y. $P_{i,x}$ represents the predicted rating of patient i on doctor x. $U^i(x)$ is the overall rating of patient i on doctor x.

However, the above metric suffers from the inherent flaw of relying solely on the predictions error of co-rated ratings; to address this, Salton's cosine index [22] is adopted to be incorporated as a structural similarity metric to take into account the number of patients who have rated both doctors. The degree to which doctors are similar is proportional to the number of patients who rated both doctors in terms of

$$SCI_{x,y} = \frac{|T_x \cap T_y|}{\sqrt{|T_x| \times |T_y|}} \tag{4}$$

where $|T_x \cap T_y|$ is the total number of patients who rated both doctors x and y. $|T_x|$ and $|T_y|$ are the total numbers of patients who rated doctors x and y, respectively. Eventually, the final similarity metric between any pair of doctors is expressed as follows:

$$MCCF_{Sim_{x,y}} = QN_{x,y} \times SCI_{x,y} \tag{5}$$

Step 2: Compute the doctor's overall reputation score

In addition, the doctor's overall reputation score has been included for the purpose of enhancing the approach's ability to predict unobserved doctors. This is because the sparsity challenge has resulted due to the insufficient number of reliable nearest neighbors. In order to determine a doctor's reputation, a number of factors are taken into consideration. These factors include the average variation in ratings between the doctor's ratings and the patients' mean ratings, as well as the number of associates the doctor has with other doctors in the doctor-doctor similarity matrix:

$$OverallRep_x = exp\left(-\frac{\sum_{t \in T_x} |U^t(x) - \overline{r}_t|}{|T_x|}\right) \times \sqrt{\frac{|I_x|}{|I|}} \tag{6}$$

where $U^t(x)$ is the overall utility/rating of patient t on doctor x, $\overline{r}_t$ is the mean rating of patient t, and $|T_x|$ depicts the total number of patients who rated doctor x. $|I_x|$ depicts the total number of doctors with similarity relationships to doctor x, while $|I|$ represents the total number of doctors in the dataset.

Step 3: Compute MC-based CF predicted rating

To produce MC CF-based predicted ratings, the mean-based prediction metric is used as follows:

$$Pred_{t,x}^{MCCF} = \begin{cases} \overline{r}_x + \frac{\sum_{y \in NN} MCCF_{Sim_{x,y}} \times (U^t(y) - \overline{r}_y)}{\sum_{y \in NN} MCCF_{Sim_{x,y}}}; \text{if } MCCF_{Sim_{x,y}} \neq 0. \\ \\ \overline{r}_x + \frac{\sum_{y \in NN} OverallRep_y \times (U^t(y) - \overline{r}_y)}{\sum_{y \in NN} OverallRep_y}; \text{if } MCCF_{Sim_{x,y}} = 0. \end{cases} \tag{7}$$

where NN depicts the set of nearest neighbours of doctors to the target doctor x based on the multi-criteria CF-based similarity.

3.2.2. The content filtering module

Step 4: Compute doctor-doctor content-based similarity

The content filtering module perceives the doctor's specialty as being the most important factor for doctors in order to boost the quality of doctor recommendations. By utilizing the content filtering module, the proposed system would help current patients who have seen doctors in a given specialty in the past but are considering a switch by providing them of the perceptions of other patients who have been treated by the same doctors. As an illustration, suppose a patient encounters a scheduling conflict with their current dermatologist. In such a scenario, the proposed approach can suggest alternative dermatologists who closely match the preferences and characteristics of the existing dermatologist. This recommendation is achieved by leveraging the feedback of other patients who have visited the same dermatologist.

Using a hierarchical tree-based relatedness measure, the content-based similarity of doctors is computed. Fig. 1 given in [23] depicts a tree structure illustration. The doctor tree begins with a "Doctor" node, which is connected to various Specialty branches (Family, Pediatrician, Orthopedician, Rheumatologist, and Dermatologist) via a "Has a Specialty" relationship type. Following this, a "Has a Doctor" relationship type is used to link the doctors to the relevant specialty types. It should be noted that a doctor may have multiple specialties and thus be affiliated with multiple specialty branches.

In order to measure the content-based similarity of doctors based on their specialty, we adopt a vector-based representation where each doctor's specialty is encoded as a binary vector:

$$\begin{aligned} &\vec{V}_x = (v_{x,1}, v_{x,2}, ..., v_{x,s}), \text{ where} \\ &v_{x,s} = \begin{cases} 1 & \text{Doctor } x \text{ has specialty } s \\ 0 & \text{Doctor } x \text{ does not have specialty } s \end{cases} \end{aligned} \tag{8}$$

where $\vec{V}_x$ is the vector of doctor x and s is the doctor specialty. Then, the Sokal and Sneath I metric [24] is exploited to represent the content-based similarity among doctors:

$$\begin{aligned} &Content_{Sim_{x,y}} = \frac{F_{11}}{F_{11} + 2F_{01} + 2F_{10}}, \text{ where} \\ &\begin{cases} F_{11} = \text{Total number of events where } v_{x,s} \text{ is 1 and } v_{y,s} \text{ is 1} \\ F_{01} = \text{Total number of events where } v_{x,s} \text{ is 0 and } v_{y,s} \text{ is 1} \\ F_{10} = \text{Total number of events where } v_{x,s} \text{ is 1 and } v_{y,s} \text{ is 0} \end{cases} \end{aligned} \tag{9}$$

Step 5: Compute content-based predicted rating

To generate content-based predicted ratings, we employ the mean-based prediction metric, as follows. This metric calculates the predicted rating for a specific item based on the mean ratings of similar items. By taking into account the ratings of items that are similar to the target item, the expected rating for the target item is estimated in terms of

$$Pred_{t,x}^{Content} = \overline{r}_x + \frac{\sum\limits_{y \in NN} Content_{Sim_{x,y}} \times (U^t(y) - \overline{r}_y)}{\sum\limits_{y \in NN} Content_{Sim_{x,y}}} \tag{10}$$

where NN represents the set of nearest neighbours of doctors to the target doctor x based on the content-based similarity.

3.2.3. The hybrid prediction module

Step 6: Compute hybrid-based predicted rating

In this module, the switch-based hybridization is used to combine the predictions of multi-criteria CF and content-based filtering approaches to determine the final hybrid-based predicted rating:

$$Pred_{t,x}^{Final} = \begin{cases} 0 & ;\text{ if } Pred_{t,x}^{MCCF} \text{ and } Pred_{t,x}^{Content} = 0 \\ Pred_{t,x}^{MCCF} & ;\text{ if } Pred_{t,x}^{Content} = 0 \\ Pred_{t,x}^{Content} & ;\text{ if } Pred_{t,x}^{MCCF} = 0 \\ \frac{2 \times Pred_{t,x}^{MCCF} \times Pred_{t,x}^{Content}}{Pred_{t,x}^{MCCF} + Pred_{t,x}^{Content}} & ;\text{ Otherwise} \end{cases} \tag{11}$$

To summarize, Fig. 2 given in [23] shows the pseudo-code for the proposed HMCCCF approach.

4. Testing

Using a real-world MC dataset and evaluation metrics, a number of tests were carried out to compare the performance of the proposed approach to other baseline recommendation approaches.

4.1. Validation Setup

A validation study was conducted to evaluate the proposed approach. The MC RateMDs dataset containing 31,180 multi-criteria ratings of 3118 doctors by 3464 patients is utilized. The doctors in the dataset have 21 different specializations, such as dermatologists, pediatricians, gynecologists, physiatrists, families, etc. The dataset is crawled from the well-known online healthcare platform ratemds.com, which allows patients to rate doctors on a scale from 1 to 5 based on four criteria: punctuality, staff, knowledge, and helpfulness.

The proposed approach was evaluated based on two criteria, (1) and (2): (1) prediction quality, as measured by mean absolute error (MAE) and root mean squared error (RMSE), which are common evaluation metrics for recommender systems, and (2) prediction coverage, as measured by the coverage metric.

MAE is defined as the average absolute difference between the predicted ratings and the actual ratings for a user-item pair, while RMSE is the average of the squared differences between the predicted ratings for a user-item pair. The smaller the MAE and RMSE, the more accurately the approach predicts ratings. The RMSE has the advantage of emphasizing and penalizing significant errors [25].

Coverage is a metric that measures the proportion of all items that a recommender system can recommend. A high coverage indicates that the recommender system can suggest a wide variety of items to users, whereas a low coverage indicates that the system has a limited ability to make recommendations. In recommender systems, coverage is frequently used to evaluate the diversity of the recommendations. A system with high coverage is able to recommend a wide variety of items, which can be beneficial for users seeking new choices [25].

The efficiency and effectiveness of the proposed approach were compared to those of the following baseline approaches:

- The SC Item-based CF recommendation approach [26].
- The MC Item-based CF recommendation approach [27].

- The MC Semantic-based CF recommendation approach [3], which leverages MC ratings and underlying relationships between items to increase prediction accuracy and mitigate the effects of data sparsity and cold-start item issues.
- The MC Trust-based CF recommendation approach [4], which leverages MC ratings and implied trust associations among users to enhance prediction accuracy and lessen the influence of data sparsity.

4.2. Results and Analysis

A series of tests were conducted to demonstrate the effectiveness of the proposed approach over the baseline approaches. First, the MAE and RMSE comparison results between the proposed algorithm and the baseline approaches with varying neighborhood sizes on the RateMDs dataset are presented. The proposed approach is then compared to baseline approaches on a variety of datasets with varying levels of sparsity in terms of MAE and Coverage. Finally, the proposed approach is compared to baseline approaches on a number of datasets with varying numbers of ratings for CS items in terms of MAE and Coverage.

4.2.1. Evaluation of performance based on different neighboring sizes

Figs. 3 and 4 given in [23] show a comparison between the performance of prediction accuracy in terms of MAE and RMSE results of the proposed HMCCCF approach among state-of-the-art baseline approaches on the RateMDs dataset. In comparison to the SC Item-based CF, MC Item-based CF, MC Semantic-based CF, and MC Trust-based CF baseline algorithms, the proposed HMCCCF approach achieves outstanding MAE and RMSE performance at differing neighboring sizes (from 5 to 50 nearest neighbors). According to the average MAE results, the proposed HMCCCF approach improves the enhancement results compared to the baseline algorithms by approximately 89%, 89%, 86%, and 33%, respectively. While the improvements attained by the proposed HMCCCF approach in terms of RMSE results are approximately 78%, 78%, 76%, and 22%, respectively. Through a comprehensive analysis and comparison of various baseline approaches with the proposed HMCCCF approach, utilizing two prediction accuracy measures on the RateMDs dataset, it is evident that the proposed approach surpasses other methods significantly in terms of prediction accuracy.

4.2.2. Evaluation of performance based on different levels of Sparsity

A variety of tests are conducted in order to show the robustness of the proposed HMCCCF approach in lessening the data sparsity issue. To simulate different degrees of sparsity, we generated six sparse datasets with varying levels of sparsity, ranging from 99.8% to 98.0%. This allowed us to examine the impact of sparsity on the performance of our proposed approach across different scenarios. In order to maintain fairness and achieve an unbiased comparison between the proposed HMCCCF approach and the baseline approaches, we conducted validations using identical parameters for all approaches, including the number of nearest neighbors ($NN = 25$). Figs. 5 and 6 given in [23] show a comparison of the proposed HMCCCF approach's prediction accuracy and prediction coverage in terms of MAE and Coverage results against state-of-the-art baseline approaches.

Fig. 5 given in [23] illustrates the average MAE results of the proposed HMCCCF approach compared to the baseline approaches, showing significant improvements of approximately 66%, 60%, 28%, and 26% respectively. This highlights the superior accuracy of the proposed approach across different levels of sparsity. Furthermore, Fig. 6 given in [23] demonstrates the substantial enhancement in prediction coverage achieved by the HMCCCF approach, further validating its effectiveness. Comparatively, when compared to baseline approaches, the proposed approach improves Coverage by 57%, 44%, 12%, and 9%, respectively. Thus, in terms of prediction coverage, the proposed approach also outperforms baseline approaches. The notable enhancements in MAE and Coverage outcomes emphasize the superiority of the proposed approach compared to other baseline methods when handling highly sparse datasets. These substantial improvements highlight the higher accuracy and effectiveness of the proposed approach in addressing the challenges posed by sparse data.

4.2.3. Evaluation of performance based on different numbers of ratings for Cold-Start items

In order to evaluate the impact of the cold-start item problem on the recommendation performance of the proposed HMCCCF approach, we conduct comparative tests in relation to prediction accuracy and prediction coverage. We introduced six datasets, each with a different number of ratings for cold-start items (i.e., from 2 to 25). To ensure a rigorous and unbiased comparison, we validated both the proposed HMCCCF approach and baseline approaches using identical parameters, including the number of nearest neighbors ($NN = 25$). Figs. 7 and 8 given in [23] show the performance of the proposed HMCCCF approach in comparison to state-of-the-art baseline approaches. As can be seen in Figs. 7 and 8, due to the insufficiency of ratings for cold-start items, the MAE increases as the number of ratings for cold-start items decreases while the Coverage increases.

Fig. 7 given in [23] illustrates that the proposed HMCCCF approach achieves an average improvement of 40%, 39%, 14%, and 13% in MAE compared to the baseline approaches. These results clearly demonstrate the superior prediction accuracy of the proposed approach for cold-start items across different numbers of ratings, outperforming the baseline approaches. Additionally, Fig. 8 given in [23] highlights the substantial enhancement in prediction coverage achieved by the proposed HMCCCF approach. Comparing it to the baseline approaches, the proposed approach improves Coverage by 68%, 62%, 15%, and 8%, respectively. Hence, the proposed approach excels in terms of prediction coverage, surpassing the performance of the baseline approaches. To conclude, the proposed approach is more reliable and effective than other baseline approaches in dealing with cold-start items, as evidenced by the significant improvements in MAE and Coverage.

5. Conclusion and Future Work

Online healthcare platforms are progressively unable to effectively meet patients' medical needs, and the issue of not being able to locate a reliable doctor has become more prevalent. In this study, we propose an efficient approach for recommending doctors that assists patients in locating doctors who precisely match their preferences, regardless of location or time. The proposed approach employs multi-criteria CF and content filtering modules to improve the quality of recommendations by alleviating the effects of data sparsity and cold start issues.

The multi-criteria CF module employs a novel similarity metric that considers both distance and structural similarities, as well as an overall doctor reputation score, to improve the approach's capacity to represent the more complex preferences of each patient and to compensate for the insufficient number of credible nearest neighbors. The content filtering module makes use of the underlying relationships between doctors in terms of their specialties to improve the accuracy and relevance of doctor recommendations. Validation results on a real-world dataset demonstrate that the proposed approach is superior to state-of-the-art approaches in terms of reducing the stated problems and enhancing prediction accuracy and coverage.

The proposed HMCCCF approach can benefit from the following directions for future work to provide more accurate, personalized, and effective recommendations for patients seeking healthcare providers on online platforms:

- Incorporating decision-making models: Building on the modeling of observation processes within cognition [28], future research could explore how patients' observation and perception of doctors' attributes can be incorporated into the recommendation process of the HMCCCF approach, which may provide a more comprehensive understanding of patients' preferences.

- Utilizing optimization techniques: Drawing inspiration from Bojan-Dragos et al. [29], future work could investigate the application of optimization techniques to fine-tune the recommendation process of the HMCCCF approach.

- Enhanced modeling of complex systems: Building on the tensor product-based model transformation approach [30], future research could explore how similar transformation techniques can be applied to capture the complex relationships between doctors and patients to enhance the recommendation accuracy of the HMCCCF approach.

- Exploiting experiment-based learning approaches: Taking inspiration from the work proposed by Precup et al. [31], future work can explore the integration of experimental learning techniques into the recommendation process. By involving patients in interactive experiments or simulations, the HMCCCF approach can provide personalized recommendations while actively engaging patients in decision-making processes, leading to improved patient satisfaction and decision outcomes.

- Employing fuzzy logic techniques: Drawing from the work of Ramathilagam and Pitchipoo [32], future research can investigate the utilization of fuzzy inference rules and expert insights in the HMCCCF approach to address uncertainties and variances in patient preferences, which may lead to more precise doctor recommendations.

- Utilizing feature engineering and preprocessing techniques: Inspired by the study conducted by Bal and Gunal [33], future work could explore the application of advanced natural language processing techniques in the analysis of patient ratings and reviews, which can yield deeper insights and enhance the HMCCCF approach.

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