REPUBLIC OF TURKIYE
AKDENIZ UNIVERSITY

A MULTI-CRITERIA HOTEL RECOMMENDER SYSTEM BASED ON NEURAL COLLABORATIVE FILTERING

Ceren DURSUN

INSTITUTE OF NATURAL AND APPLIED SCIENCES

DEPARTMENT OF COMPUTER ENGINEERING

MASTER THESIS

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This thesis unanimously accepted by the jury on 16/07/2024.

Assoc. Prof. Dr. Alper ÖZCAN (Supervisor)
Assoc. Prof. Dr. Taner DANIŞMAN
Assoc. Prof. Dr. Emrah DÖNMEZ

ÖZET

SİNİRSEL İŞBİRLİKÇİ FİLTRELEME TABANLI ÇOK KRİTERLİ OTEL TAVSİYE SİSTEMİ

Ceren DURSUN

Yüksek Lisans Tezi, Bilgisayar Mühendisliği Anabilim Dalı

Danışman: Doç. Dr. Alper ÖZCAN

Temmuz 2024; 41 sayfa

Günümüzde, internet üzerinde kullanıcılara birçok farklı otel alternatifi sunulmaktadır. Bu durum, farklı alternatifleri online olarak değerlendirme ve karar verme imkanı sunmak ile birlikte, konaklama planlaması açısından pek çok avantaj sağlasa da çeşitli zorlukları da beraberinde getirmektedir. Mevcut bilgi yoğunluğu nedeniyle, otel seçimi yaparken karar verme süreci kullanıcılar için zorlayıcı olabilir ve fazla miktarda zaman harcanmasına ve nihayetinde zayıf tercihler yapılmasına neden olabilir. Kullanıcıların daha iyi kararlar vermesine yardımcı olmak için, online rezervasyon platformlarının bu aşırı bilgi yükünü yönetecek yenilikçi çözümleri benimsemesi gerekmektedir.

Farklı platformların varlığı ve artışı her ne kadar kullanıcıların tercih imkanlarını arttırıyor ve alternatifleri birbiriyle kıyaslamasına olanak sağlıyor olsa da aynı zamanda bilgi artışının sürekliliği nedeniyle karar verme sürecini olumsuz etkileyebilecek bir noktaya evrilmiş durumdadır. Kullanıcılara kişiselleştirilmiş öneriler sunma sürecini geliştirmek için, otellerin sadece puanına göre değerlendirilmesinden ziyade, farklı kriterlerinin öneri sürecine dahil edilmesi, kişiselleştirilmiş öneriler sunma sürecine destek olacaktır.

Bu tez, bu ihtiyacı karşılamak için çok kriterli bir nöral işbirlikçi filtreleme otel tavsiye sistemi sunmaktadır. Önerilen model, çok kriterli derecelendirmeleri tahmin etmek için kullanıcı ve otel tanımlayıcılarını girdi olarak kullanarak bir otel için kriter derecelendirmelerini tahmin eder, ardından tahmin edilen çok kriterli derecelendirmelere dayalı olarak genel derecelendirmeyi tahmin ederek kullanıcılar için tavsiyeler oluşturulmasını sağlar.

Yapılan deneylerde, önerilen model, tek kriterli bir tavsiye sistemi ve çok kriterli girdileri genel değerlendirme için kullanan bir sistem ile test edilmiştir. Tek kriterli tavsiye sisteminde, çok kriterli değerlendirmeler modele dahil edilmemiştir ve çok kriterli girdileri genel değerlendirme için kullanan sistemde ise, bu çok kriterli değerlendirmeler model tarafından tahmin edilmeden, genel değerlendirmeyi tahmin etmek amacıyla bir girdi olarak kullanılmıştır. Bu deneyler, sonuçlarında önerilen model test edilen modellere oranla daha yüksek performans göstererek, çok kriterli karar vermenin tekli derecelendirme sistemlerine göre üstünlüğünü ve genel derecelendirmeler üzerindeki önemli etkisini ortaya koymuştur.

ANAHTAR KELİMELER: Çok-Kriterli Tavsiye Sistemleri, Kişiselleştirilmiş Tavsiyeler, Nöral İşbirlikçi Filtreleme, Otel Tavsiye Sistemi, Tavsiye Sistemleri

JÜRİ: Doç. Dr. Alper ÖZCAN

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Doç. Dr. Emrah DÖNMEZ

ABSTRACT

A MULTI-CRITERIA HOTEL RECOMMENDER SYSTEM BASED ON NEURAL COLLABORATIVE FILTERING

Ceren DURSUN

MSc Thesis in Computer Engineering

Supervisor: Assoc. Prof. Dr. Alper ÖZCAN

June 2024; 41 pages

Nowadays, users are offered numerous hotel alternatives available online to meet their accommodation demands. Although this provides many advantages regarding accommodation planning and the opportunity to evaluate and decide on many alternatives online, it also presents various difficulties. Due to the abundance of information available, the process of deciding on a hotel might be demanding for users, resulting in spending an excessive amount of time and potentially making poor choices. To assist users in making better decisions, online booking platforms need to embrace innovative solutions to manage this information overload.

The existence and increase of different platforms allow users to choose and evaluate, but at the same time, due to the constant increase in information, it has evolved to a point that can negatively affect the decision-making process. Instead of evaluating hotels based only on their overall score, including different criteria in the recommendation system will support the personalized recommendation process.

This thesis presents a multi-criteria neural collaborative filtering hotel recommendation system to address this need. The proposed model utilizes user and hotel identifiers as inputs to estimate multi-criteria ratings, then estimates the overall rating based on the predicted ratings to generate recommendations.

The single-criterion model, which does not use multi-criteria ratings, and a conventional multi-criteria recommender system, which does not predict multi-criteria ratings but instead uses them as input, were both used to test the proposed model.

These tests demonstrated that the proposed model outperforms other models, showcasing the superiority of multi-criteria decision-making over single rating systems and its significant impact on overall ratings.

KEYWORDS: Hotel Recommender System, Multi-Criteria Recommender Systems, Neural Collaborative Filtering, Personalized Recommendations, Recommender Systems

COMMITTEEE: Assoc. Prof. Dr. Alper ÖZCAN
Assoc. Prof. Dr. Taner DANIŞMAN
Assoc. Prof. Dr. Emrah DÖNMEZ

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My interest in data science and machine learning has never faded since I started my master's program; on the contrary, it has only strengthened. I will always continue to thank my dear elder sister, Aslıhan Dursun, for introducing me to this world. I would like to emphasize that this program made me acknowledge that this is a lifelong learning process and the applications are limitless.

I deeply appreciate my beloved mother, Sema Dursun, and my beloved father, İsmail Dursun for their efforts, and for providing me with the greatest support in this process. Thank you for always emphasizing the importance of education and providing me with all the possibilities to pursue it.

I would like to thank my dear friends for doing their best to motivate me and for reminding me once again that I have true friends.

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The biggest thank you is to my beloved Barış for prioritizing this journey as much as I do, believing in my potential, trusting me, and always encouraging me.

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TEXT OF OATH

I declare that this study "A MULTI-CRITERIA HOTEL RECOMMENDER SYSTEM BASED ON NEURAL COLLABORATIVE FILTERING", which I present as master thesis, is in accordance with the academic rules and ethical conduct. I also declare that, I cited and referenced all material and results that are not original to this work.

16/07/2024

Ceren DURSUN

SYMBOLS AND ABBREVIATIONS

Abbreviations

CF	: Collaborative Filtering
DNN	: Deep Neural Network
GB	: Gigabytes
GPU	: Graphics Processing Unit
IJSON	: Iterative Javascript Object Notation
JSON	: Javascript Object Notation
MAE	: Mean Absolute Error
MCRS	: Multi-Criteria Recommender System
NCF	: Neural Collaborative Filtering
WGET	: World Wide Web Get

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1. INTRODUCTION

The widespread use and easy accessibility of the Internet have led to significant changes in the way we access and exchange information. Since the internet serves as a platform where ideas and thoughts are easily shared, it has evolved into a comprehensive tool that covers various aspects of our daily lives, including communication, media, research, entertainment, and commerce. Given that more individuals gain easy access to the internet with the development of modern technologies, digital platforms have begun to emerge as a tool through which individuals can connect, share information, and engage in various activities online.

As it has become easier for individuals to meet their needs and requirements online, the majority of industries have begun to rapidly digitalize and adapt to the digital world, including the tourism industry with online booking platforms. Online booking platforms are digital tools that assist users in planning the related processes for a wide range of requirements and needs. The hotel booking platforms are one of the most significant within these online booking platforms as they cater to the users' needs for travel, accommodation, activities, and experiences (Raghavendra et al. 2024).

Nowadays, there are many different online hotel booking platforms where users can be informed about different alternatives, compare the options, and examine the prior experiences of other users. Online reviews, which represent users' previous impressions, are valuable in helping other users decide on a hotel (Xia et al. 2022). Numerous hotel reviews and a variety of accommodation alternatives are assessed by users to determine the most suitable option for their requirements and preferences. While there are numerous benefits in terms of accommodation planning, it also has its drawbacks. The existence and proliferation of different platforms grant users the opportunity to choose and evaluate; concurrently, due to the constant increase in information, it has evolved to a point that might negatively affect the decision-making process. Considering the diverse selection of accommodation options that users could reach through online booking platforms, deciding on the most convenient option to fit one's needs and preferences might be challenging. When presented with a range of diverse and varied alternatives, people tend to seek recommendations from a variety of sources to aid their decision-making process (Swearingen et al. 2002).

Recommendation systems are essential in the process of filtering the content that users encounter to meet their preferences and requirements. Any digital platform where user-item interaction exists can adapt recommender systems to its structure, including online hotel booking platforms. Since user satisfaction relies on tailored recommendations, personalization of the recommendations represents the biggest challenge facing currently available recommender systems (Liu et al. 2022). Despite the importance of understanding user preferences to provide personalized recommendations, existing recommender systems often rely on a single overall rating rather than a holistic approach where multiple criteria are considered.

Instead of a singular overall rating score, ratings for different criteria can be incorporated into the recommendation process to enhance the efficiency of providing personalized recommendations. Users may be interested in items based on different criteria, and an overall rating is insufficient to reflect user choices comprehensively (Aggarwal, 2016; Adomavicius et al. 2007). Multi-criteria recommendation is crucial for hotel recommendations since it allows for personalized and tailored recommendations by considering the diverse and complex preferences of users and understanding their concerns on aspects such as location, service, rooms, cleanliness, and more.

The aim of this study is to propose a multi-criteria neural network-based hotel recommender system to meet this need. The primary objective is to enhance recommendation accuracy and personalization by incorporating certain aspects of the hotel, such as cleanliness, service, or location. By leveraging neural networks and multi-criteria ratings, this study seeks to provide a comprehensive solution for hotel recommendations.

The primary contributions of this thesis involve the development of a Neural Collaborative Filtering (NCF) based recommender system that incorporates multiple criteria. This was achieved by converting the real-life HotelRec dataset into a suitable format for assessment. This study demonstrates that using NCF to estimate ratings based on multiple criteria and generate an overall rating for recommendations can improve performance compared to both single-criteria recommender systems and NCF models that use multi-criteria ratings as input.

The thesis covers the entire process, from data collection and preprocessing to model training and evaluation, showcasing the effectiveness of multi-criteria approaches in addressing user preferences in the tourism industry. It consists of five main chapters, and its structure is as follows. The second chapter discusses the related work in the realm of multi-criteria recommender system; the third chapter delves into the background of the development of the proposed model and outlines the baseline models. Finally, in Chapter four the study is concluded with the results, evaluations of the experiments, and Chapter five covers the suggestions for the direction of future work.

1.1. Recommendation Systems

Recommender systems are defined as tools and methods that offer recommendations of items that align with the requirements and personal preferences of a particular user (Ricci et al. 2011). In today's rapidly evolving digital environment, recommender systems has an important role in improving user experiences across various platforms, including social media, streaming services, and e-commerce websites. This is achieved through the analysis of consumer behavior data, which is collected both implicitly and explicitly from users. As recommendation systems provide more accurate, tailored recommendations, they support the decision-making process (Liu et al. 2020).

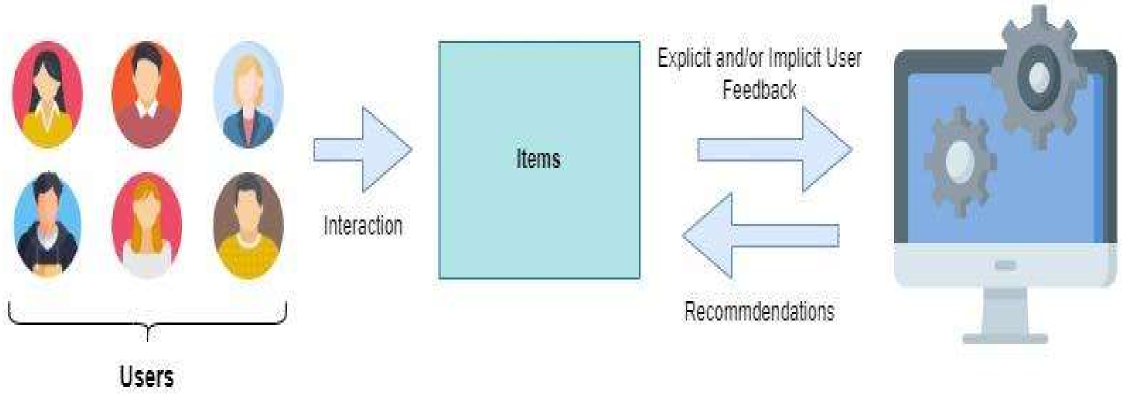

Figure 1.1. Recommender System Architecture

In Figure 1.1. the architecture and the principles behind the recommender system could be observed. In recommender systems, the feedback left by users on the items they engage in is processed and items that users may like are recommended to them (Ekstrand et al. 2011; Zhao et al. 2018). Recommender systems are tools that filter content and provide a personalized experience to the user. These systems are implemented to enhance user satisfaction and engagement levels. The users could find the items according to their niche preferences and needs. Providing the most appropriate content for users will result in improved satisfaction and engagement, a higher likelihood of making a purchase, and consequently enhance both user satisfaction and platform owners' profits. Companies that receive positive feedback from users will have a better understanding of their users through increased user-item interaction, thereby supporting their recommender systems. As an example of how significant recommender systems are for companies, we can consider the recommendation system competition organized by Netflix in 2006 (Bennett et al. 2007). As stated by Linden (2007), Netflix's recommender system generates over $1 billion in revenue, with over 80% of the movies viewed on the platform being recommended by it.

By analyzing the feedback from the user, recommender systems filter the most suitable item and aid in user satisfaction and experience. The feedback provided by users during their interaction with the item can be categorized into two distinct types: explicit and implicit. Explicit feedback occurs when users intentionally and willingly rate an item, whereas implicit feedback is not intentionally provided but inferred from user-item interaction to determine whether the user liked or disliked an item (Aggarwal, 2016). User-item interactions drive the recommender systems with explicit and/or implicit user-generated feedback to generate personalized recommendations and assist in decision-making in alignment with user needs and preferences.

Recommender systems typically consider two approaches for evaluating items: single-criterion and multi-criterion. Single-criterion systems focus on a single rating, like a star rating, to recommend items based on what users previously liked. Nevertheless, this does not explicitly show which product features the user finds satisfactory or unsatisfactory, thus failing to accurately represent user preferences (Al-Ghuribi et al. 2019). Multi-criterion systems address this issue by considering multiple aspects of an item. For instance, on one of the most popular online booking platforms, TripAdvisor, users provide an overall rating as well as multi-criteria ratings for aspects such as cleanliness, location, rooms, service, sleep quality, and value when sharing their experiences (Antognini and Faltings, 2020)

Users' ability to rate different points of their experience separately, rather than being limited to a general evaluation, will enable their satisfaction with different aspects of their experience to be easily observed. Among the existing challenges for recommender systems, the most important challenge is personalized suggestions because the user's satisfaction is achieved when he receives the best and most appropriate suggestion from the system (Liu et al., 2022). Multi-criteria systems strive to enhance user satisfaction by considering specific item aspects and providing more accurate and relevant recommendations.

1.2 Recommender System Techniques

This section covers the different methodologies behind recommender systems and how they deal with personalization. Numerous filtering algorithms exist that are appropriate for various purposes. Recommendation systems generally fall into the following categories: content-based filtering, collaborative filtering, and hybrid recommendation approach (Adomavicius and Tuzhilin, 2005). Each of these methods has advantages, disadvantages, and certain limitations, and these issues will be discussed in this section.

1.2.1 Content-Based Filtering

The methodology behind content-based recommender systems is based on the assumption that if a user is interested in a topic, will likely remain interested in the near future, as users do not tend to change their interest profile often (Felfernig et. al, 2014). The architecture of content-based filtering could be observed in Figure 1.2.

Content-Based Filtering relies on the characteristics of items to recommend new items similar to items the user has previously shown interest in based on their previous actions or explicit feedback. They are not dependent on other users and user-item interactions. The similarity of items is calculated based on their associated features. Considering an example from online booking platforms would be recommending a hotel with similar amenities and properties.

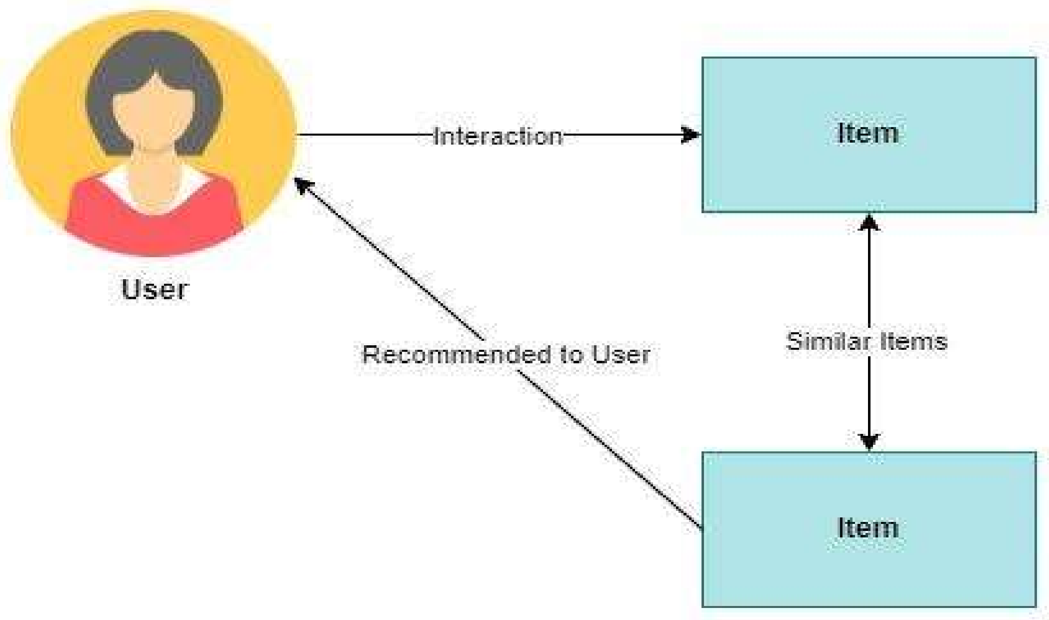

Figure 1.2. Content-Based Filtering

Content-Based Filtering offers many benefits; however, these systems also have drawbacks and limitations. Although these systems do not require additional information about users and can recommend niche items, they are limited in expanding user interests and require domain knowledge to extract the item's features.

1.2.2 Collaborative Filtering

Collaborative Filtering (CF) systems are designed to analyze both implicit and explicit feedback users provide to understand similarities between different users and items. By identifying patterns in user behavior, these systems can generate suggestions based on the behavior of similar user groups. This approach allows for personalized recommendations that are tailored to individual preferences and interests.

In Figure 1.3, the Collaborative Filtering model architecture could be observed.

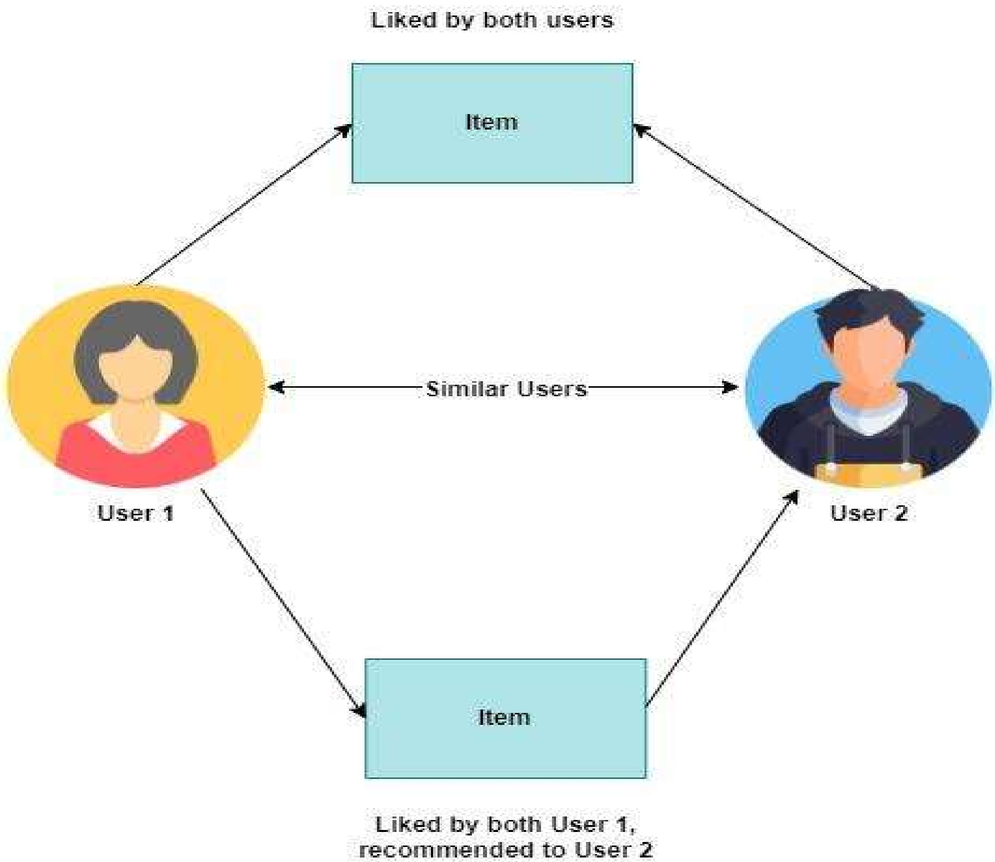

Figure 1.3. Collaborative Filtering

One of the major benefits of CF is that it does not necessitate user segmentation or item metadata values, as long as there is an available user-item interaction matrix. CF discovers the latent factors of the user-item interactions, allowing users to expand their interests however, it also has drawbacks and limitations.

One of the common difficulties in CF recommender systems is the cold start problem. This issue occurs when any new user or item is introduced into the platform, as there are not enough interactions between users and items. Other challenges encountered include the sparse user-item interaction matrix, indicating that the majority of items may only receive ratings from a small number of users, or conversely, most users may solely rate a minority of the items. The user-item interaction matrix could also be skewed: some items could be popular among users, and some users might be very prolific in the system.

1.2.3 Hybrid Recommender Systems

The purpose of hybrid recommender systems is to optimize performance by merging content-based and collaborative filtering techniques (Burke, 2002).

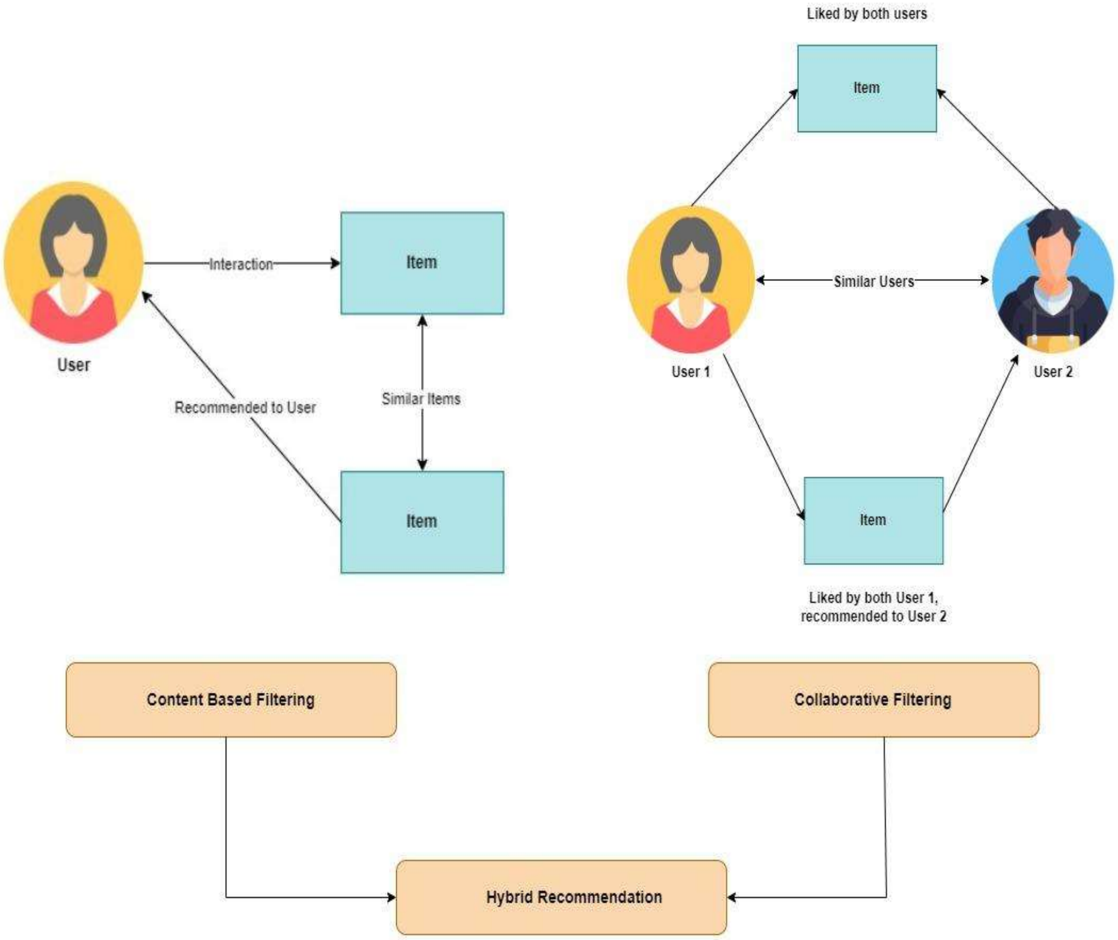

Figure 1.4. Hybrid Recommender Systems

The goal of the hybrid approach is to minimize the weaknesses of each method by taking advantage of its strengths. The system aims to provide users with a more holistic approach to providing a personalized experience by studying both the similarities of users and the interrelationship of products.

2. LITERATURE REVIEW

This section presents and discusses the previous literature on multi-criteria recommender systems. The literature survey delves into the basic principles, framework, and advantages of multi-criteria-based systems over single-criteria systems and the research in this field.

According to Adomavicius and Kwon (2007), while single-criteria recommendation systems are successful in many applications, multi-criteria rating systems are increasingly used in many fields and industries. Providing users with a customized experience requires acknowledging and addressing the fact that each user has unique needs and preferences. In this regard, single-criteria systems are insufficient to provide a detailed analysis while identifying user preferences (Shambour, 2021). Multi-criteria recommender systems aim to offer a more comprehensive and tailored user experience by integrating multiple criteria, thereby outperforming single-criteria models in terms of understanding and explaining user choices. Single-criteria systems are seen as inadequate, as the relevance of a recommendation to a given individual might be dependent on a variety of considerations, and the inclusion of multiple criteria influencing users' views could result in greater efficiency and precision in recommendations (Ricci et al. 2015).

Through utilizing multi-criteria ratings, Multi-Criteria Recommender Systems (MCRS) significantly improve the recommendation process. These ratings, by explicitly capturing various aspects of user preferences through multiple rating dimensions, offer a greater comprehension of user preferences. This in-depth analysis of user ratings on different criteria significantly enhances the effectiveness of recommendation systems, as highlighted by Musto et al. (2017). For instance, Shambour et al. (2022) propose a hotel recommendation model, which is a hybrid approach that fuses enhanced user-based and item-based collaborative filtering techniques within a multi-criteria collaborative filtering framework using explicit multi-criteria ratings.

Jhalani et al. (2016) suggested a method for an MCRS that relies on multiple linear regression to determine the weights attached to individual criteria. These weights have a dual function in the process: first, they establish user similarity by combining the traditional similarities of these criteria, and second, they determine the overall rating by combining the weighted multi-criteria ratings. In contrast to the single-criteria baseline model, the model produced more accurate outcomes. In this regard, several studies have similarly concluded that MCRS systems yield better results (Kaya and Kaleli 2016; Wasid and Ali 2018; Al-Ghuribi and Noah 2019).

Nassar et al. (2020) proposed a multi-criteria recommender system that utilizes two distinct multi-criteria collaborative filtering Deep Neural Networks (DNNs) to predict both individual criterion ratings and the overall rating based on these criteria. Their model demonstrated greater accuracy compared to a single-criteria DNN. Similarly, Nithin et al. (2021) emphasized the importance of implementing a recommender system that can adapt to users' varying preferences in contexts where decisions may be based on multiple criteria, such as hotel recommendations. They introduced an innovative NCF-based recommender system designed to estimate multi-criteria scores. The authors modified the final layer of the NCF model to generate outputs corresponding to the number of criteria ratings and incorporated cosine similarity metrics to enhance item recommendations. Their results showed that the proposed model outperformed traditional methods, including Matrix Factorization (Koren et al., 2009) and Hybrid Auto Encoder (Strub et al., 2016).

Moreover, MCRS are not limited to explicit ratings. For example, MCRS can also be developed by analyzing user sentiments expressed in textual reviews to assess preferences related to specific aspects. One of the earliest studies in this area is by Plantie et al. (2005), who proposed a movie recommendation system that employs text mining to extract user sentiments on multiple criteria from movie reviews and uses a weighted average of these criteria scores to calculate an overall score. Dursun and Ozcan (2022) proposed an NCF-based hotel recommendation system by integrating extracted aspect-based sentiment from textual user-generated reviews utilizing opinion mining.

Covington et al. (2016) proposed a DNN model that can generate personalized video recommendations for YouTube users based on their viewing history and several demographic characteristics. In order to overcome the drawbacks of item-based CF systems, Shambour and Lu (2011) proposed the Multi-Criteria Semantic-Enhanced CF approach, which combines an item-oriented memory-based MCRS system with semantic filtering as a hybrid approach to generate tailored recommendations.

Consequently, the previous literature suggests that once the domain knowledge of the descriptive criteria for an item is present, utilizing the user's implicit and/or explicit feedback, multi-criteria-based recommendations can be provided to users using a variety of existing methods and techniques.

3. MATERIAL AND METHOD

This section outlines the research design, methodologies, and procedures employed in the study. Each process is described in detail, including data gathering, data preparation, data preprocessing, exploratory data analysis, and the processed model, single-criterion model, and traditional NCF filtering-based MCRS. The platform and tools used are also described, providing a comprehensive overview of the methods and materials that contributed to achieving research results.

3.1 Dataset

In this section, the dataset is examined and given an overview. The main data source for this study was HotelRec, as it is perfectly aligned with the needs of this study by not only being one of the largest publicly available hotel review datasets but also containing both the overall rating and multi-criteria ratings given by the users (Antognini and Faltings, 2020). The initial HotelRec dataset contains approximately 50.2 million hotel reviews from the TripAdvisor platform between the years 2001 and 2019. However, in this study, to work with more recent data, reviews as of 2014 are included. Each row includes information on the author and the hotel, a textual review, the title of the review, the review date, and the associated overall and multi-criteria ratings, with the multi-criteria regarding cleanliness, rooms, sleep quality, service, and location.

Table 3.1 shows the columns and their descriptions. The initial format of the HotelRec dataset includes each review, review title, textual review content, the general rating and multi-criteria ratings given to the hotel between 1 and 5, and the hotel's hotel_url containing the hotel name.

Table 3.1. Dataset Attributes and Descriptions

Columns	**Description**
hotel_url	URL link to hotel review page
author	The username of the reviewer
date	Date of the review
rating	The overall rating is given by the reviewer
title	Title of the review
text	The main content of the review
rooms	Rating for the rooms
sleep_quality	Rating for the sleep quality
cleanliness	Rating for cleanliness
value	Rating for value
service	Rating for service
Location	Rating for location

A sample review from the dataset with the related columns and the multi-criteria ratings could be observed in Table 3.2.

Table 3.2. A sample from the Dataset

Column	**Value**
hotel_url	Hotel_Review-g60745-d94368-Reviews-DoubleTree_by_Hilton_Hotel_Boston_Bayside-Boston_Massachusetts.html
author	bradh339
date	2014-02-01T00:00:00
rating	3.0
title	Clean and attentive staff
text	This is a fine location if your business has you near the Expo Center or South Boston. For me, it was just a little remote and didn't offer any walkable dining locations or shuttle service to the same. Be aware that it is not near the airport although they do have an airport shuttle. A trip in Boston traffic could take 20 minutes to Logan.
rooms	3.0
sleep_quality	4.0
cleanliness	4.0
value	3.0
service	5.0
location	2.0

3.1.1 Data Gathering

The dataset has been retrieved as a 13.40 GB compressed zip file using the Google Colab platform from the link that has been provided on the HotelRec repository on GitHub, utilizing the wget command. The unzip command within the Colab environment decompressed the Full_HotelRec.zip archive, revealing a HotelRec.txt file containing data in JSON format, which is roughly 50.4 GB. The JSON format serves as a compact method for storing and transporting data, with the intention of making data structures simple to read and encode (Jackson, 2016).

The unprocessed data includes hotel_url, the author review, the date of the review, the overall rating, the title of the review, the textual review, and the multi-criteria ratings in a dictionary in each line.


```
{
    "hotel_url": "Hotel_Review-g194775-d1121769-Reviews-Hotel_Baltic-
Giulianova_Province_of_Teramo_Abruzzo.html",
    "author": "violettaf340",
    "date": "2019-01-01T00:00:00",
    "rating": 5,
    "title": "Xmas holiday",
    "text": "We went here with our kids for Xmas holiday and we really liked it.
Large options of food for breakfast and lunch , you can really taste the quality
of the food in there. The surrounding area is nice and clean. Good experience.
Hardly recommended .",
    "property_dict": {}
}
```


Figure 3.1. Sample Unprocessed Data in JSON Format

3.1.2 Data Preparation

In this study, the data preparation process is critically important due to the retrieved data's raw state. Although the JSON data contains valuable information, its raw format cannot be directly used by the model. The initial step before converting the JSON data to a data frame was to filter the data using the date column, focusing on more recent data as the initial data spans from 2001 to 2019, with reviews up to 2014 being employed in this study. To filter out the dates, the JSON parser ijson library was utilized, as it differs from other JSON parsers by reading and parsing each line incrementally (Tobar and Sagalaev). After the parsing process, the JSON values were converted to a data frame which contains 7,054,588 rows and 13 columns. Raw data contained multi-criteria columns in dictionary format in a column called property_dictionary, as could be observed in Figure 3.1. The json_normalize function was used to parse these dictionary values as column names and values. Afterwards, if there are any empty values in these columns, those rows are dropped.

Reviewers are required to give the hotel an overall rating, but they are not obligated to rate all aspects of the hotel, resulting in numerous null values in multi-criteria columns. As null values would impact the model's performance, they were dropped during the data preparation process. Additionally, anonymous users with no username, labeled as "/undefined" and totaling 850,442 rows, were also dropped. The overall rating distribution of these undefined users could be examined in Figure 3.2.

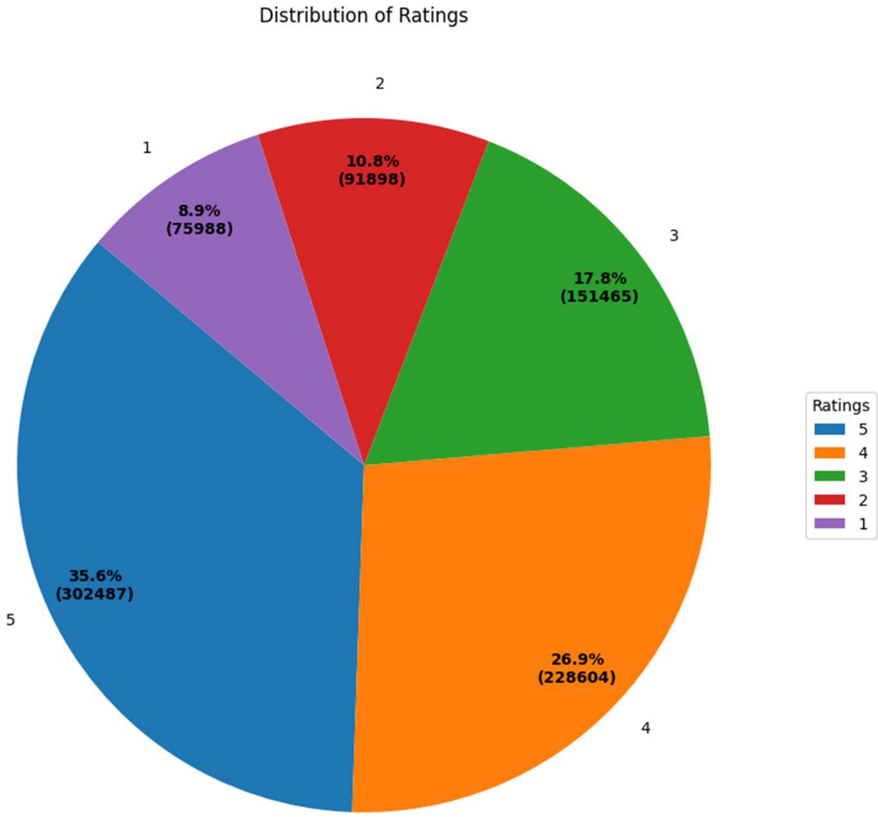

Figure 3.2. The Overall Rating Distribution of Undefined Users.

Additionally, the hotel_url column was processed to extract the hotel_url, and a new column, hotel_name, was created.

The dataset includes a variety of users and hotels; however, it is very sparse and requires preprocessing. Many users have only one review, and many hotels have just one rating. To address this issue, two different datasets were generated for this study: one where users have at least 3 reviews and hotels have at least 3 ratings, and another where users have at least 5 reviews and hotels have at least 5 ratings. Filtering the dataset in this manner reduces data sparsity, enhances the reliability of the model, and ensures the analysis focuses on active users and frequently rated hotels. These datasets have been named hotelrecw3 and hotelrecw5 accordingly. This approach ultimately improves the overall quality of the recommendations.

Table 3.3. Datasets

Dataset	Number of Rows	Number of Unique Users	Number of Unique Hotels
hotelrecw3	757.958	192.341	111.293
hotelrecw5	251.012	40.933	67.846

The two datasets, hotelrecw3 and hotelrecw5, have distinct properties. The hotelrecw3 dataset consists of 757,958 rows, with 192,341 unique users and 111,293 unique hotels. In comparison, the hotelrecw5 dataset contains 251,012 rows, with 40,933 unique users and 67,846 unique hotels. The hotelrecw3 dataset is significantly larger and more comprehensive than the hotelrecw5 dataset, both in terms of the number of interactions and the number of unique users and hotels, so hotelrecw5 will not be employed in this study. As significant data loss was observed in hotelrecw5 compared to hotelrecw3, the number of filters was not increased, and no further datasets were created.

3.1.3 Data Visualization

In this section, data visualization is made in order to have a preliminary look at the data. This section includes visualizations such as users with the most reviews, hotels with the most reviews, users' rating distribution, and correlation between sub-ratings and overall ratings. This section aims to provide an overview of the data and to better understand the structure and distribution of the data.

In order to highlight the most common terms in the reviews, a word cloud was generated. The reviews were analyzed to identify the most significant words, with up to 100 unique terms featured in the final word cloud.

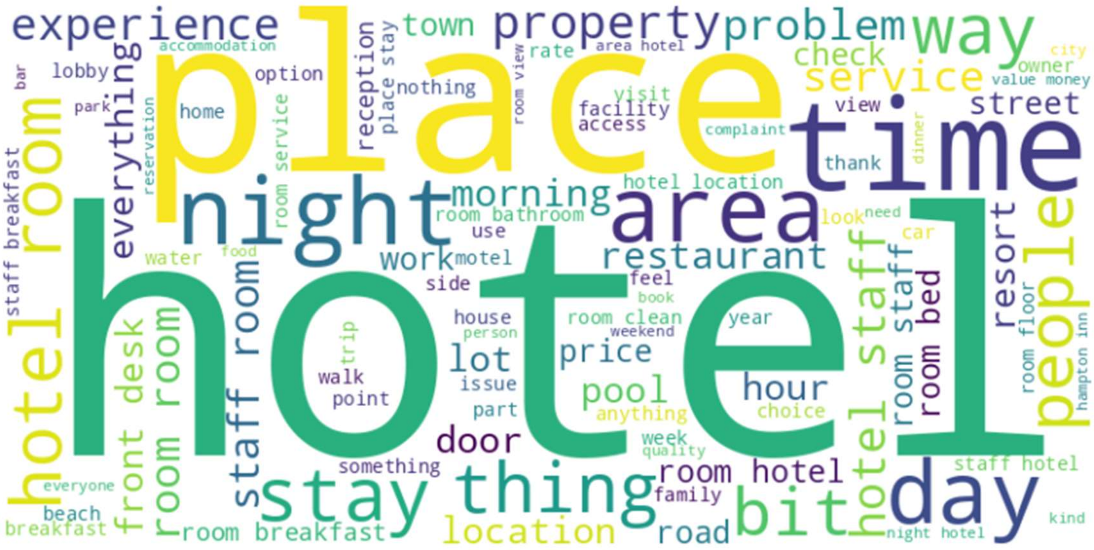

Figure 3.3. WordCloud

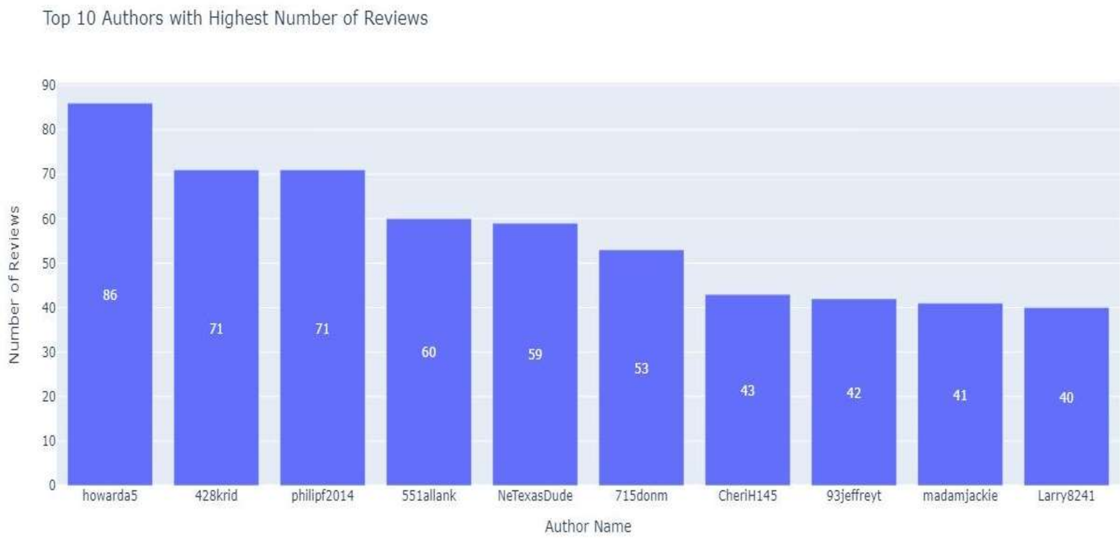

Figure 3.4. Top 10 Authors with Highest Number of Reviews

Figure 3.5. Top 10 Hotels with the Highest Number of Reviews

The hotels where users voted the most and the users who voted the most were visualized with bar charts. This visualization assisted in identifying users' preferences and hotels' popularities. It also allowed to analyze how much users interacted with the platform.

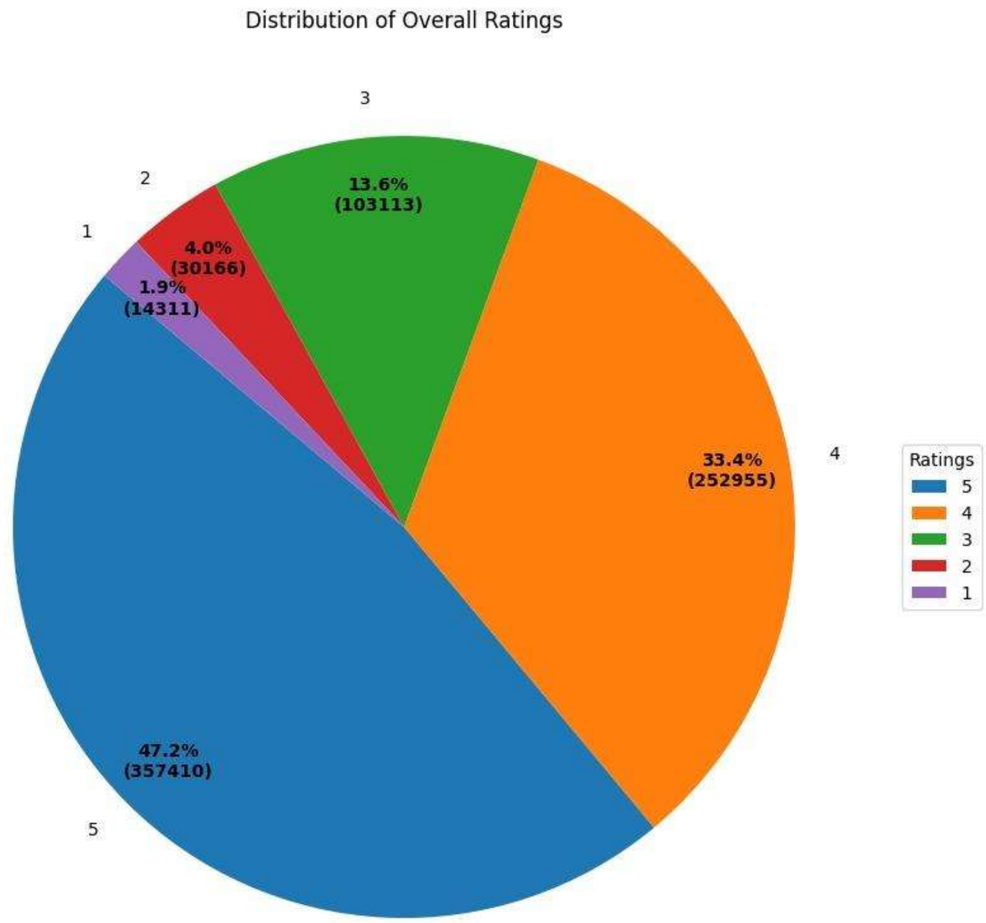

Figure 3.6. Distribution of Overall Ratings

A pie chart was created to visualize the distribution of users' votes. This visualization allowed for a better understanding of the overall vote distribution and its presentation in terms of percentages. In comparison to Figure 3.2. it could be observed that undefined users has had given lower ratings by the examination of the overall rating percentages however, the general distribution of the overall rating scores are observed as 4 and 5 in both figures.

Figure 3.7. Correlation of Multi-Criteria Ratings with Overall Rating

Figure 3.7. demonstrates that the overall rating has the highest correlation with the ratings for rooms (0.79), value (0.75), and service (0.75), indicating that these three factors have the greatest impact on determining overall satisfaction. It was observed that the location had the lowest impact on the overall rating. This result was expected since users have information about the location prior to their accommodation.

Figure 3.8. Correlation Matrix of Overall Rating & Multi-Criteria Ratings

The correlation matrix serves as a useful visual tool for understanding the relationships between various aspects and their impact on the overall user experience. Figure 3.8. indicates that cleanliness and rooms have the strongest interrelationship, followed by the overall rating's strong dependency on rooms and service. The location appears to have weaker correlations with other sub-ratings, as it is not related to service quality or amenities.

3.2 Neural Collaborative Filtering

Integrating neural network techniques into recommender systems has led to significant development and progress in this field. One of the most groundbreaking works in this field is the Neural Collaborative Filtering method proposed by He et al. (2017). Unlike traditional CF methods, it learns non-linear interactions and provides more accurate and personalized recommendations by combining the strengths of matrix factorization and neural networks. The general idea behind matrix factorization is to describe users and items as combinations of different amount of each latent feature, which is achieved by representing the user-item interaction matrix into to product of user and item matrices. Reviews and user-item interaction are widely acknowledged as valuable data for improving representation learning skills in recommender systems. One of the variants of matrix factorization is non-negative matrix factorization which is where the user and item matrices are constrained to non-negative value, this is useful for data that is inherently non-negative, such as user preferences. Although its not the primary focus of this thesis, non negative matrix factorization is valued for its ability to produce interpretable representations that enhances the understanding and performance of recommendation systems.

As it could be observed from Table 3.1 neither item and user attributes were given in this dataset. When user and item information is not provided in the dataset, NCF is preferred due to the advantages of deep learning techniques. NCF learns more complex and hidden relationships by modeling user and item interactions using DNNs, which perform better than simple matrix factorization methods. While normal CF methods usually capture nonlinear relationships, NCF discovers richer and deeper hidden factors. Therefore, the higher generalization capacity and flexible nature of NCF make it more successful than regular CF, especially in large and complex data sets.

3.3. Evaluation Metrics

In this section, the metrics to evaluate the models' performance was described briefly. In order to assess the models' performance in this study, four different metrics has been used. These metrics are Mean Absolute Error (MAE), the accuracy and the F1, F2 scores. The MAE is the absolute mean of all the errors meaning in this thesis, the errors are the falsely predicted overall rating scores. The accuracy score is a straightforward method that measures the proportion of correct predictions made by the model out of the total number of predictions. In this study, as the overall rating distribution is imbalanced, F1 and F2 scores have been used. The calculation of the F2 and F1 scores are similar, but the F1 provides a balance between precision and recall, while the F2 score gives more weight to recall. The F1 score measures the overall success of the model by balancing the model's true positive and false negative predictions, while the F2 score measures how accurately the recommended items are predicted to be of real interest to the user.

3.4. Proposed Model

In this study, hotel recommendations are made with multi-criteria neural collaborative filtering. When users review their experience of a hotel, they vote on many different aspects such as rooms, service, value, cleanliness, location, and service. In hotels, multi-criteria evaluations are critical in meeting the different expectations of customers. Each customer emphasizes different aspects such as cleanliness, comfort, and service quality. Therefore, when recommending hotels to hotel customers, it is necessary to recommend them by understanding the importance of these aspects for them.

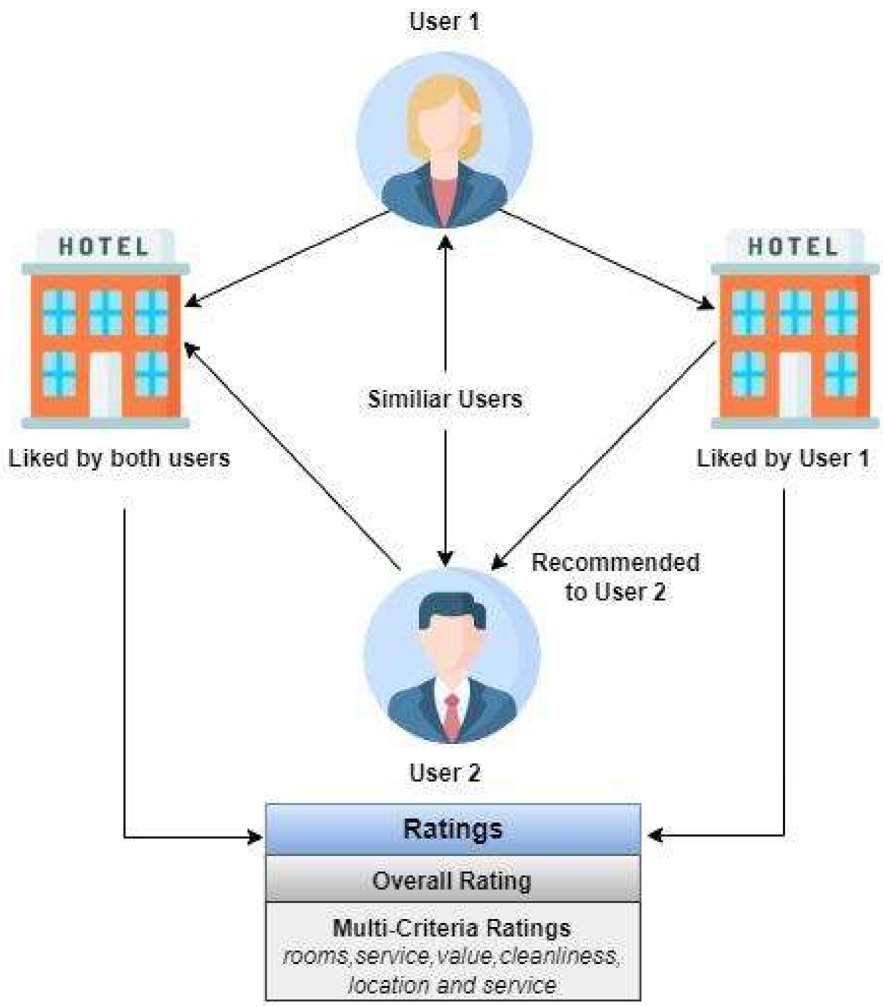

Figure 3.9 Multi-Criteria NCF Architecture

In the dataset used in this study, users voted according to 6 different aspects provided by the platform about the hotels while sharing their experiences about the hotels along with the overall rating. It is important to understand how the overall vote of users changes according to these aspects and to extract user similarities according to users who attach importance to similar criteria.

The model is built using Keras, and the development and training of the model were performed using the Google Colab platform. Google Colab was preferred because it facilitates working with large data sets thanks to its strong GPU support.

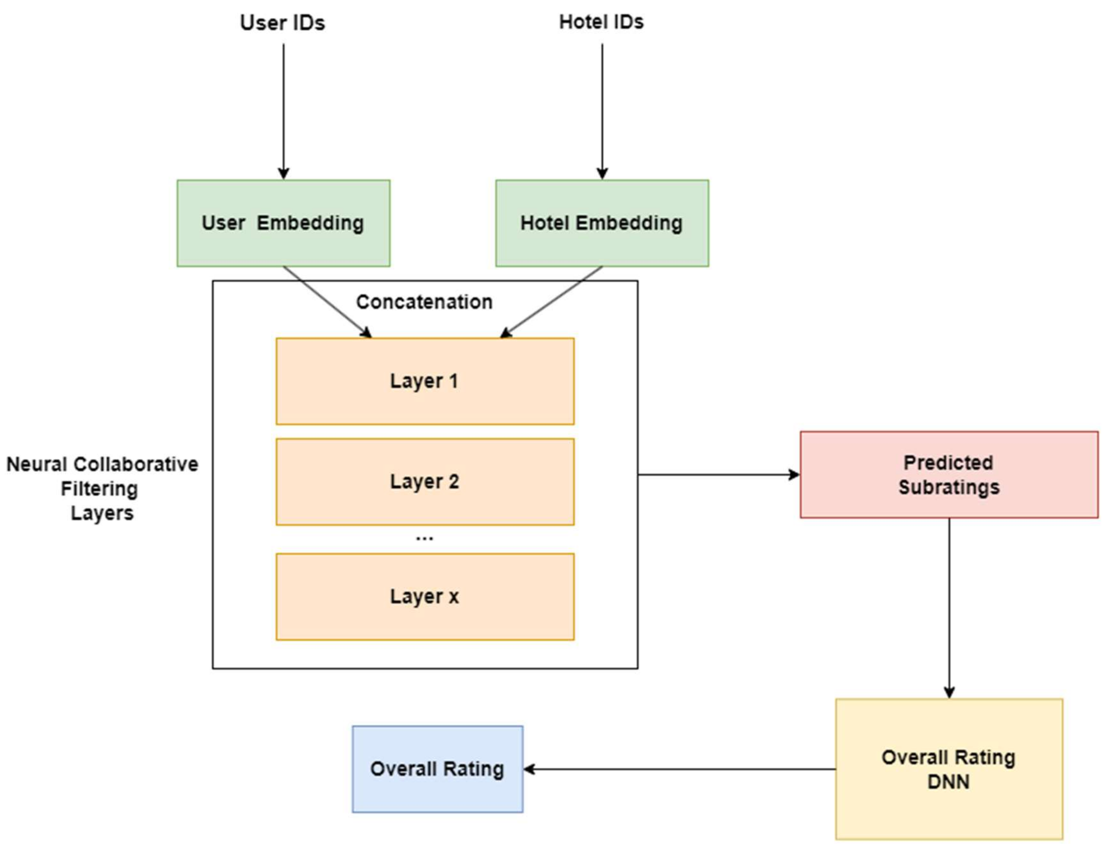

Figure 3.10 Proposed Model

The model proposed in this study is a variation and enhancement of the deep multi-criteria model previously proposed by Nassar et al. (2020). Nassar et al. (2020) presented a two-stage DNN that predicts multi-criteria ratings using the ReLU (Rectified Linear Unit) activation function as an aggregation function and, as a second stage, a second DNN that predicts the overall rating based on these criteria. The model proposed in this study predicts multi-criteria ratings based on user similarities using NCF. It then incorporates these user ratings as input for a DNN, ultimately producing an overall rating as the output. Although the proposed model differs from the study of Nassar et al. (2020) by using NCF instead of DNN in the first phase, it utilizes the aggregation of multi-criteria ratings to determine the output overall rating using a similar methodology.

3.4. Single- Criterion Model

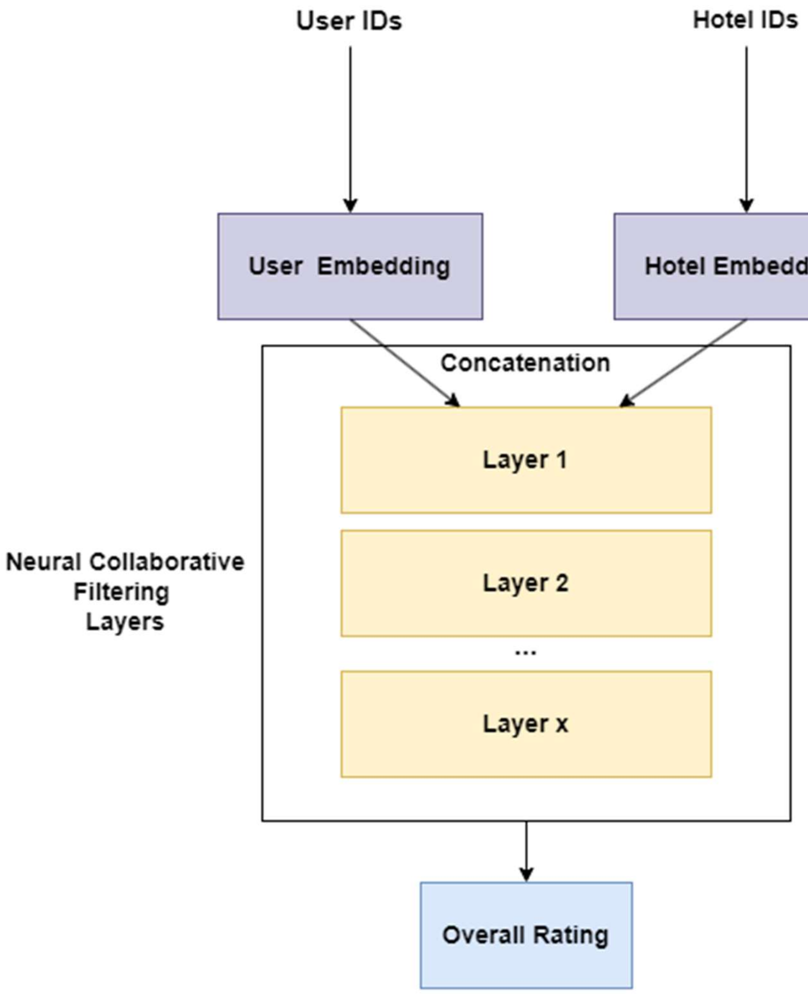

Figure 3.11. Single - Criterion Model

To examine the effectiveness of multi-criteria recommender systems over single-criteria recommender systems, this study compared the proposed model with a single-criteria-based NCF recommender system. This model follows a standard NCF architecture that utilizes user and hotel embeddings to offer recommendations by considering the interactions between users and items.

3.4. NCF-TF Model

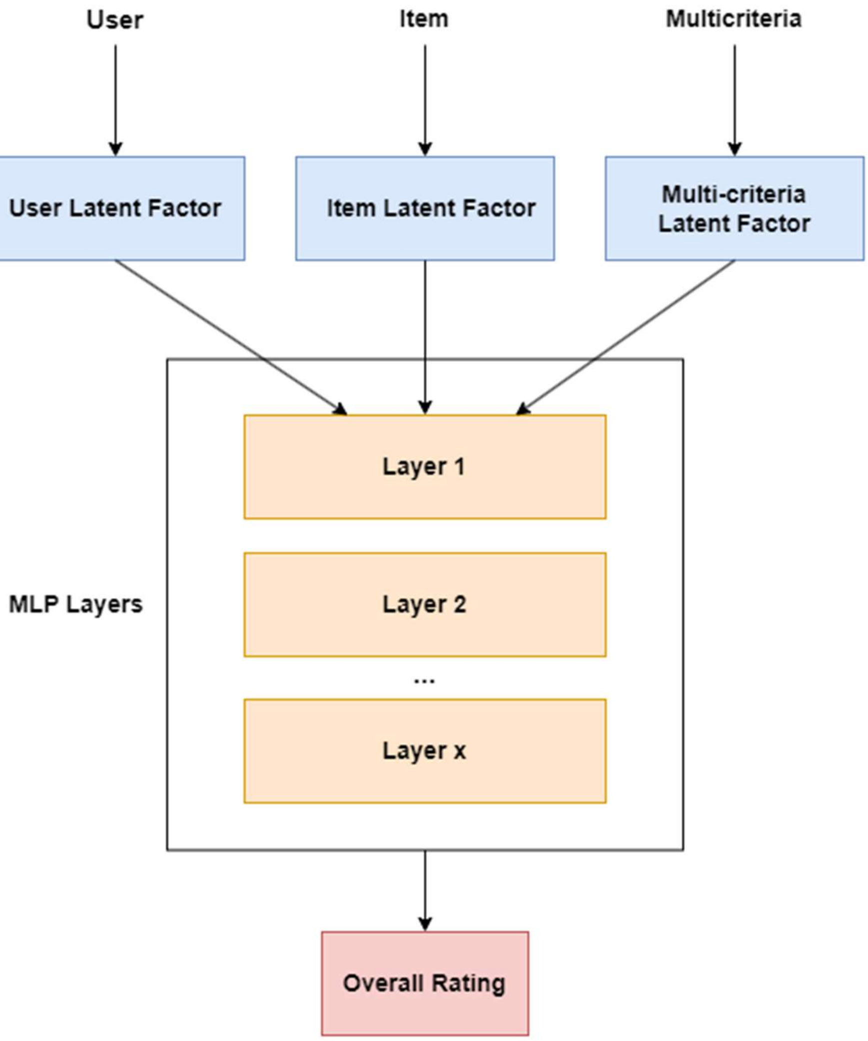

Figure 3.12. NCF-TF Model

In the Neural Collaborative Filtering for Tensor Factorization (NCF-TF) model, a similar model structure proposed by Morise et. al. (2022) is utilized. This model also incorporates multi-criteria ratings to enhance prediction accuracy, like the proposed model however there is a significant difference between the two models. Unlike the proposed model, in the NCF-TF model, user and item identifiers are used as inputs as well as the multi-criteria ratings, and these features are combined through a neural network to predict the overall rating.

4. RESULTS AND DISCUSSION

This section presents the proposed model, which we compare with the single-criterion model and the NCF-TF model. In this section, the results are thoroughly evaluated and discussed, including the tests performed, model parameters, and model settings. Furthermore, the impact on the overall performance and effectiveness of the model is analyzed with comparison to a single-criteria recommender system and the NCF-TF model. The purpose of comparing the proposed model with these mentioned models is to observe the effect of the multi-criteria ratings on overall rating prediction. Since the single-criteria model does not include multi-criteria ratings and the NCF-TF model, unlike the proposed model, uses multi-criteria ratings as input; these models are perfectly aligned with the aim of observation.

As previously stated, the proposed model consists of two separate models, each trained sequentially. The first model is used to predict the multi-criteria ratings by utilizing NCF. The second model then takes these predicted ratings as input and the aggregation and prediction of the user's overall rating on hotels they haven't rated yet are learned through the dense layers.

TensorFlow and Keras were used to build and train the models, with hyperparameter optimization manually performed. Pandas and Numpy were employed for data manipulation and preprocessing, and Scikit-Learn provided additional machine-learning tools. These libraries offered an efficient framework for implementing and optimizing the proposed and tested models.

4.1 Hyper-parameter Optimization

In order to optimize the model's performance, hyper-parameter optimization is conducted in the first step of the proposed model. Since the results of the first model will feed into the second model, it is essential to work with the appropriate model parameters. The aim is to determine the best possible model configuration that minimizes the mean absolute error (MAE) of verification by tuning key parameters such as embedding dimensions, hidden layer configurations, and optimizers. MAE metric assists in evaluating the model performance, as it indicates the absolute error of the prediction result from the actual rating.

Embedding Dimensions: The embedding sizes were manually tuned using the range of embedding sizes [8, 16, 32, 64, 128], reflecting the dimensionality of the embedding vectors for users and hotels, to identify the optimal embedding dimension with the lowest MAE.

Table 4.1. Embedding Dimensions

Embedding Dimensions	**MAE**
8	0.6112
16	0.5604
32	0.5379
64	0.5330
128	0.5376

The impact of the embedding size on the MAE metric can be observed in Table 4.1. According to the results, the optimal embedding size is 64, as it produces the lowest MAE (0.5330).

Hidden Layers: In order to experiment with various hidden layer architectures, 3 different configurations were utilized in the hyper-parameter optimization, including [32, 16, 8], [64, 32, 16, 8], and [128, 64, 32, 16, 8]. This allowed for exploring different network depths and complexities.

The results indicated that adding more hidden layers slightly improved the performance, as the configuration [128, 64, 32, 16, 8] achieved the lowest MAE.

Table 4.2. Hidden Layers

Hidden Layers	MAE
[32,16,8]	0.5702
[64,32,16,8]	0.5686
[128,64,32,16,8]	0.5676

Optimizers: During the hyperparameter optimization step, several optimizers were tested to determine the most effective one for the model.

Table 4.3. Optimizers

Optimizer	Proposed NCF Model
Adam	0.5322
Adamax	0.6207
Adagrad	0.5787
SGD	0.5463

Adam was chosen as the optimizer because it has a very low MAE compared to other optimizers.

4.2 Model Settings

In the first phase of the proposed model, the optimal parameters are used according to the results of the hyperparameter optimization performed previously. In the second phase of the proposed model, the overall rating DNN utilized the predicted multi-criteria ratings as input and therefore did not include any embedding layers. To achieve optimal results, extensive hyperparameter tuning was conducted. The different numbers of units in the hidden layers, varying dropout rates, and adjusting regularization strengths are experimented with to tune the model manually, and the most effective configuration is identified and applied. Likewise, the hyperparameters of the test models were tuned manually after several attempts. Batch size has remained consistent as each model runs with the same dataset. For each model, the epoch size has been calculated using early stopping.

Table 4.4. Model Parameters

Model	Embedding Size	Hidden Layer	Optimizer	Epochs	Batch Size
Proposed Model First Phase	64	128->64->32->16->8	Adam	20	256
Proposed Model Second Phase	-	128->64->32	Adam	13	256
Single Criterion Model	64	128->64	Adam	4	256
NCF-TF Model	64	128->64	Adam	7	256

4.3. Model Results

The table 4.5. presents the comparison of three models: the Proposed Model, the Single Criterion Model, and the NCF-TF Model, evaluated on four key metrics: MAE, F1 score, F2 score, and Accuracy. These metrics are critical for assessing the performance of multi-criteria recommendation systems.

Table 4.5. Model Results and Comparison

Model	MAE	F1	F2	Accuracy
Proposed Model	0.5789	0.9128	0.9577	0.8478
Single Criterion Model	0.6114	0.8917	0.9487	0.8061
NCF-TF Model	0.7670	0.8261	0.7501	0.7605

Based on the results, the proposed model consistently performs better than the other two models across all evaluated metrics, demonstrating its effectiveness in predicting multi-criteria ratings with greater accuracy and comprehensiveness. The low Mean Absolute Error (MAE) and high F-scores indicate its robustness in both precision and recall, while the high accuracy suggests it is reliable in making correct recommendations. Although the Single-Criterion model shows good performance, it does not achieve the same level of precision as the proposed model, particularly concerning MAE and accuracy. This indicates that taking multiple criteria into account provides a more detailed understanding of user preferences, resulting in more accurate predictions. The NCF-TF model exhibits the least effective performance, especially in terms of F2 and accuracy, suggesting that while it can process multi-criteria data, it may not integrate user similarities and multi-criteria ratings as effectively as the proposed model.

To facilitate a visual comparison of the models' performances, a data frame is used that includes both the actual overall rating and the predicted overall rating columns for each model. A subset of 150 random samples is selected from the data frame to create a visualization that effectively represents the data without overcrowding the plot. The plot features two lines: a blue line indicating the actual overall ratings and a red line representing the predicted overall ratings.

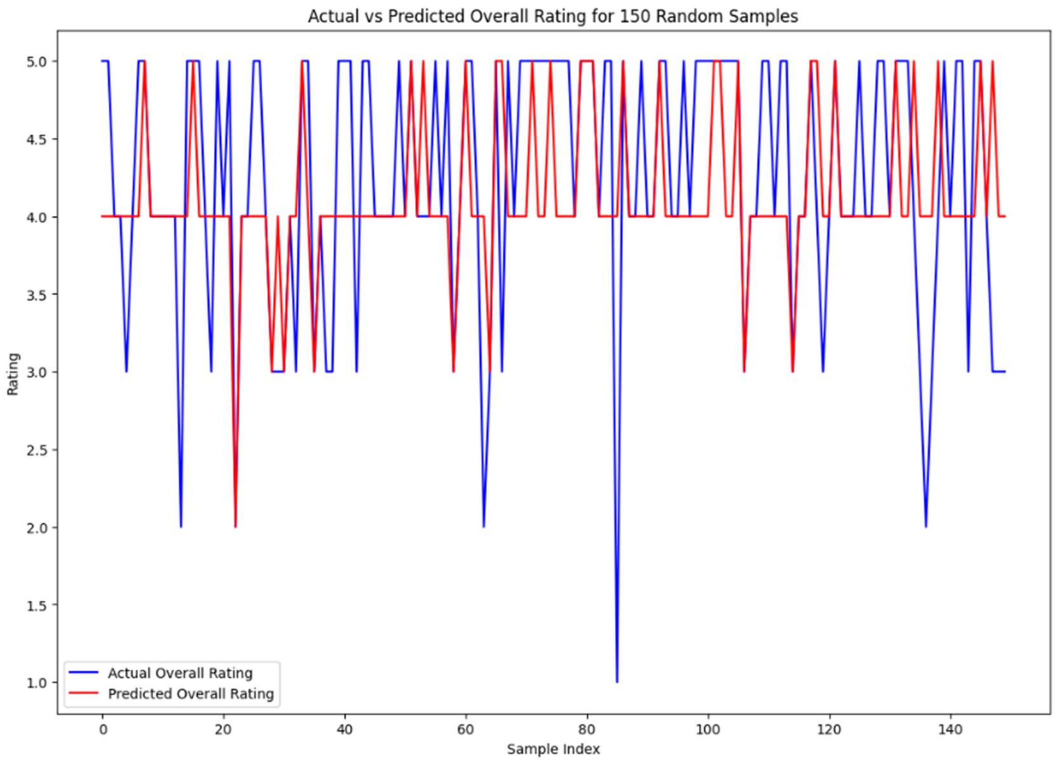

Figure 4.1. Actual vs Predicted Ratings of the Proposed Model

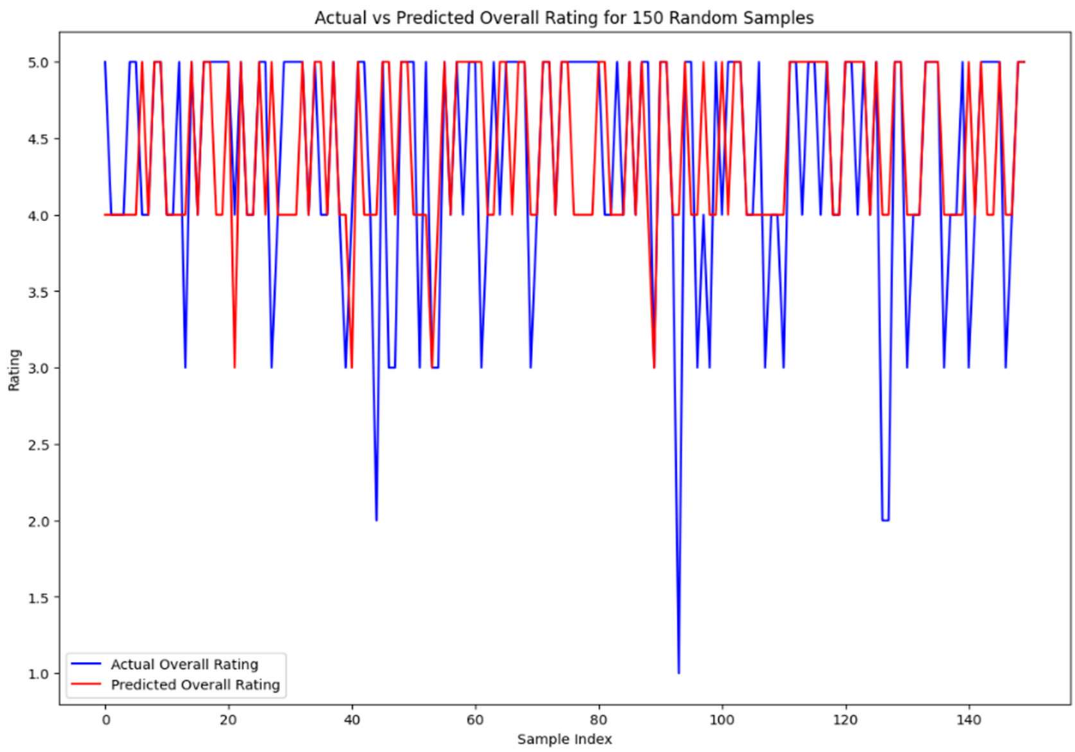

Figure 4.2. Actual vs Predicted Ratings of the Single-Criterion Model

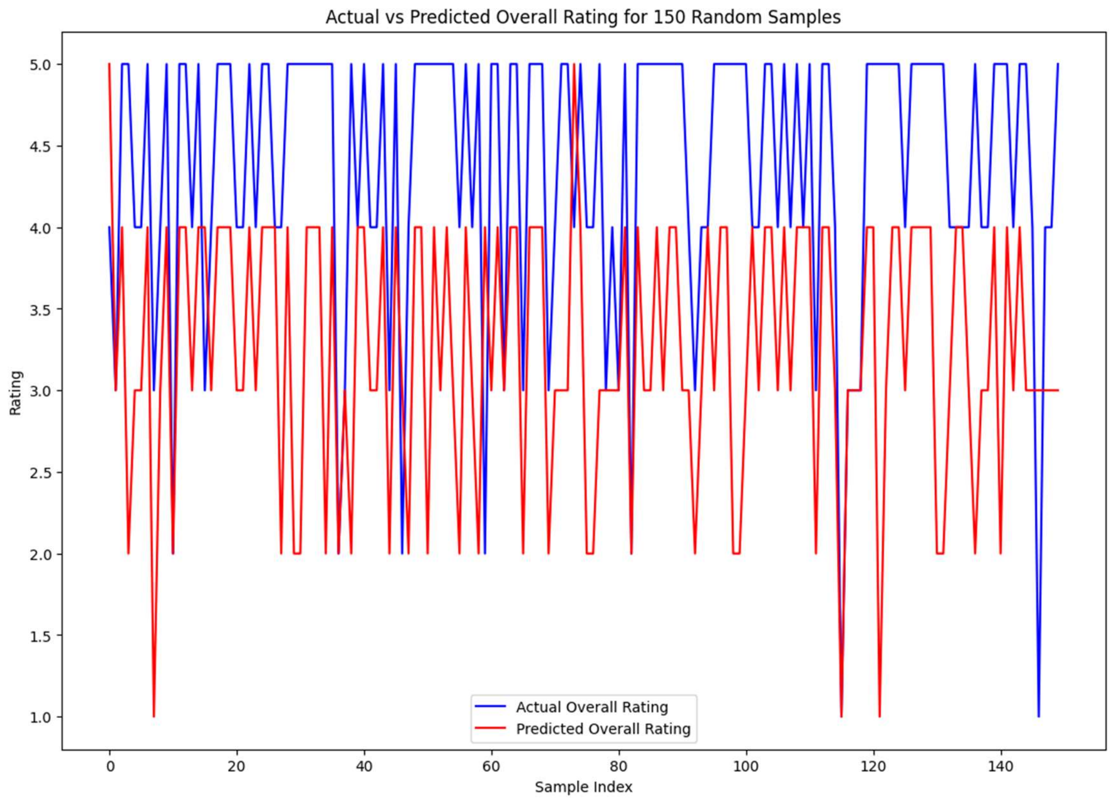

Figure 4.3. Actual vs Predicted Ratings of the NCF-TF Model

The analysis of these graphs reveals that the proposed model performs more comprehensively across the various ratings and is able to make more precise predictions.

5. CONCLUSION

In today's information-intensive online booking platforms, more advanced and personalized recommendation systems are required to facilitate users' decision-making processes. Due to the existence of many different platforms and the widespread use of the internet nowadays, users are faced with a large number of different hotel alternatives to compare and consider, as well as a large number of reviews that contain other users' past experiences. The content that users encounter must be filtered in accordance with the users' preferences and needs. Hence, recommender systems are integrated within the infrastructure of several digital platforms. MCRS are essential for hotel recommendations as it enables personalized and tailored recommendations by taking into account the diverse and nuanced preferences of users whilst addressing their concerns regarding various aspects.

This thesis aims to demonstrate the effectiveness and advantages of a multi-criteria neural collaborative filtering model for hotel recommender systems. The model proposed in this study first estimates multi-criteria ratings using user and hotel identifiers and then predicts an overall rating based on these estimates. In order to better understand the impact of the proposed model, the dataset is also trained with a single-criteria NCF model and an NCF-TF model using multi-criteria as input and the results are obtained. Based on this study's findings, the suggested model outperforms both two models in all metrics, demonstrating its efficacy in accurately and comprehensively predicting multi-criteria ratings.

As the findings demonstrate the effectiveness and potential of the multi-criteria neural collaborative filtering model, several areas for improvement can be addressed in future work to enhance the model's performance. The introduction of hybrid models that will be developed by combining multi-criteria neural collaborative filtering techniques and content-based filtering methods by combining demographic characteristics of users such as age, gender, nationality, and features such as the concept, location, amenities, and services offered by hotels can take personalized recommendations to a further advanced position by fulfilling user needs and desires more effectively.

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