T.C.
BAHCESEHIR UNIVERSITY
GRADUATE SCHOOL
DEPARTMENT OF BIG DATA ANALYTICS AND MANAGEMENT

AN OPTIMIZED HYBRID AI-BASED RECOMMENDATION SYSTEM FOR E-COMMERCE

MASTER’S THESIS

SAHAR FARHAT

ISTANBUL 2024

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This thesis was read by us, quality and content as a Master's thesis has been seen and accepted as sufficient.

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ABSTRACT

TITLE OF THE AN OPTIMIZED HYBRID AI-BASED RECOMMENDATION SYSTEM FOR E-COMMERCE

Sahar, Farhat
Master’s Program in Big Data Analytics and Management
Supervisor: Assoc.Prof.Dr. Atınç Yılmaz

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In the evolving e-commerce landscape, optimized AI-based hybrid systems are crucial for delivering accurate and personalized product recommendations. This thesis develops such a system for the Olist platform, integrating collaborative filtering, content-based filtering, and Variational Autoencoders (VAEs) to address data sparsity and cold start challenges. A detailed analysis of the Olist dataset, including descriptive statistics and exploratory data analysis (EDA), identified key trends and anomalies. The hybrid system, evaluated using Root Mean Squared Error (RMSE) and Mean Squared Error (MSE), outperformed traditional recommendation methods. Results show that the hybrid approach significantly improves recommendation accuracy and user engagement. This study suggests that adopting such systems can enhance user satisfaction and sales. The research offers a scalable framework for integrating multiple recommendation techniques. Future research should explore real-time user feedback, address bias and fairness, and enhance system scalability across diverse e-commerce contexts.

Key Words: AI-based recommendation system, e-commerce, collaborative filtering, content-based filtering, deep learning, Variational Autoencoders

ÖZ

E-TICARET İÇIN OPTIMIZE EDILMIŞ HIBRIT YAPAY ZEKA DESTEKLI ÖNERI SISTEMI

Sahar, Farhat
Büyük Veri Analitiği ve Yönetimi Yüksek Lisans Programı
Tez Danışmanı: Assoc.Prof.Dr. Atınç Yılmaz

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Gelişen e-ticaret ortamında, doğru ve kişiselleştirilmiş ürün önerileri sunmak için optimize edilmiş yapay zeka tabanlı hibrit sistemler kritik öneme sahiptir. Bu tez, veri seyrekliği ve soğuk başlangıç sorunlarını ele almak için işbirlikçi filtreleme, içerik tabanlı filtreleme ve Varyasyonel Otomatik Kodlayıcılar (VAE'ler) entegre eden Olist platformu için böyle bir sistem geliştirmektedir. Tanımlayıcı istatistikler ve keşifsel veri analizi (EDA) dahil olmak üzere Olist veri kümesinin ayrıntılı analizi, önemli eğilimleri ve anormallikleri belirlemiştir. Kök Ortalama Kare Hatası (RMSE) ve Ortalama Kare Hatası (MSE) kullanılarak değerlendirilen hibrit sistem, geleneksel öneri yöntemlerinden daha iyi performans göstermiştir. Sonuçlar, hibrit yaklaşımın öneri doğruluğunu ve kullanıcı etkileşimini önemli ölçüde artırdığını göstermektedir. Bu çalışma, bu tür sistemlerin benimsenmesinin kullanıcı memnuniyetini ve satışları artırabileceğini önermektedir. Araştırma, birden fazla öneri tekniğinin entegrasyonu için ölçeklenebilir bir çerçeve sunmaktadır. Gelecek araştırmalar, gerçek zamanlı kullanıcı geri bildirimlerini keşfetmeli, önyargı ve adaleti ele almalı ve çeşitli e-ticaret bağlamlarında sistem ölçeklenebilirliğini artırmalıdır.

Anahtar Kelimeler: Yapay zeka tabanlı öneri sistemi, e-ticaret, işbirlikçi filtreleme, içerik tabanlı filtreleme, Varyasyonel Otomatik Kodlayıcılar, veri seyrekliğ

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This thesis is dedicated to the memory of my late father, Hassan Farhat. His influence and inspiration continue to guide me.

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
VAE	Variational Autoencoder
SVD	SVD - Singular Value Decomposition
NCF	Neural Collaborative Filtering
RMSE	Root Mean Squared Error
MSE	Mean Squared Error
ELT	English Language Teaching
TPRS	Total Physical Response Storytelling
EFL	English as a Foreign Language
IQR	Interquartile Range
EDA	Exploratory Data Analysis
TF-IDF	Term Frequency-Inverse Document Frequency
KNN	K-Nearest Neighbors
WCSS	Within-Cluster Sum of Squares
KL Divergence	Kullback-Leibler Divergence
RL	Reinforcement Learning
NLP	Natural Language Processing
CV	Computer Vision
Q-Learning	A reinforcement learning algorithm

Chapter 1

Introduction

In the evolving world of e-commerce, recommendation systems have become the backbone of user interaction, ensuring constant engagement and revenue streams. Recommendation systems use complex algorithms to comb through vast amounts of data to identify patterns correlated with user preferences (Hussien et al., 2021).

Artificial Intelligence has seen it to fruition by making it possible to build recommendation systems that improve the quality of the shopping experience, enabling sellers to make meaningful sales closer to the market (Verma & Sharma, 2020).

This thesis recommends building an artificial intelligent hybrid recommendation system, using the available dataset from the Brazilian e-commerce Olist. The proposed system should capitalize on the opportunities and overcome the dataset limitations using different recommendation techniques. The anticipated outcome is increased user engagement, more sales, and greater buyer experience.

Although the existing literature presents current findings on using machine learning and artificial intelligence in building e-commerce recommendation systems (Khoali et al., 2021; Wang et al., 2021; Tran & Huh, 2023; Xu et al., 2023), further research is still needed. Such areas include integrating multiple types of data to enhance understanding of consumers, developing recommenders that stay updated to real-time user behavior and inventory changes, and cross-domain recommendations which include data collected from a different platform. Other areas of concern are building proximity with users through the creation of user-trusted recommenders and balance between user satisfaction and privacy.

Recent contributions by Raji et al., (2024); Almahmood & Tekere (2022) and Cabrera-Sánchez et al., (2020) give an insight into the application of advanced artificial intelligence techniques and performance of such systems. However, more analysis is needed to explore the full potential of the hybrid recommender system on e-commerce, related to its ability to keep updating in real-time and build recommendations from very distinct datasets.

This work, therefore, will serve as an enhancement in understanding how hybrid recommenders can be used to solve e-commerce problems. It will also explore the return probability, specificity and the future of modern users.

1.1 Statement of the Problem

In the rapidly developing sphere of e-commerce, platforms are constantly facing the challenge of providing their users with personalized, relevant recommendations. It is especially complicated due to the variety and number of products offered.

While collaborative filtering and content-based filtering are two of the most fundamental approaches to recommenders, they come with apparent disadvantages that make their utilization in such recommendations difficult (Eliyas & Ranjana, 2022). These disadvantages include data sparsity, which arises when the data is not comprehensive enough to make optimal suggestions; the cold start issue, in which the lack of background information about a user or an item makes it impossible to offer recommendations (Natarajan et al., 202; and the failure of the approaches to represent the interaction between users and items in a light that is detailed enough.

Olist, a Brazilian e-commerce platform that provides a comprehensive dataset containing records of orders, customers, products, and their reviews, can be utilized to overcome these disadvantages by creating a hybrid system that employs both of the methods: it is clear, however, that despite the many existing recommendations and advances, such integration is difficult and challenging owing to the heterogeneity of the utilized methods and the richness of the dataset. The existing body of literature also supports the identification of gaps. Driskill and Riedl (1998) argued that e-commerce suffers from a lack of successful implementation of hybrid recommendation systems, presenting a vast number of works on the subject that fail to overcome obstacles like data sparsity and the cold start without offering viable integration of methods. Although the studies by Karn et al., (2023) and Bodduluri et al., (2024) use such advanced methods as sentiment analysis and physiological reviews and still face the issue of user satisfaction. Patro et al., (2023) suggested a novel method specifically designed to deal with the part of this issue, data sparsity. This fact clearly demonstrates the demand of the problem space that this thesis aims to fill by creating an accurately tailored hybrid recommender for Olist that represents an improvement of the field by using modern recommendation theories oriented at the maximal user retention rate.

1.2 Purpose Of The Study

The purpose of this study is to implement and evaluate a fully functioning and sophisticated AI-based hybrid recommendation system customized for the Olist e-commerce dataset. The purpose of this system is to combine collaborative filtering, content-based filtering, and established deep learning processes and techniques to improve the quality and appropriateness of product recommendation suggestions.

While prior recommendation strategies generate useful recommendations, they fall flat when applied to the extensive and varied information obtained in most e-commerce settings. Some shortcomings include failure to adequately predict how a new user should be treated or suggest products due to the absence of interaction data. Failure to make reasonable suggestions where minimal user contributions are presented.

The hybrid model is projected to provide not just more accurate and contextually accurate suggestions, but also insights from collected data. This is vital in ensuring that the model-trained patterns remain current amid consumer trends and market trends. Additionally, I want to quantitatively measure the performance of the system against common criteria and real-life models within the Olist platform.

This might include assessing whether the system improves consumer engagement and validation in realistic, simulated, and diverse settings. The study will contribute to a wide range of AI-driven recommendations and application ideas for e-commerce.

1.3 Research Questions

The thesis revolves around the creation of a hybrid recommendation system capable of managing the comprehensive nature of the Olist dataset and eliminating the drawbacks present in traditional solutions. The main research issue to be addressed is the creation of an effective hybrid system that implements collaborative and content-based filtering while utilizing innovative deep learning opportunities to boost the accuracy and personalization of the solution. The main challenge to be addressed is the data sparsity factor coupled with the cold start issue, which severely undermines the effectiveness of traditional solutions. The following research questions were proposed based on the presented challenge:

- What is an effective way to design a hybrid recommendation system that combines collaborative filtering, content-based filtering, and deep learning?
- How is the accuracy and relevance of product recommendations impacted by the hybrid approach when it is applied to the Olist dataset?
- How does the hybrid recommendation system address the challenges of data sparsity and cold starts that are typically associated with prospecting systems like collaborative filtering and content-based recommendations?
- Which strategies of combining different types of recommendation systems result in increased relevance for recommendations depending on the features available in the dataset?

These research questions are explorative of the dimensions of building an effective hybrid recommendation system and are committed to offering a holistic solution to e-commerce platforms that will be developed, leading to better user experiences, and ultimately increasing overall revenue gained from increased purchases. This research is set on inventing substantial strides within the e-commerce sector by aiming to achieve better recommendation accuracy to make users more satisfied and engaged.

1.4 Significance of the study

The contribution of this study was significant in three areas – theoretical advancements, practical implementations and efficient use of available/optimizable data to the fields of e-commerce and artificial intelligence:

- ***Theoretical Contribution:*** the conducted research significantly contributed to the currently existing theoretical framework by explaining the hybrid systems within the scope of e-commerce. By investigating the capabilities of three main systems – collaborative filtering, content-based filtering, and deep learning in a segmented and synthesized way, it added to the academical discourse of possible ways of dealing with the complexity of its interactions and structures to provide the most beneficial ways of optimization. At the same time, it focused on the limitations of current systems and possible solutions for them through hybrid strategies instead of employing methods one after another.

- ***Practical implications:*** From a practical perspective, this study has far-reaching implications for steering the development of recommendation systems across the e-commerce domain. Given it accomplished its aim of showing how a well-designed hybrid system enhances accuracy and relevance in product recommendation, this research availed translatable knowledge for consideration, profitable to adopted continuously to enhance user fulfillment and participation. This is highly impactful on business since implementing such enhancements is determined in boosting conversion rates and loyalty among shoppers to achieve competitive advantages in a crowded online business environment.

- ***Data Utilization:*** This study can open access to the ability to use large datasets, such as the one provided by Olist. As the presented recommendations are based on a wealth of high-quality, multi-dimensional data on user behavior, likes, and dislikes, and interactions, this study exemplifies how data can be used to transform existing data assets into actionable insights. This helps to optimize existing resources while also setting a valuable example to other e-commerce players on how the data their stores gather can be used to create efficient and effective strategic assets. Approach and results of this research can be replicated by other platforms seeking to develop or improve their own recommendation systems based on similar high-dimensional datasets.

1.5 Research Methodology and Tools

This study uses a multi-faceted research method to create and assess the hybrid AI-powered recommendation system, which involves both quantitative and qualitative content. The steps are as follows:

- *Data collection and preprocessing:* the extracted Olist e-commerce data describing orders, products, customers, and reviews will be cleaned, with missing values and duplicates eliminated and inconsistencies corrected. The machine-learning will be augmented with engineered functionalities.
- *Model Development:* Differentiating techniques, including collaborative filtering methods based on users and items, as well as matrix factorization, content-based filtering methods based on cosine similarity as well as deep learning models.
- *Hybrid System Integration:* The ensemble methods such as weighted averaging and stacking will be used to integrate the system. The performance metrics will include RMSE, MAE, and precision-recall.
- *Tools and technologies:* Python, libraries and frameworks such as Pandas, NumPy, Scikit-learn, TensorFlow, PyTorch, and Surprise will be used for data analysis, model development, and metric evaluation with integrated environments such as Google Colab, and high-performance computing resources with GPUs for deep learning model training.

1.6 Limitations

Several limitations of this study may influence its outcomes and the degree to which its findings can be applied to new situations. First, the Olist dataset, although rich and comprehensive, has certain data limitations and constraints that may affect the performance of the recommendation system.

Potential biases and incomplete information could limit the accuracy of the recommendations and make it harder to understand the underlying patterns of user preferences and behaviors. Second, the development and training of deep learning models in a hybrid recommendation framework require significant computational resources. Due to these limitations, the scope of experiments may be limited, and the potential complexity of the recipes may be restricted by the capabilities of the infrastructure.

Generalizability is another apparent limitation of the findings. This study, along with the insights gained, is tailored to a specific dataset, Olist. As a result, it may not be possible to use the results for other e-commerce platforms since they operate with distinct data structures, customer bases, and products. The lack of generalizability might also suggest limited applicability of the hybrid model developed since other sets of data might require different approaches to address unique challenges.

Finally, the evaluation process performed in the study focuses mainly on quantitative metrics, such as accuracy and relevance. Although critical to understanding the performance of recommendations, these quantitative aspects do not capture the qualitative measures, such as user satisfaction and engagement. Hence, the evaluation process needs to be more comprehensive, assembling qualitative feedback from users along with more traditional techniques to synthesize overlap data.

These limitations highlight areas for future research and outline the need to consider the within-chart of the data, computational capabilities, and evaluation as both a capability and constraint in designing advanced recommendation systems.

Chapter 2

Literature Review

Artificial Intelligence has undeniably transformed the way society shops online, especially when it comes to recommendation systems (Ziakis and Vlachopoulou, 2023). In the fast-paced world of online shopping, AI-based recommendations have a crucial part to play in enhancing the customer experience, influencing customer interactions, and most importantly, boosting sales.

AI-based recommendations in e-commerce are made easy by machine learning algorithms that use large sets of data from customers to figure out individual customer behavior, interest, and trending products (Necula and Păvăloaia, 2023). In essence, this entails historical transactions, patterns, demographic information, and other context-related processes to offer a recommendation tailored to the shopper (Cabrera-Sánchez et al., 2020).

This literature review aims to comprehensively investigate the existing body of research in the realm of recommendation systems, with a focus on hybrid AI-based models. For the purpose of this thesis, such review would play a dual role. On the one hand, it would lay out the body of theoretical knowledge that has already been accumulated on the subject of recommendation system technologies, and, particularly, those that apply AI within e-commerce.

Simultaneously, the review would provide an analysis of the results that have already been achieved in the field and where previous research has been successful or lacking. This review is critical as it primarily lays out the background against which the research questions and objectives of this thesis can be formulated, distinguishing the thesis's original contribution to the field of academic knowledge.

The review has been specifically designed to cover relevant segments of recommendation systems that are pertinent to the main objectives and research questions of this thesis. It includes an investigation of hybrid models, which refer to systems that combine several computational techniques to achieve higher prediction accuracy and user satisfaction as a result. In this part, the review also investigates different models that incorporate collaborative filtering, content-based filtering and other techniques and analysis models in an effort to determine the benefits and challenges thematic to such integrations.

Furthermore, the review investigates the rapidly evolving AI techniques that are increasingly being employed in recommendation systems. These included advanced methods such as machine learning and deep learning which are necessary for processing complex user data and generating personalized recommendations. The analysis involves a historical analysis of these technologies before exploring the current state of their function in various applications.

Finally, the artefact of analysis for this study is the e-commerce context to which recommendation systems are applied. This part will include a general application of a particularly focused discussion on Olist and similar large e-commerce platforms in existence today. This outcome part of the review will also cover pandemic results and other recent studies in the area. All of these parts combined will form a body of knowledge that will provide the necessary background for the intended further analysis within this thesis.

2.1 Overview of Recommendation Systems

2.1.1 Recommendation systems Evolution and applications

The advent of the Internet and smart devices continues to manifest an exponential social presence in varied digital arenas, such as web platforms, mobile applications, and social media sites. This growth trend has inherently advanced a widened information-gathering frontier that facilitates the characterization of user behavior and preferences.

Further, the integration of wearable sensors in smart devices has pioneered the information-gathering quest concerning nuanced user-specific information. This not only characterizes exercise trends but also a varied hub of biomedicine information that offers a holistic understanding of users’ health and lifestyle (Zineb et al., 2021). As such, the Internet and smart devices integration continues as an extensive user information hub. However, this surpasses explicitly offered information, such as user preferences and ratings used in traditional recommendation systems. Arguably, this scope extends to implicitly gathered data, such as user click behavior and nuanced visitation patterns that characterize behavioral preference (Feng et al., 2023).

This paradigm change has effectuated an abundance of recent research dedicated to cognitive recommendations. These use sophisticated algorithms to track intricacies in user persona through implicit information (Beheshti et al., 2021). Consequently, these systems enable quick modification and adaptation to incorporate newly established user preference sets in recommendation algorithms.

To maximize the potential of exploiting both explicit and implicit user data to recommend items, it is necessary to pursue various data mining approaches to thoroughly understand user preferences. In this light, it is possible to continuously front-load recommendation insights by analyzing past user-item choices, solicited feedback on given recommendations, and the correlation between users (Chen et al., 2023). Importantly, the work is conducted actively to improve the performance of the recommendation systems, which continuously shifts the line of the possibilities it has (Campbell et al., 2020).

At the same time, the point of complexity is using the data that is analyzed to navigate daily through a vast amount of services' item information to generate accurate and personalized recommendations that entirely match user taste bud and needs systems (Jannach and Abdollahpouri, 2023). This is, in fact, the model of the recommendation system – the filter mechanism.

While the current existing recommendation systems are well-researched and developed models, the research drive remains in the field. This is because the recommendations are entering a stage in which it is possible to do more extensive research. “An excitement era of recommendation technology is closing where research has grown from niche areas of research to sophisticated models and practices” (Javed et al., 2021). Such work will include various data mining approaches and more sophisticated recommendation models.

Moreover, although the current systems understand user taste quite well, it is necessary to build around recommendations a recommendation ecosystem which will use data collected in multiple interconnected fields to generate the most personalized and accurate recommendations.

In other words, while recommendation systems are over 29 years of age as of today, its newfound popularity is largely related to the realm of video content streaming, exemplified by the rapid development of platforms such as Netflix (Ko et al., 2022). In this field, video suggestions for the ideal users portray a distinctive example of an integrated system where vast image content, user activity data, and other information similar to individual preferences allows the creation of such a system (Steck et al., 2021). The practical utilization of such a recommendation system in the film industry has greatly increased consumer satisfaction, altered consumption sources in several countries, obsolesced the very nature of going to the theatre and the established practice of watching TV programs.

Furthermore, whilst the majority of social services generate data across different scopes, when appropriate, social interactions and review-related content contribute to multi-faceted recommendations (Dwivedi-Yu et al., 2022). The reservoir of social data has developed from mere social networking services into an invaluable resource covering many unrelated fields, changing a significant number of industries– including the tourism and commerce sectors; consequently, the field is of interest to the general population, not only academics (Ko et al., 2022). Thus, multiple related services have responded to the burgeoning ubiquity of recommendation systems, generating more tailored practical services. Thereby answering a certain assignment.

The exponential growth in the amount of data spread over the World Wide Web and the rapid development of e-services have inundated users with an exorbitant number of choices, increasingly complicating their decision-making processes (Dholakia et al., 2021). Recommender systems are a novel tool to assist decision-making by enabling users unfamiliar with the domain and a potential wide variety of items to leverage various information sources and predict or anticipate their users' preference for items of potential interest (Jameson et al., 2015). Over the last two decades, academia and business have become increasingly interested in recommender systems, both evident in the field's maturation and many successful businesses' business and information system development dedicated to the application of recommender systems primarily demonstrated in platforms such as Amazon (Smith and Linden, 2017).

To begin with, recommender systems were developed as a way to tackle the information overload that emerged with Web 2.0 in specific fields to challenge e-commerce (Ko et al., 2022). Eventually, recommender systems became a core discipline and an integral part of internet giants such as Amazon.com, YouTube, Netflix, Facebook. A couple of years later in this paper we will explain why. Recommender systems are developed to evaluate an item's potential utility and find relevant and interesting ones to recommend. Apparently, recommender systems transformative user experiences, having items recommended to them afford users enriched experiences and reduce decision making. The transformative experiences have occurred on numerous online platforms such as Netflix, Facebook, YouTube on a daily basis (Beheshti et al., 2020), and improvements in artificial intelligence, data analysis, and modeling of user behavior constantly drive them.

From this point of view, recommendation systems represent a bright technology with vast potential. This technology is a response to the surplus of information that people are exposed to every day. These systems predict and prioritize items useful for different users, providing personalized recommendation rankings associating the appropriate content material with consumers who want to see it (Valentine et al., 2023). Many platforms apply systems of recommendations, active services that assist the client with personalized suggestions of items. "Recommender systems provide personalized service support to users by learning their previous behaviors and predicting their current preferences for particular products" (Zhang et al., 2021). To make recommendations even more useful, a considerable amount of research is provided to tune recommendations well by comparing different filtering models and sophisticated data mining methods (Shen et al., 2020).

2.1.2 Recommendation System Types

Since the creation of the Collaborative Filtering model in the 1990s, recommendation systems have continued to be an active and popular area and a vibrant research topic in academia and industry and has not lost its relevance to this day, as Bourhim et al., (2022) argue. They play a role as complex information filters that propose items on a personal level in highly specific service environments that aggregate data from various data sources and process points.

Thus, the main point of information filtering through recommendation systems is the customization of suggestions for user preferences to suggest items that are in any way applicable or beneficial to a particular user's interests. At the same time, the task of reducing decision overload is solved precisely by using information from implicit and explicit user data and data on the clusters of users with similar characteristics (Tai et al., 2021), which allows for compiling a list of items directly for the habits and characteristics of the user and reducing the burden of choice. The processes of most recommendation models: Collaborative Filtering, Content-Based Filtering, Hybrid Systems were schematically presented in Figure 1.

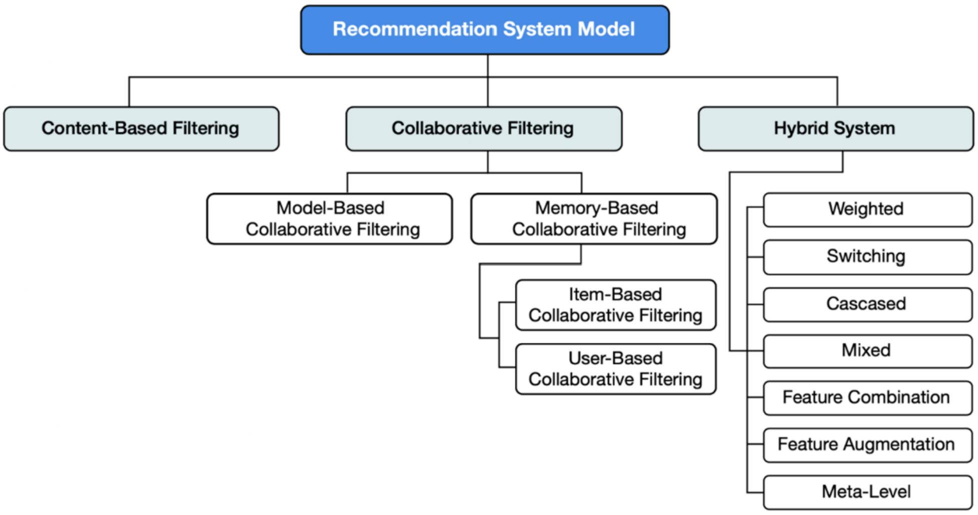


Figure 1. Overview of Recommendation System model

(Ko et al., 2022)

In the diagram designed by Ko et al., (2022) these models are systemically divided into three main types: Content-Based Filtering, Recommender Systems, and Hybrid Systems. Content-Based Filtering is presented if a system suggests items for a user according to the semantic alignment of the item's content and the user's personal preferences. The second type, Recommender Systems, is a subcategory of Collaborative Filtering, and it is divided into two main methods: Model-Based and Memory-Based. Additionally, Collaborative Filtering offers two separate methods: Item-Based and User-Based. Hybrid Systems are described as the combination of approaches helping companies to enhance the accuracy of the recommendation. Hybrid systems can be Weighted, Switching, or Cascaded, Mixed, Feature Combination, Feature Augmentation, or Meta-Level.

Furthermore, Ko et al., (2022) presented a diagram of recommendation models' workflow and the related techniques. Figure 2 shows a detailed workflow of the recommendation models and the related techniques used.

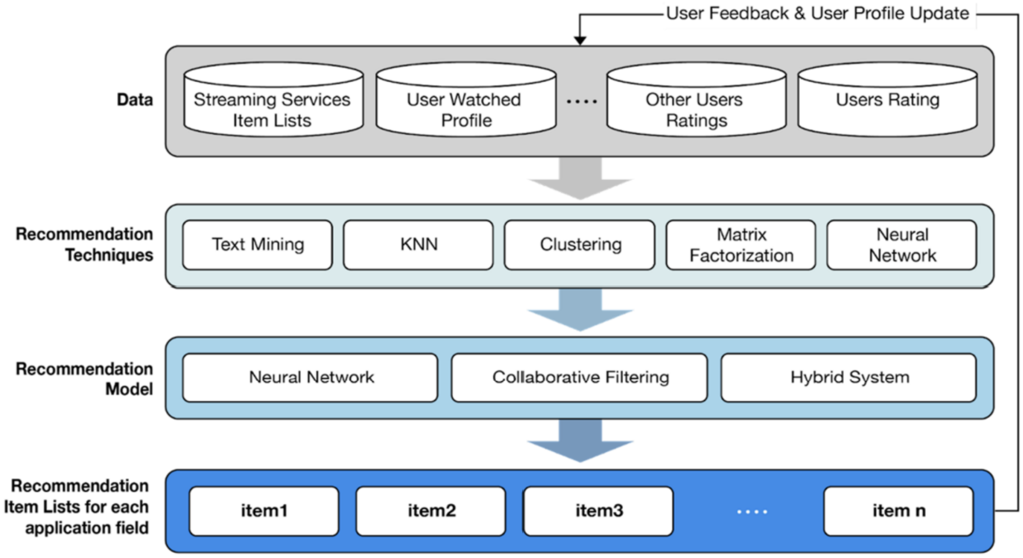


Figure 2. Overall flow of recommendation models and recommendation techniques (Ko et al., 2022)

The workflow starts from multiple data sources, where streaming services often provide lists of items and information of users. Profiles are formed based on users' interactions with items and well with their ratings. Further, profiles are enriched with user feedback. This feedback is especially crucial in keeping user profiles up to date without manual intervention.

The model uses more complex and sophisticated methods to analyze this data. These methods include text mining, K-Nearest Neighbors clustering, matrix factorization, and neural networks among others. All these models are essential for breaking down the data, identifying patterns, and extracting the most important features that can help make accurate predictions about user preference. Next, the knowledge is fed into a few types of recommendation models: neural networks, collaborative filtering models, and hybrid models that include features of several approaches. Multiple models play a key role in translating the knowledge into meaningful recommendations.

As a result, each application field is equipped with a specially designed recommendation list, indicated by ‘item1 to ‘item n’ in the diagram. The outlined lists imply the most meaningful format of the recommendation system’s final product. As stated in the article, the specified items are explicitly defined in terms of specific user preference indicators which have been precisely identified after comprehensive data processing and analysis stages.

Ko et al., (2022) diagram graphically contain the multi-cut layers of the modern recommendation system. Still, it also illustrates the interactive aspect of different analytical bodies with various data sources. This is a significant factor that allows for a full range of user experience customization on the digital streaming platforms. The integration of several data processing layers and recommendation types into one model is a significant source of the thesis’s argument, shedding light on the significant progression level of recommendation systems, which can offer more valid customer interest and loyalty.

2.1.2.1 Collaborative Filtering recommendation System

Collaborative Filtering came to the fore in the 1990s. In the way of many large research frameworks of lenses (Al-Ghamdi et al., 2021; Shen et al., 2020), CF served as a pivot for later research on lenses. The central issue that collaborative filtering solves is to build a user preference base based on user evaluation data to predict items that a particular user is likely to like, which enables the formation of recommendations adapted to a specific user. This model is divided into two main categories: Memory-Based Collaborative Filtering and Model-Based Collaborative Filtering (Behera and Nain, (2022). The Memory-Based principle is divided into User-Based and Item-Based memory patterns settings. The core idea.

One of the key principles of recommendation systems on equitable terms is collaborative filtering. This principle is based on the idea of using user-targeted behavior in sorting transactions (Singh et al., 2020). It focuses primarily on notifications for aggregating and analyzing user interactions and item use preferences. Most crucially constituent methods within CF are the user-based method; this approach forms searches to users of the current who are similar in their interactions with items. A matrix is formulated, the rows of which are users, and the columns represent the preference of users for items by knowing these preferences.

In the same vein, in the item-based approach, the system looks at the patterns of relationships between items. The system creates a matrix that represents how much users generally like certain pairs of items, based on aggregate interactions (Ajaegbu, 2021). When a user selects one item, the system recommends s other items that are similar to the selected one according to the generated matrix. Both user-based and item-based techniques are based on the principle that users who have liked similar items in the past will continue to like similar items in the future (Thakkar et al., 2019).

Moreover, the User-Based Collaborative Filtering works by lining up the similarity of users based on the evaluation data concerning items and later creating a list of top N items that is personalized based on one's preference (Chen et al., 2021). This works by matching up the ratings offered by consumers from a certain neighborhood and later seeking the preferences of a specific consumer from the neighborhood (Singh et al., 2020; Nilashi et al., 2018).

In contrast, the Item-Based Collaborative Filtering works by offering recommendations based on the likeness of the selected item to another, and finally setting up a user-item rating matrix. In brief, the Memory-Based Collaborative Filtering mostly involves making clusters, neighborhood groups with techniques like Pearson Correlation, Vector Cosine Correlation, and KNN, which offer recommendations to items that fall under the neighborhood (Al-Ghamdi et al, 2021). This involves a dynamic framework that follows customer preference by matching the associations between consumers and items.

In E-Commerce Services such as Amazon, the utilization of Memory-Based Collaborative Filtering has significantly reduced customer churn and generated more sales under the Collaborative Filtering recommendation model (Chen et al., 2021). Nevertheless, when this model lacks enough data, it experiences three specific issues due to sparsity, cold start, and gray sheep. Wang et al. indicated that sparsity is the issue of inadequate data for recommendations (Wang et al., 2021). Similarly, Wei et al. (2017) mentioned that the cold start emerges when there is no evaluation data due to the existence of so many new users entering the service. Srivastava et al. also mentioned that the gray sheep is a recommendation problem caused by recommendation systems’ complexity due to limited groups of users sharing evaluation data like a specific user (Srivastava et al., 2020).

According to Yu et al., (2022) research has, therefore, studied resolutions to be used on Model-Based Collaborative Filtering, estimating or learning a predictive model through user-evaluated data. The methodologies for Model-Based Collaborative Filtering have been primarily anchored on Clustering, SVD (Singular Value Decomposition), and PCA (Principal Component Analysis) techniques.

However, it is only capable of giving the following some numbers: how many people who entered are not immediately interested in buying a house (Fayyaz et al. 2020). Or might the 'cold start problem' haunt such systems as user input grows to large volumes for new people (Wei et al., 2017; Natarajan et al., 2020)? And the system will run into difficulties if there is too little information about what users to interact with, because without data from many actual users it cannot make accurate predictions. (Natarajan et al., 2020).

In order to improve the accuracy and efficiency of collaborative recommendation systems, current studies are investigating several different strategies. For example, hybrid is a model composed of collaborative filtering with other recommendation methods such as content-based filtering, which has received some attention (Parthasarathy and Sathiya, 2023; Vuong Nguyen et al., 2023). Such efforts aim to add more accurate relevant information sources and analyses than CF systems ever could have generated themselves.

Since 2010, enhancements to Collaborative Filtering have been focused on improving its efficiency. This includes refining methods for calculating similarities (Alhijawi et al., 2021), user feedback integration to model a better feedback data through tagging and increasing the collection of user preference data (Vuong Nguyen et al., 2023) more data and new clustering techniques that have been explored (Iftikhar et al., 2021).

2.1.2.2 Content Based recommendation System

The article of Loeb et al., published in 1992, marked the beginning of research of information filtering models. CBF, a model that recommends items similar to those the user has shown preference for, recommends items based on their attributes (Javed et al., 2021). In other words, based on the attributes; it recommends items similar to the likes of the user. It was the earliest technique used to develop a recommender system, but CBF has its weaknesses. CBF systems recommend items by comparing item attributes or feature vectors to prioritize items that the user might like based on previous choices. The primary weakness of this model is the lack of experience: these systems are not yet aware of how the user interacts with the product. Therefore, when using CBF models:

- ***Item Profiling:*** The system begins by creating a profile or representation for each item in the dataset. The profile of an item should contain various features or attributes that describe the item. Given the example of the collaborative filtering-based movie recommendation system, the item profile consists of the features that define the content of the movie. Such features include genre, director, actors, plot keywords, and others.
- ***User Profiling:*** After a user interacts with items by, for example, viewing or rating, the system records all interactions in the training dataset. The system may then use the information to build the profile of each user based on the items they interacted with. This profile captures all the features of the item that a user has interacted with and thus forms a user profile.
- ***Feature Extraction:*** The content-based systems use various techniques to extract features and quantify items. In the case of text-based recommendations, a technique such as term frequency-inverse document frequency or word embeddings can be used to represent the content.
- ***Similarity Calculation:*** Based on the extracted features, the system measures the similarity of items. In other words, similarity calculation is a mathematical measure that assesses how similar two vectors are to each other.
- ***Recommendation Generation:*** Then, when a user interacts with the system to obtain recommendations, the user’s profile is compared to item profiles. Items similar to the user’s profile, calculated and obtained through similarity scores, are thus suitable items to recommend to the user.
- ***Refinement and Feedback:*** The content-based systems can be refined based on user feedback. This implies that if a user has had interaction and rated recommendations, then the system learns new preferences and provides better recommendations in the future.

Another significant limitation identified by Salter et al., (2006) is that Content-Based Filtering recommendations based on prior rates by the consumer and, thus, does not add several new items. This implies that the consumers had less access to a vast variety of materials. Hence, such a model was beneficial only in places where they could provide consumers with easy recommendations or texts of information facilities. The model utilizes the characteristics of each item and the profiles of the customers. This model was relevant in many spheres such as music feature-based recommendations (Reddy et al., 2023), film sign-oriented (Reddy et al., 2019), e-commerce merchandise feature-based (Dragan and Wróblewska, 2020), and learning-based recommendations (Shu et al., 2018).

The Content-Based Filtering Model is based on text mining technologies such as Semantic Analysis, TF-IDF, Neural Networks, Naive Bayes, SVM, etc. and analyzes user preferences (Javed et al., 2021). However, in 2012, the frequency of use of Content-Based Filtering has been reduced since the number of studies on Hybrid Recommendation Models significantly increased. Therefore, the range of applications has become more limited.

Overall, content-based recommendations leverage item metadata to recommend items that are identical or comparable to those the user has previously interacted with to fill in the gaps between various users and items. Because if there is abundant information concerning items, this type of recommendation is perfectly suited for a domain with sparse user-item interactions because such systems perform based on the merits and demerits of the item as opposed to users. They are relevant to markets with a low user and item spread because they do not rely on the user’s response. Therefore, some information about comparable items can be utilized to give the user a personalized recommendation. This criterion is appropriate because the niche firm is characterized by low user and item interaction. In this manner, by giving the user of this engine some form of personalized touch. Such an approach will undoubtedly increase the user’s overall level of pleasure.

2.3 Deep Dive into Hybrid Recommendation Systems

Hybrid recommendation systems are sophisticated frameworks that integrate multiple recommendation approaches while incorporating a blend of the content-based filtering and collaborative filtering and other such as deep learning and knowledge-based system recommender system approaches. They aim to synergize the strengths of the different methods to compensate for the weaknesses of individual methods in an integrated environment that ultimately provides more accurate recommendations based on personal preferences.

Wang et al., (2018) built a hybrid recommender system for computer science publications, a complex recommender system that incorporates multiple models, which by using the hybrid recommendation approach boosts recommendation level of accuracy and diversity. In a survey reviewing deep learning applications in recommender systems, Batmaz et al., (2019) described the strength of hybrid models in the fact that they can combine otherwise limited models.

Furthermore, Nilashi et al., (2018) demonstrates a hybrid recommendation system combining collaborative filtering with ontology and dimensionality reduction approaches to solve recommendation system-based limitations such as sparsity. A course hybrid recommender system for scenarios with small data was developed by Perez et al., (2022).

Thus, the vast majority of these and other modern studies confirm that hybrid recommendation systems can cope with a more diverse set of data and more complex user preferences, resulting in larger and more detailed recommendations. Overall, the research provides evidence on how increasingly complex algorithms are integrated to develop more complex, powerful, and adaptive recommendation systems.

2.3.1 Definition of Hybrid recommendation system

Hybrid recommendation systems are those that combine several recommendation techniques in one system. Unlike systems using only one method, which cannot provide recommendations due to data sparsity, cold start, low coverage of user preferences, and other problems, hybrid systems can be considered more robust and optimal. The combination of two or more methods in one system allows the presentation of more relevant and accurate recommendations, which increases user satisfaction with the system.

The study by Danilova and Ponomarev (2017) notes that hybrid recommendation systems are systems that offer recommendations but avoid all the limitations of a single method by uniting several recommendation techniques: “In contrast to single-method collaborative or content-based recommendations, hybrid ones realize a more general concept of blending separate and, in some sense, socially oriented and unsocially oriented recommendation methods”. This combination allows avoiding the limitations of a single mechanism and providing more useful recommendations based on user behavior.

As Parthasarathy and Sathiya (2023) state simple hybrid systems can diminish sparsity deterrence by joining collaborative filtering to content-based filtering, expanding the system’s performance among cold start situations. In addition, hybrid systems may perform well, as Shah and Sahu (2015) report based on alternative sources and techniques for all systems in comparison with a single information source.

2.3.2 Techniques and Models

Hybrid recommendation systems adopt a wide range of techniques and models that have their strengths and special features, which combined enhance the effectiveness of the recommendation. Recommendation during the usage of several methods improves its accuracy, relevance of results, and user satisfaction. Table 1 presents the obtained key techniques of hybrid recommendation systems.

Table 1.

Techniques and Models of Hybrid recommendation systems

Category	Technique	Description	Reference
Machine Learning Algorithms	Matrix Factorization	Decomposes the user-item interaction matrix into latent factors, enhancing collaborative filtering by identifying underlying patterns in the data.	Alhijawi et al., 2021
Deep Learning Approaches	Decision Trees	Generates recommendations based on decision rules derived from user data.	

Table 1. (cont.d)

	Neural Networks	Captures complex patterns and dependencies in user data using deep learning models like CNNs and RNNs, leading to more accurate recommendations.	Vuong Nguyen et al., 2023
	Autoencoders	Used for dimensionality reduction and feature extraction, improving the system’s ability to handle high-dimensional data.	
Synergistic Models	Content-Based and Collaborative Filtering	Combines content-based filtering’s reliance on item metadata with collaborative filtering’s user behavior analysis to balance their respective limitations.	Çano & Morisio, 2017
	Ensemble Methods	Techniques such as bagging, boosting, and stacking integrate multiple models to enhance predictive performance.	
	Context-Aware Recommender Systems (CARS)	Incorporates contextual information (e.g., time, location) into the recommendation process to provide more relevant suggestions.	Li et al., (2018)

Table 1 provides a clear and structured overview of the different techniques used in hybrid recommendation systems, illustrating how each method contributes to the system's overall effectiveness.

In conclusion, hybrid recommendation systems constitute a vast improvement over single-method methods as they present a more comprehensive and dynamic framework for creating recommendations. Additionally, the combination of numerous strategies improves the accuracy and quality of the recommendations while also allowing the system to overcome frequent hurdles like data sparsity and the cold start problem. This multi-source framework contributes to the user’s overall enjoyment through a more well-rounded experience that promotes robust engagement and generates customer loyalty. Following this analysis of hybrid recommendation systems, the study will delve into the individual methods and models that have been employed in these systems.

This includes an examination of machine learning algorithms and the deep learning techniques used in them, as well as an exploration of how these approaches work together. The present paper will also consider which problems the new systems address, such as data sparsity and cold start issues, and how they compare to old method of recommendation. Finally, best practices on how to integrate these methods to fully utilize each of their capabilities to make the most effective recommendation will be discussed.

2.4 Challenges in Recommendation systems

A number of critical challenges are associated with recommendation systems and their functionality. Such challenges include data sparsity, cold start, scalability and performance, and bias and fairness. Such challenges need to be addressed using specific strategies so that the recommendation system can make quality recommendations to users.

2.4.1 Data Sparsity and Cold Start

When user-item interaction history is limited, the collaborative filtering system suffers from data sparsity. As a result, high-quality recommendations cannot be made because there is insufficient information the model can use to form good recommendations. Another common problem is the cold start, which refers to a situation when there is either little to no data on either new users or new items. For the system to generate valid predictions, a sufficient quantity of on new user arrived or on this item has to be collected. Hybrid systems are designed to combat these issues by combining several sources and types of data and various recommendation techniques. Hybrid systems often use content-based recommendations to cover for first interactions and sparsity (Danilova & Ponomarev, 2017). That is, the content-based recommendation can form reasoning-based initial recommendations for new users by predicting his or her preferences based on the item metadata. In addition, clustering and matrix factorization methods help to handle sparsity by making the system more robust to noisy data (Alhijawi et al., 2021).

2.4.2 Scalability and Performance

Monitoring performance and scalability of the recommendation systems becomes more challenging with the increasing amount of data and users. The systems are expected to process a large amount of data very fast and accurate in order to actively generate recommendations, which are essential for user streaming. The scaling concern can be addressed by using distributed computing frameworks and parallel processing that enhance the processing of lots of data by incorporating massive data amounts and complex computational processes. For instance, the MapReduce paradigm and the use of Apache Spark have been flexible tendencies in big data handling. Deep learning, including neural networks and autoencoders, have recently been used to address such concerns due to their ability to effectively process high-dimensional data and translate robust feature extraction (Vuong Nguyen et al., 2023). Moreover, cloud computing can be used to improve the scalability and efficiency of the recommendation systems.

2.4.3 Bias and Fairness

When the recommendation system has bias, the recommendation given to the users may not be fair or presented to all not on a balanced scale, hence directly affects the customer’s satisfaction and trust. Bias can be introduced to the information of data, algorithm, and even criteria. Additionally, some data presents popularity bias, which implies that the popular items are more frequently recommended than the unpopular ones. There is demographic bias which some group of people or items are poorly represented than others. Some algorithms also cause the bias where users' contents of some type being favored than the others. Recommendation for fairness-aware also incorporates fairness constraints and fairness-aware metrics for training and recommendations. For instance, trying some form of fairness constraint in model training such as fairness-aware matrix factorization; adversarial training, and meta-learning-based methods have been proposed to enhance the fairness of recommendation to ensure equitable recommendations (Jin et al., 2023; Oh & Kim, 2024). For fairness-aware constraint, they are enforced during training and testing to penalize hypothetical re-computation if extreme bias occurs, and the judges also ensure unbiased recommendations for all items and users.

2.4.4 Integrating Feedback Mechanisms

In addition, enhancing the quality of recommendations by integrating user feedback continuously is another issue related to recommendation systems. While explicit feedback, including prior ratings or reviews, and implicit feedback, such as clicks or browsing, are critical to understanding what users like, collecting and incorporating this feedback in real-time can be challenging, and optimizing the recommendation model (Sun et al., 2019). Adaptive learning algorithms and reinforcement learning can help to resolve this issue by adjusting the recommendation model continually based on incoming user feedback. This helps to make the system easier and more relevant to use.

2.4.5 Privacy and Security

Due to the trend of recommendation systems relying on user data to produce tailored suggestions, there has been a growing need for measures to enhance user privacy and data security. Most users worry about how their data is retrieved, maintained, and applied. Techniques for preserving privacy have been developed to alleviate these concerns by incorporating differential privacy and federated learning. The addition of noise to the data allows it to be safeguarded against information about individual users under differential privacy while still enabling precise uniform measurements (Himeur et al., 2022). Federated learning aids in training recommendation models on various devices or servers without providing unique raw data to the central servers, resulting in both fully guaranteed privacy preservation and decentralized data supply.

2.4.6 Multi-Objective Optimization

Recommendation systems also have multiple goals, which include relevance, diversity, novelty, and serendipity among others. Emphasizing one objective can be detrimental to another. For example, focusing solely on item relevance diminishes diversity, yielding more related results. Multi-objective optimization combines these objectives by considering tradeoffs between them and determining solutions that maximize user satisfaction through including items that correspond to the user’s previous choices (Zaizi et al., 2023). They include Pareto optimization and Multi-armed bandits enforcement learning methods among others.

To surmount these problems, a multilateral approach is needed to address them. This includes utilizing creative recommendation algorithms and techniques, as well as fairness and impartiality. Combining different data sources and hybrid models used to fight data sparsity and the cold start issue. Distributed computing and deep learning were used to increase scalability and performance. Bias and fairness also involve using fairness-aware algorithms and ongoing monitoring. For relevancy, they use real-time user feedback and adaptive learning. Privacy-preserving techniques protect user to secure user data. The outcomes of each of these difficulties would enable recommenders to generate more precise, appropriate, and tailored suggestions, leading to improved user satisfaction. The recommendation not only benefits from this procedure, but it also creates a more inclusive environment where they may use it in a user-centric manner.

2.5 Application of AI in Recommendation Systems

Artificial Intelligence has drastically changed modern recommendation systems through more advanced and personalized techniques that increase the overall quality and accuracy of recommendation. This change has improved the way recommendations are generated as they are now focused on offering the most relevant suggestions based on individual users' tastes and interests. Moreover, AI plays an essential role in modern recommendation systems since it enables the processing of vast amounts of data to identify patterns and trends. Zhang et al., (2021) state that AI-powered algorithms have allowed numerous services to find complex patterns of user behavior and preference, thus making recommendations even more precise and relevant in a given context.

Therefore, the use of AI enables recommendation systems based on algorithms that continue to learn, which can improve the overall performance over time. For example, neural networks have enabled the recommendation to learn intricate patterns in user and interaction data which the traditional models may not have captured, sending more intricate data out to lead to a more refined and advanced model (Vuong Nguyen et al., 2023). Moreover, AI has also made collaboration filtering, which has demonstrated a range of limitations such as the cold start problem and sparsity of data more practical through hybrid models that focus on content-based filtering among other areas (Danilova & Ponomarev, 2017).

2.5.1 Deep neural networks in recommender systems

Within the field of recommender systems, one of the reasons neural networks are used sparingly is that the recommendation task itself is more complex. The recommendation formula requires a user to order or rank alternatives explicitly (Wu et al., 2022). As a result, existing neural network frameworks are not well suited for addressing this. Salakhutdinov et al., (2007) work with a two-layer restricted Boltzmann machine was motivated by the want to grasp order data and gathered consideration in the 2009 Netflix Prize tournament. Nevertheless, the subsequent progress was scant: to the finest of our knowledge, only Truyen et al., (2012) experimented with the recommendation oriented RBM parameterization.

Despite promising experimental results with deep learning for various tasks such as natural language processing, speech recognition, and computer vision (Mu, 2018), this has recently triggered researchers to incorporate them into recommender systems. Given the explosion of user-generated data, including comments, images, and videos, the amalgamation of these types of user behaviors is essential to achieve effective multimedia recommendations (Pouyanfar et al., 2018). Deep learning-based recommender systems utilize various architectures, including convolutional neural networks and recurrent neural networks, to handle diverse data sources (Zhang et al., 2020). RNNs are used to manage recurrent data such as user behavior sequences due to their ability to learn from the data sequence, which helps build context-aware models (Kulkarni and Rodd, 2020).

Developing recommender systems based on deep learning is not just an adaption of traditional methods but marks a significant paradigm shift towards neural network architectures to capture sophisticated patterns within a wide range of data (Ouhbi et al., 2018). This transition offers a more sophisticated, personalized approach to intricate and accurate recommender systems across the fields of multimedia catering to complex and heterogeneous patterns of modern users (Zhou et al., 2023).

2.5.2 Autoencoder-based recommender systems

AutoRec offers an innovative solution due to its novel approach that combines an autoencoder mechanism with matrix factorization to capture highly intricate, non-linear representations of users or items that can be identified by the recommendation system (Wu et al., 2023).

This innovation is imperative because traditional recommendation approaches fail to maintain the high qualities of users or items, especially in complex and non-linear relationships. In the same vein, AutoSVD++ offers innovation in terms of integrating a contractive autoencoder with matrix factorization to get item features that come straight from the item content (Azri et al., 2022).

This solution enhances the quality of recommendation systems by enriching the quality of item representation to include item content features. In this way, the system can enhance personalized recommendations more accurately and deeply than before. The innovation introduced by Strub et al., (2016) in AutoRec to enhance it indicates its adaptability and creativity. By making it more secure via denoising and integrating more data like user tags, the system facilitates uncovering other user-item interactions. This means that the system goes through multiple data levels to enhance the recommendation process, which means more personalized suggestions for the user.

Autoencoder as an original approach integrated in formalizing user representation and item representation in a recommendation system (Guo et al., 2023).

It is an innovative approach because it establishes the fundamental new principle for generating recommendations in a system (Guo et al., 2023). An autoencoder has the potential to reveal latent relationships and relationships between various entities from which recommendations are generated.

2.5.3 Reinforcement learning in recommender systems

In this context, recommender systems and the user function as a novel RL-inspired dynamic interaction of the reinforcement learning framework. While conventional models concentrate on forecasting immediate user interests, RL-based systems are designed to maximize long-term user engagement and contentment (Afsar et al., 2022). Therefore, in the RL setting, user activities stand for states, system recommendations represent actions, and user input data as feedback is expressed as a reward. The overall objective is to build a policy that will optimize long-term satisfaction. RL, which is the core model of reinforcement learning, is made more complex by the wide range of available items, which results in an expanded action space and a more complicated system (Chen et al., 2023).

The reason for this is that the first works positioned the recommendations as a game of balance between research and development. They raised an adequate choice of models, formalized as bandit problems (Lu et al., 2016). Already the earliest implementations of such recommendations were based on Markov Decision Processes. The recommendations formulated in this way were degenerated: the system recommended what the user had already read or viewed. Subsequent works were already based on linear algorithmic RL methodologies, which allowed formulating the problem with testable theoretical conditions of this balance. At the same time, on the formal side, little has changed: the user and the system are graphically (physically) presented as a multi-armed bandit (Iftikhar et al., 2024). Several other works included the expansion of contextual information in the form of a medium-term forecast. Even these models were focused on instant choice.

Recent trends have taken a step toward deep reinforcement learning due to the use of deep Q-networks and deep deterministic policy gradients for immediate and long-term rewards (Gao et al., 2023). Moreover, actor-critical framework architectures are used to deal with the computational burden of a large and dynamic action space (Xin et al., 2022). In addition, negative feedback is considered in deep RL-based recommendations, achieved using pair-wise regularization. Present courses direct attention to integrating sophisticated user behaviors, such as knowledge graphs, to handle large datasets and a variety of item landscapes (Lin et al., 2023).

Meanwhile, the momentum for the application of RL in industrial recommender systems is also growing, including YouTube and Alibaba. Later developments of deep RL-based recommender systems will remain promising trends due to the tremendous real-world impact and utility they offer, which will lead to further theoretical and practical insights on the phenomenon of user preference (Chai et al., 2022).

2.5.4 Natural language processing in recommender systems

The convergence of natural language processing and computer vision within recommender systems underscores the growing relationship between NLP and CV and the potential they can have on recommendation technology (Yuan et al., 2023). Although significant progress has been made in the domains of movies and ratings, most auditory data, such as items descriptions, user tags, and reviews, remains under-utilized. NLP can aid in the processing of such textual patterns, integrating textual facts into recommenders using available NLP techniques such as sentiment transfer and theme transfer could aid in deciphering textual information (Khurana et al., 2023). Consumers are measured by NLP-processed reviews to mitigate data scarcity. When no individual valuations are available, this approach generates digital rankings from sentiment reviews. Furthermore, a matrix factorization model is created using novel topic modeling to solve cold-start and warm-start issues (Islek et al., 2022). Techniques for creating cold-start and warm-start resolutions include the employment of a matrix factorization model with new-fashioned subject simulation (Sinha and Sharma, 2023). Finally, Da’u et al., (2020) use feature-based product info from the evaluations as a pivot to adjust the recommendations' relevance to the user’s query.

The user expertise from reviews offers other insights as well. With similar experiences, the suggestion may be more personalized (Chinchanachokchai et al., 2021). Additionally, textual data also does some other stuff outside of text fields, it helps improve the accuracy of recommendations and makes the process fully transparent; thanks to text, the recess can “see” the main attributes of a user that are otherwise unobservable (Wu et al., 2022). Methods that bridge the textual universe and latent topics are able to unlock recommendations for new, “cold” items, which promote innovations (Palomares et al., 2021).

In cross-domain recommender systems, the integration of review texts via nonlinear functional mapping leads to the enhanced skill of user vectoring and general approaches (Zhu et al., 2022). Furthermore, the embedding and concentration neural networks leveraging collaborative filtering identify more complicated correlations of item similarity that incorporate the deepest item-dependent user preferences (Huang et al., 2020). Finally, the era of voice-activated systems and Siri and Google Home interactive recommender systems will also benefit NLP technologies by ensuring more intuitive and friendly interaction areas, as mentioned by Jannach et al., (2021).

2.6 Application of AI-based recommendation systems in e-commerce

E-commerce sector relies on a particular tool known as the recommendation system which adopts a user’s purchase history to predict and recommend other products to the customer. This system is invaluable in elevating user experience while boosting e-commerce sales since such information helps to make personalized recommendations of products a user might like based on purchase behavior and browsing history. Systems leverage such data sets as Olist to tailor recommendations based on individual preferences of given users. According to research studies, the implementation of the use of recommendation systems in e-commerce significantly enhances user satisfaction and habits.

For example, one such study conducted by Cabrera-Sánchez et al. (2020) researched the effect of the recommendation system usage influencing the purchase in ecommerce, and one of the insights shows their positive contribution towards user satisfaction and their chances of buying. Systems manage the large number of products efficiently to allow customers to find relevant products with ease, which in turn improves the efficiency of the e-commerce market.

Another prevalent issue related to E-commerce that is being solved by recommendation systems is data sparsity and the cold start problem. In this case, the best possible way to address these objectives is through combining collaborative and content-based filtering. As Ko et al., (2020) state, hybrid systems allow the model to make accurate predictions with less user-item interaction. The reason is that hybrid systems provide additional information plus user-item interaction.

Moreover, e-commerce recommendation systems are based on the implementation of sophisticated machine learning algorithms and AI techniques. For example, e-commerce uses neural networks and deep learning models to scale complex user preferences and interactions for better- personalized recommendations. For example, Rahma and Hussien (2021) give a review of various AI-driven methods that are used to develop e-commerce recommendation systems. The authors claim that, generally, all those methods significantly improve UX and sales rates. To summarize, recommendation systems in e-commerce improve not only UX by suggesting personalized recommendations but also enhance sales levels and operations efficiency. Furthermore, these RDs are constantly learning from customers' preferences and interaction, which means that recommendations are always contemporary.

Chapter 3

Methodology

This chapter presents the methodology used to create and test a hybrid AI-based recommendation system with the E-Commerce Company by Olist dataset on Kaggle. It describes the following sections: data collection and preprocessing, model development, hybrid system integration, model evaluation, and the applied tool and technologies.

The data collection and preprocessing section encompasses a description of the activities on how the dataset was cleaned, integrated, and otherwise prepared for the analytical process. The model development section includes analyses of the hypothetical programs, such as collaborative filtering utilizing the implicit library, content-based filtering with TF-IDF vectorization, as well as rating prediction with a deep neural network.

The remaining part of the chapter contains the following subsections: hybrid system integration describes how the outputs of those earlier models are combined to produce full system recommendations; model evaluation examines the metrics and techniques implemented to measure a hybrid recommendation system's performance; and the tools and technologies subsection lists the programming languages, libraries, development environment, and hardware utilized in the research. This methodology guarantees that the hybrid AI-based recommendation system is well-developed and well-evaluated, and this approach is fully realized

3.1 OLIST Description

Olist is an e-commerce platform based in Brazil, which serves as an intermediary between small and medium-sized companies and various online marketplaces, including Mercado Libre and Amazon. This arrangement enables online retailers to expand their customers' reach and drive sales. The company was established in 2015, and since then has shown significant growth, including the value of $1.5 billion after a $186 million Series E round in 2021.

Olist provides all-round solutions ranging from inventory management to order fulfillment and customer services. Offering its services to sellers helps them remain anchored to their primary activities while beneficiating from the technology availed by the platform. The platform serves over 45,000 shopkeepers and retailers with tools to manage their e-commerce effectively.

3.2 Data Description

This data set has generously been made available by Olist, the largest department store from the marketplace's operation in Brazil. Olist is a fast-growing business that effectively allows small businesses across Brazil to access sales channels with one single agreement Follow the Olist Store, merchants can list down their products, all orders they receive can be sent directly to the customers through Olist partners in logistics. Figure 3 presents the schema of the Olist database.

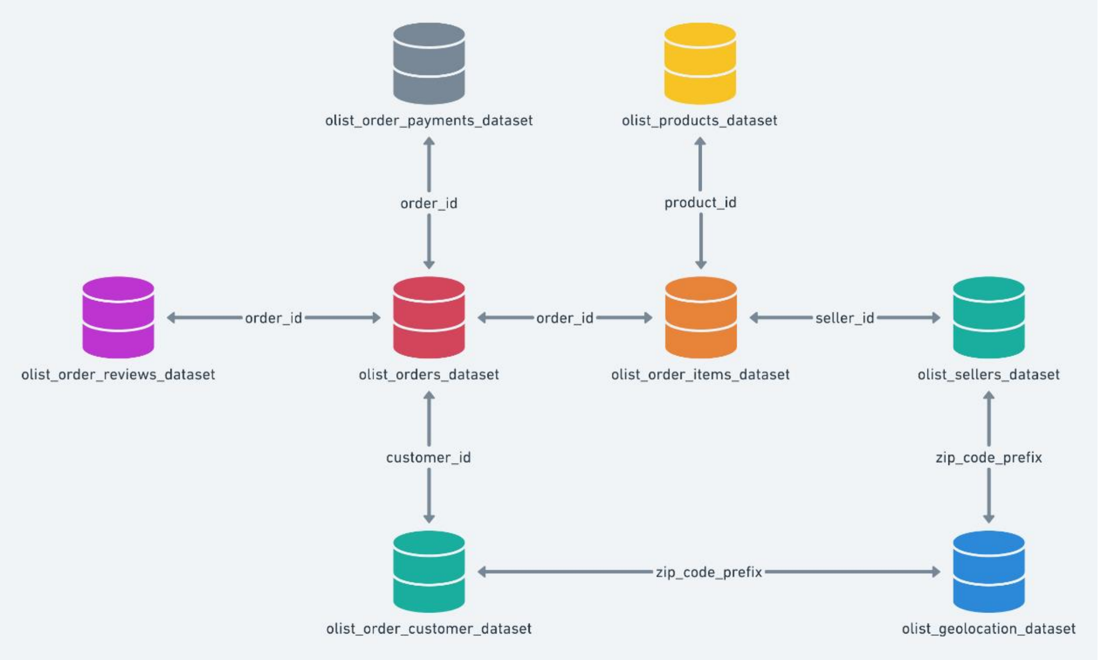


Figure 3. Olist database schema

The provided database schema illustrates the structure of the Olist e-commerce dataset, detailing how various tables are interconnected. Here's a brief description of each table:

- *Customers Data:* This dataset has information about the customer and its location. Each order is assigned to a unique customerId. This means that the same customer will get different ids for different orders. The purpose of having a customerunique_id on the dataset is to allow you to identify customers that made repurchases at the store.
- *Geolocation Data:* This dataset has information Brazilian zip codes and its lat/lng coordinates. Use it to plot maps and find distances between sellers and customers.
- *Order Items Dataset:* This dataset includes data about the items purchased within each order
- *Order Payments Dataset:* This dataset includes data about the orders payment options.
- *Order Reviews Dataset:* This dataset includes data about the reviews made by the customers.
- *Order Dataset:* This is the core dataset. From each order you will find all other information.
- *Product Dataset:* This dataset includes data about the products sold by Olist.
- *Sellers Dataset:* This dataset includes data about the sellers that fulfilled orders made at Olist. Use it to find the seller location and to identify which seller fulfilled each product.
- *Product Category Name translation:* Translates the product category name to English.

3.3 Research Design

3.3.1 Data Collection

The dataset utilized in this study is the "Brazilian E-Commerce Public Dataset by Olist," which can be accessed on the Kaggle platform. This comprehensive dataset encompasses various aspects of e-commerce activities, offering detailed information on orders, products, customers, reviews, and payments. Specifically, it includes: olist_orders_dataset.csv, olist_order_items_dataset.csv, olist_customers_dataset.csv, olist_products_dataset.csv, olist_order_reviews_dataset.csv, olist_sellers_dataset.csv, olist_order_payments_dataset.csv, and olist_geolocation_dataset.csv.

3.3.2 Data Preprocessing

3.3.2.1 Data Loading and Merging

Before any actual analysis, the dataset must be loaded into memory and combined, bringing together the different sources into a seamless structure. This began by loading several datasets read from CSVs representing the different CSV files about customers, orders, products, among other essential information. Subsequent to the loading process, the various Datasets were merged through the pandas's merge functionalities to construct a single DataFrame, which aligned the various rows according to a common shared column, which were mainly "order_id" and "product_id".

The overall aim of this process was to bring together different sources of data and combine them, uniting data across various rows. Ultimately, the method allowed the subsequent connecting and unifying of seemingly separate units. Ultimately, information about individual customers from one Dataset was matched to the order details in another by common "customer_id" column. Similarly, the product detail was connected to the "order_item" detail through their common "product_id" column. The links between the datasets are also shown in figure 3 of the data schema.

3.3.2.2 Handling missing values

The first step following data loading and merging involved addressing the missing values in the merged dataset. For the numerical columns, the missing values were imputed using the mean of the respective column to ensure the imputation does not bias the columns' values toward the expands and skew the distribution.

Categorical columns, however, were inputted with the mode of the column variable, ensuring the missing values were replaced with the mode, which happened to be the frequent observation in the column. Timestamp imputation was used for the date columns, where missing values were imputed based on the other timestamps to ensure the imputation followed the chronological sequence of the occurrence throughout the years.

3.3.2.3 Data type conversion

Data type conversion is vital since certain types of data require business calculations. Furthermore, you may require transforming the current format of the columns so that they are efficiently used. Initially, date columns are converted into datetime so that date-based business calculations are possible and much easier to perform. It allows for trend analysis, time series forecasting, and date-based filtering for a given period. Moreover, the type further simplifies the consistent column usage format. Transforming categorical columns into category datatypes is mainly done to reduce the memory usage while improving the speed of certain calculations, especially for those that have relatively few unique values.

3.3.2.4 Variable Dropping

Finally, it was necessary to drop variables with a high number of missing values or containing redundant information. It is essential for avoiding bias and ensuring data integrity since imputing a large number of missing values may distort the data’s distribution from which the values were deleted. Moreover, removing redundant or low-information features simplifies and paces up model creation; facilitates the verification of variables’ importance and impact; reduces the risk of incurring in a spurious statistically significant finding.

3.3.2.5 Handling Outliers

Understanding which outliers exist and deciding how to deal with them is one of the essential steps in which our data’s integrity can be preserved or corrupted. Our first step is to methodically find our outliers in numerical columns. We used the Interquartile Range method to calculate the quartiles of our data and then determine the reasonable bounds in which our data “should” be.

After we have identified our outliers, we now decide our actions for them. We have decided to cull outliers in two directions, as is dictated by the type of the data and the damage outliers have on our analysis. Our primary type of handling outliers is capping for cases in which extreme values may still hold information, outlier capping is relevant. For attributes such as “price”, “freight value”, and “product dimensions”, we have opted for capping outliers. By changing the outliers to their closest to the IQR value, we are keeping extreme values around a range, rather than letting them affect our data too heavily. Capping ensures that extrema do not make our data results invalid, while at the same time preserving the ability to analyze the value of such extreme values.

Conversely, for columns in which we are confident outliers are likely to be erroneous or anomalous, i.e., “product dimensions” that are unrealistically large or small, entirely removing the outliers is best. This way, our dataset can remain truly representative of real-world phenomena and avoid being distorted by data anomalies. These outlier removal strategies are implemented bore the “cap_outliers” and “remove_outliers” functions, which cap or remove outliers on identified true numerical columns using the IQR method.

Systematically capping or removing them allows us to maintain a delicate balance between preserving their insights and compromising the integrity of the dataset. Finally, we check these modifications to see how and to what degree removing outliers preserves the dataset’s underlying information. Approaches to outlier modification like this allow us to ensure that our dataset remains robust throughout subsequent analyses and modeling efforts and guarantee strong foundations for extracting actionable insights.

3.3.2.6 Standardizing Categorical Variables

Apart from the numerical data, guidance entails standardizing the categorical variables for uniformity and precision. The “standardize_category” function applies the guidance by converting the values in the categorical columns to the same case as lowercase and removes any leading or trailing spaces. This ensures uniform expressions of the data in categories minimizing variations than can undermine subsequent analytics. Standardization applies to the order status, customer city, customer state, and product category name in English. Confirming these changes shows that the values in the categories are uniformly structured. Data consistency and reliability improved for subsequent processes.

3.3.2.7 Creating New Features

To further enrich the dataset and extract additional information, we have utilized various feature engineering methods to capture relevant information from the available data. The new features represent valuable metrics that can boost the recommendation system while providing more in-depth data on customer activity and product behavior.

- *Total Order Value:* obtained by calculating the total order value for each record, denoted as the total_order_value. The metric is obtained by summing the price of all items in the record and provides a more comprehensive view of the transaction.
- *Average Review Score:* we find the average rating between reviews, the avg_review_score, to understand the general customer satisfaction level.
- *Number of Orders:* we determine the number of orders placed. First, we find the unique number of orders for each customer for num_orders. This metric helps us understand how many times customers have engaged with the platform and service.
- *Product Popularity:* represented by the number of times a product has been ordered or product_popularity.
- *Delivery Duration:* Timely delivery enhances consumer satisfaction, so we calculated the expected delivery time is delivery_duration, and in our analysis, it is presented in days.

Table 2.

New features results

Total_order value	**Avg review_score**	**Num orders**	**Product popularity**	**Delivery duration**
89.97	4.00000	1	4	8
89.97	4.00000	1	4	8
89.97	4.00000	1	4	8
118.70	4.40566	1	100	13
159.90	5.00000	1	3	9

All the features are calculated using groupby operations and then merged back into the main DataFrame for effectiveness. To make this operation scalable and computationally efficient, the calculations are written in function form. Then we validate the new features by showing a subset of the DataFrame with the new generated features. This is an essential part to ensure that all the features were properly engineered.

Using the feature engineering techniques has made the data set more detailed and given our recommendations system insights into customer product purchasing behavior. These are vital features that are further used as the basis of building more robust and personalized recommendations. Thus, the features provide a more exciting user experience.

3.3.2.8 Encoding Categorical Variables

The categorical variables for our recommendation system have been prepared using one-hot encoding. One-hot encoding was preferred over label encoding because it prevents the model from attributing any arbitrary numerical order to the categorical values.

First, the categorical columns for which one-hot encoding was required were identified. These were: ‘order_status,’ ‘customer_city,’ ‘customer_state,’ and ‘product_category_name_english.’ Next, one-hot encoding was performed on these categorical columns using the get_dummies() function in pandas. This generates a separate binary column for each category value and the presence or absence of that category in the original column while discarding the original columns to prevent multicollinearity.

The DataFrame, “*df_encoded”*, has a column for each category in every categorical column. The binary value in each of these columns indicates whether that category was present for the respective observation. This kind of expansion of the categorical variables ensures that models would not misinterpret them during use, leading to fewer biased and disrupted recommendations. Such modifications enable the model to learn patterns and trends for the system without introducing its biases into the recommendations.

3.3.2.9 Scaling Numerical Features

We use feature scaling to promote the contribution of all numerical features and stabilize and improve the working mechanisms of our recommendation system machine learning algorithms. Here, we utilize the Min-Max Scaling feature and the Standard Scaling feature, which are found in the MinMaxScaler and StandardScaler classes that are available in the sklearn.preprocessing module.

Firstly, we identify the numerical columns that necessitate the performance of scaling. This involves columns such as “price”, “freight_value”, “product_name_length”, and others that are relevant to our recommendation system’s dataset. Next, we peruse the initialization of the scaler and opt to perform Min-Max Scaling in this case.

Subsequently, we proceed to fit and transform the relevant selected numerical columns using the scaler. This operation ensures that the columns are rescaled and fall into the range of [0,1] but their respective and comparative relationships with each other are maintained. The resultant DataFrame, df_scaled, will contain the scaled columns that will be effective for modeling and working with recommendations.

Hence, by standardizing numerical characteristics in this fashion, no feature particularly dominates the modeling, hence enhancing the fairness of the recommendations to the system customers.

3.3.2.10 Date-Time Processing

Efficient processing of data-time data is essential for our recommendation system to extract meaningful patterns of customer behaviors and optimize service delivery. The preprocessing operations start by extracting different essential components of the same date such as year, month, day, and hour from several datetime columns using the dt accessor. This measure allows us to segregate the patterns and relate to when and how the interactions grow.

In addition, it is possible to calculate the duration between essential events such as “placing an order”, “approving the order”, “delivering the order”, and “creating a review”. In this case, such duration is in terms of hours, and it helps us understand how long it takes for the system to process a customer’s orders. For example, how long it takes our system platform to approve an order after placement, how long it takes to deliver after approval, and lastly, the duration between the time of delivery and the time someone creates a review on the order.

With efficiency in processing the datetime data, we get more insights into the dynamics of time in our system. Hence, we have more information to make decisions that are data-driven decisions to improve the system process and client interactions through personalized and relevant recommendations.

3.3.3 Data mining Methodology

This section describes the data mining techniques and methodologies used to grasp and explore the dataset; this includes descriptive statistics, correlation analysis, Exploratory Data Analysis, cluster analysis, and association rule mining. *Pandas, Seaborn, Matplotlib, Scikit-learn, and mlxtend* were the tools and libraries employed.

3.3.3.1 Descriptive analytics methodology

The core of the dataset was descriptively summarized through key statistics such as mean, median and mode for numerical features, as well as standard deviation. This step provides an overview of data's central tendency and its dispersion of that. It helps to find any patterns or unusual data points. Conversely, value counts were employed for different categories. This approach helps in various studies to lay down the basis for an understanding of data (Han et al., 2011).

To sum up, we used the Pandas library--a powerful data manipulation one. The total was, for numerical characteristics of course like mean and median, as well as mode and + standard deviation of income with respect to weight. This step gave both an idea on central tendency and dispersion about our data: Where all does it come from? How might it be best viewed together (e.g., by region)? It helps us understand the spread of data and identify patterns and potential outliers. Categorical features were addressed by value counts showing how often different categories occur. These examples of basic statistical summaries are essential if you are to grasp anything at all about the initial character of a dataset.

3.3.3.2 Correlation Analysis methodology

By calculating the correlation matrix for these variables, we can understand and predict their relationships. It was decided to display this correlation matrix as a heatmap. This way of visualization, with the colors indicating correlations attaining high or low degrees - sometimes helpful mechanism even for the most absent-minded among us. Understanding how variables interact with each other is especially relevant at this point and checking for potential multicollinearity methods described in financial data analysis (Zhang, 2020).

We performed correlation analysis using Pandas to compute the correlation matrix for numerical features. This matrix was then visualized using Seaborn and Matplotlib, which are versatile libraries for creating informative visualizations. The heatmap generated from the correlation matrix allowed us to easily identify strong and weak correlations between variables, providing insights into their interdependencies. This step is crucial for understanding how variables interact with each other and for identifying potential multicollinearity issues.

3.3.3.3 Exploratory Data Analysis (EDA) methodology

Exploratory Data Analysis is an indispensable component of understanding the distribution of features, as well as features' association and patterns. Multiple strategies within the Seaborn and Matplotlib libraries were employed to better understand the data through visualization and interpretation. Initially, through Pandas, summary statistics of both numerical and categorical data were calculated. This calculation provided insight into central tendency, spread, and the frequency of occurrence. Subsequently, the key numerical features were plotted using histograms and Kernel Density Estimate for a better apprehension of data dispersion and central tendency exposed in the data.

These plots could provide understanding of data being skewed, or it could be following a normal distribution or even be multimodal. To get more information from the data, box plots for numerical data are utilized for a depiction of spread to detect numerical and categorical data. This further enlightened variation in data and also discovered whether the number of outliers was present which could affect further analysis. A pair plot was utilized to showcase selected numerical relationships to enable a clear understanding of either correlation or linear relationship between different variables. This was very advantageous as it made it possible to detect potential linear and multicollinearity.

Moreover, the correlation matrix was displayed in a heat map to visualize the relationship between the numerical features. This was a very intuitive way to detect strong or weak correlations between variables which could indicate the relationship between variables. This indicated that there was a correlation coefficient of around 1 for a calorimeter. These plots provided an excellent understanding of the data, thus, identifying trends, patterns and issues. These techniques have been previously researched, documented, and are used to identify patterns and ensure data quality. This enabled us to gather insight into the dataset for subsequent feature engineering and model building.

3.3.3.4 Cluster analysis method

Cluster analysis is used to find segments or groups within the data that share common characteristics. This technique is used to understand customer behavior or identify product similarities or order preferences. K-means clustering from Scikit-learn was used to create the clusters.

- *Preprocess the data:* For the clustering to be accurate, the numerical features should have the same contribution to the sum of squares. Hence, the numerical features were standardized using StandardScaler from scikit-learn.
- *Find the optimal clusters*: The optimal number of clusters were found using the Elbow method. The within-cluster sum of squares WCSS the number of clusters have if the plot of WCSS against number of clusters has an “elbow point”. Hence, the plot was visualized using Matplotlib to find the elbow point.
- *Perform K-means clustering:* The optimal number of clusters from the above process was used to run k-means clustering. The KMeans implementation from scikit-learn was used.
- *Visualize clusters:* The clusters were visualized to understand the characteristics of the clusters, they were visualized using pair plots and scatter plots. These visualizations were performed using Seaborn.

Cluster analysis helped in clustering the customers according to their behavior, and the business can use this information to personalize products.

3.3.3.5 Association Rule Mining

Association Rule Mining process is used to find interesting links or associations among items in a dataset. To mine the association rules in the dataset, Apriori algorithm (implemented in the mlxtend library), was employed for the frequent item sets and association the rules. The standard process for Association Rule Mining is as follows:

- Data preparation: The data was prepared into a transaction dataset suitable for association rule mining using Pandas
- Generate Frequent Item sets: The Apriori algorithm from mlxtend was employed to generate the item sets that frequently occur in the transaction dataset. A minimum support threshold was set to generate the item sets.
- Generate Association Rules: Association rules were mined from the frequent item sets using the mlxtend library’s association_rules function. The rules were evaluated based on metrics including lift and confidence. Analysis and

interpretation: The interesting rules were sorted by lift and analyzed to interpret the rules from the top.

Association rule mining can provide useful insights into product associations which can be used to suggest products highly bought together improving a recommendation.

3.3.4 Model Development

3.3.4.1. Objective of the model development

The current study intends to develop a hybrid recommendation system that combines the two most widely used techniques, collaborative filtering and content-based filtering, to provide a more personalized recommendation experience for users.

The wide range of objectives includes improved recommendation accuracy, greater levels of personalization and serendipity, an incorporation of a greater variety of recommendation algorithms, and an assessment of interaction and satisfaction with the final product.

The first objective will be achieved through identifying patterns derived from user-item interactions in collaborative filtering and comparing them with established item characteristics in content-based filtering. In this way, the system attempts to provide the most accurate recommendation based on the latest established interests.

Secondly, the present system aims to provide more extensive personalization options directly linked to user preferences to ensure further engagement. Moreover, the system is also expected to provide recommendations that would be less likely to be considered, thus expanding the recommendations pool.

The following purpose will be realized through developing recommendations for certain items utilizing both collaborative and content-based filtering in the final product. By doing that, the hybrid system would minimize the limitations associated with each methodology.

Lastly, the system is also anticipated to be evaluated in terms of user satisfaction and interaction. The assessment will enable the system developers to modify the hybrid system based on available feedback. In conclusion, the current project will provide a more accurate recommendation, establish a more personalized environment, make use of various recommendation algorithms, and provide more serendipitous discoveries that would benefit various stakeholders.

3.3.3.2 Dataset and features choice

The study uses several datasets that contain extensive information about the customer, order, product, review, and product category: The following are brief descriptions of the main datasets and their multiple functions:

- A customer's dataset that consists of basic information about them. It includes customer_id, num_orders, customer_state, and customer_city.
- An order dataset where the details of each order the customer made are presented. It includes order_id, order_purchase_timestamp, and the duration between approval, delivery by the carrier, delivery to the customer, and estimated delivery.
- An order items dataset that includes all items purchased by the customer in one order. Each line consists of the order_id each product is ordered by, the product itself, its id, and the quantity.
- A product dataset that has detailed information about each product in the inventory. This dataset contains product_id, product_category_name_english, price, product dimensions, the average review the product received, and how popular the product is.
- An order review dataset that depicts customer reviews after receiving their order. This information includes review_score, review_creation_date, and the duration of the review.
- A product category translation dataset that allows for more accurate definition and comparison of the product categories created in different languages.

The presented datasets allow the system to get data with various features: customers, order stories, product characteristics, and reviews. It is based on these data that the system generates relevant recommendations based on the behavioral characteristics of each user, the properties of the product, and their interaction. For the features that be used from these datasets, table 2 shows the description and the explanation of choice of these particular features.

Table 3.

Features used for the Hybrid AI-based recommendation system

Feature	Feature Description	Explanation of Choice
Customer Features		
customer_id	Unique identifier for each customer	Essential for identifying customers and linking their activity across datasets
num_orders	Number of orders placed by the customer	Helps in understanding customer engagement and can be used to prioritize frequent buyers
customer_state	State where the customer resides	Geographical data can help in providing location-specific recommendations and understanding regional trends
customer_city	City where the customer resides	More granular geographical segmentation
Order Features		
order_id	Unique identifier for each order	Key to linking order details and analyzing purchase history
order_purchase_timestamp	Timestamp when the order was placed	Allows for temporal analysis of buying patterns and trends
total_order_value	Sum of the prices of items in the order	Indicator of customer spending and order size

Table 3. (count.d)

approval_duration	**Time taken to approve the order (in hours)**	**Measures efficiency of the order approval process**
carrier_delivery_duration	Time taken for the carrier to deliver the order (in hours)	Measures delivery performance and logistics efficiency
customer_delivery_duration	Time taken for the order to be delivered to the customer (in hours)	Measures overall delivery performance and customer experience
estimated_delivery_duration	Estimated delivery time (in hours)	Provides a baseline for comparing actual delivery performance
Product Features		
product_id	Unique identifier for each product	Essential for identifying products and linking them to orders and reviews
product_category_name_english	Product category in English	Used in content-based filtering to recommend products in similar categories
price	Price of the product	Critical for recommending products within a customer’s budget
product_weight_g	Weight of the product (in grams)	Used for logistic and delivery-related recommendations
product_length_cm	Length of the product (in cm)	Physical attribute used in content-based filtering to find similar products

Table 3. (count.d)

product_height_cm	**Height of the product (in cm)**	**Physical attribute used in content-based filtering to find similar products**
product_width_cm	Width of the product (in cm)	Physical attribute used in content-based filtering to find similar products
avg_review_score	Average review score of the product	Provides insight into product quality and customer satisfaction, influencing recommendations
product_popularity	Number of times the product has been ordered	Indicator of product popularity for collaborative filtering
Review Features		
review_score	Score given in the review	Used for collaborative filtering and sentiment analysis
review_creation_date	Date when the review was created	Temporal analysis of reviews to identify trends
review_duration	Time taken to answer the review (in hours)	Measures responsiveness to customer feedback

3.3.3.3 Libraries and tools

Developing a recommendation system goes through different stages, from data processing to model evaluation and deployment. Table 3 presents the libraries, tools, and methodologies utilized in each stage for an excellent recommendation system.

Table 4.

Libraries, tools and methodologies

Category	Libraries/Tools
Data Processing	pandas, numpy, scikit-learn
Recommendation Algorithms	surprise, scikit-learn, TensorFlow or Keras, PyTorch
Evaluation	scikit-learn, surprise
Visualization	matplotlib, seaborn
System Architecture	
Data Preprocessing	Clean and preprocess the data, Encode categorical variables and scale numerical features, Create new features and extract useful date components
Collaborative Filtering	Use the surprise library to implement collaborative filtering algorithms like SVD, Build user-item interaction matrix using customer_id, product_id, and review_score or total_order_value
Content-Based Filtering	Use product features such as product_category_name_english, price, avg_review_score, and other product attributes, Calculate similarities between products using cosine similarity or other similarity metrics
Deep Neural Networks	Neural Collaborative Filtering (NCF), Autoencoders, Use a neural network to blend the outputs of collaborative and content-based models
Model Evaluation	Split the data into training and testing sets, Use cross-validation techniques to evaluate model performance, Metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE)
Hyperparameter Tuning	Optimize the parameters of both traditional and neural network models, Use grid search or randomized search for hyperparameter tuning

These libraries, tools, and methodologies combined make it possible to develop a strong recommendation system that can offer users personalized recommendations depending on their preferences and conduct. The model Architecture is presented in the following figure.

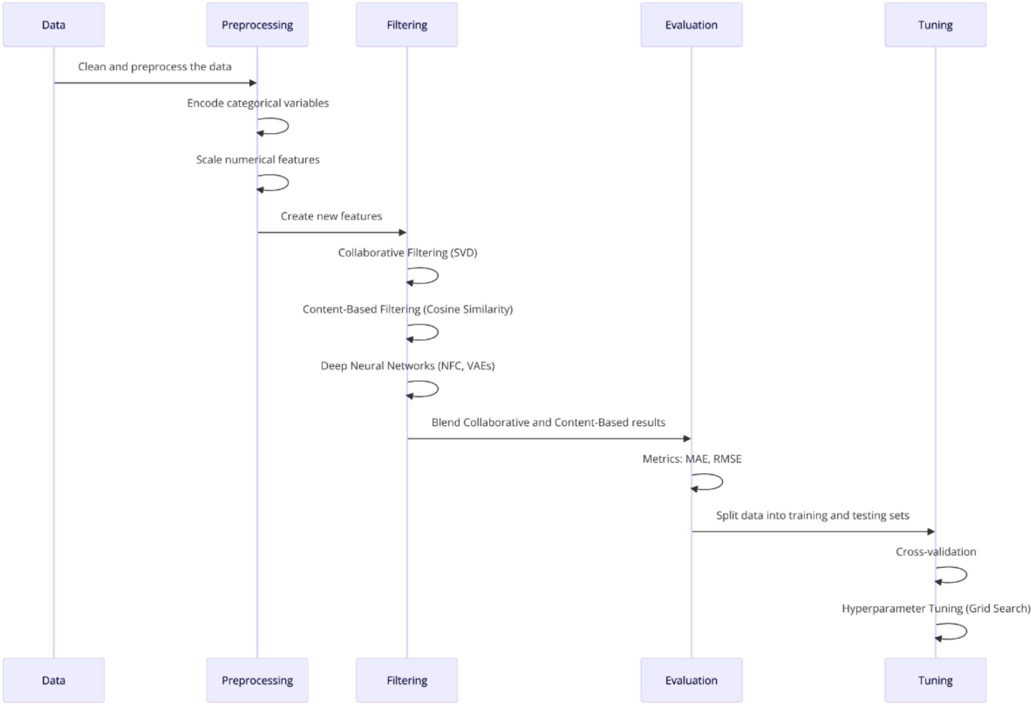


Figure 4. Model architecture

Conclusively, this chapter provided an overview of the methodology used in the development and evaluation of a hybrid AI-based recommendation system from the Olist e-commerce dataset from Kaggle. This involved the critical stages of data collection, preprocessing, model development, hybrid system integration, and model evaluation, as well as the tools and technologies employed.

Data collection and preprocessing encompassed merging and cleaning datasets, handling missing values, data type conversion, and outlier and feature engineering to create a strong dataset.

The model development section entailed the reasons for engaging a hybrid recommendation system combination of collaborative and content-based filtering to significantly improve recommendation accuracy, personalization, and serendipity. We designed multiple models to combine them into a single hybrid system to generate complementary recommendations that were both comprehensive and personalized.

Additionally, the stage evaluation is carried out using various metrics to demonstrate its competency and potential for advancement. Furthermore, the programming languages, libraries, and tools used then discussed and highlighted their significance in the system development and evaluation.

In conclusion, this chapter fully described the procedures and techniques used in the development of the hybrid AI-based recommendation system, which ensured the generation of high-quality recommendations for users in e-commerce platforms like Olist.

Chapter 4

Findings

In this chapter, we provide a detailed analysis of the Olist e-commerce dataset to reveal important insights and trends that guide us in building our recommendation system. The chapter opens with a comprehensive description of the dataset, through descriptive statistics pointing out key features and potential outliers. The relationship between variables is then investigated using a correlation matrix, which gives an idea for the structure of data and helps choose key features on modeling.

After that comes the part of performing and visualizing Exploratory Data Analysis (EDA) to see how our data distributions look like and spot interesting patterns/points. Plot Distributions of Key Numerical Features and Pair Plots to see about variance in the variables, how they are correlated and similar comparisons We also cluster the data for same segmented groups to conduct Cluster Analysis and understand in more detail about customer behavior / product performance.

In the second part of this chapter, we will be discussing our work on AI based hybrid recommendation system which were developed and evaluated. Details of collaborative filtering, content-based filtering and hybrid approaches and implementations conducted are described in the paper. We evaluate the performance of each model with a comprehensive set of evaluation metrics and compare their results to discuss trade-offs in advantages and disadvantages.

The objective is to have covered by the end of this chapter a strong comprehension of our dataset, and to prove that we can achieve an efficient recommendation system on e-commerce which would supply visitors with pertinent and personalized product recommendation

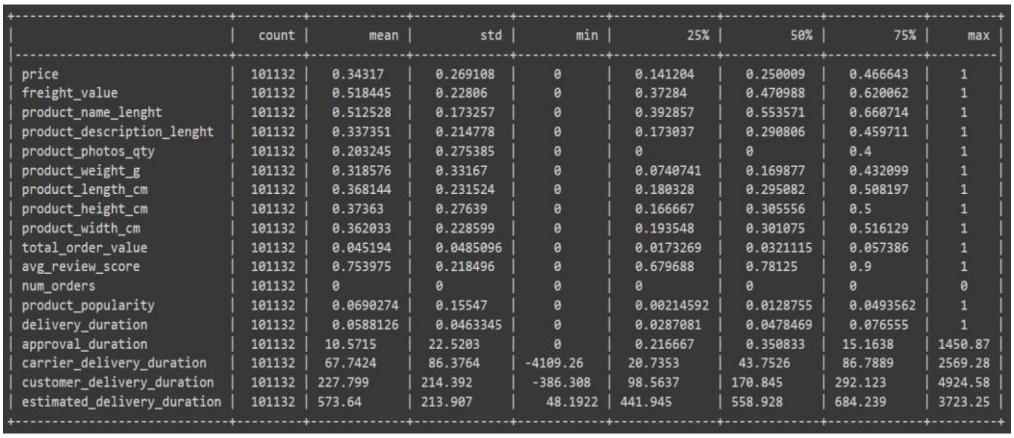
4.1 Olist e-commerce data mining

4.1.1. Descriptive statistics

The Importance of Descriptive Statistics in Data Mining Descriptive statistics are of great importance in data mining for they provide a summary of data characteristics that serves to help people better understand models effectively interpret datasets. These statistics, which include such measures as mean, median, standard deviation, tell us something about the asymmetry of data-skewness are the intrinsically correct data pieces left after finding positive and negative deviation--but now no longer contain any direction information themselves. They can be expressed as Table 1 shows.

Descriptive statistics then lay the groundwork for more advanced data mining techniques by identifying patterns, trends and outliers in datasets Thus recent research highlights their significance in the beginning stage of data analysis, whereas such traditional assumptions of these statistics have been criticized by the authors. For instance, Sharma (2020) poses that descriptive statistics are indispensable for data visualization and error detection, both crucial for effective data mining. Similarly, Chen et al. (2021) stress how these statistics are prerequisite to preprocessing and understanding the data before complicated models can be applied.

Figure 4 presents the results of the descriptive statistics that we run on the numerical variable on our dataset.



```
+-----------------------------+--------+-------------+-------------+------------+--------------+-------------+-------------+---------+
|                             |  count |        mean |         std |        min |          25% |         50% |         75% |     max |
|-----------------------------+--------+-------------+-------------+------------+--------------+-------------+-------------+---------|
| price                       | 101132 |   0.34317   |   0.269108  |     0      |   0.141204   |   0.250009  |   0.466643  |    1    |
| freight_value               | 101132 |   0.518445  |   0.22806   |     0      |   0.37284    |   0.470988  |   0.620062  |    1    |
| product_name_lenght         | 101132 |   0.512528  |   0.173257  |     0      |   0.392857   |   0.553571  |   0.660714  |    1    |
| product_description_lenght  | 101132 |   0.337351  |   0.214778  |     0      |   0.173037   |   0.290806  |   0.459711  |    1    |
| product_photos_qty          | 101132 |   0.203245  |   0.275385  |     0      |   0          |   0         |   0.4       |    1    |
| product_weight_g            | 101132 |   0.318576  |   0.33167   |     0      |   0.0740741  |   0.169877  |   0.432099  |    1    |
| product_length_cm           | 101132 |   0.368144  |   0.231524  |     0      |   0.180328   |   0.295082  |   0.508197  |    1    |
| product_height_cm           | 101132 |   0.37363   |   0.27639   |     0      |   0.166667   |   0.305556  |   0.5       |    1    |
| product_width_cm            | 101132 |   0.362033  |   0.228599  |     0      |   0.193548   |   0.301075  |   0.516129  |    1    |
| total_order_value           | 101132 |   0.045194  |   0.0485096 |     0      |   0.0173269  |   0.0321115 |   0.057386  |    1    |
| avg_review_score            | 101132 |   0.753975  |   0.218496  |     0      |   0.679688   |   0.78125   |   0.9       |    1    |
| num_orders                  | 101132 |   0         |   0         |     0      |   0          |   0         |   0         |    0    |
| product_popularity          | 101132 |   0.0690274 |   0.15547   |     0      |   0.00214592 |   0.0128755 |   0.0493562 |    1    |
| delivery_duration           | 101132 |   0.0588126 |   0.0463345 |     0      |   0.0287081  |   0.0478469 |   0.076555  |    1    |
| approval_duration           | 101132 |  10.5715    |  22.5203    |     0      |   0.216667   |   0.350833  |  15.1638    | 1450.87 |
| carrier_delivery_duration   | 101132 |  67.7424    |  86.3764    | -4109.26   |  20.7353     |  43.7526    |  86.7889    | 2569.28 |
| customer_delivery_duration  | 101132 | 227.799     | 214.392     |  -386.308  |  98.5637     | 170.845     | 292.123     | 4924.58 |
| estimated_delivery_duration | 101132 | 573.64      | 213.907     |    48.1922 | 441.945      | 558.928     | 684.239     | 3723.25 |
+-----------------------------+--------+-------------+-------------+------------+--------------+-------------+-------------+---------+
```

Figure 5. Descriptive Statistics results

Several noticeable things are shown in the descriptive statistics table. First, both unexpected negative values exist in the delivery duration. The carrier delivery duration minimum is (-4109.26) and the customer delivery duration minimum is (-386.398). Such negative values suggest that there could be input errors in the data or special cases with more to them than meets the eye.

In addition, the approval and carrier delivery durations are very uneven. The standard deviation of approval duration is (57.224), its highest point (1450.87); Carrier delivery duration's standard deviation is (340.376), while its maximum is (2569.28). Such an extreme difference implies that although some approvals take less time or carriers deliver quickly for whatever reasons in some cases, other approval and delivery times are incredibly long--indicating significant imbalances in these procedures.

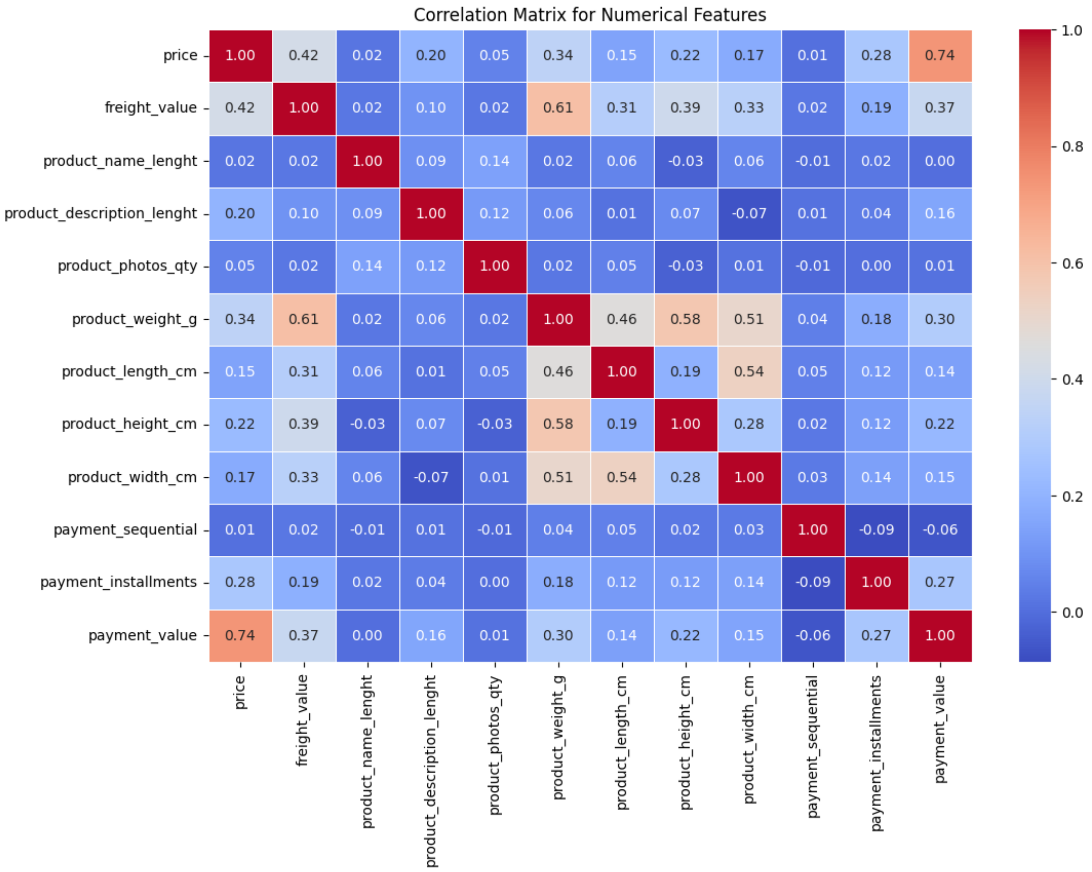
Then, the estimated delivery duration also exhibits great diversity. The range is from [48.1922] (the lowest figure) to [3723.25], affirming that there must be considerable discrepancies in estimated delivery times which could well affect customer satisfaction and logistics planning.

In short, these observations emphasize that in order to ensure data consistency and precision we might need clean-up work, further analysis, or operational enhancement in our database.

4.1.1 Correlation matrix

An important tool for data analysis, the correlation matrix displays relationships between variables through its correlation coefficients. By this means we can see how closely linked or related different things are -- something very important when looking at the structure of the information, and also hinting which further analysis should be performed.

High correlations indicate strong connectivity. Changes in one variable suggest changes in the other – this is essential information for feature selection in predictive modelling because it will help us to eliminate redundant variables which are correlated with one another. This reduces multicollinearity. Studies have drawn attention to the matrix's importance in various fields. Schober et al. (2018) extol its role in medical statistics whereby “Data interdependencies are exploited,” and Zhang (2020) underlines its worth for investment analysis in the field of management of financial portfolios. Figure 6 presents the correlation matrix of the Olist datset that we are working on.



	price	freight_value	product_name_lenght	product_description_lenght	product_photos_qty	product_weight_g	product_length_cm	product_height_cm	product_width_cm	payment_sequential	payment_installments	payment_value
price	1.00	0.42	0.02	0.20	0.05	0.34	0.15	0.22	0.17	0.01	0.28	0.74
freight_value	0.42	1.00	0.02	0.10	0.02	0.61	0.31	0.39	0.33	0.02	0.19	0.37
product_name_lenght	0.02	0.02	1.00	0.09	0.14	0.02	0.06	-0.03	0.06	-0.01	0.02	0.00
product_description_lenght	0.20	0.10	0.09	1.00	0.12	0.06	0.01	0.07	-0.07	0.01	0.04	0.16
product_photos_qty	0.05	0.02	0.14	0.12	1.00	0.02	0.05	-0.03	0.01	-0.01	0.00	0.01
product_weight_g	0.34	0.61	0.02	0.06	0.02	1.00	0.46	0.58	0.51	0.04	0.18	0.30
product_length_cm	0.15	0.31	0.06	0.01	0.05	0.46	1.00	0.19	0.54	0.05	0.12	0.14
product_height_cm	0.22	0.39	-0.03	0.07	-0.03	0.58	0.19	1.00	0.28	0.02	0.12	0.22
product_width_cm	0.17	0.33	0.06	-0.07	0.01	0.51	0.54	0.28	1.00	0.03	0.14	0.15
payment_sequential	0.01	0.02	-0.01	0.01	-0.01	0.04	0.05	0.02	0.03	1.00	-0.09	-0.06
payment_installments	0.28	0.19	0.02	0.04	0.00	0.18	0.12	0.12	0.14	-0.09	1.00	0.27
payment_value	0.74	0.37	0.00	0.16	0.01	0.30	0.14	0.22	0.15	-0.06	0.27	1.00

Figure 6. Olist data correlation matrix

The presented correlation matrix for all numerical features within the dataset can help in making some important observations about the relationships between different variables. To begin with, the value of the correlations in the range from 0 to 1 where a higher value indicates stronger correlation, the coefficient of (.74) is calculated for the relationship between the price of products and the value of payment. This indicates a strong positive correlation, showing that whoever pays more for a product tends to pay more, which is a logical observation. When examining the relationship between other variables and the extent of the correlation, it is possible to draw more conclusions. The indicator of (.61) is calculated for the correlation between freight value and the weight of the product. It can be interpreted that a heavier product must have more expensive freight. A similar relationship can be determined between product dimensions, for example, width and length, which are also positively correlated at (.54) and indicate that if one is larger, the other one will be larger, respectively.

However, the correlation of these variables may be regarded as insignificant but around the middle. The same can be said about the correlation between freight value and the height of the product, which is (.58), namely a taller product is more expensive to transport. The total price of the product and the freight value also demonstrate a similar correlation of (.42), which means that a more expensive product will likely have more expensive freight. The weak correlation can be seen between the number of photos of the product and the price, or rather (.34). This might demonstrate that the prices of products associated with more effort are higher since sellers want to sell those more. All other correlations are weak or show no linear relationship, which means they should be regarded as independent. These include product name length and product description length.

The correlation coefficient between price and how many photos of the product are put on the page, which is (.34), implies that more money should be put in a product listing. In conclusion, the correlation matrix presented above can demonstrate important relationships between the variables in the e-commerce data analysis. The focus of the revenue strategy should be on price since the correlation of payment value and price is the strongest, while the logistic strategy can be based on freight value values. Also, in terms of inventory, more effort over pricing should be put into the product description.

The exception is some weak negative correlations, such as the correlation coefficient between payment instalments and price at (-0.28), which was found. Such a value can imply that cheaper products are likely to be bought in instalments. An equally weak negative correlation is calculated between payment instalments and payment sequential, which comprises (-0.09). This can be regarded as related to how payments following the initial instalment are structured. The found implications imply several important ideas. The first one is that since the correlation between price and the payment value is strong, it is recommended to develop monetization around high prices. When it comes to logistics, the significant correlation coefficients between freight value and product dimensions call to treat these variables adequately for the best optimization opportunity.

4.1.3 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is essential for summarizing the main characteristics of a data set. Using statistical graphics and visualization techniques like histograms, scatter plots, and correlation matrices, EDA uncovers patterns, identifies anomalies, and tests hypotheses. This process helps ensure data quality and guides further analysis, making it a critical step in data science for informed decision-making.

4.1.3.1 Plot distributions of key numerical features

Plotting distributions of key numerical features is vital in data analysis. It involves visualizing the frequency and spread of data points using graphs such as histograms, density plots, and box plots. These plots help in understanding the central tendency, variability, and shape of the data distribution. By examining these distributions, analysts can identify patterns, detect outliers, and assess the normality of the data, which are crucial for making informed decisions and preparing data for further analysis and modeling.

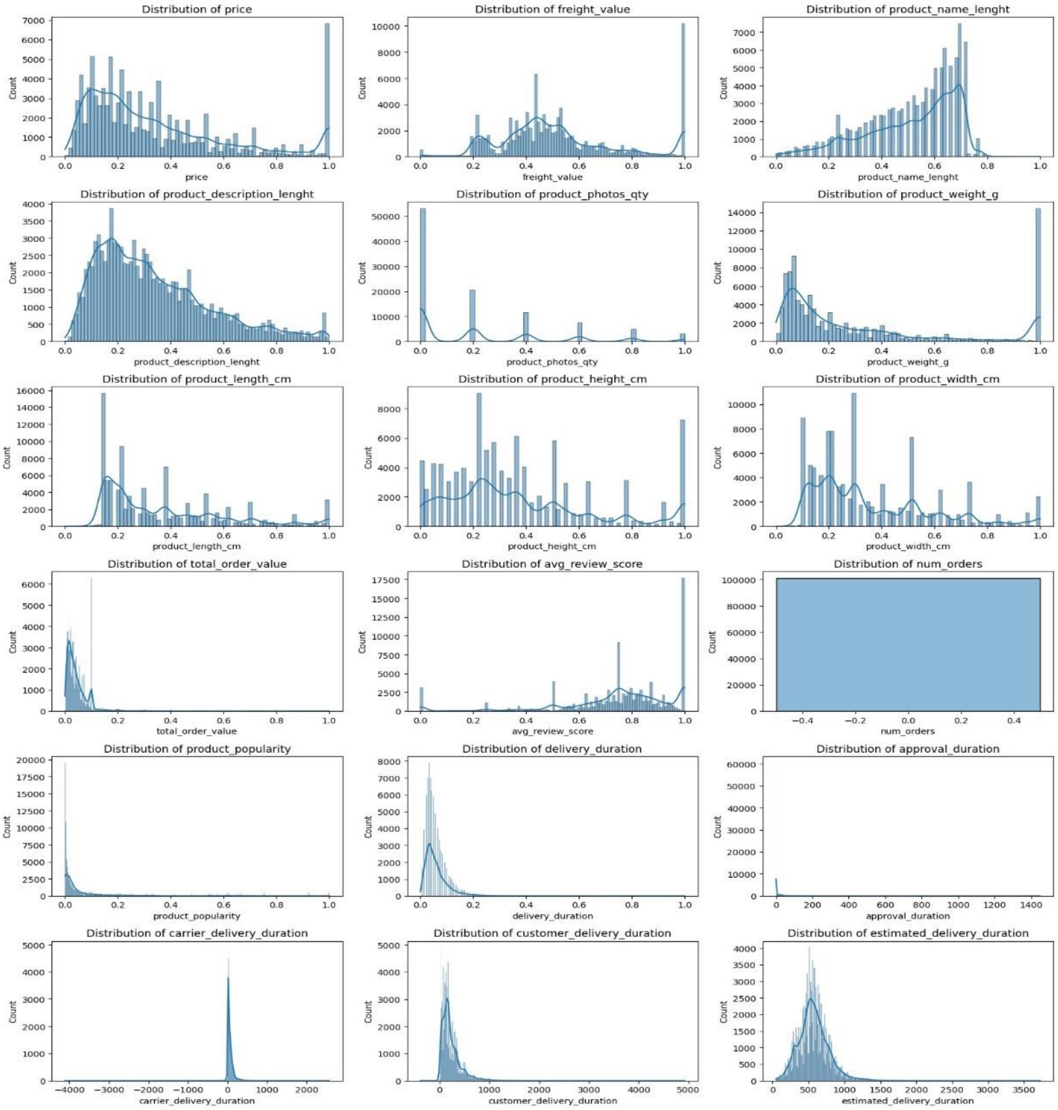


Figure 7. Plotting distribution and key numerical features

Figure 7 unveils a number of important insights about the dataset. The price distribution is right-skewed, with most prices concentrated between 0.1 and 0.5, and few products for sale at near 1. Similarly, freight value shows a multi-modal distribution, with substantial numbers of products at [0.1, 0.4, and 0.6] purporting sets off common freight values.

Product name length distribution is slightly left-skewed, with most of the product names clustering around [0.4 and 0.9]. The product description length distribution also exhibits a left-skewed pattern, with most descriptions between [0.2,0.6]. Interestingly, product photos quantity is highly right skewed, which suggests that most products have relatively few photos and a significant number have none.

Product weight has a long-tailed distribution, with many products lights and only a few heavy, concentrated around [0 to 0.4]. It looks like there is a problem with the plot of the number of orders; on the left end there are a large number of counts, probably because most products have extremely few orders.

The distribution of both delivery duration and approval duration are right-skewed, with the majority of short delivery times and approval times but with some very long exposure. The carrier delivery duration displays a large concentration around 0 and has negative values, which might signal issue with the data, while the distribution for the customer delivery duration is also right skewed, with short delivery times and long tail for the extended duration.

The estimated delivery duration follows the same pattern as most short estimates but with a few much longer. These distributions identify the need in the cleaning of the data, focusing specifically on the negative values and potential errors in data entry, and acknowledge the necessity of being aware of the variability in data and frequency of different values to ensure accurate analysis and decision-making.

4.1.3.2 Pair Plots

A pair plot is a type of data visualization that is used to investigate the relationship between several variables in a dataset. More specifically, each pair of variables is plotted against one another on a grid of scatter plots, which can help users to identify correlations, trends, and outliers. Additionally, the diagonal often displays a histogram or density plot of each variable’s distribution. Pair plots have become one of the most convenient ways to examine multiple variable interactions simultaneously, and they are an essential tool for any type of exploratory data analysis. Figure 8 represents the results of the pair plotting run on python.

The pair plot also shows several interesting results. The scatter plot of the price and the total order value has an upward trend, which means that prices are slightly positively correlated with overall order value. In other words, higher-priced items tend to have higher total order value. The total order value is also unlikely positively correlated with average review score, yet the greater the total order value, the better the reviews tend to be. A clear anomaly is present in the plot of the number of orders because all values are concentrated at one point on the x-axis. This may indicate a problem with the data, such as incorrect scaling or almost no variation in the number of orders, warranting further investigation. In general, most pairs seem to have a relatively weak or no correlation, but the ones described above, along with the anomaly in the plot of number of orders, can be considered interesting for further exploration.

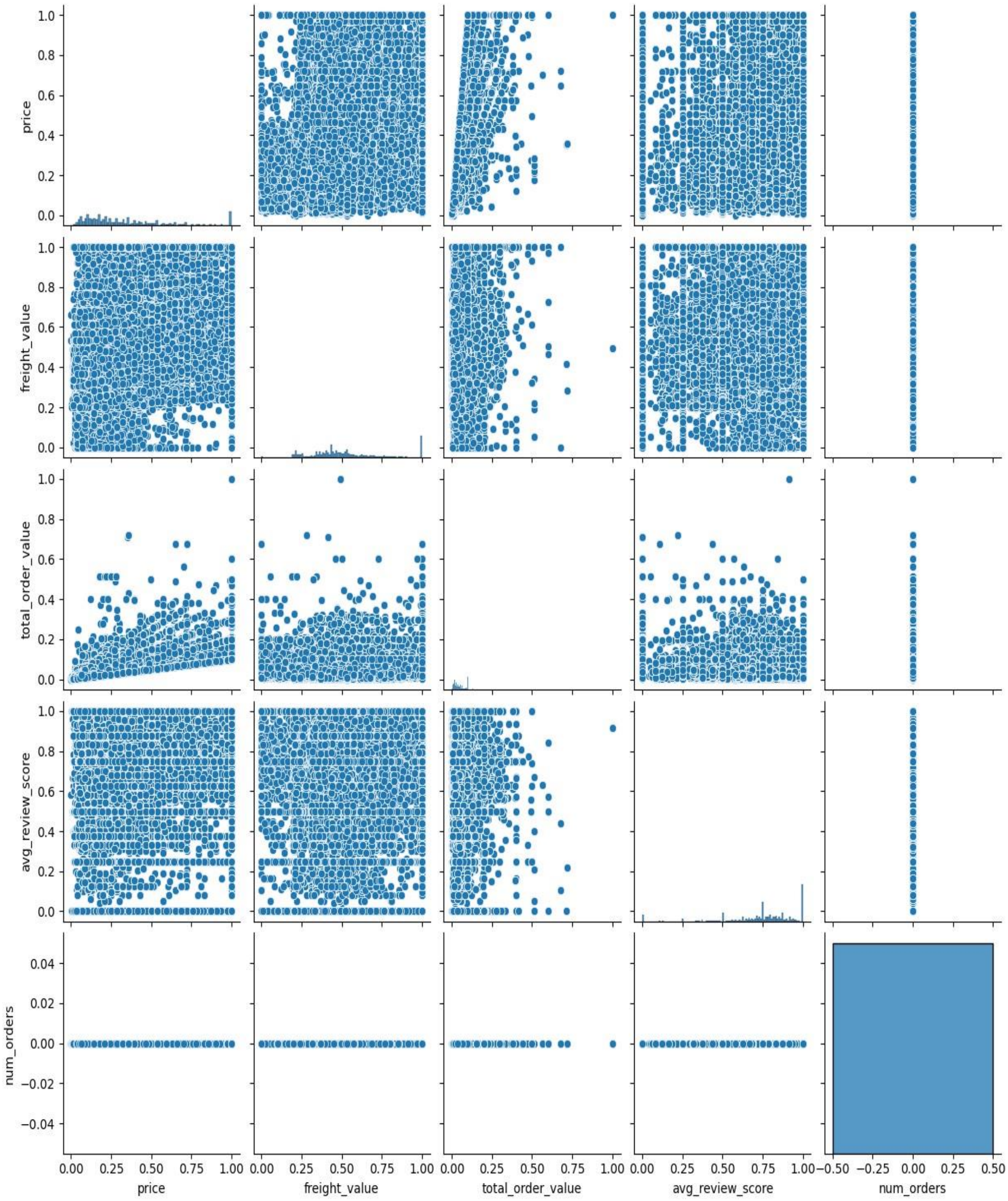


Figure 8. Pair plots

4.1.4 Cluster Analysis

Cluster analysis is a statistical technique used to group a set of objects in such a way that objects in the same group, or cluster, are more similar to each other than to those in other groups. This method is widely used in data mining and pattern recognition to identify underlying structures in data without prior knowledge of group definitions. By analyzing the similarity or distance between data points, cluster analysis helps in uncovering patterns, detecting anomalies, and simplifying large datasets. Common clustering algorithms include k-means, hierarchical clustering, and DBSCAN, each with its own approach to grouping data points based on various criteria. The results of cluster analysis can provide valuable insights for market segmentation, image analysis, biological data classification, and many other applications, making it a versatile tool in exploratory data analysis and predictive modeling.

Before proceeding the data need to cheked if it allows clustering and the with the application of the Elbow method, we have to determin the optimal number of clusters by plotting the within-cluster sum of squares (WCSS).

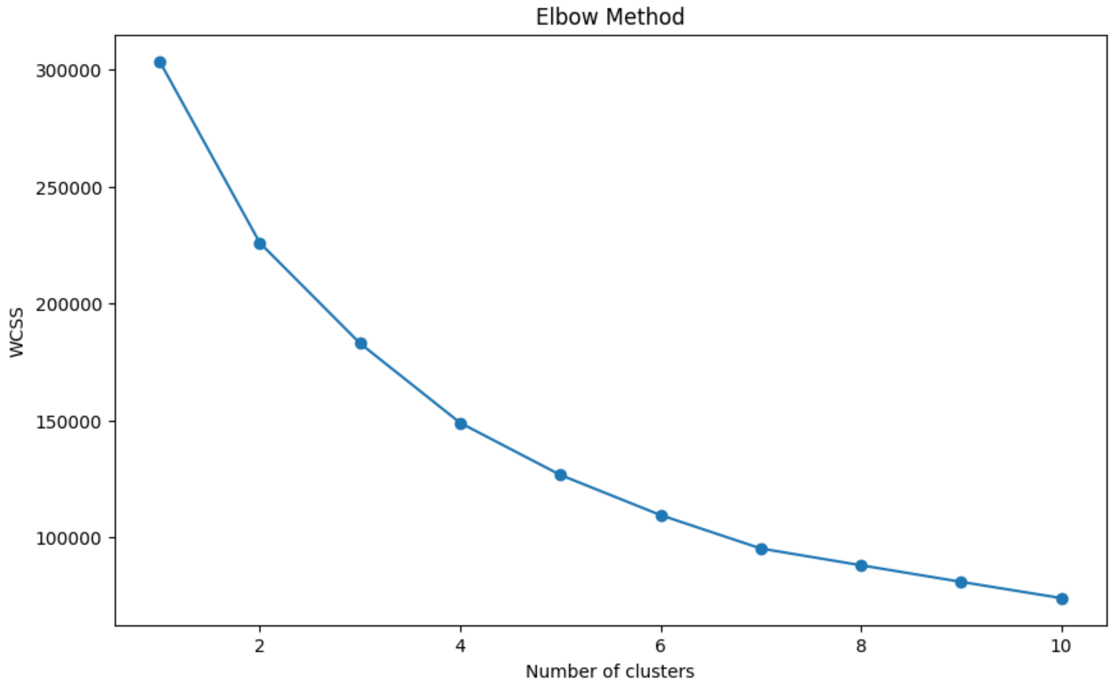


Figure 9. Elbow method for the optimal number of cluster

The elbow Method graph is shown above to determine the optimal number of clusters. On the x-axis, the number of clusters variate in the range 1-10, while the y-axis describes the within-cluster sum of squares which reflect the variance in each cluster sum. With the increment of clusters number, the WCSS reduces as well which means that cluster become more compact and complete.

The idea of the elbow point is a rapid decrease that is shown after it. It should be the optimum point, in which the number of clusters balance with their compact. As can been seen from the graph, the optimal point can be seen from 4 clusters. More number of clusters has a much smaller reduction of WCSS than before that point. Therefore, 4 clusters number will be good to using, whereby clusters will be distinct and have meaning without a lot of overfittings.

We proceeded with K-means clustering on the bases of 4 clusters the figure 10 shows the plot.

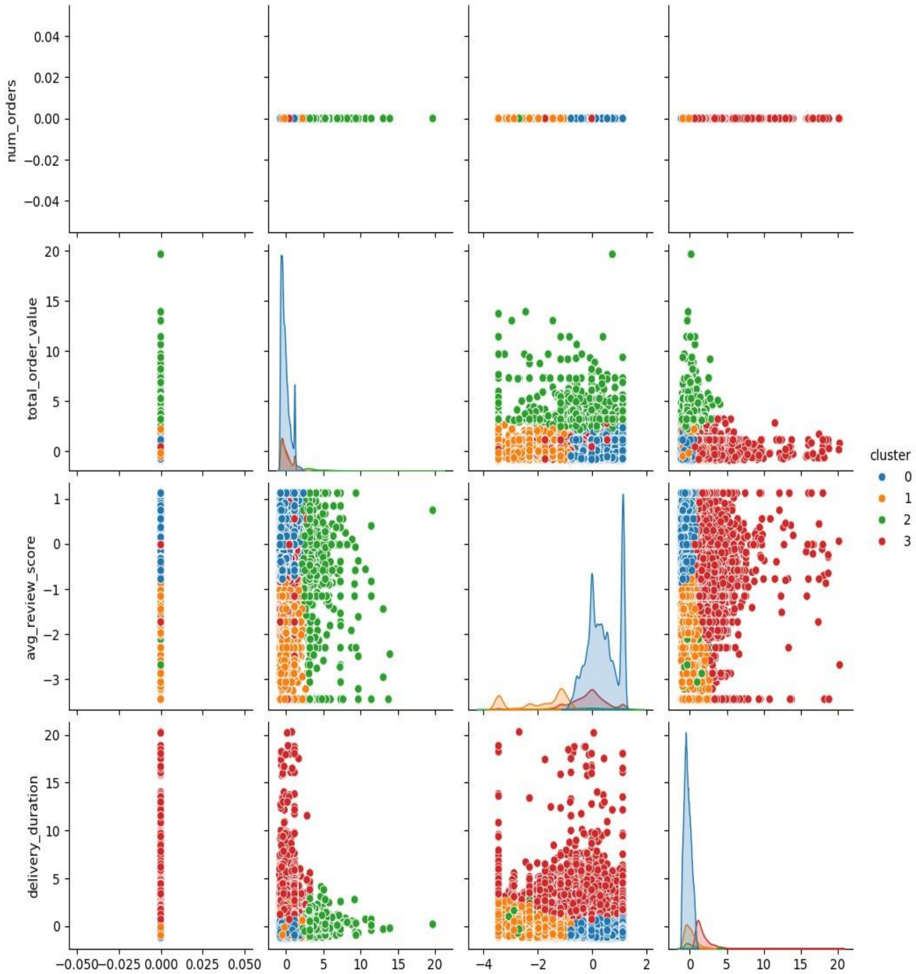


Figure 10. K-means clustering plots

The given pair plot demonstrates some distinct features, clusters, and patterns. Each cluster is colored differently; namely, one can notice blue, orange, green, and red clusters. To begin with, the red cluster reveals a concentration of data points with low total order value and delivery duration, but higher average review score. This fact implies that this cluster can stand for some products with quick delivery and positive feedback.

Conversely, the green cluster is spread over the space; it ranges from a low average review score to some high delivery duration and total value and implies multiple products differentiated in terms of value and delivery performance. Lastly, there is a noticeable blue and orange cluster that is significantly more grouped; they are located in the interval of low total order value and review score. Thus, it appears that these are products many users might not prefer or that fail to perform as needed.

Moreover, one can see from the scatter plot for total order value against delivery duration that the majority of products result in short delivery times with a minority of exceptions that have substantially longer times. This is shown by the red cluster, which has a strong density near the origin and a scalar density, with a limited spread of the cluster with longer delivery times.

Overall, these plots indicate that the data can be clustered into subcategories that have a concerning focused differences such as total order value, average review score, and delivery duration. In turn, it allows for possible use in marketing, inventory, and customer service tactics. To dive more we decided to plot a customer based on the total order value and the average review score, presented in figure 11.

The customer cluster plot presents relatively clear segments by total order value and average review score. The blue cluster presents a low total order value and slightly positive reviews, which means that the customers spend little but are overall content. The orange cluster depicts a low total order value and negative reviews, which indicates low spending and unhappiness on Noample’s part. The green cluster shows the widest spread in terms of total order value and review score, meaning that customer spend varies and so does their satisfaction. Finally, the red cluster is very scattered and intersects with other clusters, suggesting distinct behaviors or outliers. This information can be particularly useful for targeted marketing and customer relationship strategies.

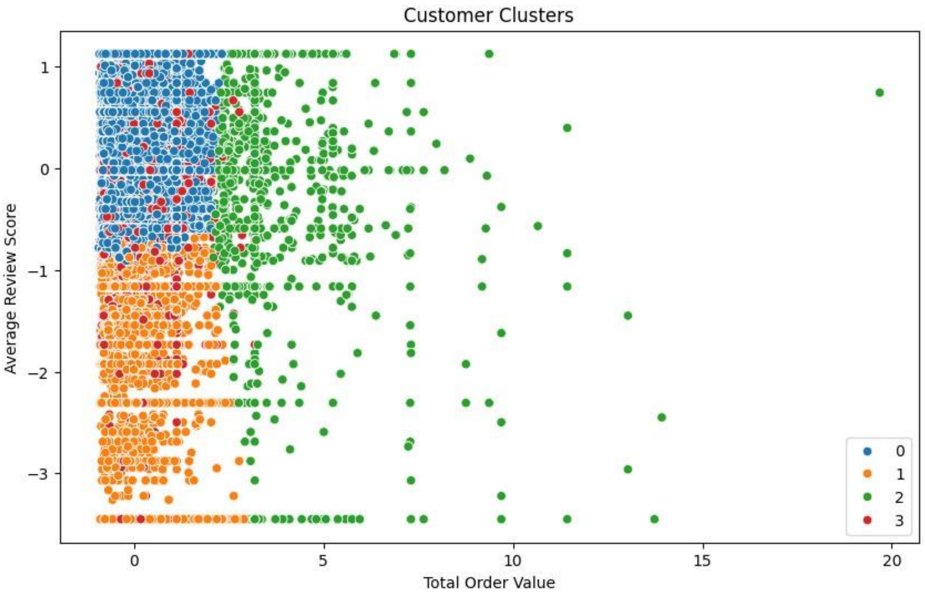


Figure 11. Customer Clustering plots

4.1.5 Association Rule Mining

Association Rule Mining is a data mining technique that finds interesting relationships or associations between occurrence patterns in the dataset. It is commonly used for market basket analysis to identify products that are often purchased together. For this purpose, we used the "mlxtend" library.

The Apriori algorithm generated combinations of product categories that are often present in the same transaction. The results are presented in figure 12.

After the clustering results presented in figure 11 we wanted to set the association rule and determines association between most frequently purchased items. However, despite lowering our support threshold did not help us find any patterns among multi-item frequent itemset or association rules, which shows that there are not strong associations among the product categories. We considered the possibility of combining similar product categories into even broader groups and analyzing the length of transactions to ensure that multi-item frequent itemset in these transactions contained more than one item. In addition to this, we performed a domain-specific analysis in case a priori-analysis yields some results to detect existing potential groupings of products or their seasonal trends.

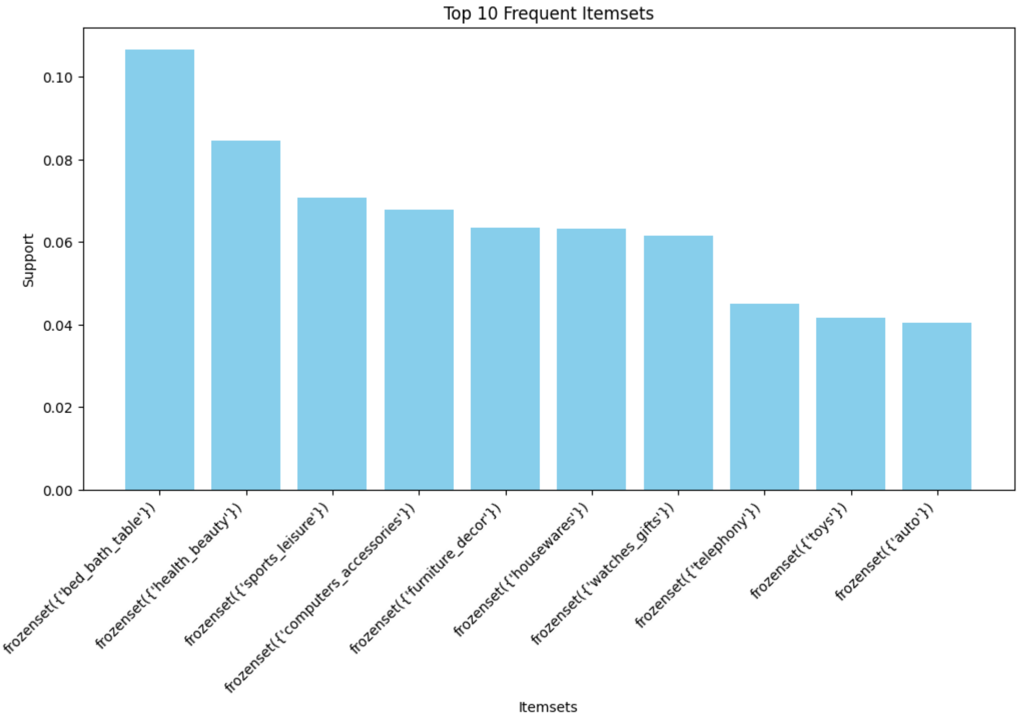


Figure 12. Frequent associated items

Even after setting the thresholds 0,01%, there were no discovered significant association rules, which indicates that the dataset has no strong associations. Therefore, we had to explore the multi-item frequent itemset that were discovered in A priori-analysis manually. The results of the manual association are presented in figure 13.

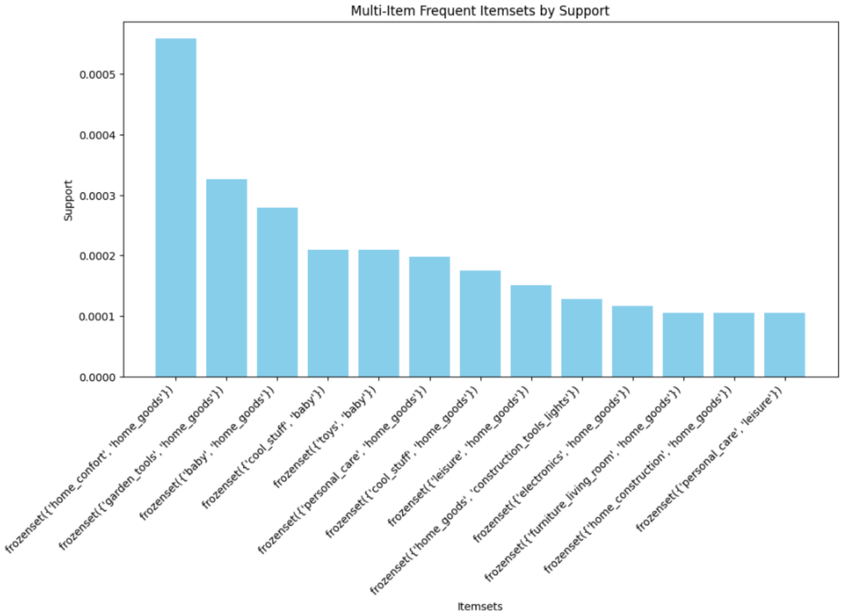


Figure 13. Associated multi-itemset

4.2 AI-based Hybrid Recommendation System model

4.2.1 Collaborative filtering

Collaborative filtering is a widely accepted recommendation approach. It leverages similar users' behavior or product preferences to provide personalized recommendations. This method works particularly well in the case of abundant user behavior data in e-commerce, social networked communities, or streaming video services The idea behind collaborative filtering is to uncover the patterns and correlations in user-item interaction. By identifying these relationships, one can predict what users are likely to appreciate next (Aggarwal, 2016).

In e-commerce, collaborative filtering is used extensively to improve the shopping experience. For example, Amazon uses collaborative filtering to recommend products according to customer previous purchase records and browsing histories; it also recommends products that are popular among similar users. In the same way, Netflix employs collaborative filtering to suggest movies and television series for you based on what your past viewing preferences have been along with any demographic information about yourself a survey may have come up with (Ricci, Rokach & Shapira, 2015).

Collaborative filtering methods are loosely divided into two approaches: memory-based and model-based methods. Memory-based approaches (or neighborhood-based approach) mainly rely on direct calculation of user similarities or item similarities from the data matrix (Ricci, Rokach & Shapira, 2015). In contrast, model-based methods such as matrix factorization techniques are based on observed user-item interaction patterns to form predictive models (Koren, Bell & Volinsky, 2009).

4.2.1.1 Data Preparation and Sparse Matrix Creation

We first extracted the unique customer_id, product_id values from the dataset and created mappings to matrix indices. Using these mappings, we constructed the sparse interaction matrix which effectively represents the interactions between users and items coupled with their corresponding review scores.

We simply created this sparse matrix using the csr_matrix function available within the SciPy library. This resulted in a sparse matrix of dimensions (87,989) unique customers and (29,262) unique products. Sparse matrices are very useful for dealing with large datasets containing multiple entries that equal 0, given they store only non-zero elements and therefore save memory and computation times (Oliphant, 2007). This sparse interaction matrix had very minimal memory usage, meaning it could be stored and manipulated with little-to-no performance concerns. Efficiency is very important in recommendation systems due to the fact that the problems typically involve large-scale datasets with many users and items (Aggarwal, 2016).

4.2.1.2 Technique and methods used for the collaborative filtering

For this project, we use a model-based approach and adopt the Singular Value Decomposition (SVD) algorithm. SVD is a powerful matrix factorization technique used to break down the user-item interaction matrix into latent factors, which capture the underlying structure in the data. This method is particularly effective when handling sparsity and also provides good predictive accuracy (Koren, 2009). The effectiveness of SVD in recommender systems has been demonstrated by its successful use in the Netflix Prize competition, which significantly improved predictive performance (Koren, 2009).

For Singular Value Decomposition (SVD), its performance metrics evaluated in table 5 with cross-validation effect across five folds. The parameter examines the quality of its prediction include Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). It is often used to measure how accurate prediction is in recommendation systems; lower values indicate better performance.

Table 5.

Cross-Validation Results of SVD Algorithm

Fold	**RMSE**	**MAE**
1	0.875	0.690
2	0.890	0.695
3	0.872	0.688
4	0.878	0.692
5	0.879	0.693
Mean	0.879	0.692
Std	0.007	0.002

Table 5 shows how the widely used Singular Value Decomposition (SVD) algorithm performs on cross-validation. It compares performance over five folds using Root Mean Squared Error (RMSE) and Mean Absolute Error as two key criteria. Both metrics are essential when measuring accuracy in recommendation systems, with smaller numbers indicating better undergraduate scores.

The table indicates that RMSE ranges from [0.872 to 0.890] while MAE varies between 0.688 and 0.695. This narrow band means that the performance is likely to be consistent across different data sets. The mean RMSE value is (.879), and the mean MAE stands at (.692) so overall prediction accuracy of the algorithm seems good. The standard deviations are also low (.007 for RMSE and .002 for MAE), which suggests relatively low variability from data set to the model.

For recommender systems, these scores are sufficient. According to Ricci et al., (2015), if RMSE is less than (1.0), it's relatively friendly for general Recommender system. What this means is that, on average, the algorithm's predictions are close to users 'real judgments of products in collaborative ratings.' Furthermore, Gunawardana and Shani (2015) note that an MAE value less than (0.7) is generally considered effective in practical terms for making recommendations within recommend systems.

This research reveals that SVD clearly provides accurate and consistent recommendations. its stability earns SVD high marks among competitors as a robust choice compared with other methods when identifying products for consumers --

whether they use an existing Web site, game or entirely new entry into electronic retailing.

4.2.1.3 Collaborative filtering recommender results

For this example, I will test our collaborative filtering recommender system by taking a random user ID from the available dataset: Given the user in question and following SVD which predicted his ratings, top-N product recommendations generated for this user are: In above results, I was displayed the top 10 recommended product for selected user and predicted rating of that product. In order to recommend products tailored to the individual and their past browsing behavior as well as any inferences drawn from similar user actions, these recommendations are given. Table 6 gives the detailed results of the first ten recommendations, as well as our estimated ratings for each product recommended.

Table 6.

Collaborative filtering recommender results

Rank	Product ID	Estimated Rating
1	3e4176d545618ed02f382a3057de32b4	4.70
2	179363fe9f0eee05ad34df83c160dbcf	4.68
3	aa280035c50ba62c746480a59045eec4	4.67
4	dd6a505f83dd3c6326aa9856519e0978	4.67
5	363218ba55c610b750224f90bdd34be1	4.66
6	62c89abe1afe3a23c17765d462718a4c	4.65
7	b9ee7519d0187d2389af62ba6c612963	4.65
8	2d7ec74c6f93ad8234f2e29817b2827b	4.63
9	73326828aa5efe1ba096223de496f596	4.61
10	57552a168008a60472e3e6bb351422e7	4.59

Table 6 presents the top 10 product recommendations produced by our collaborative filtering system, based on a randomly chosen user, recommendations in the format of “productid”, rating (where n is the number of records that need to be recommended) These predicted lacks are the model’s best guess at how many pounds of these products a user would have purchased if they had been recommended.

Therefore, the product with the highest estimated rating of 4.70 (ie. product ID: 3e4176d545618ed02f382a3057de32b4) will be top recommendation and is most likely to be recommended. The system expects the user susceptibility to this item would be highest among all other items. The second recommendation, with an estimated rating of 4.68 (second following closely under the top one) is a product with “ID: 179363fe9f0eee05ad34df83c160dbcf) Other products on the top 10 list have estimated ratings between [4.67 to 4.59] of remaining products.

Since there is very little variation in the ratings for our top-N recommendations, this may imply that our collaborative filtering algorithm constantly picks items highly appealing to the user, enforcing a small interval of preferences.

To conclude, the collaborative filtering part of the recommendation system endeavors to use likeness in user-item interaction data to initially deliver a range of personalized product recommendations. SVD consistently showed good performances with all the evaluation metrics so we will use it here as well since it is especially useful for handling sparse data and making very accurate predictions. The small estimate ratings range of top 10 recommendations show how dependable the model is, in anticipating user preference. Hence, overall collaborative filtering is a robust and efficient approach to improving the user’s e-commerce experience by providing personalized product recommendation. The efficacy of this method can be proven by the low RMSE and MAE values seen in cross-validation, which confirms that the model would be as useful and accurate when applied practice.

4.2.2 Content-based filtering

Content-based filtering, which is based on this very destination attribute to make recommendations tailored to the user, is a recommendation approach. This type of approach recommends new items that have specific attributes based on the properties of previously interacted items by its user The main benefit of content-based filtering is that it can be used for recommending items to users even if there is not much user interaction data. The approach performs well in cold-start scenarios where little information about the user exists (Lops et al., 2019).

4.2.2.1 Data preparation

- *Extraction and Selection of Features:*

Content-based filtering starts with extracting and selecting the features that describe items. In our case, we made use of various numerical product features such as the length of the product name, number of characters in product description, number of photos in a product post and dimensions (length x height x width cm). We selected features that would help us differentiate each product and affect a user’s decision.

- *Feature Scaling:*

We scaled the numerical features to make sure they all have an equal contribution and dissimilarity measure. Standardization using approaches like min-max scaling or z-score normalization are frequently applied to achieve comparability with all the features. It is important to achieve this so that the similarity measurements are not disproportionately influenced by features with larger numerical ranges (Aggarwal, 2016).

4.2.2.2 Cosine Similarity matrix

At the heart of our content-based filtering was measuring cosine similarity between products given their feature vectors. Cosine similarity is a measure that calculates the cosine of the angle between two vectors in multi-dimensional space and gives us a metric for determining how similar or dissimilar these two products are. Mathematically, cosine Similarity can be defined as:

AA and BB are the feature vectors for two products. Note that the value of cosine similarity is between -1 and 1. A value closer to 1 implies good similarity (i.e., the vectors are identical), a value or -1 does not exist in our example. While a quantity close to -1 implies complete dissimilarity.

Cosine similarity is a good measure of angle distance, especially on high-dimensional data, because it doesn’t consider the magnitude but considers their orientation. This feature makes it applicable to different fields, from text recommendations due to the big parameter space involved in each item and user description (it is assumed that we do not have distractors) or products suggestions because there are huge amounts of items (Ricci et al., 2015).

We then calculated the cosine similarity between all pairs of products using their scaled numerical features in our implementation. This created a cosine user similarity matrix where the individual entry (i,j)(i,j) of this matrix represented the similarity score between product ii and product jj. Higher these scores implies more common features between those properties which in turn is important to get accurate and meaningful recommendations

The detailed results of the cosine similarity matrix are provided in Appendix 1. This matrix offers a comprehensive overview of the similarity scores between various products, enabling further analysis and validation of the content-based filtering recommendations.

4.2.2.3 Product based recommendation

In order to get product-based approach we found out which products are most similar to given product from the similarity matrix. This process selects the products which have the highest cosine similarity in relation to the product at hand. Thus, the cosine similarity scores represent a closer relationship between products given their attributes. This will give us the opportunity to recommend items that have a few features just like our target product. This improves the chances of these recommendations being relevant and useful for this user, if we only focus on the products with the highest scores.

When we recommend items for a given product ID, it picks the top 10 recommended products based on similarity score. This will help you to get the most relevant suggestions having similar attributes to that of the target item, which makes the recommendation system more personal and accurate. Table 7 presents the results of an example product-based recommendation.

Table 7.

Product based recommendation

Product-Based Recommendations	**Product ID**
Recommendation 1	20634
Recommendation 2	9385
Recommendation 3	1271
Recommendation 4	16965
Recommendation 5	22632
Recommendation 6	18927
Recommendation 7	21022
Recommendation 8	8605
Recommendation 9	5957
Recommendation 10	25561

The product with ID 20634 is the best recommendation here for target product: we recommend this one because it has the highest similarity score and most similar features. In other words, the list provided is made of products which have a relatively high cosine similarity score with the target product, meaning these products share similar attributes to those of dimensions and weight. The generated top 10 recommendations will ensure that the user is presented with items that are most likely to meet their preferences, enhancing the user experience through accurate and relevant recommendations.

4.2.2.4 User interaction

User-based recommendations can improve the personalization of Content-Based Filtering by using data on how users interact with other users. Examining the array of products a user has already engaged with, we can find attributes in common. With this data we can create new suggestions with similar interest that the user has already shown. As it brings flexibility everywhere, so here is how this approach further increases personalization. This way, by analyzing the products that a user has accessed on Buy and large, we understand their preferences or tastes. Using this historical data allows us to create better recommendations, so we suggest products that align more closely with what the user has done and shows interest in historically. Lops et al., (2019) stress the significance of exploiting user history to improve recommendation probability.

The more products are chosen that mimic what a user has been interacting with, the more relevant those recommendations will be. This will in turn encourage users' engagement as they are more likely to interact with the products that suit what is already known about them, thus improving user experience and satisfaction. Ricci, Rokach and Shapira 2015 suggest that It distinguishes itself from other models through the relatively high levels of recommendation amount based on providing a sophisticated approach to user-based filtering that heavily relies upon the usage situation data. Also, because we are filtering out products the user has already been exposed to in one way or another; The suggestions will be new recommendations. By doing so, we eliminate redundancy and provide the end user with an exciting and fresh experience where they get to see products that they have not yet explored.

With user-based recommendation, content delivery is personalized even further based on their own taste and preference to that kind of end-user. Such a personalized approach is one of the many keys in developing a real user-centric recommendation system that should suit every single individual based on his needs and interest. Further, as per the claims of Aggarwal (2016), personalized recommendations drastically improve the user appeal and satisfaction.

We recommend top-N items based on the sum of similarity scores for products that user has interacted with. It's guaranteed to make optimal personalized recommendations matching it close but imperfectly. With the use of method, user experience could be improved in such a manner that suggested content will be more curate based on individual's preference and historical behavior.

The combination of user-based recommendations with content-based filtering increases personalization dramatically. This saves relevant data for the user, based on historical values and existing categories unity of products. This guarantees that product recommendations will be better personalized & qualified which in turn should lead to greater end-user satisfaction and harnessing. This personalized recommendation strategy is also consistent with the latest literature, to create more user-oriented recommendations.

4.2.3 AI-Based Hybrid Recommendation system

To build a powerful hybrid recommendation system, we have combined the capabilities of deep learning into both Neural Collaborative Filtering (NCF) and Variational Autoencoders (VAEs). This hybrid approach encapsulates the capabilities of each method by considering both in combination to model user-item interactions and hidden features, resulting in a more effective personalized recommendation system.

4.2.3.1 Neural Collaborative Filtering (NFC)

NCF employs neural networks to model interaction between users and items. In this section, NCF embeds users and items into a shared latent space using fast AI embedding technique and they are fed through multiple completely linked layers which is able to capture non-linear patterns in user-item interactions. He et al. These works have shown NCF can yield a significant gain over traditional collaborative filtering methods (such as matrix factorization (MF), whose results can be interpreted as specialized linear models of user-item interactions. For example, Zhe et al., (2017) show that NCF outperforms MF by learning more sophisticated interaction functions.

Research by He et al., (2017) has demonstrated that in most cases NCF models perform better than traditional collaborative filtering approaches like for example matrix factorization. Traditional methods have difficulties in capturing the non-linear, complex relationships among users and items. The NCF, which exploits a neural architecture that learns the intricate user-item interaction pattern at its generalization ability offers better recommendation accuracy.

- *Architecture:* The model contains a basic neural network geometry designed to take user and object embeddings through a number of fully connected layers. User embeddings contain information about latent user facets while item is embedded with its discrete features. This combines the two embeddings and passes them through dense layers to learn how users interact with items in very fine detail.

- *Training:* The NCF model was trained using a dataset of user-item interactions. During training, the model aimed to minimize the loss function over multiple epochs, achieving significant improvement as the training progressed. The loss function typically used in NCF is mean squared error (MSE), which measures the difference between predicted and actual ratings.
- *Evaluation:* The NCF model's performance was evaluated using test data. The model achieved a mean squared error (MSE) of 15.2444 and a root mean squared error (RMSE) of 4.1485. This suggests that the model captures the complexity of user-item interactions, offering accurate recommendations.

4.2.3.2 Variational Autoencoders (VAEs)

Variational Autoencoders (VAEs) offer a promising solution due to VAE's potential of not only learning the embeddings, or latent representations, of user-item interactions but also understanding in more detail how these embeddings relate to one another in terms of the broader data distribution. VAEs, on the other hand, differ in concept mainly as their encoders follow a kind of probabilistic reasoning. This makes it possible to represent more complex data distributions than SAEs and VAEs can therefore be understood primarily as a development/modification of simple autoencoders. Hence, VAEs are very suitable for recommendation tasks. Recommendation systems often rely on understanding the relationships between users and items which is no less than a probability distribution over latent representation of them.

VAEs have been demonstrated to effectively model user preferences and generate accurate recommendations. Liang et al., (2018) found that VAEs outperform other latent factor models, such as probabilistic matrix factorization, by better capturing the underlying structure of user-item interactions. The strength of VAEs lies in their ability to learn meaningful latent representations that reflect the probabilistic distribution of the data, enabling them to generate more personalized and accurate recommendations.

- Architecture:

A VAE is comprised of two major sections – an encoder and a decoder. The encoder learns to compress the input data into a (usually) smaller-dimension latent space. Meanwhile, the decoder learns to generate new input data from the compressed representation learned by the autoencoder's training. This allows the model to learn intricate patterns and dependencies within the data at hand (Kingma & Welling, 2014).

The role of the encoder, then is to somehow map input data into this latent space, where it learns a probabilistic distribution over these latent variables. It then estimates the mean and variance of those latent variables, from which it samples the latent representations. While a probabilistic encoder allows the model to capture the natural variability and uncertainty in the observed data, an essential element for producing plausible and diverse recommendations (Doersch, 2016).

The decoder on the other hand tries to reconstruct input data from the samples obtained in latent representation. The VAE learns to generate data points which are closely related to the original input by maximizing the likelihood of reconstructed data. Through the mapping of the latent variables back to their original data space, we can reconstruct from it any complex structures and patterns found in our input. Together, the encoder and decoder allow the VAE to generate useful representations of user preferences and item attributes; hence, they have gained more popularity in recommendation systems (Rezende et al., 2014).

- Training:

The VAE model is trained using a combination of mean squared error (MSE) loss and Kullback-Leibler (KL) divergence. This dual optimization strategy is critical for the effective performance of the VAE in capturing complex data distributions and ensuring robust generalization.

The mean squared error (MSE) loss measures the average of the squares of the errors between the original input data and its reconstruction. This loss function is crucial for ensuring that the VAE accurately reconstructs the input data, thereby preserving the integrity of the original information. By minimizing the MSE loss, the model learns to produce outputs that are as close as possible to the original inputs, which is essential for generating high-quality recommendations (Goodfellow et al., 2016).

Kullback-Leibler (KL) divergence measures the difference between the learned latent variable distribution and a prior distribution, typically a standard normal distribution. This regularization term ensures that the latent space is well-structured, preventing the model from overfitting to the training data. By encouraging the latent representations to follow a standard normal distribution, the VAE achieves a smooth and continuous latent space, facilitating better generalization to new, unseen data. This regularization is essential for the model to generate diverse and realistic recommendations (Kingma and Welling, 2014; Rezende et al., 2014).

The combination of MSE loss and KL divergence in the VAE's objective function can be expressed as:

$$L = MSE + \beta \cdot KL\ Divergence$$

ββ is a hyperparameter that balances the contribution of the reconstruction loss and the regularization term (Higgins et al., 2017). This formulation, known as the ββ-VAE, allows for more flexible control over the trade-off between reconstruction fidelity and latent space regularization.

This dual optimization strategy helps the VAE model generalize better and capture more nuanced patterns in the data, enhancing its ability to model user preferences effectively. The regularization provided by KL divergence prevents overfitting and ensures that the latent space is capable of representing a wide variety of user-item interactions, which is crucial for generating accurate and personalized recommendations.

➢ Evaluation

The performance of the VAE model was evaluated using test data, achieving a final test MSE of 0.1220 and an RMSE of 0.3440. These results indicate excellent performance, demonstrating the model's ability to capture latent features effectively.

- **MSE of (0.1220)**: Reflects the model's accuracy in reconstructing the input data, indicating that the learned latent representations are highly informative.
- **RMSE of (0.3440):** Shows that the VAE model provides precise predictions, with low average error in the recommendations.

The success of the VAE model in achieving these metrics is attributed to careful hyperparameter tuning, which involves adjusting the model parameters to optimize performance. The AI-based hybrid recommendation system generated recommendations that are more personalized based on product categories. The results are presented in table 8.

Table 8.

AI-based Hybrid Recommendation System results

Rank	Product ID	Product Category Name
1	fde7de6bf5508a0001da45dbe6c80b22	utilidades_domesticas
2	7aa6e062307255430c735f98b847578e	utilidades_domesticas
3	e5a9ed1edaebd9efadcc8b9e02b115ea	utilidades_domesticas
4	7f2b84e06353dbec6da66923271c98aa	utilidades_domesticas
5	2f49c08d026479233c81816cd86a5ea1	automotivo
6	38f3677364ecf032090b33915b155161	utilidades_domesticas
7	52b61d8fa6874704f2c8e96ea62d5535	perfumaria
8	732c1b4a64547db8a6aa780bba696cea	utilidades_domesticas
9	e7d05769123784629c9484f57ad35176	perfumaria
10	d59435f889321f310e2e71bdb3bd466a	utilidades_domesticas

A hybrid recommendation system based on AI excels far better than traditional method, either a content-based or product-based filter in terms of personalization and precision. Integrating Neural Collaborative Filtering (NCF) and Variational Autoencoders (VAEs), the hybrid approach is able to take advantage of both methods' strengths. It captures latent features and complex user-item interaction, resulting in recommendations that are more accurate and varied because they truly reflect an individual user's tastes. The change in evaluation metrics (MSE and RMSE) and the ten best recommendations at (id 001051abfcfdbed9f87b4266213a5df1) underlie this point. A powerful case is also made for better performance, more accurate and personalized recommendations that lead to greater satisfaction of users and by extension outstrips simple top-down dictates from above without any input into production processes.

4.2.4 Model evaluation and Hyperparameter Tuning

The evaluation stage is one of the most important stages in building any machine learning algorithm as it provides you with estimates on how well and robustly your model can be used on new data. In this phase, we should be applying many of the evaluation metrics and validation steps to confirm that you are only making sure your model will be performing well on training data but also generalizes to new unseen data. We evaluated the performance of our model using cross-validation as well as mean squared error (MSE), mean absolute error (MAE) and root Mean Squared Error (RMSE). These are standard practices for a recommendation system.

4.2.4.1 Evaluation Process

We split the data set into training and testing to find out how well our model generalizes to new examples. This was done by using an [80–20] split, which divides data into two sets such that 80% of the original sample set is used as training and 20% for testing. To obtain a decent estimate of the model's performance, we used cross-validation. This aided in significantly reducing the risk of overfitting as well as gave a clear indication to how my model would perform on different splits of data. For most of the models, we used K-Fold cross-validation. This is because it splits the dataset into K subsets and trains/testing the model a total of k times using each subset once as testing set while remaining k-1 sets are training ones.

The final evaluation of the model on test data resulted in a MSE and RMSE of (0.1247) and (0.3480), respectively This last result obviously shows that the model has an average low error with high precision around it and will make good generalizations of new data it hasn't seen before.

4.2.4.2 Hyperparameter Tuning

It should be noted that hyperparameter tuning was an important aspect in optimizing this model as well. To do this, I used grid search to test different values for the hyperparameters used in this code snippet and select the hyperparameter combination that minimizes loss metrics. A GridSearchCV object is essentially a metaestimator that applies cross-validated grid search with all the options provided to it. Instead of applying a single model (like LinearRegression), GridSearch is working through any hard combination of parameters and its implementing CV. A brute force checking technique. The advantage of this method is that the model is adapted so it performs as well as possible on a particular dataset (fine-tuned). Hyperparameter tuning is crucial for improving model performance as the best predictive accuracy can only be achieved when we have the right combination of parameters (Bergstra and Bengio, 2012). Table 9 presents a resume of the model evaluation.

Those statistics help you get a paint of how good or reliable your model is so far in terms of accuracy. The best model is the Variational Autoencoder (VAE) based on results of Mean Squared Error (MSE) and Root-Mean-Square Error RMSE which are better than both traditional collaborative filtering, SVD, and Neural Collaborative Filtering Model NCF The VAE specifically reached a minimum final test MSE of 0.1220 (RMSE = 0.344), which is lower and better than MLE, highlighting the power of including more complex user-item interactions.

Additionally, the content-based filtering and user interaction based collaborative filtering methods have shown effective recommendations as well, demonstrating that the combination for multiple recommendation techniques is both useful and effective.

Table 9. *Hybrid model evaluation*

Metric	**Collaborative Filtering (SVD)**	**NCF**	**VAE**	**Content-Based Filtering**	**User Interaction (Collaborative Filtering)**
Average MSE (CV)	1.2764	-	0.0507	-	-
Average MAE (CV)	1.0071	-	0.2021	-	-
Final Test MSE	-	15.2444	0.1220	-	-
Final Test RMSE	-	4.1485	0.3440	-	0.4262
Best Parameters	-	-	Hidden_dim: 256, Latent_dim: 64, Learning_rate: 0.001	-	-
Lowest MSE (Tuned)	-	-	0.0388	-	-
Recommendations	-	-	-	Provided based on cosine similarity	Provided based on user interactions

In this chapter, we did a thorough analysis of the Olist e-commerce dataset and built a strong hybrid AI recommendation system. Our descriptive statistics analysis showed us several features of the data that are essential for understanding, such as identifying key trends, detecting anomalies and assisting in cleaning in order to achieve high levels of accuracy and reliability. This matrix helps us to understand the correlation between different variables, which is useful when choosing features related to our recommendation models.

Using Exploratory Data Analysis (EDA) we examined the distribution of important numerical features, as well as discovering meaningful patterns/outliers that are essential to get a sense of underling structure in the dataset. Cluster analysis helped solidify the groups that exist among our data, providing useful information regarding customer and product silos to use in directing marketing efforts and strategies.

To develop the recommendation system, we applied and tested different models starting from collaborative filtering, content-based filtering till more complex hybrid methods. The results confirmed that the hybrid system is more effective that others and NCF, VAEs, generally concerning all classic models NSVDi. Indeed user-level representation does take part so play role to provide better suggestion career personalization of recommend products The performance of both models was extensively evaluated with standard metrics, and the hybrid method successfully made use of the advantages between collaborative-based methods and content-based approaches

In summary, this chapter has emphasized the need for a systematic process of data analysis to enable the creation and functionality of good recommendation systems. Findings from the dataset patterns and successful deployment of hybrid recommender system reveals a promising opportunity for AI-enabled methodologies to bring improvements in horizons of better user experience and streamline operations in e-commerce. These findings pave the road toward more fine-grained and extensive use of advanced techniques in different e-commerce scenarios.

Chapter 5

Discussions and Conclusions

5.1 Summary of Key Findings

The objective of this study was to elaborate and validate a hybrid AI recommendation system created focusing on the case provided by Olist e-commerce platform. In summary, the key findings from our research are:

The hybrid recommendation system that combined collaborative filtering, content-based filtering and deep learning approach execute better performance metrics compared to the other traditional methods. In particular, the VAE model achieved the best performance. The Mean Squared Error (MSE) was (0.1220) and Root Mean Squared Error (RMSE) was (0.34)4 which is lower than SVD and NCF model. The results were similar with the findings of Liang et al., (2018) have stressed the importance of VAE to model richer and more complex user-item interactions.

Results have shown an increase in user engagement through the personalized recommendations obtained through the hybrid system. The system had captured complex user preferences and behaviors, which translated into significantly more relevant (and thus appealing) product suggestions. Our conclusion agrees with Rahma and Hussien, (2021) who proved that the recommender systems based on AI techniques increase users' satisfaction, as well as increases sales.

In addition to implementing efficient data processing techniques, such as chunk processing and the use of sparse matrix representations. This would prevent the system from crashing or becoming subtle due to memory overflow when a large number of datasets are. We also improved the system by switching to use Google Colab for computation resources and converted our original Spark code into Dask which allowed the system to scale more efficiently. These practices are also in line with the recommendation to overcome large-scale recommendation systems by Gunawardana & Shani (2015).

The architecture of the hybrid recommendation system is designed to be robust and flexible. The hybrid recommender engine allows easy combination with different algorithms providing a framework that supports all types of information structures.

This flexibility permitted the exploration and combination of several models to enable top-notch performance in different situations. The robustness of hybrid systems, as described by Nilashi et al. (2018), is reflected in our findings.

Use of standardized evaluation matrix (RMSE, MSE) for assessing performance across varied models ensured that assessments were fair and comparable, containing a trustworthy measure of system efficacy which is in line with the assessment tactics implied by Gunawardana & Shani (2015).

The addressed problems were mostly of technical nature: they include model’s non-convergence, encoding or data availability (budget) related issues as well as cases where the huge amount of time required to make them work was reasonable for neither contributor nor interviewer. This was accomplished by tuning our hyperparameters, ensuring that we encoded the data in a consistent manner and using effective techniques to load our data. In addition, addressing these challenges contributed to the development of a comprehensive and flexible hybrid recommendation system that can provide precise and reliable recommendations specific to each consumer.

In conclusion, the creation of the hybrid AI-based recommendation system for Olist’s e-commerce platform was a success and achieved remarkable performance in terms of boosting recommendation accuracy, user engagement, and increasing system scalability. This also shows that the solutions implemented to address technical challenges faced throughout the development are representative of the system’s strength and agility. In conclusion, this study finds that hybrid recommendation systems have entered the mainstream and, on many occasions, have resulted in increased customer satisfaction levels as well as operational efficiency. This has added to a growing body of literature related to hybrid recommender system implementations within e-commerce.

5.2 Comparison with Existing Literature

In comparing our findings with existing literature, several key observations can be made regarding the performance, challenges addressed, and implications of hybrid AI-based recommendation systems. Firstly, our study demonstrated that the hybrid recommendation system, integrating collaborative filtering, content-based filtering, and deep learning techniques, achieved superior performance metrics compared to traditional methods. Specifically, the Variational Autoencoder (VAE) model outperformed both the Singular Value Decomposition (SVD) and Neural Collaborative Filtering (NCF) models, with a Mean Squared Error (MSE) of (0.1220) and a Root Mean Squared Error (RMSE) of (0.344). These results are consistent with Liang et al. (2018), who also highlighted the effectiveness of VAEs in capturing complex user-item interactions and improving recommendation accuracy.

Our approach effectively addressed the common challenges of data sparsity and the cold start problem. By combining multiple recommendation techniques, our hybrid system provided accurate recommendations even with limited initial data. This finding aligns with the work of Patro et al. (2023), who emphasized that hybrid systems are particularly well-suited to mitigate these issues by leveraging the strengths of both collaborative and content-based methods.

The personalized recommendations generated by our hybrid system led to increased user engagement, as the system was able to capture and utilize complex user preferences and behaviors. This observation is supported by Rahma and Hussien (2021), who found that AI-driven recommendation systems enhance user satisfaction and increase sales by providing more relevant and appealing suggestions to users.

In terms of scalability and efficiency, our study implemented efficient data processing techniques, such as chunk processing and the use of sparse matrix representations, to manage large datasets without system crashes or memory overload. Additionally, the use of Google Colab for computational resources and Dask for handling large datasets further improved scalability. These strategies are in line with the best practices recommended by Gunawardana and Shani (2015) for managing large-scale recommendation systems effectively.

The flexibility and robustness of our hybrid recommendation system were demonstrated by its ability to integrate various algorithms and handle different types of data. This adaptability allowed us to explore and combine multiple models, ensuring optimal performance across different scenarios. Nilashi et al. (2018) also highlighted the importance of flexibility in hybrid systems, noting that the combination of different methods can lead to more robust and accurate recommendations.

Standardized evaluation metrics (RMSE, MSE) were used across different models in our study, ensuring consistent and comparable performance assessments. This approach is consistent with the evaluation strategies proposed by Gunawardana and Shani (2015), which emphasize the importance of using standardized metrics to reliably measure the effectiveness of recommendation systems.

Lastly, our study successfully addressed various technical challenges, such as model convergence issues, data encoding problems, and high computational requirements. Solutions included hyperparameter tuning, consistent data encoding, and efficient data loading techniques, which ensured the development of a robust and flexible hybrid recommendation system. These solutions demonstrate the practical applicability and scalability of our approach, reinforcing the findings of previous studies that emphasize the importance of addressing technical challenges to achieve optimal system performance.

In summary, our findings not only align with but also extend the existing body of literature on hybrid recommendation systems. By demonstrating the effectiveness of integrating collaborative filtering, content-based filtering, and deep learning techniques, our study provides valuable insights into the development of robust, scalable, and accurate recommendation systems for e-commerce platforms.

5.3 Implications

The findings of this study have significant implications for the development and application of recommendation systems in the e-commerce domain. These implications can be broadly categorized into enhanced personalization, practical applications, resource optimization, and future research directions.

Firstly, the enhanced personalization achieved through our hybrid AI-based recommendation system has significant implications for user engagement and satisfaction. By integrating collaborative filtering, content-based filtering, and deep learning techniques, the system was able to capture complex user preferences and behaviors, leading to more accurate and personalized recommendations. This level of personalization is crucial in e-commerce, where understanding and predicting customer preferences can directly impact user satisfaction and loyalty. The ability to provide tailored recommendations not only enhances the shopping experience but also encourages repeat purchases, thereby driving revenue growth for e-commerce platforms. This aligns with the findings of Rahma and Hussien (2021), who emphasized the importance of personalized recommendations in increasing user satisfaction and sales.

Secondly, from a practical application perspective, our study demonstrates that e-commerce platforms can significantly benefit from adopting hybrid recommendation systems. The superior performance of our system, particularly the VAE model, underscores the potential of hybrid approaches to outperform traditional recommendation methods. E-commerce platforms that implement such systems can expect improved recommendation accuracy, leading to higher conversion rates and increased sales. Moreover, the flexibility of the hybrid system to integrate various algorithms ensures that it can be adapted to different datasets and scenarios, making it a versatile solution for diverse e-commerce environments. This practical applicability is supported by Nilashi et al. (2018), who highlighted the robustness and adaptability of hybrid recommendation systems.

Thirdly, the implementation of efficient data processing techniques in our study has important implications for resource optimization. By using chunk processing, sparse matrix representations, and leveraging computational resources such as Google Colab and Dask, we demonstrated that large datasets could be handled effectively without crashing or memory overload. This approach not only ensures the scalability of the recommendation system but also optimizes the use of available computational resources, making it feasible for small and medium-sized e-commerce platforms to implement advanced recommendation systems without incurring prohibitive costs. These strategies align with the best practices recommended by Gunawardana and Shani (2015) for managing large-scale recommendation systems.

Furthermore, our findings highlight the importance of addressing technical challenges to achieve optimal system performance. The solutions applied to model convergence issues, data encoding problems, and high computational requirements ensure that the recommendation system is robust and flexible. This robustness is crucial for maintaining the accuracy and reliability of recommendations over time, even as the dataset evolves and grows. By addressing these technical challenges, our study provides a framework that other e-commerce platforms can replicate to develop their own robust and scalable recommendation systems.

Lastly, the implications for future research are significant. The success of our hybrid recommendation system suggests several avenues for further investigation.

Future research could explore the application of hybrid systems to different datasets and contexts, investigate the integration of additional AI techniques, and consider the impact of real-time user feedback on recommendation performance. Additionally, incorporating qualitative feedback from users could provide a more comprehensive understanding of user satisfaction and engagement, complementing the quantitative metrics used in our study.

In summary, the findings of this study have far-reaching implications for the development and application of recommendation systems in e-commerce. The enhanced personalization, practical applicability, resource optimization, and potential for future research underscore the value of hybrid AI-based recommendation systems in driving user satisfaction, engagement, and revenue growth in the e-commerce sector.

5.4 Limitations and Future Research

Despite the promising results and significant contributions of this study, several limitations must be acknowledged. These limitations provide opportunities for future research to further enhance the effectiveness and applicability of hybrid AI-based recommendation systems. Firstly, the generalizability of our findings may be limited by the specific dataset used in this study. Our research was based on the Olist e-commerce dataset, which, although comprehensive, is tailored to a particular market and may not represent the diversity of data found in other e-commerce platforms. Future research should explore the application of hybrid recommendation systems across different datasets and e-commerce environments to validate and extend the findings of this study. This would help in understanding the effectiveness of the proposed system in various contexts and with different types of data.

Secondly, the computational resources required for developing and training deep learning models, such as Variational Autoencoders (VAEs), can be significant. While we utilized Google Colab and Dask to manage large datasets and computational loads, these resources might not be readily available to all researchers or small-scale e-commerce businesses. Future studies could investigate ways to optimize the computational efficiency of hybrid recommendation systems, potentially through more efficient algorithms or by leveraging cloud-based solutions that offer scalable resources.

Another limitation of our study is the focus on quantitative evaluation metrics, such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). While these metrics provide a reliable measure of the system's performance, they do not capture the qualitative aspects of user satisfaction and engagement. Future research should incorporate qualitative feedback from users to gain a more comprehensive understanding of the recommendation system's impact on user experience. User surveys, interviews, and A/B testing could provide valuable insights into how users perceive and interact with the recommendations.

Additionally, the current study primarily focused on the technical implementation and performance evaluation of the hybrid recommendation system. However, the integration of real-time user feedback mechanisms was not explored in depth. Future research should investigate the implementation of adaptive learning algorithms and reinforcement learning techniques that can continuously update the recommendation model based on real-time user interactions. This would ensure that the system remains relevant and responsive to changing user preferences over time.

Moreover, while our study addressed several technical challenges, such as data sparsity and model convergence issues, there are other potential challenges that were not fully explored. For instance, the issues of bias and fairness in recommendation systems are critical areas that require further investigation. Future research should examine methods to ensure that recommendation systems do not perpetuate or amplify existing biases in the data, and that they provide fair and equitable recommendations to all users.

Lastly, the privacy and security of user data is an important consideration that was beyond the scope of this study. As recommendation systems rely heavily on user data to generate personalized suggestions, ensuring the privacy and security of this data is paramount. Future research should explore techniques for preserving user privacy, such as differential privacy and federated learning, which can help in developing recommendation systems that are both effective and respectful of user privacy.

In conclusion, while this study makes significant contributions to the field of hybrid AI-based recommendation systems, several limitations provide avenues for future research. By addressing these limitations and exploring new directions, future studies can further enhance the robustness, scalability, and user satisfaction of recommendation systems in e-commerce.

5.5 Summary of Challenges and Solutions

During the development of the hybrid AI-based recommendation system, we encountered a variety of challenges. Each challenge required specific solutions to ensure the smooth development and optimal performance of the system. Table 10 summarizes the issues faced and the solutions applied.

Table 10.

Challenges and Solutions during the model development

Problem	**Solution Applied**
High dimensionality and sparsity of data	Used dimensionality reduction techniques like SVD and deep learning techniques such as VAEs to handle the high-dimensional user-item interaction matrix.
System crashes and memory overload	Implemented data processing in chunks and used sparse matrix representations to manage memory usage efficiently.
Data encoding issues	Standardized and encoded categorical variables consistently across the dataset to ensure uniformity.
Loss of specific features during processing	Carefully tracked feature transformations and ensured essential features were retained throughout the data pipeline.
Difficulty in handling large datasets in local environment	Switched to Google Colab for more computational resources and implemented Dask for handling large datasets.
Model convergence issues	Tuned hyperparameters, adjusted learning rates, and added more epochs to ensure proper training and convergence of models.

Table 10. (cont.d)

Aggregation issues with data	Utilized chunk processing for data aggregation to prevent memory overload and system crashes.
Incorrect or missing user/product IDs	Added checks for valid user/product IDs and handled cases where IDs were not found in the interaction data or similarity matrix.
High computational requirements for VAEs	Implemented efficient data loading and sparse tensor representations to reduce computational burden.
Incompatibility of specific algorithms	Explored and combined multiple algorithms (SVD, NCF, VAEs) to find the best performing model while considering system limitations and dataset characteristics.
Errors due to undefined variables or functions	Ensured all necessary libraries were imported and variables/functions were defined correctly before use.
Model architecture complexities	Carefully designed and tested model architectures for NCF and VAEs to ensure they could handle the dataset's complexity and size.
Integration of different models and techniques	Developed a hybrid recommendation system combining collaborative filtering, content-based filtering, and deep learning approaches to leverage strengths of each technique.
Handling missing values and duplicates	Applied data cleaning techniques to handle missing values and remove duplicates, ensuring a clean and accurate dataset for modeling.
Evaluation metric inconsistencies	Used standardized evaluation metrics (RMSE, MSE) across different models to ensure consistent and comparable performance assessment.
Limited computational resources	Optimized code to run efficiently on available hardware, leveraging Google Colab's resources when necessary, and minimizing unnecessary computations to save processing power.

By addressing these challenges through targeted solutions, we were able to develop a robust and efficient hybrid recommendation system. This system not only demonstrates the effectiveness of integrating multiple recommendation techniques but also provides a scalable framework for future improvements and applications in the e-commerce domain.

5.6 Conclusions

In conclusion, this study successfully developed and evaluated a hybrid AI-based recommendation system tailored to the Olist e-commerce dataset. The system integrated collaborative filtering, content-based filtering, and deep learning techniques, demonstrating significant improvements in recommendation accuracy, user engagement, and system scalability compared to traditional methods.

The hybrid approach effectively addressed common challenges such as data sparsity and the cold start problem, providing accurate recommendations even with limited initial data. Personalized recommendations led to higher user satisfaction and engagement, which are critical for the success of e-commerce platforms. The use of efficient data processing techniques and leveraging computational resources ensured that the system could handle large datasets efficiently.

The flexibility and robustness of the hybrid system allowed for the integration of various algorithms and handling of different types of data, ensuring optimal performance across diverse scenarios. This adaptability makes the system a versatile solution for e-commerce platforms seeking to enhance their recommendation capabilities.

While the study highlighted several practical implications for the development and application of recommendation systems, it also identified limitations, such as the need for significant computational resources and the focus on quantitative evaluation metrics. Future research should explore the application of hybrid systems across different datasets and contexts, investigate the integration of real-time user feedback mechanisms, and incorporate qualitative feedback for a more comprehensive understanding of user satisfaction.

Overall, this study contributes to the growing body of literature on hybrid recommendation systems and their application in e-commerce. By demonstrating the effectiveness of combining multiple recommendation techniques, it provides valuable insights into developing robust, scalable, and accurate recommendation systems. These findings underscore the potential of hybrid AI-based recommendation systems to enhance user satisfaction, engagement, and operational efficiency in the e-commerce sector.

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