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Dissertation

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Option : Artificial Intelligence

Product Recommendation System for E-Commerce

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Abstract

by

This thesis addresses the challenges in e-commerce by developing a neural collaborative filtering recommendation system integrated into a Google Chrome extension. The objective is to provide personalized, real-time product suggestions directly within users' browsing experiences. The study begins with an overview of e-commerce growth and the importance of recommendation systems, followed by a literature review on various types and algorithms. The methodology details data collection, preprocessing, and algorithm implementation. The integration strategy discusses the benefits of the Chrome extension, such as enhanced user experience and ease of use. Comprehensive testing on a dedicated test website showed promising results. Despite limitations like manual data input and Chrome exclusivity, the research demonstrates significant potential. Future work will focus on automating data retrieval, improving scalability, and expanding compatibility. This study presents a scalable, user-friendly solution to improve e-commerce through advanced, personalized recommendations.

key words:E-commerce,Recommendation systems ,Collaborative filtering,Neural Collaborative Filtering,Hybrid models,Pattern recognition,User experience

Résumé

Cette thèse aborde les défis du commerce électronique en développant un système de recommandation de filtrage collaboratif neuronal intégré à une extension Google Chrome. L'objectif est de fournir des suggestions de produits personnalisées et en temps réel directement dans l'expérience de navigation des utilisateurs. L'étude commence par un aperçu de la croissance du commerce électronique et de l'importance des systèmes de recommandation, suivi d'une revue de la littérature sur les différents types et algorithmes. La méthodologie détaille la collecte de données, le prétraitement et la mise en œuvre de l'algorithme. La stratégie d'intégration discute des avantages de l'extension Chrome, tels que l'amélioration de l'expérience utilisateur et la facilité d'utilisation. Des tests complets sur un site web de test dédié ont montré des résultats prometteurs. Malgré des limitations comme la saisie manuelle des données et l'exclusivité à Chrome, la recherche démontre un potentiel significatif. Les travaux futurs se concentreront sur l'automatisation de la récupération des données, l'amélioration de l'évolutivité et l'élargissement de la compatibilité. Cette étude présente une solution évolutive et conviviale pour améliorer le commerce électronique grâce à des recommandations avancées et personnalisées.

Mots-clés : Commerce électronique, Systèmes de recommandation, Filtrage collaboratif, Filtrage collaboratif neuronal, Modèles hybrides, Reconnaissance de formes, Expérience utilisateur.

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Dedication of Zerarka Mohamed Wail

I dedicate this work to my beloved parents, who have been my pillars of strength and the driving force behind my accomplishments. Your boundless love, guidance, and unwavering support have been invaluable to me, and I am deeply grateful for the sacrifices you have made for my sake.

Mom, your unconditional love, care, and wisdom have profoundly shaped who I am today. Your steadfast belief in me and continuous encouragement have been a guiding light during difficult times. I am deeply grateful for your unwavering dedication to my well-being and success.

Dad , your unwavering support, guidance, and encouragement have been indispensable on my journey. Your belief in my abilities and continual motivation have propelled me to pursue excellence. I am deeply thankful for your role modeling and for imparting in me the virtues of perseverance, determination, and hard work.

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Dedication of Hazmani Ilyes

I dedicate this work to my beloved parents, whose unwavering support and encouragement have been the foundation of my achievements. Your endless love, guidance, and sacrifices have been a source of strength and inspiration throughout this journey, and I am profoundly grateful for everything you have done for me.

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List of Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
CF	Collaborative Filtering
CF	Collaborative Filtering
CBF	Content-Based Filtering
MF	Matrix Factorization
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
AUC	Area Under the Curve

General Introduction

In the rapidly evolving landscape of e-commerce, recommendation systems have become a pivotal component for enhancing user experience and driving sales. These systems employ sophisticated algorithms to analyze user data and deliver personalized suggestions, thereby streamlining the shopping process and introducing customers to products they are likely to find appealing. By tailoring recommendations to individual preferences and behaviors, e-commerce platforms cannot only increase customer satisfaction and loyalty but also boost conversion rates and average order values.

At the core of recommendation systems is the objective to predict and present products that a user might be interested in based on their past interactions and preferences. This involves processing large volumes of data generated from user activities such as browsing history, purchase history, product ratings, and reviews. By leveraging this data, recommendation systems can identify patterns and correlations that inform the personalized recommendations offered to each user.

Several techniques underpin the functionality of recommendation systems, with Collaborative Filtering (CF) and Content-Based Filtering being the most prominent. Collaborative Filtering operates on the principle that users who have shown similar preferences in the past will continue to do so in the future. This method utilizes a user-item matrix to find similarities between users or items, predicting preferences by referencing the behavior of similar users or items. On the other hand, Content-Based Filtering focuses on the attributes of items and recommends products that share characteristics with those the user has previously liked or interacted with.

Despite their effectiveness, traditional recommendation techniques face challenges such as data sparsity, scalability, and the cold-start problem, where new users or items with insufficient data hinder the recommendation process. To address these issues, recent advancements have incorporated machine learning approaches, hybrid models combining multiple recommendation strategies, and clustering methods that group users or items into communities based on shared preferences.

In e-commerce, the implementation of robust recommendation systems is crucial for creating a competitive edge. By continuously refining these systems and integrating new methodologies, e-commerce platforms can offer increasingly relevant and diverse product suggestions. This not only enhances the overall user experience but also encourages deeper engagement and higher sales, ultimately contributing to the growth and success of the e-commerce industry.

In summary, recommendation systems are integral to modern e-commerce, transforming how consumers discover and interact with products. By harnessing user data and employing advanced algorithms, these systems deliver personalized shopping experiences that drive customer satisfaction and business growth. As the field continues to evolve, ongoing innovations promise to further refine the precision and impact of recommendation systems in e-commerce.

Background of e-commerce and its growth

E-commerce, an abbreviation of electronic commerce, denotes the exchange of goods and services conducted via the Internet. This encompasses various transactions, spanning from retail purchases and auctions on online platforms to business-to-business (B2B) sales and digital ticketing systems..(Willing, n.d.) Electronic commerce leverages information technology to boost sales, enhance business efficiency, and create new products and services. In its operations, a company interacts with numerous entities, including private or corporate clients, business partners, and suppliers. These interactions involve the exchange of various types of information: sharing details about products and services, negotiating transaction terms, exchanging documents, placing and receiving orders, addressing service complaints, and distributing press releases.(Išoraitė and Miniotienė, 2018)

The evolution of e-commerce traces back to its roots in the mid-20th century, primarily through the development of Electronic Data Interchange (EDI) in the 1960s. EDI facilitated electronic document exchange and laid the groundwork for future digital transactions, albeit with limited functionality.

However, the true revolution of e-commerce commenced with the widespread adoption of the Internet in the 1990s. This period witnessed the emergence of secure online payment systems and user-friendly web interfaces, empowering businesses to explore online sales opportunities.

Throughout the late 1990s and early 2000s, e-commerce experienced exponential growth, driven by increasing Internet accessibility and technological advancements. Major online marketplaces like Amazon and eBay emerged, offering consumers a diverse array of products and services from various sellers.

The advent of mobile devices further accelerated e-commerce expansion, enabling consumers to shop conveniently via mobile apps and responsive websites. Additionally, the integration of social media platforms facilitated novel ways for businesses to interact with and engage customers (Willing, n.d.). Recent advancements in artificial intelligence and machine learning have significantly impacted various fields, from sentiment analysis (Tibermacine et al., 2023) to human-machine interaction (Boutarfaia et al., 2023). Meanwhile, deep learning techniques have been pivotal in imagery classification, enhancing human-machine interaction and assistive robotics (Guettala et al., 2022), (Tibermacine and Amine, 2021). This impact also passed on to the field of e-commerce with the objective of boosting sales and improving user experience.

Importance of recommendation systems in e-commerce

The increasing adoption of e-commerce, coupled with advancements in related technologies, underscores the significance of recommendation systems (RS). These systems offer a wide array of items such as products, movies, events, alerts, and articles to diverse user groups, including customers, visitors, system administrators, and content creators. By doing so, recommendation systems contribute to heightened conversion rates, enhanced customer loyalty, and increased satisfaction. Furthermore, empirical evidence suggests that RSs play a crucial role in bolstering key e-commerce metrics, as highlighted in recent research(Kwon and Kim, 2007).For example in platforms like Netflix or Spotify, recommendation algorithms function much like adept salespeople in physical stores. They analyze user behavior and preferences to offer tailored content suggestions, mirroring the personalized service of a skilled salesperson. Researchers also explore leveraging social connections to improve recommendation accuracy. This approach enhances user satisfaction and platform engagement by providing more relevant suggestions.

Problematic

In the expansive realm of e-commerce, both customers and businesses grapple with formidable challenges hindering the smooth exchange of goods and services.

On the customer side, navigating through a multitude of products across various categories presents a daunting task, often resulting in frustration and time wastage. Moreover, customers frequently struggle to articulate their preferences accurately, compounding the difficulty of finding suitable products.The inconsistency in product descriptions and categorizations further muddles the search process, exacerbated by limited filtering options and subpar search functionalities.

Conversely, from the e-commerce business standpoint, these challenges translate into dire consequences, including diminished customer retention, lower conversion rates, and ultimately, reduced revenue. To alleviate these issues, the implementation of advanced recommendation systems is imperative. These systems can deliver personalized recommendations, improve search algorithms, standardize product information, and offer enhanced filtering options, thereby enhancing the overall user experience, streamlining the path to purchase, and fostering greater customer satisfaction and business success.

This thesis aims to delve into the development and deployment of such advanced recommendation systems, exploring their efficacy in addressing the identified challenges and their impact on both customer experience and business outcomes within the e-commerce domain.

The work's objective

Our proposed solution takes the form of an extension that serves as a versatile solution designed to seamlessly integrate into any e-commerce platform, augmenting its capabilities with a robust recommendation system.

By harnessing the power of our extension, users gain access to personalized recommendations tailored to their preferences, irrespective of the website they're browsing. This innovative tool acts as a valuable asset for both customers and e-commerce businesses, enhancing the overall shopping experience while driving sales and engagement. Through sophisticated algorithms and data analysis, our extension ensures that users receive relevant and timely suggestions, optimizing their journey towards finding desired products. Whether it's fashion, electronics, home goods, or beyond, our extension adapts to diverse product categories and user preferences, offering a comprehensive solution for improved discovery and satisfaction. With our extension in place, e-commerce websites can elevate their offering, providing users with a more intuitive and personalized shopping experience that fosters loyalty and drives conversion.

Research Requirements

Before we dive into our research, it's crucial to establish a strong foundation by exploring the key elements that drive our objectives. Here's a structured outline to help shape our understanding and develop a strategic approach:

- **Understanding AI:**
  - Define the core principles and applications of artificial intelligence (AI).
  - Explore various AI techniques, such as machine learning, deep learning, and natural language processing.
  - Investigate the current state-of-the-art advancements in AI research and their implications for our project.
- **Recommendation System Techniques:**
  - Conduct a comprehensive review of recommendation system methodologies.
  - Explore collaborative filtering, content-based filtering, and hybrid recommendation approaches.
  - Investigate recent developments and emerging trends in recommendation system research.
- **Data Handling:**
  - Analyze strategies for data collection, preprocessing, and feature engineering.

  - Explore data storage and management solutions, including databases and data lakes.
  - Investigate techniques for data cleaning, transformation, and augmentation to ensure data quality and usability.
- **Planning the Research Strategy:**
  - Define clear research objectives and goals aligned with our overarching mission.
  - Develop a roadmap outlining the research methodology and timeline.
  - Identify potential challenges and risks and devise mitigation strategies.
  - Establish criteria for evaluating the success of our research efforts.
  - Define roles and responsibilities within the research team and establish effective communication channels.
  - Allocate resources, including budget, personnel, and technology, to support the research endeavor.

Structure of the Dissertation

The dissertation is divided into five chapters, each of which focuses on a different component of the research. An overview of the chapters is given below:

- **Chapter 2: state of art**
  This chapter provides a comprehensive review of recommendation systems, categorizing them into collaborative filtering, content-based, and hybrid models. It discusses evaluation metrics, previous studies, and the challenges faced by existing systems.
- **Chapter 3: Methodology**
  This chapter details the research approach, data collection methods, preprocessing techniques, algorithm selection, evaluation methodology, and the tools and technologies used.
- **Chapter 4: Results**
  This chapter presents the dataset description, performance evaluation metrics, comparative analysis of algorithms, and visualizations of the results.
- **Chapter 5: Integration and Deployment**
  This chapter covers the integration strategy, development, and implementation of a Google Chrome extension to enhance recommendation system functionalities.
- **General Conclusion**
  The final conclusion summarizes key findings, addresses study limitations, and suggests future research directions.

Chapter 1

State of Art

1.1 Introduction

As the amount of information on the Internet continues to grow, having a system that can provide users with personalized recommendations becomes increasingly crucial.

Artificial intelligence (AI) has rapidly permeated various domains, revolutionizing industries and transforming everyday life. In healthcare, AI assists in diagnosing diseases, predicting patient outcomes, and personalizing treatment plans through advanced data analysis and machine learning algorithms. The automotive industry benefits from AI through the development of autonomous vehicles and advanced driver-assistance systems, improving safety and efficiency. In energy sector, AI algorithms enable more efficient and intelligent management of power grids (Naidji et al., 2018; Naidji. et al., 2019), optimizing the balance between energy supply and demand in real-time. In renewable energy, AI enhances the efficiency of solar and wind farms by predicting weather patterns and adjusting operations accordingly. Energy storage systems, like batteries, benefit from AI through improved charge and discharge cycles, maximizing their lifespan and performance (Naidji et al., 2019). AI also plays a crucial role in energy conservation by analyzing consumption patterns and suggesting ways to reduce waste in residential, commercial, and industrial settings (Naidji et al., 2020; Naidji., Choucha., and Ramdani., 2023). AI also plays a crucial role in education, offering personalized learning experiences and automating administrative tasks. In entertainment, AI curates content, generates music and art, and creates immersive gaming experiences. Additionally, AI enhances customer service with chatbots and virtual assistants, streamlines manufacturing processes through predictive maintenance and quality control, and optimizes supply chains.

The widespread adoption of AI across these diverse sectors underscores its transformative potential and the ongoing shift towards intelligent, data-driven decision-making.

In this chapter, we'll cover several key aspects of recommendation systems. We'll begin by exploring the history of these systems, tracing their development over time. Next, we'll define recommendation systems and introduce some fundamental concepts to provide a solid understanding. Then, we'll delve into various classifications of recommendation systems, examining the different approaches used within each classification. Finally, we'll discuss the advantages and disadvantages of these systems and provide examples to illustrate their practical application.

1.2 Recommendation Systems

1.2.1 History of Recommender Systems

In 1992, (Belkin and Croft, 1992). conducted an analysis comparing information filtering and information retrieval. They identified information retrieval as the foundational technology behind search engines, while recommender systems primarily rely on information filtering techniques. In the same year, (Goldberg et al., 1992) introduced the Tapestry system, which marked the inception of collaborative filtering in information filtering, utilizing human evaluations. This study inspired researchers from Massachusetts Institute of Technology (MIT) and the University of Minnesota (UMN) to develop GroupLens (Resnick et al., 1994), a news recommendation service leveraging a user-user collaborative filtering model. Similar recommendation technologies have been applied in various domains, such as music and video. Examples include the Ringo system for music (Shardanand and Maes, 1995) and Video Recommender for video content (Hill et al., 1995). The recognition of the business value of recommendation systems grew with the emergence of e-commerce. Net Perceptions, founded in 1996, was among the pioneering companies focusing on marketing recommender engines, catering to clients like Amazon and Best Buy (Schafer, Konstan, and Riedl, 1999)elaborated on how recommender systems contribute to increasing sales on e-commerce platforms, analyzing aspects like interfaces, recommendation models, and user inputs across six websites. This marked a significant turning point where academic studies and industrial applications synergized, propelling the progress of recommender system technologies.

In 1997, the GroupLens research lab launched the MovieLens project (Harper and Konstan, 2015), leveraging the EachMovie dataset to train the first version of their recommender model. Subsequently, MovieLens datasets were regularly released between 1998 and 2019, establishing themselves as some of the most utilized datasets for recommendation studies.

In 2006, Netflix launched the highly-publicized Netflix Prize competition with the goal of advancing the field of movie recommendation algorithms. This initiative sought to significantly improve the accuracy and effectiveness of movie recommendations provided to users. Noteworthy is the vast selection available on Netflix, comprising over 17,000 films(Ekstrand, Riedl, Konstan, et al., 2011)

Fast forward to the present day, recommendation systems have evolved into indispensable components of virtually all e-commerce websites, playing a pivotal role in guiding users towards relevant products and content.(Dong et al., 2022)

1.2.2 Definition and Basic Concepts

A recommender system (RS) comprises software designed to suggest the most appropriate items to individual users by predicting their interest in an item. This prediction is based on data about the items themselves, the users, and their interactions with items. RS utilize various information sources to deliver predictions and recommendations to users. They aim to achieve a balance between accuracy, novelty, diversity, and stability in their recommendations. (Bobadilla et al., 2013).

There have been multiple interpretations of recommendation systems over time. However, the most widely accepted and overarching definition, attributed to Robin Burke, is as follows: "A recommendation system is a subclass of information filtering system that seeks to predict the 'rating' or 'preference' a user would give to an item."(Burke, 2002)

At the core of these systems lie two fundamental entities: users and items.

Users

Users are the starting point for any recommendation system. Each user has their own unique tastes, preferences, and behaviors, which serve as the foundation for personalized recommendations. Information about users can come from various sources, such as:

- **Purchase or activity history** : Items purchased, movies watched, songs listened to, or books read reveal users' preferences and interests.
- **Demographic data** : Age, gender, location, and other demographic information can provide contextual clues about potential tastes.
- **Interactions with the system** : Ratings, reviews, comments, and searches conducted by users help refine their profiles and identify trends.

Items

Items represent the set of choices that the recommendation system presents to users. These can be physical products, digital content, services, or any other entity relevant to the system's context. The description of items varies depending on the domain, but typically includes characteristics such as:

- **Attributes** : Objective characteristics like color, size, genre, price, or number of pages.
- **Metadata** : Descriptive information like title, author, director, or associated keywords.
- **Content**: The text, images, videos, or other multimedia elements that represent the item.

1.3 Objectives of a Recommendation System

Previously, we defined recommendation systems as tools and methodologies that offer users suggestions for items they may want to purchase or utilize. In this section, our aim is to refine this definition by highlighting the various potential applications of such systems. For example, Amazon's recommendation system suggests personalized products, driving sales and enhancing customer satisfaction.

For the User:

- Amazon suggests products based on browsing and purchase history.
- Helps users find items they're likely to be interested in.
- Offers a tailored shopping experience.

For the Company (Amazon):

- Increases sales by suggesting relevant products.
- Improves customer retention and loyalty.
- Collects and analyzes user data to refine recommendations.
- Provides a competitive advantage in the e-commerce market.

and there are several reasons why service providers implement recommendation engines:

- Enhancing Online Shopping: Recommender systems provide benefits to both service providers and users. They lower the transaction costs associated with finding and selecting items in online shopping environments. Additionally, these systems have been shown to enhance the decision-making process and improve the overall quality of recommendations.(Isinkaye, Folajimi, and Ojokoh, 2015)
- Revenue Boost: Essentially, this involves selling more items. In the realm of recommendation systems (RS), this objective holds paramount importance. The aim is to increase sales beyond what would occur without recommendations by suggesting items tailored to user preferences and needs
- Understanding Users: Recommendation systems also help businesses understand what their users like, which helps them manage their products better.
- Increase User Engagement:By providing relevant and timely recommendations, recommendation systems aim to increase user engagement and interaction with the platform, leading to longer sessions and repeat visits.(Jannach et al., 2010)

- Optimize Inventory Management: Recommendation systems help businesses better manage their inventory by understanding user preferences and predicting demand for different products. (Adomavicius and Tuzhilin, 2005a)

1.4 Types of recommendation systems

In this section, we'll explore the different types of recommendation systems. These systems play a vital role in guiding users to relevant content or products based on their preferences. From collaborative filtering to content-based filtering and hybrid approaches, each type offers unique insights into user behavior and preferences.

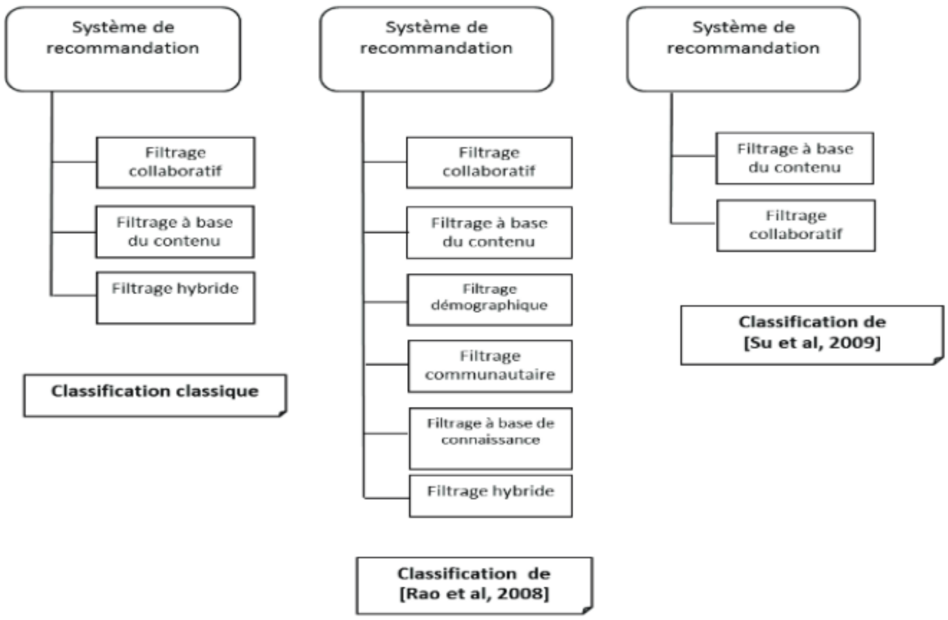

FIGURE 1.1: Types of recommendation systems(Hossain et al., 2022)

1.4.1 Content-based filtering

The content-based technique is a domain-specific algorithm that focuses on analyzing the characteristics of items to make predictions. It is particularly effective for recommending documents such as web pages, publications, and news articles.(Isinkaye, Folajimi, and Ojokoh, 2015)In content-based filtering, recommendations are generated by analyzing user profiles, which are constructed using features extracted from the content of items that the user has previously rated or evaluated.(Burke, 2002)(Bobadilla et al., 2013) and it works by analyzing the attributes or features of items and building a user profile based on the items the user has interacted with positively in the past.

These attributes could include keywords, genres, actors, or authors, depending on the type of items being recommended. The system then compares the attributes of items to the user's profile and recommends items with similar attributes that the user has not yet interacted with. This approach allows for personalized recommendations based on the user's preferences and interests, without relying on the behavior or preferences of other users.(Jannach et al., 2010)

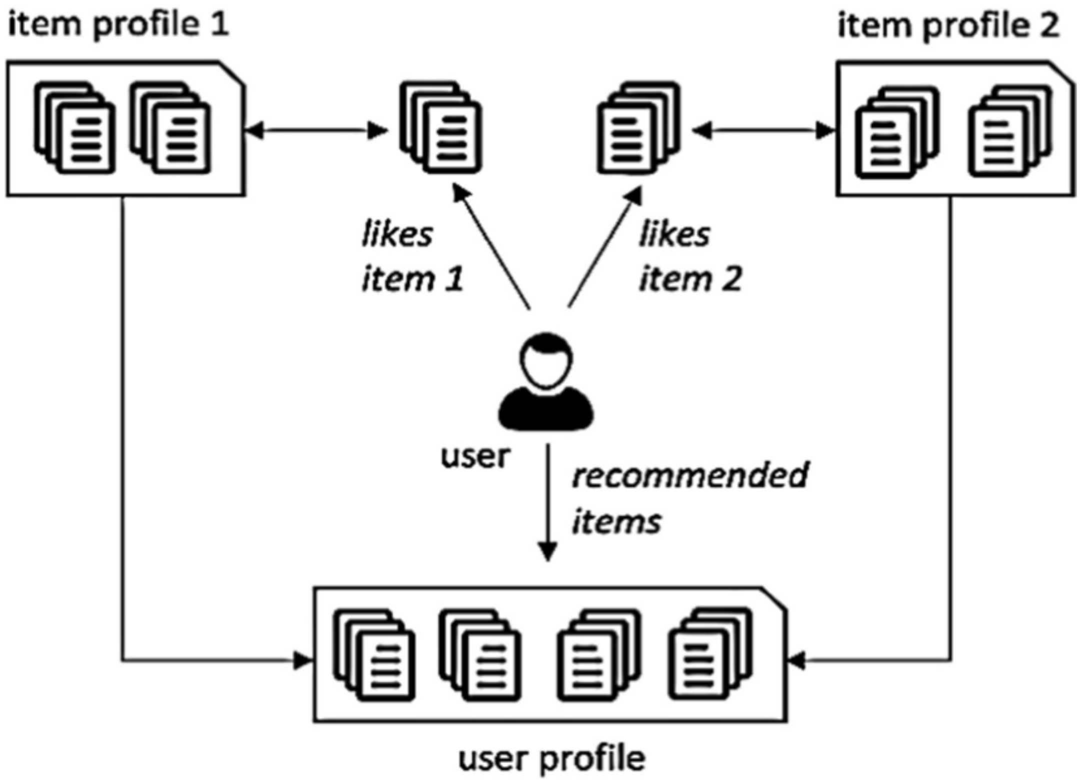

FIGURE 1.2: Content-based recommender system

Advantages

- **Personalization:** Content-based recommendation systems offer personalized suggestions by analyzing the user's preferences derived from their past interactions with items.
- **Independence from User Population:** In contrast to collaborative filtering techniques, content-based systems operate independently of other users' preferences. Consequently, they can suggest items, including new or less popular ones, based solely on their attributes.
- **Reduced Cold Start Problem:** Content-based systems address the cold start issue encountered in collaborative filtering by recommending items to new users solely based on the characteristics of those items.

Disadvantages

- **Limited Serendipity:** Content-based systems might find it challenging to suggest items beyond the user's established preferences, potentially limiting unexpected discoveries.
- **Limited Diversity:** Content-based systems may suggest items that closely resemble each other, resulting in recommendations lacking in diversity.
- **Difficulty Handling New Item Types:** Content-based systems may encounter difficulties when recommending unfamiliar or novel item types if their attributes are not adequately defined or comprehended.

Examples of content-based filtering systems

- **LIBRA**(Mooney and Roy, 2000), operates as a content-based book recommendation system leveraging data sourced from the web. It employs a Naïve Bayes classifier to analyze web-extracted information and construct a user profile. This profile is then utilized to generate a ranked list of titles, drawing from training examples provided by individual users. Notably, LIBRA offers users insights into the rationale behind each recommendation by identifying the features that significantly influence the highest ratings. This transparency empowers users to trust the system's recommendations with confidence.
- **ETSY** is an e-commerce platform that utilizes a content-based recommendation system to suggest handmade or vintage items to users. It analyzes the attributes of products (e.g., category, material, style) that a user has interacted with to recommend similar items.

1.4.2 Collaborative filtering

Collaborative filtering is a prediction method that is applicable across different domains, particularly for content like movies and music that is not easily described solely by metadata. This technique involves constructing a database (known as a user-item matrix) that captures user preferences for items. By calculating similarities between user profiles, collaborative filtering matches users with similar interests and preferences to generate personalized recommendations.(Herlocker et al., 2004; Isinkaye, Folajimi, and Ojokoh, 2015). Such users form a group referred to as a neighborhood. An individual user receives recommendations for items they haven't rated before but that have been positively rated by users in their neighborhood. Recommendations generated by collaborative filtering can take the form of either predictions or recommendations. A prediction is represented by a numerical value, R_{ij}, indicating the predicted score of item j for user i, while a recommendation is a list of the top N items that the user is most likely to enjoy, as depicted in Figure 3. Collaborative filtering techniques can be categorized into two main types: memory-based and model-based (Breese, Heckerman, and Kadie, 2013; Bobadilla et al., 2013)

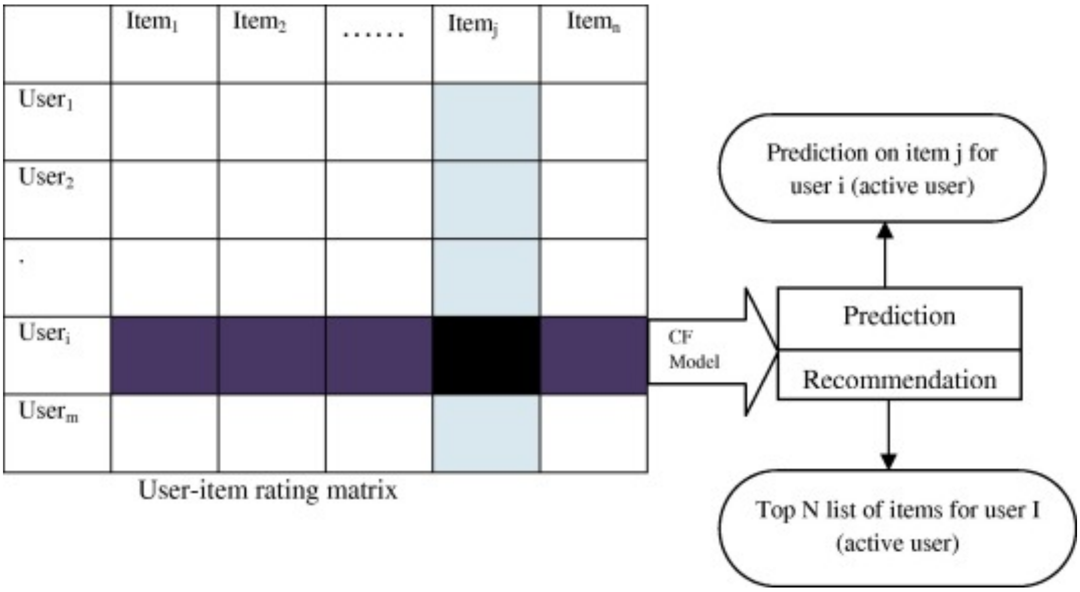

FIGURE 1.3: Collaborative filtering process.(Al-Barznji and Atanassov, 2017)

Memory based techniques

The items that a user has rated in the past are crucial for finding neighbors who have similar preferences. Once neighbors with similar preferences are identified, various algorithms can be used to combine their preferences to produce recommendations. These methods have shown significant efficacy in practical applications.(Zhao and Shang, 2010; Zhu, Ye, and Gong, 2009) Memory-based collaborative filtering can be implemented in two ways: user-based and item-based techniques.

User-based collaborative filtering

In user-based collaborative filtering, the similarity among users is assessed by comparing their ratings on common items. To predict the rating of an item by a user, the system calculates a weighted average of ratings assigned to the item by users who are similar to the active user. These weights are based on how similar these users are to the active user in terms of their ratings on items.

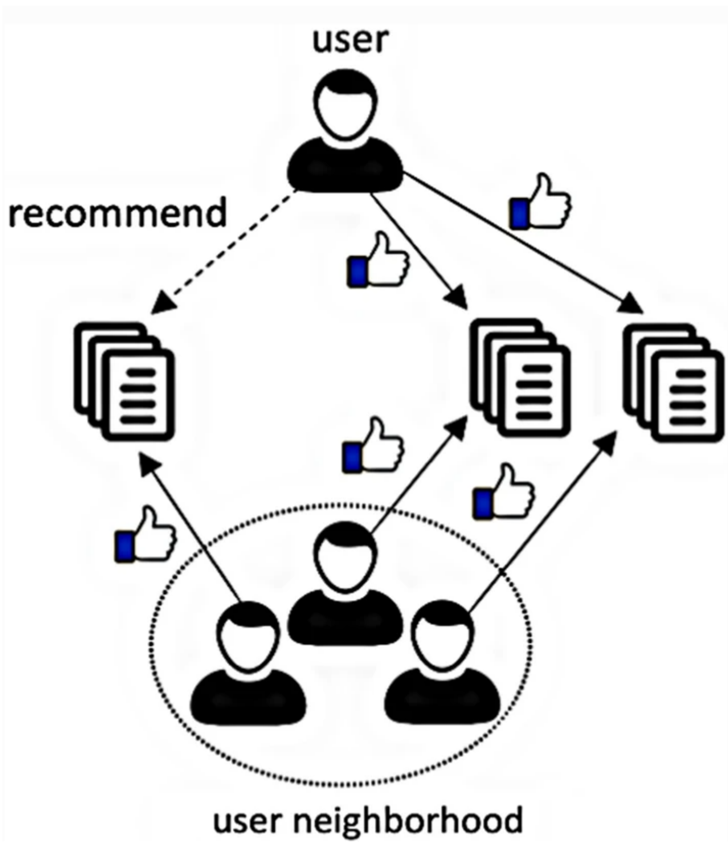

FIGURE 1.4: User-based collaborative filtering(Roy and Dutta, 2022)

Item-based collaborative filtering

On the other hand, item-based filtering techniques compute predictions using item similarities rather than user similarities. It constructs a model of item similarities by examining all items rated by an active user from the user-item matrix. The technique determines the similarity between the retrieved items and the target item, selecting the k most similar items and their corresponding similarities. Predictions are made by computing a weighted average of the active user's ratings on the similar items. Various similarity measures are utilized to compute similarity between items or users. The two predominant similarity measures are correlation-based and cosine-based.(Isinkaye, Folajimi, and Ojokoh, 2015)

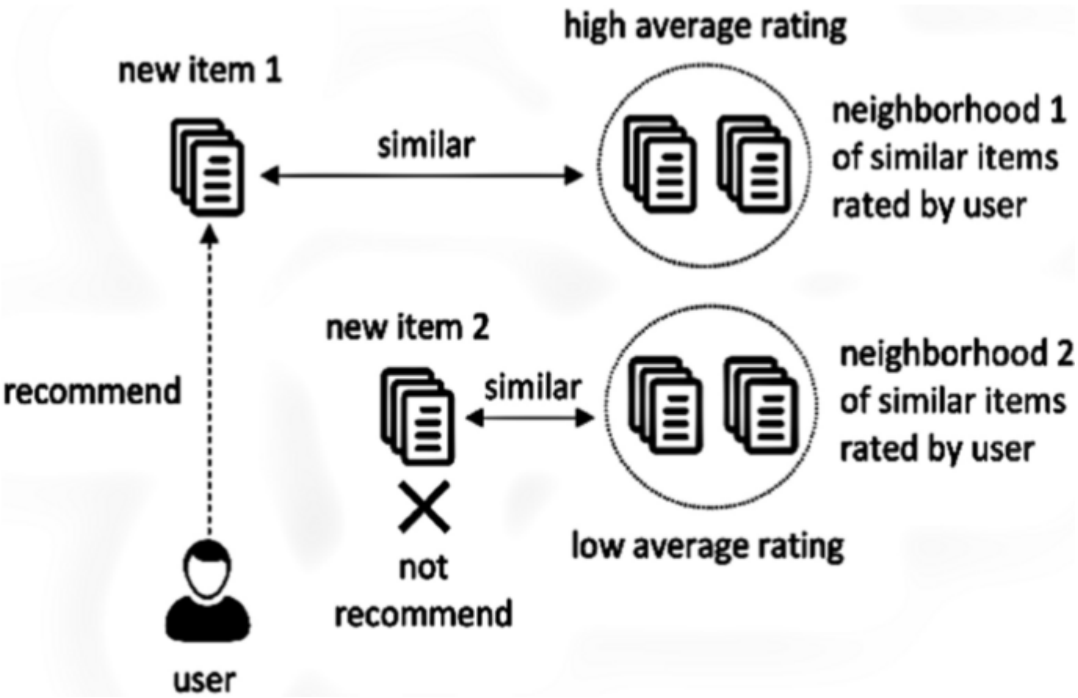

FIGURE 1.5: Item-based collaborative filtering(Roy and Dutta, 2022)

Model-based techniques

In model-based collaborative recommendation systems (Gong, Ye, and Tan, 2009), various machine learning algorithms are employed to construct recommendation models. These algorithms include Bayesian networks, clustering, Markov decision processes, sparse factor analysis, dimensionality reduction techniques, rule-based approaches, among others. The integration of these algorithms allows for the creation of sophisticated recommendation models capable of effectively capturing user preferences and providing accurate suggestions

Advantages

- **Personalized Recommendations:** Collaborative filtering offers personalized suggestions tailored to individual user preferences by leveraging collective user behavior.
- **Scalability and Flexibility:** With the ability to scale to large datasets and adapt to changing user preferences, collaborative filtering systems provide versatile recommendation solutions.
- **Enhanced Serendipity:** By recommending items based on similarities with other users' preferences, collaborative filtering algorithms facilitate the discovery of new and unexpected items, enriching the user experience.

Disadvantages

- **Cold Start Problem:** Collaborative filtering may struggle to provide accurate recommendations for new users or items with limited data, leading to suboptimal suggestions until sufficient information is available.
- **Popularity Bias:** Collaborative filtering tends to recommend popular items more frequently, which can result in a lack of diversity and overlook niche or less-known items that may be of interest to users.
- **Sparsity of Data:** In systems with a large number of users and items, the data matrix used in collaborative filtering can become sparse, making it challenging to compute accurate similarities and generate reliable recommendations.

Examples of collaborative systems

- **Ringo**(Shardanand and Maes, 1995)In Ringo, a user-based collaborative filtering system recommends music albums and artists. When a user joins the system, they are initially presented with a list of 125 artists to rate based on their preference for listening to them. This list comprises two sections: the first section includes frequently rated artists, allowing users to rate artists that others have also rated frequently, thus promoting similarity among user profiles. The second section randomly selects items from the entire user-item matrix, ensuring that all artists and albums eventually receive ratings during the initial rating phase.(Isinkaye, Folajimi, and Ojokoh, 2015)
- **Amazon.com**This e-commerce recommendation engine employs scalable item-to-item collaborative filtering techniques to recommend online products to users, with an algorithm that operates efficiently regardless of the number of users or items(Linden, Smith, and York, 2003) within the database.

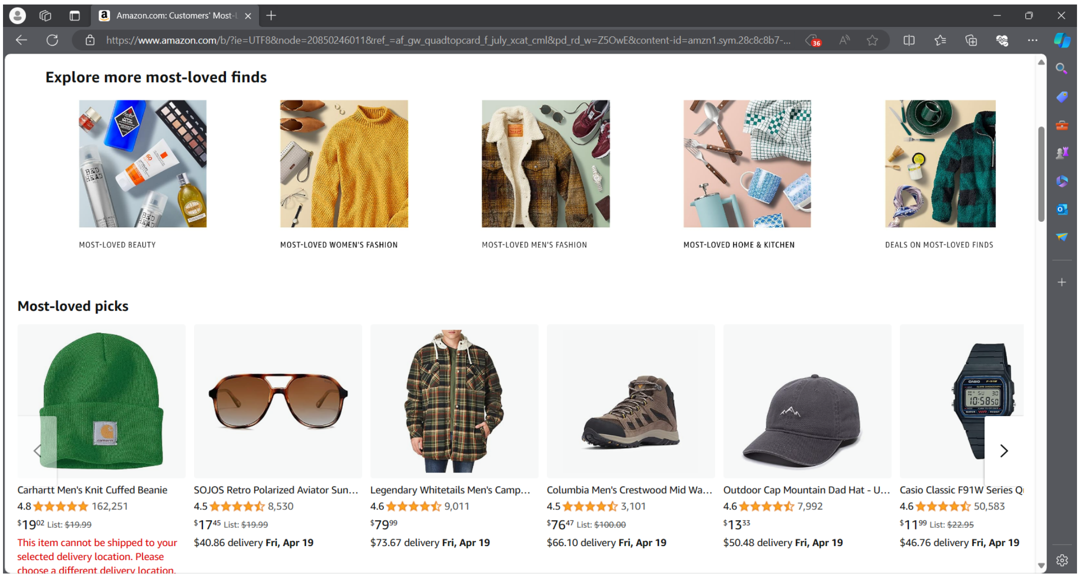

FIGURE 1.6: Amazone interface.

1.5 Hybrid recommender system

As its name implies, a hybrid recommender system results from integrating multiple filtering techniques. One of the most widely adopted combinations involves content-based and collaborative recommendation systems. The objective behind blending different filtering approaches is to enhance the precision of recommendations. (Burke, 2007). The concept of hybrid techniques is based on the notion that combining algorithms can yield recommendations that are more accurate and effective compared to using a single algorithm. This approach leverages the strengths of different algorithms to mitigate the weaknesses of each other. (Schafer et al., 2007)Using multiple recommendation techniques can address the limitations of a single approach when integrated into a combined model. This can be accomplished through different methods: applying algorithms independently and merging their outcomes, blending elements of content-based filtering into a collaborative approach, integrating aspects of collaborative filtering into a content-based approach, or developing a unified recommendation system that harmoniously integrates both approaches.

Advantages

- **Enhanced Recommendation Accuracy:** By combining multiple recommendation techniques, hybrid systems can leverage the strengths of each approach, leading to more accurate and personalized recommendations.

- **Increased Coverage:** Hybrid systems can provide recommendations for a wider range of items by incorporating both collaborative and content-based filtering methods, addressing the limitations of each approach individually.

TABLE 1.1: Hybridization methods

Hybridization method	Description
Weighted hybridization	In weighted hybridization, different recommenders' results are combined using a linear formula to create a recommendation list or prediction
Switching hybridization	The system switches between different recommendation techniques based on the recommendation outcome
Cascade hybridization	A recommendation technique is used to produce an initial ranking of candidate items,with a second technique then refining the list of recommendations.
Mixed hybridization	Mixed hybrids simultaneously combine recommendation results from different techniques rather than providing just one recommendation per item.
Feature-combination	The features generated by a particular recommendation technique are inputted into another recommendation technique.
Feature-augmentation	The technique utilizes the ratings and other data generated by the previous recommender, along with additional functionality from the recommender systems.
Meta-level	The internal model produced by one recommendation technique serves as input for another, leveraging its enriched information compared to a single rating.

- **Robustness to Cold Start Problem:** Hybrid systems can mitigate the cold start problem by using content-based techniques to recommend items for new users or items with limited data, while also leveraging collaborative filtering for users with sufficient interaction history.

Disadvantages

- **Complexity:** Implementing and maintaining a hybrid recommendation system can be complex and resource-intensive, requiring expertise in multiple recommendation techniques and integration of diverse data sources.
- **Scalability:** As hybrid systems combine multiple algorithms, they may face scalability challenges, particularly with large datasets, which can impact performance and responsiveness.
- **Difficulty in Interpretation:** The combination of different recommendation techniques can make it challenging to interpret and understand the recommendations provided, reducing transparency and user trust in the system.

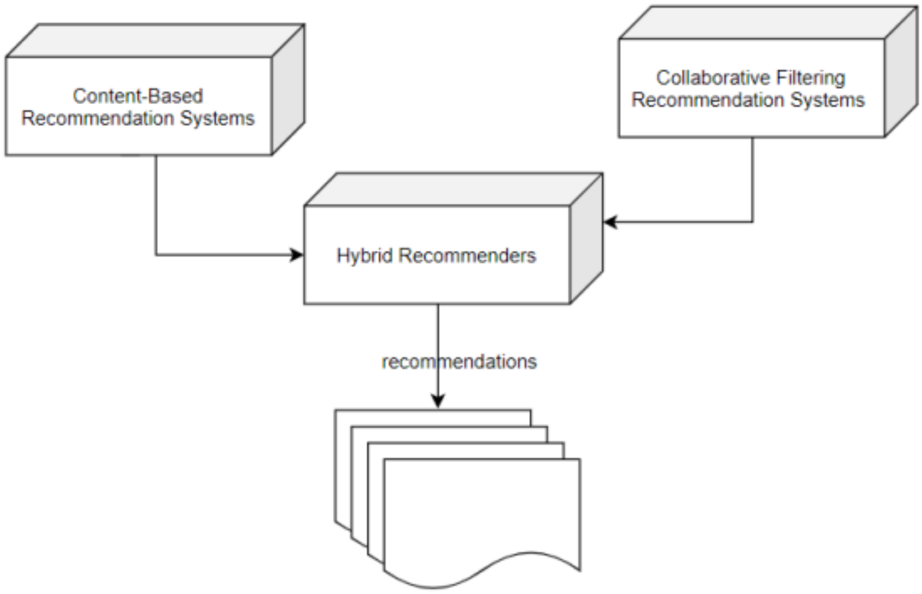

FIGURE 1.7: Hybrid Recommender System

Examples of Hybrid recommender systems

- **DailyLearner**(Billsus and Pazzani, 1999)The DailyLearner is an example of a recommendation system that employs a hybrid approach, combining both content-based and collaborative filtering techniques. In DailyLearner, the recommendation process begins with a content-based approach. However, if the content-based system lacks sufficient evidence to make recommendations, the system then switches to collaborative filtering to provide suggestions based on user interactions and preferences.

- **Pipper** Pipper exemplifies a feature combination method that integrates collaborative filter ratings into a content-based recommendation system as a feature to suggest movies. This approach offers the advantage of not solely depending on collaborative data for recommendations.

1.6 Evaluation Metrics for Recommendation Systems

Evaluation metrics play a crucial role in assessing the performance of recommendation systems. Here's a brief overview of some common evaluation metrics:

- **Recall** : measures the proportion of relevant items present in the top K recommendations out of all relevant items, where K is the number of recommendations generated(Aher, 2023). For instance, Suppose you have a music streaming service that recommends 20 songs to each user. A particular user has listened to 8 songs, and out of those, 6 are included in the recommendation list. In this case, the Recall@20 for that user would be calculated as follows:

$$\text{Recall@K} = \frac{\text{Number of relevant items in recommendation list}}{\text{Total number of relevant items}} = \frac{8}{6} = 0.75 \tag{1.1}$$

- **Precision**:Precision gives a measure of “out of K” items recommended to a user and how many are relevant, where K is the number of recommendations generated for a user.For a recommendation system where we recommend 10 movies for every user. If a user has watched 5 movies and we are able to predict 3 out of them (3 movies are present in our recommendation list) then our Precision@10 is 3/10.(Aher, 2023)

$$\text{Precision@K} = \frac{\text{Number of relevant items in recommendation list}}{\text{K}} \tag{1.2}$$

- **F1**: The F1@K metric serves as a unified measure combining precision@K and recall@K into a single evaluation metric. It calculates the harmonic mean of precision@K and recall@K, thereby offering a balanced assessment of the recommendation system’s performance(Deutschman, 2023)

$$\text{F1@K} = \frac{2 \times \text{Precision@K} \times \text{Recall@K}}{\text{Precision@K} + \text{Recall@K}} \tag{1.3}$$

- **Mean Average Precision (MAP)**:Mean Average Precision (MAP) at K is a quality metric used to evaluate the effectiveness of a recommender or ranking system in returning relevant items within the top-K results. It measures the system’s ability to place more relevant items at the top of the recommendation list. MAP at K considers the precision of the recommendations, focusing on the proportion of relevant items retrieved within the top-K recommendations(EvidentlyAI, n.d.). By aggregating the Average Precision (AP) scores across all users, MAP at K provides a comprehensive assessment of the recommendation system’s performance, emphasizing the importance of returning relevant items promptly to users.

$$\text{MAP@K} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i \tag{1.4}$$

- **Mean Reciprocal Rank (MRR)**:Mean Reciprocal Rank (MRR) assesses the position of the first relevant item encountered within a recommendation list. Reciprocal Rank (RR) is particularly valuable when prioritizing the highest ranked result. In this context, ’rank’ refers to the position of an item in the recommendation list. The reciprocal nature of MRR ensures that items with lower ranks (e.g., Rank 20) receive lower scores, as the reciprocal of a larger rank yields a smaller score. Consequently, the metric rewards systems that accurately predict relevant items at the top of the recommendation list.

$$\text{MRR} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\text{rank}_i} \tag{1.5}$$

- **Mean squared error** (MSE) is a measure used to evaluate the average square of the differences between predicted values and actual values in a dataset. It is determined by averaging the squared residuals, which are the discrepancies between predicted and actual values for each data point.(GeeksforGeeks, n.d.)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1.6}$$

Where:

MSE represents the Mean Squared Error,
n is the number of data points,
y_i represents the actual value of the ith data point,
$\hat{y}_i$ represents the predicted value of the ith data point.

- **Root Mean Squared Error**(RMSE) is the square root of the mean squared error between the predicted and actual values, commonly used as a performance metric in regression analysis.(Allwright, 2022)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1.7}$$

Where:

RMSE represents the Root Mean Squared Error,
n is the number of data points,
y_i represents the actual value of the ith data point,
$\hat{y}_i$ represents the predicted value of the ith data point.

1.7 Previous studies and research in recommendation systems for e-commerce

In this section, I will discuss previous studies and research related to recommendation systems in e-commerce. I will provide a brief overview of their methodologies and findings, and offer a critique of their approaches and results

The authors illustrated in (Koren, Bell, and Volinsky, 2009) how matrix factorization techniques enhance recommender systems by decomposing the user-item interaction matrix and capturing latent factors representing user preferences and item characteristics. These models offered superior recommendations compared to traditional methods. However, the study's exclusive emphasis on rating prediction accuracy as the primary evaluation metric is critiqued. This narrow focus may overlook essential aspects of a recommender system's real-world effectiveness.

This work (Adomavicius and Tuzhilin, 2005b) provides a comprehensive survey of state-of-the-art recommender systems and discusses potential extensions for the next generation. However, a critique of this work is its primary focus on traditional recommendation techniques, which may overlook newer approaches and advancements, such as deep learning-based methods that have since gained significant traction in the field.

In this study, (Zhang et al., 2019) it provides a comprehensive overview of deep learning-based recommender systems, offering novel perspectives and insights. Their thorough examination advances our understanding of how deep learning techniques can be effectively applied to recommendation tasks. However, a potential critique is the broad scope of the study, which may result in a lack of in-depth analysis of specific deep learning architectures or techniques.

In this study(Zheng, Noroozi, and Yu, 2018), the authors introduce spectral collaborative filtering, a novel approach that leverages spectral graph theory to enhance traditional collaborative filtering methods. Their study shows that spectral collaborative filtering effectively captures complex user-item interactions and improves recommendation accuracy over conventional techniques. However, a potential critique is the limited exploration of the scalability and computational efficiency of the spectral collaborative filtering algorithms.

The authors in this study (Wang, Wang, and Yeung, 2015) showcase how collaborative deep learning techniques enhance recommender systems, leading to improved recommendation performance compared to traditional methods. By employing deep learning architectures, the model adeptly captures intricate user-item interactions and learns latent representations. However, a critique lies in the limited exploration of the interpretability of collaborative deep learning models, which often operate as black boxes, making it challenging to discern the reasoning behind generated recommendations.

The study (Covington, Adams, and Sargin, 2016) showcases the effectiveness of deep neural networks in enhancing YouTube recommendations. Leveraging the platform's rich data, their model significantly improves recommendation accuracy and user engagement metrics compared to traditional methods. However, a potential critique is the limited generalizability of the findings beyond the specific context of YouTube. The unique characteristics of YouTube's user behavior and content may not fully represent other recommendation scenarios, such as e-commerce or news platforms.

The study (Hu, Koren, and Volinsky, 2008) showcases the utilization of collaborative filtering techniques on implicit feedback datasets, revealing encouraging outcomes in recommendation performance. Nonetheless, a notable critique pertains to the limited investigation into the scalability and robustness of collaborative filtering algorithms when confronted with large-scale implicit feedback datasets. Furthermore, the study may have inadequately addressed the challenges stemming from sparse and noisy implicit feedback data, potentially undermining the reliability of recommendations in practical settings.

The study (He et al., 2017) introduces a novel approach called "Neural Collaborative Filtering" (NCF) for recommendation systems. NCF integrates neural networks into collaborative filtering, aiming to enhance recommendation accuracy by capturing intricate user-item interactions. The authors demonstrate the effectiveness of NCF through experiments on real-world datasets, achieving significant improvements in recommendation performance compared to traditional methods.However While NCF presents promising results in recommendation accuracy, a potential limitation lies in its computational complexity and resource requirements. The integration of neural networks may increase the computational overhead, especially for large-scale recommendation systems, which could pose challenges in real-time recommendation scenarios. Additionally, the study primarily focuses on the enhancement of recommendation accuracy without extensively addressing potential issues such as interpretability and fairness in recommendations, which are crucial considerations in practical deployment.

The authors in (Guo, Yao, and Gong, 2017) introduces a deep collaborative filtering approach utilizing a marginalized denoising autoencoder. By leveraging the power of deep learning, the proposed method aims to enhance the recommendation performance by capturing complex user-item interactions in collaborative filtering tasks. Through experiments on benchmark datasets, the authors demonstrate that the deep collaborative filtering model achieves significant improvements in recommendation accuracy compared to traditional methods.While the deep collaborative filtering model presents promising results in recommendation accuracy, a potential limitation is the increased complexity and computational requirements associated with deep learning techniques. Training deep models may require substantial computational resources and time, making it challenging to deploy in real-time recommendation systems, especially for large-scale datasets.

This study (Wen, Yan, and Zhu, 2017) investigates collaborative filtering techniques tailored for sparse datasets. The authors compare various similarity measures and implementation techniques to determine their effectiveness in handling data sparsity in recommendation systems. Their experimental results demonstrate that certain similarity measures and optimized implementation strategies significantly enhance the performance of collaborative filtering in sparse data environments.While the study provides valuable insights into the performance of different similarity measures and implementation techniques for sparse data, a potential limitation is the scope of the datasets used in the experiments. The study might benefit from a broader range of real-world datasets to validate the generalizability of the findings.

1.8 Conclusion

In this chapter, we provided a comprehensive examination of recommendation systems, covering their various types, including collaborative filtering, content-based approaches, and hybrid models. We have delved into the metrics used to evaluate their performance. Furthermore, we reviewed previous research and studies focused on recommendation systems within the e-commerce sector, highlighting their effectiveness and the challenges they face. These challenges, including scalability, cold-start problems, and data sparsity, underscore the need for continued innovation and improvement in the field.

As we move forward to the next chapter, we will build upon this foundation by detailing our research approach, which may involve qualitative, quantitative, or mixed methods. We will outline our data collection methods, focusing on user interaction data and product metadata, and describe the preprocessing techniques essential for data cleaning and normalization. Additionally, we will discuss the selection and implementation of algorithms tailored to our research objectives, and our evaluation methodology, to ensure robust and reliable results. Finally, we will explore the tools and technologies, such as programming languages, libraries, and frameworks, that will support our research and development efforts.

Chapter 2

Methodology

2.1 Introduction

In this chapter, we outline the methodology used in our research on recommendation systems. Building on our literature review, we aim to address existing challenges through a structured approach. We will begin by detailing our research approach, followed by our data collection methods, focusing on user interaction data and product metadata. We will then discuss preprocessing techniques for data cleaning and normalization, and the selection and implementation of algorithms. Finally, we will describe our evaluation methodology, and the tools and technologies utilized, such as programming languages and frameworks. This comprehensive methodology will guide us in developing an effective and robust recommendation system.

2.2 Research Approach

The research approach adopted for this study is a quantitative approach. This approach was chosen due to the nature of the data available and the objectives of evaluating the performance of recommendation systems in e-commerce using large-scale datasets.

2.2.1 Rational for Choosing Quantitative Methods

The primary reason for selecting a quantitative approach is to objectively measure and analyze the performance of different recommendation algorithms using extensive datasets. Quantitative methods are suitable for this study because they allow for:

- **Objective Measurement:** Quantitative data provides a means to objectively measure the performance of recommendation algorithms through various metrics such as accuracy, precision, recall, and Mean Absolute Error (MAE).

- **Scalability:** The large-scale datasets used in this study require robust quantitative methods to efficiently process and analyze the data.

- **Reproducibility:** Quantitative methods ensure that the findings of this study can be consistently replicated and verified using the same datasets and algorithms.

2.3 Data Collection Methods

Data collection is a critical step in developing and evaluating recommendation systems. The success of these systems heavily relies on the quality and diversity of the data used. For this study, multiple sources of data were utilized to ensure a comprehensive evaluation of the recommendation models. The primary data sources include Amazon Product Reviews and the Clothing Fit Data from UC San Diego. These datasets were selected due to their relevance and richness in user interaction information.

2.3.1 Data Sources

Amazon Product Reviews

- **Description:** This dataset contains a vast collection of product reviews from Amazon, covering a wide range of categories. Each review includes information such as the product ID, user ID, review text, rating, and timestamp.
- **Relevance:** The Amazon Product Reviews dataset provides valuable insights into user preferences and behaviors, as well as the effectiveness of different products. This data is instrumental in training and testing recommendation algorithms that rely on user reviews and ratings to make predictions.

Clothing Fit Data (UC San Diego)

- **Description:** This dataset contains detailed information on clothing fit feedback, including user ratings and reviews specifically related to clothing items. It includes data points such as user demographics, product descriptions, and fit feedback.
- **Relevance:** The Clothing Fit Data is particularly useful for testing recommendation models in the fashion and apparel sector. It provides a focused view on how users interact with clothing items, their fit preferences, and satisfaction levels. This dataset helps in understanding the nuances of recommending fashion products, which often have higher subjective variability compared to other categories.

2.3.2 Data Collection Process

The data was sourced through extensive searches on the internet, focusing on publicly available datasets that are relevant and comprehensive. The following steps were taken to collect and prepare the data for analysis:

Identification of Relevant Datasets

- Conducted a thorough search for datasets related to e-commerce and recommendation systems.
- Evaluated the datasets based on criteria such as data richness, user interaction details, and category relevance.

Data Acquisition

- **Amazon Product Reviews:** Acquired from public repositories that host Amazon's review data.
- **Clothing Fit Data:** Downloaded from the UC San Diego website, specifically from the dataset repository maintained by Julian McAuley.

Data Preprocessing

- **Data Cleaning:** Removed any duplicates and handled missing values to ensure data integrity. This involved filling in missing values where appropriate or excluding incomplete entries to maintain the quality of the dataset.
- **Normalization:** Standardized numerical features, such as ratings and timestamps, to a consistent scale. This step is crucial for ensuring that the data is suitable for machine learning algorithms.
- **Categorization:** Converted categorical data, such as user demographics and product categories, into numerical formats using techniques like one-hot encoding. This process helps in making the data usable for algorithmic processing.

Data Analysis

The data analysis process involves applying machine learning algorithms and statistical methods to evaluate the performance of the recommendation systems:

- **Algorithm Implementation:** Implemented various recommendation algorithms, including collaborative filtering, content-based filtering,Reinforcement Learning-based Approach, and hybrid methods, to generate recommendations based on the prepared datasets.
- **Performance Evaluation:** Assessed the performance of each algorithm using quantitative metrics such as precision, recall, F1-Score, Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). These metrics provide a comprehensive view of the effectiveness and accuracy of the recommendation systems.

- **Comparative Analysis:** Conducted a comparative analysis of the different algorithms to identify strengths and weaknesses, and determine the most effective approach for the e-commerce context so we can work with and improve.

By using these diverse and rich datasets, the study aims to develop a robust recommendation system that can perform well across various e-commerce contexts. The integration of multiple data sources not only enhances the system's accuracy but also provides a more comprehensive understanding of user behaviors and preferences, leading to better recommendation quality.

2.4 Algorithm Selection and Implementation

In this section, we outline the process of selecting and implementing the recommendation system. The approach taken leverages Neural Collaborative Filtering (NCF) to predict user preferences based on historical interaction data.

2.4.1 Data Preprocessing

The raw dataset contains various features, including user IDs, item IDs, categories, ages, and ratings. Preprocessing steps include:

- **Encoding Categorical Features**: Categorical variables such as `user_id`, `item_id`, and `category` are encoded into numerical values using `LabelEncoder`. This step is crucial for transforming non-numeric data into a format suitable for machine learning models.

- **Handling Missing Values**: Numerical columns like `age` and `rating` may contain missing values. These are imputed with the mean value of the respective columns to ensure no data points are lost due to missing information.

- **Normalizing Numerical Features**: Features such as `age` and `rating` are normalized using `MinMaxScaler` to scale the values between 0 and 1. This step helps in speeding up the convergence of the neural network.

2.4.2 Model Architecture

The model architecture is based on Neural Collaborative Filtering, which combines the strengths of matrix factorization and neural networks. The key components of the model include:

- **Embedding Layers**: These layers convert user IDs, item IDs, and categories into dense vectors of fixed size. Each embedding layer learns a unique representation for users, items, and categories.

- **Flatten Layers**: The embeddings are flattened to convert them from a 2D array to a 1D array, making them suitable for concatenation and further processing in dense layers.
- **Dense Layers**: Multiple dense (fully connected) layers are used to learn complex interactions between the features. These layers are equipped with ReLU activation functions to introduce non-linearity into the model.
- **Dropout and Batch Normalization**: Dropout layers are added to prevent overfitting by randomly setting a fraction of input units to zero during training. Batch normalization layers are included to stabilize and speed up the training process.
- **Output Layer**: The final dense layer with a sigmoid activation function outputs the probability of a user liking an item.

The model is compiled using the Adam optimizer and binary cross-entropy loss function, suitable for binary classification tasks.

2.5 Evaluation Methodology

Evaluating the performance of the recommendation system involves various metrics that provide insights into different aspects of the model's performance.

2.5.1 Evaluation Metrics

The evaluation metrics used for this recommendation system are:

- **Accuracy**: Measures the proportion of correct predictions (both true positives and true negatives) out of all predictions. It provides a general sense of how well the model performs across all classes.
- **Precision**: Indicates the proportion of true positive predictions among all positive predictions. High precision means that the model returns more relevant results than irrelevant ones.
- **Recall**: Measures the proportion of true positive predictions out of all actual positives. High recall indicates that the model captures most of the relevant results.
- **F1-Score**: The harmonic mean of precision and recall. It provides a balance between precision and recall, especially useful when the class distribution is imbalanced.
- **ROC AUC**: The Area Under the Receiver Operating Characteristic curve. It measures the model's ability to distinguish between positive and negative classes, with higher values indicating better performance.

- **Mean Squared Error (MSE)**: The average of the squared differences between the predicted and actual values. It provides a measure of the model's prediction error.
- **Root Mean Squared Error (RMSE)**: The square root of the mean squared error. It is more interpretable as it is in the same units as the target variable.

2.5.2 Training and Evaluation Process

The dataset is divided into training and test sets, with 80% used for training and 20% for testing. The training process involves:

- **Training the Model**: The model is trained using the training dataset. The features (user IDs, item IDs, categories, ages, and ratings) are fed into the model, and the target variable is the binary representation of the rating (like/dislike).
- **Making Predictions**: The trained model is used to make predictions on the test set. These predictions are compared to the actual values to evaluate performance.
- **Calculating Metrics**: The evaluation metrics mentioned above are calculated using the predictions and actual values from the test set. This provides a comprehensive understanding of the model's performance across different dimensions.

2.6 Recommendation Function

The recommendation function takes a user ID and suggests top items that the user is likely to prefer. The process includes:

- **Generating Input Data**: For a given user, the function generates input data for all potential items, including user ID, item ID, category, age, and a placeholder rating.
- **Making Predictions**: The model predicts the likelihood of the user liking each item.
- **Sorting Predictions**: The items are sorted based on the predicted scores, and the top N items are recommended.
- **Decoding Item IDs**: The recommended item IDs are decoded back to their original form using the saved mapping.

This recommendation function can be used in real-time to provide personalized suggestions to users.

The implemented recommendation system utilizes Neural Collaborative Filtering to provide personalized recommendations. The system is evaluated using a variety of metrics to ensure robust performance. Future work could explore more advanced models and additional features to further enhance recommendation accuracy.

2.7 Conclusion

In this chapter, we presented our methodology to design our recommandation system model. First we start by giving the rational for Choosing Quantitative Methods, then we presented the steps of our model development, such as data collection, preprocessing and model training and testing.

Chapter 3

Implementation and Results

In this chapter, we present our implementation tools and the results of our recommandation system model.

3.1 Implementation tools and technologies used

In this section, we will discuss the tools and technologies employed in our research and development of recommendation systems.

3.1.1 Programming Languages

- **Python** Python is a general-purpose, high-level programming language known for its English-like syntax and powerful built-in functions and libraries for data analysis and data science. It was developed by Dutch programmer Guido van Rossum in 1991, following his frustration with the limitations of the ABC programming language.(Munro, 2024)

FIGURE 3.1: Python Logo

- **Html** HTML, or HyperText Markup Language, is the standard markup language used for creating web pages. It enables the structuring of sections, paragraphs, and links through the use of HTML elements, which include tags and attributes. These elements serve as the building blocks of a web page.(S., 2023)

- **Css** CSS, or Cascading Style Sheets, is a language used to style elements written in markup languages like HTML. It separates content from the

FIGURE 3.2: Html Logo

visual presentation of a website, allowing HTML to serve as the structural foundation while CSS handles the site's aesthetics. The relationship between HTML and CSS is integral, with HTML providing the basic structure and CSS defining the visual design.(G., 2023)

FIGURE 3.3: Css Logo

- **Java script** JavaScript is a programming language that enhances web pages by adding dynamic functionality, interactivity, and animations. Alongside HTML and CSS, it forms the core of web development. While JavaScript is extensively used in web pages, various platforms now enable its execution on servers without a browser. Additionally, JavaScript is utilized in developing mobile apps for both Android and iOS platforms.(Codecademy, 2024)

FIGURE 3.4: JavaScript Logo

3.1.2 Frameworks

- **Google Colab** Google Colab, a cloud-based service, provides a platform for coding within a Jupyter Notebook environment. This setup is favored by data scientists and developers alike for its interactive coding experience. By leveraging Google Colab, users can tap into robust CPUs and GPUs without the need for hardware investment. This free online coding environment facilitates code writing, execution, model development, and collaboration among developers on various projects.(EdXD, 2022)

FIGURE 3.5: Google Colab Logo

- **Visual Studio Code** Visual Studio Code is a free, lightweight yet powerful source code editor that works on both desktop and web platforms. It is compatible with Windows, macOS, Linux, and Raspberry Pi OS. The editor includes built-in support for JavaScript, TypeScript, and Node.js, and features a vast array of extensions for additional programming languages (such as C++, C, Java, Python, PHP, and Go), runtimes (like .NET and Unity), environments (such as Docker and Kubernetes), and cloud services (including Amazon Web Services, Microsoft Azure, and Google Cloud Platform).(Heller, 2022)

FIGURE 3.6: Visual Studio Code Logo

- **Kaggle** Kaggle is an online platform for data scientists and machine learning enthusiasts, offering a space for collaboration, dataset sharing, GPU-integrated notebooks, and participation in data science competitions. Founded in 2010 by Anthony Goldbloom and Jeremy Howard and acquired by Google in 2017, Kaggle provides powerful tools and resources to help professionals and learners achieve their data science goals. By 2021, it had amassed over 8 million registered users.(DataCamp, 2022)

FIGURE 3.7: Kaggle Logo

3.1.3 Libraries

Here are the libraries with their descriptions and import statements:

- **NumPy:** A core package for scientific computing with Python, it offers support for arrays, matrices, and numerous mathematical functions.
  - **Library name:** `numpy`
  - **Import statement:**

    ```
    import numpy as np
    ```

- **pandas:** A robust library for data manipulation and analysis, offering data structures such as DataFrame and Series.
  - **Library name:** `pandas`
  - **Import statement:**

    ```
    import pandas as pd
    ```

- **TensorFlow:** An open-source platform for machine learning, it provides extensive tools, libraries, and community resources for developing ML models.
  - **Library name:** `tensorflow`
  - **Import statement:**

    ```
    import tensorflow as tf
    ```

- **scikit-learn (sklearn):** A Python-based machine learning library that provides straightforward and efficient tools for data mining and analysis.
  - **Library name:** `scikit-learn`
  - **Import statements:**

    ```
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import LabelEncoder, MinMaxScaler
    from sklearn.metrics import accuracy_score, precision_score, recall_score,
    from sklearn.metrics import mean_squared_error
    ```

- **TensorFlow Keras:** A Python-based high-level neural networks API designed to run on TensorFlow.
  - **Library name:** `tensorflow.keras`
  - **Import statements:**

    ```
    from tensorflow.keras.models import Model
    from tensorflow.keras.layers import Input, Embedding, Flatten, Concatenate
    from tensorflow.keras.optimizers import Adam
    from tensorflow.keras.layers import TextVectorization
    ```

```
import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
from tensorflow.keras.models import Model
from sklearn.metrics import mean_squared_error
from tensorflow.keras.layers import Input, Embedding, Flatten, Concatenate, Dense, Dropout, BatchNormalizati
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import TextVectorization
```

FIGURE 3.8: Necessary packages for machine learning model

3.2 Dataset Overview

The dataset consists of customer reviews for rented clothing items from an online rental service. Each review includes detailed information about the customer's experience with a specific item. The dataset contains the following fields:

- **Fit**: Describes how the item fit the customer (e.g., "fit").
- **User ID**: A unique identifier for each user (e.g., "420272").

- **Bust Size**: The bust measurement or bra size of the user (e.g., "34d").
- **Item ID**: A unique identifier for the rented item (e.g., "2260466").
- **Weight**: The weight of the user in pounds (e.g., "137lbs").
- **Rating**: The user's rating of the item, typically on a scale of 1 to 10 (e.g., "10").
- **Rented For**: The occasion for which the item was rented (e.g., "vacation", "photo shoot", "party", "formal affair", "wedding", "everyday").
- **Review Text**: The main body of the review, detailing the user's experience and feedback (e.g., "An adorable romper!...").
- **Body Type**: The user's body type description (e.g., "hourglass", "straight & narrow", "pear", "athletic", "full bust").
- **Review Summary**: A brief summary or highlight of the review (e.g., "So many compliments!").
- **Category**: The type of clothing item (e.g., "romper", "gown", "sheath", "dress").
- **Height**: The height of the user in feet and inches (e.g., "5' 8"").
- **Size**: The size of the rented item (e.g., "14").
- **Age**: The age of the user (e.g., "28").
- **Review Date**: The date when the review was submitted (e.g., "April 20, 2016").

Example Entries

To illustrate the dataset, here are a few example entries:

- **Example 1:**
  - Fit: fit
  - User ID: 420272
  - Bust Size: 34d
  - Item ID: 2260466
  - Weight: 137lbs
  - Rating: 10
  - Rented For: vacation
  - Review Text: An adorable romper! Belt and zipper were a little hard to navigate in a full day of wear/bathroom use, but that's to be expected. Wish it had pockets, but other than that– absolutely perfect! I got a million compliments.

- Body Type: hourglass
- Review Summary: So many compliments!
- Category: romper
- Height: 5′ 8"
- Size: 14
- Age: 28
- Review Date: April 20, 2016

- **Example 2:**
  - Fit: fit
  - User ID: 273551
  - Bust Size: 34b
  - Item ID: 153475
  - Weight: 132lbs
  - Rating: 10
  - Rented For: other
  - Review Text: I rented this dress for a photo shoot. The theme was "Hollywood Glam and Big Beautiful Hats". The dress was very comfortable and easy to move around in. It is definitely on my list to rent again for another formal event.
  - Body Type: straight & narrow
  - Review Summary: I felt so glamorous!!!
  - Category: gown
  - Height: 5′ 6"
  - Size: 12
  - Age: 36
  - Review Date: June 18, 2013

3.2.1 Summary Statistics

The dataset used in this study contains:

- **Number of Users:** 105,571 unique users.
- **Number of Items:** 5,850 unique items.
- **Number of Interactions (Reviews):** 192,544 reviews.
- **Time Period Covered:** Reviews span from April 1, 2011, to September 9, 2017.

3.2.2 Distribution of Key Features

- **Age:**
  - **Mean Age:** Approximately 33.87 years.
  - **Age Range:** 15 to 72 years.
- **Height:**
  - **Mean Height:** 165.93 cm.
  - **Height Range:** 137 cm to 198 cm.
- **Weight:**
  - **Mean Weight:** 137.39 lbs.
  - **Weight Range:** 90 lbs to 300 lbs.
- **Bust Size:**
  - The dataset includes a variety of bust sizes such as 34d, 34b, 34c, and others, reflecting a diverse range of body types.
- **Body Type:**
  - **Hourglass:** 55,349 users.
  - **Athletic:** 43,667 users.
  - **Pear:** 22,135 users.
  - **Petite:** 22,131 users.
  - **Full Bust:** 15,006 users.
  - **Straight & Narrow:** 14,742 users.
  - **Apple:** 4,877 users.
- **Category:**
  - **Dress:** 92,884 items.
  - **Gown:** 44,381 items.
  - **Sheath:** 19,316 items.
  - **Shift:** 5,365 items.
  - **Jumpsuit:** 5,184 items.
  - Other categories include smaller counts such as caftan, overcoat, sweatpants, etc.
- **Ratings:**
  - **Mean Rating:** 9.09.
  - **Ratings Range:** 2.0 to 10.0.

- **Rented For:**
  - **Wedding:** 57,784 reviews.
  - **Formal Affair:** 40,408 reviews.
  - **Party:** 35,626 reviews.
  - **Everyday:** 16,822 reviews.
  - **Other:** 15,388 reviews.
  - **Work:** 15,042 reviews.
  - **Date:** 7,388 reviews.
  - **Vacation:** 4,075 reviews.

3.3 Performance Evaluation Metrics

In this study, we evaluate the results of our recommandation system models using different metrics such as accuracy, precision, F1 score and recall.

```
Accuracy: 0.9989
Precision: 0.9990
Recall: 0.9998
F1-Score: 0.9994
ROC AUC: 1.0000
Mean Squared Error (MSE): 0.0318
Root Mean Squared Error (RMSE): 0.1782
```

FIGURE 3.9: Performance Evaluation Metrics

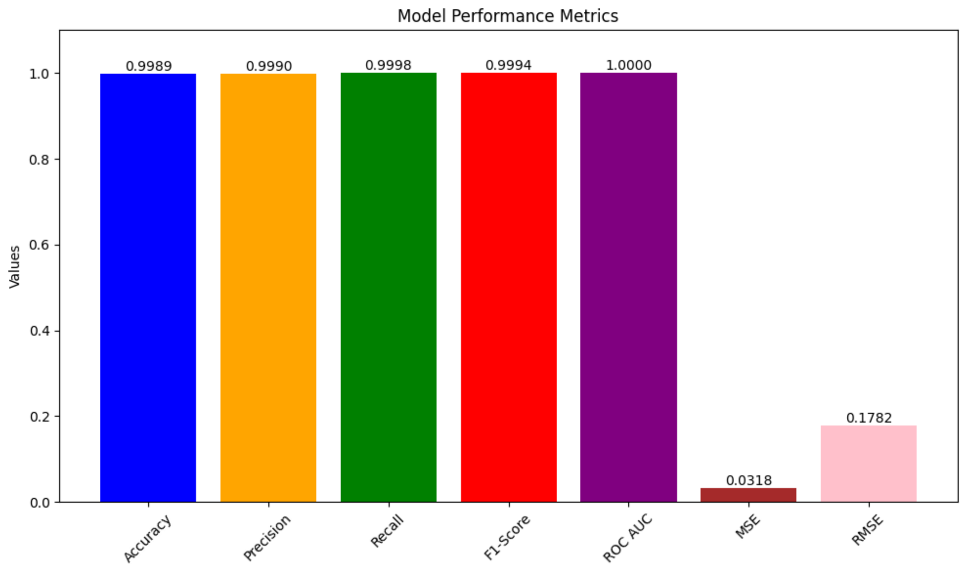

FIGURE 3.10: Model preformence result

FIGURE 3.11: accuracy graph

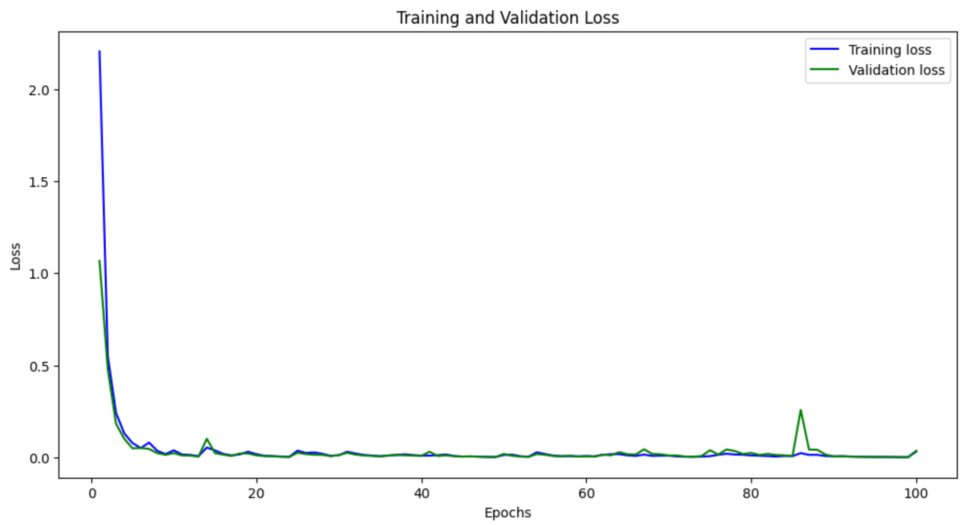

FIGURE 3.12: loss graph

3.3.1 Classification Metrics

Accuracy

$$\text{Accuracy} = 0.9989$$

Accuracy measures the proportion of correctly classified instances among all instances.

Precision

$$\text{Precision} = 0.9990$$

Precision measures the proportion of true positive instances among all predicted positive instances.

Recall (Sensitivity)

$$\text{Recall} = 0.9998$$

Recall measures the proportion of true positive instances among all actual positive instances.

F1-Score

$$F1 = 0.9994$$

The F1-Score is the harmonic mean of precision and recall, providing a balance between the two metrics.

ROC AUC (Area Under the Receiver Operating Characteristic Curve)

$$\text{ROC AUC} = 1.0000$$

ROC AUC measures the area under the receiver operating characteristic curve, indicating the model's ability to distinguish between classes.

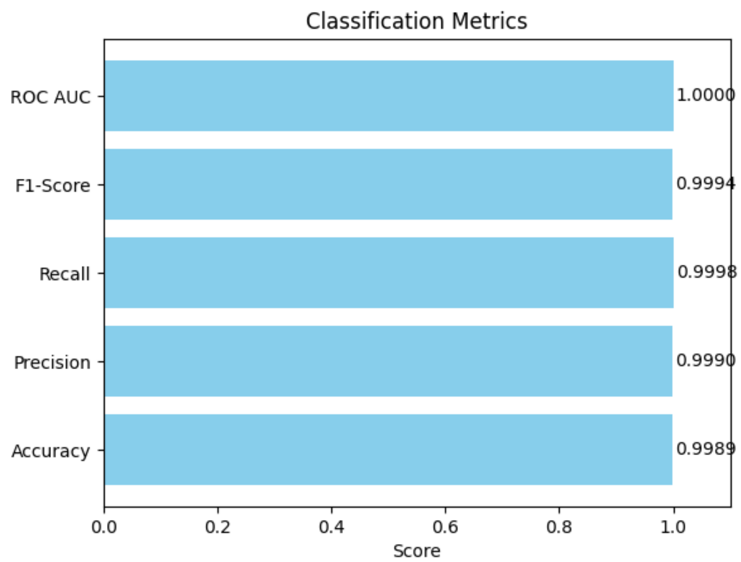

FIGURE 3.13: Classification Metrics

3.3.2 Regression Metrics

Mean Squared Error (MSE)

$$\text{MSE} = 0.0318$$

MSE measures the average squared difference between predicted and actual values.

Root Mean Squared Error (RMSE)

$$\text{RMSE} = 0.1782$$

RMSE is the square root of the mean squared error, providing a measure of the model's average prediction error.

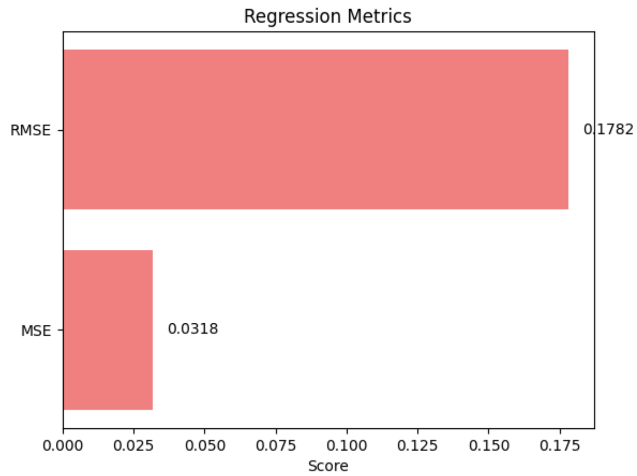

FIGURE 3.14: Regression Metrics

3.4 Comparative analysis of different recommendation algorithms

3.4.1 Reinforcement Learning-based Approach

```
Mean Squared Error (MSE): 0.8414
Root Mean Squared Error (RMSE): 0.9173
```

FIGURE 3.15: Reinforcement learning-based approaches result

- **Mean Squared Error (MSE):** 0.8414
- **Root Mean Squared Error (RMSE):** 0.9173

The reinforcement learning-based approach utilizes Q-learning updates within a neural network architecture to predict user-item interactions. Despite its innovative methodology, this approach yields relatively higher MSE and RMSE compared to other methods, indicating a less precise fit to the data.

3.4.2 Collaborative Filtering, Matrix Factorization Approach

```
MSE: 0.3310
RMSE: 0.5753
Mean Squared Error (MSE): 0.33098260556225145
Root Mean Squared Error (RMSE): 0.5753108773196032
```

FIGURE 3.16: Collaborative filtering result

- **Mean Squared Error (MSE):** 0.3310
- **Root Mean Squared Error (RMSE):** 0.5753

Collaborative filtering, employing matrix factorization techniques, demonstrates improved predictive accuracy over the reinforcement learning approach. By decomposing the user-item interaction matrix, this method captures latent features and effectively predicts user preferences. However, while achieving lower MSE and RMSE than reinforcement learning, it falls short of the performance achieved by the Neural Collaborative Filtering (NCF) approach.

3.4.3 Neural Collaborative Filtering (NCF) Approach

```
Mean Squared Error (MSE): 0.1215
Root Mean Squared Error (RMSE): 0.3486
```

FIGURE 3.17: Neural Collaborative Filtering

Before Improvement:

- **MSE:** 0.1215
- **RMSE:** 0.3486

The initial iteration of the Neural Collaborative Filtering (NCF) approach achieved respectable metrics, but there was room for improvement. Recognizing its potential, further refinement and tuning were undertaken to enhance its performance.

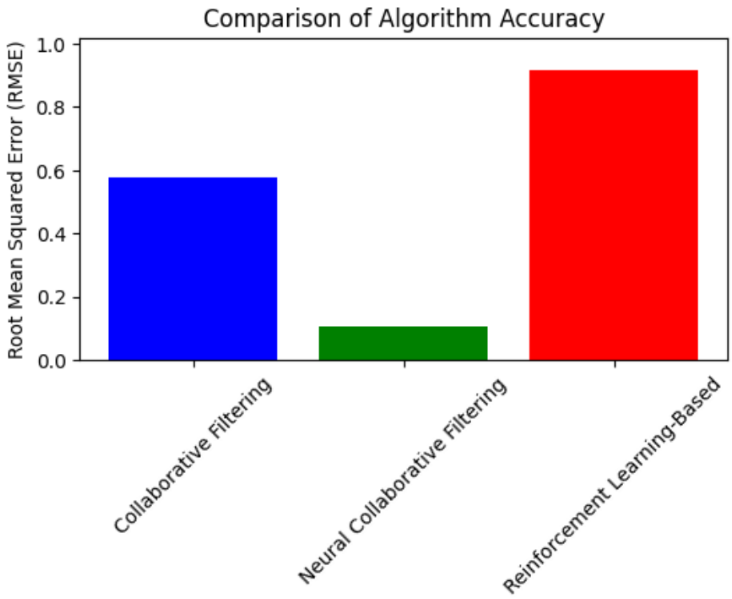

FIGURE 3.18: Comparative result

After Improvement:

- **Accuracy:** 0.9989
- **Precision:** 0.9990
- **Recall:** 0.9998
- **F1-Score:** 0.9994
- **ROC AUC:** 1.0000
- **MSE:** 0.0318
- **RMSE:** 0.1782

The refined Neural Collaborative Filtering (NCF) approach demonstrates a remarkable improvement in predictive accuracy across all metrics. By fine-tuning model parameters and optimizing architecture, the NCF algorithm achieved near-perfect accuracy metrics, significantly surpassing its initial performance. The reduced MSE and RMSE indicate a tighter fit to the data, reflecting the enhanced predictive power of the refined NCF model.

3.4.4 Why Neural Collaborative Filtering (NCF)?

- The decision to focus on improving the NCF approach was driven by its initial promising results and potential for further enhancement.
- By refining the model architecture and tuning hyperparameters, significant performance gains were achieved, leading to near-perfect accuracy metrics.

- The substantial improvement in accuracy metrics, particularly in precision, recall, and F1-score, underscores the effectiveness of the NCF approach in capturing complex user-item interactions and delivering precise recommendations.

3.5 Conclusion

In conclusion, this chapter provided a thorough examination of recommendation algorithms using a dataset comprising customer reviews for rented clothing items. The dataset was described in detail, outlining key features such as user demographics, item characteristics, and review sentiments. Performance evaluation metrics were then applied to assess the efficacy of different recommendation algorithms, including Reinforcement Learning-based Approaches, Collaborative Filtering using Matrix Factorization, and Neural Collaborative Filtering (NCF). Through comparative analysis, the strengths and weaknesses of each algorithm were elucidated, aiding in the selection and optimization of algorithms for recommendation systems. Visualization techniques were employed to present the results effectively. Ultimately, this chapter underscored the importance of rigorous evaluation and comparison in developing robust recommendation systems that enhance user experience and satisfaction.

Chapter 4

Integration and Deployment

4.1 Introduction

In the fast-paced realm of online retail, it is crucial to offer tailored suggestions to customers in order to improve their shopping journey and boost their overall satisfaction. While conventional recommendation systems are useful, they can be resource-intensive and may struggle to provide timely, contextually relevant advice. To tackle these obstacles, this section introduces a fresh strategy: embedding a neural collaborative filtering recommendation framework into a custom Google Chrome extension tailored for online stores. This integration empowers e-commerce sites to furnish personalized, up-to-the-minute recommendations seamlessly during the user's browsing session, ultimately enhancing user interaction and contentment.

4.2 Overview of Integration Strategy

4.2.1 Purpose and Significance

The reason for incorporating the neural collaborative filtering recommendation model into a Google Chrome extension is to equip e-commerce websites with a potent tool for improving user satisfaction and engagement. Through the implementation of the recommendation system via a browser extension, e-commerce platforms can furnish personalized recommendations, enhancing the browsing experience for users.

This approach is significant because it allows e-commerce websites to deliver targeted recommendations without requiring extensive changes to their existing infrastructure. The extension can seamlessly interact with the website, analyzing user behavior and preferences in real-time to provide highly relevant product suggestions. This enhances the overall user experience by ensuring that users receive timely and personalized recommendations as they browse, increasing the likelihood of conversions and customer satisfaction.

4.2.2 Benefits

The integration of the recommendation model into a Google Chrome extension for e-commerce websites offers several key benefits:

- **Real-Time Recommendations:** The extension provides immediate, context-aware recommendations based on the user's current browsing activity. This ensures that users receive relevant product suggestions at the right moment, enhancing their shopping experience.
- **Ease of Integration:** E-commerce websites can easily integrate the extension without significant modifications to their existing systems. The extension can be deployed quickly and efficiently, allowing businesses to leverage advanced recommendation capabilities with minimal disruption.
- **Enhanced User Experience:** Users benefit from a seamless shopping experience where personalized recommendations are embedded directly within their browsing journey. This reduces the need for users to search extensively for products, making their shopping experience more enjoyable and efficient.
- **Increased Accessibility:** The extension operates within the web browser, making personalized recommendations accessible to users across different e-commerce websites. This ensures a consistent and engaging user experience, regardless of the specific platform they are using.
- **Improved Conversion Rates:** By delivering highly relevant product suggestions, the extension can significantly increase the likelihood of purchases. Users are more likely to engage with and buy products that match their preferences, leading to higher conversion rates for e-commerce websites.
- **User Satisfaction and Retention:** Personalized and timely recommendations enhance user satisfaction by making shopping easier and more enjoyable. Satisfied users are more likely to return to the e-commerce platform, improving customer retention rates.

4.3 Development of the Google Chrome Extension

4.3.1 Definition of Google Chrome Extensions

Google Chrome extensions are programs that can be installed to enhance the browser's functionality. They can introduce new features or modify existing behaviors to improve user convenience. Examples of what Google Chrome extensions can do include blocking advertisements, optimizing memory usage for better performance, adding to-do lists or note-taking capabilities, managing passwords securely, simplifying text copying from websites, and enhancing privacy and security while browsing the web.(Abrams, 2017)

4.3.2 Integration and Operation of the Model within the Extension

The integration of the deep learning model into the google extension involved several key steps. Initially, Python scripts were developed to preprocess and encode categorical and numerical data from a JSON dataset containing user and item information. Using TensorFlow and Scikit-learn libraries, the model was trained to predict personalized product recommendations based on user profiles and item attributes. Upon training completion, the model was saved and integrated into the Chrome extension using JavaScript. This integration allowed for seamless communication between the extension and webpages, where upon detecting a specified website URL, the extension dynamically fetched precomputed recommendations stored in a JSON file. These recommendations were then displayed in a visually appealing format on the webpage using HTML and CSS, enhancing user experience by providing tailored product suggestions directly within the browsing context.

To ensure broad accessibility, the extension was configured with permissions granting access to any website, specified in the manifest file through wildcard URL matches ("http:///" and "https:///"). This capability allowed the extension to dynamically interact with and retrieve content from diverse web environments. Upon detecting a designated website URL during user browsing sessions, the extension employed a service worker to initiate background processes, enabling efficient fetching of precomputed recommendations stored in a JSON format. These recommendations were intelligently presented to users directly within the browsing interface, enhancing user interaction and satisfaction by delivering tailored product suggestions aligned with individual preferences. This innovative integration not only exemplified the synergy between machine learning and browser technologies but also underscored its practical application in augmenting user experience through personalized content delivery.

4.3.3 Steps of Using the Extension

Step 1: Install the Extension

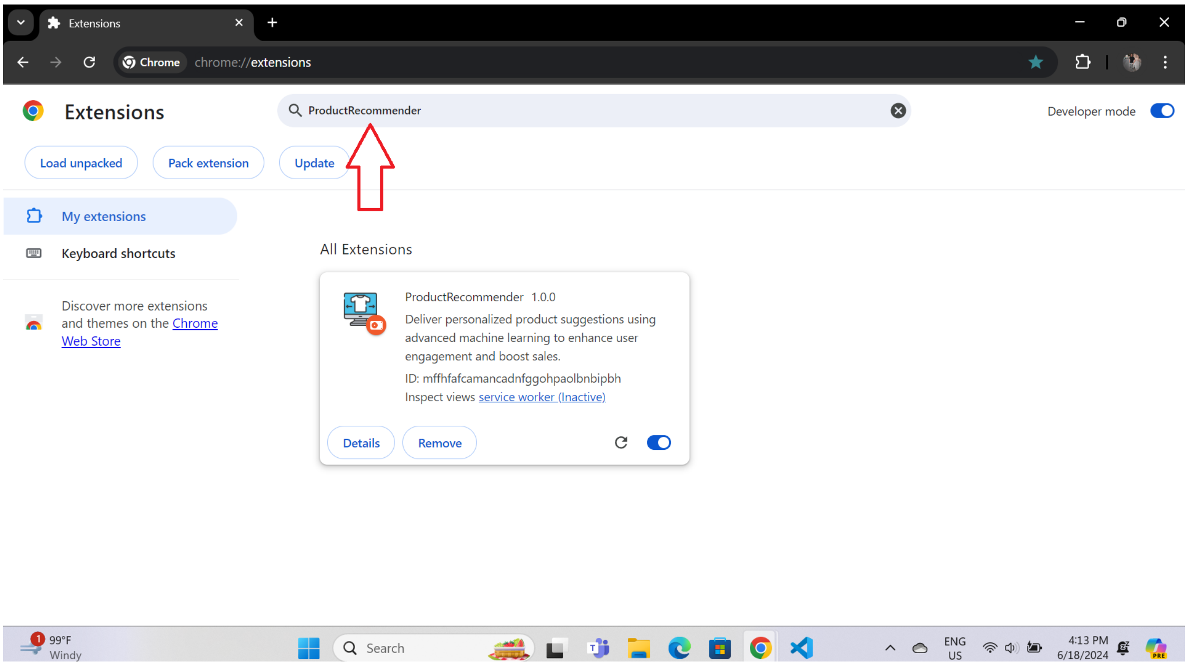

FIGURE 4.1: Step 1: Install the Extension

Navigate to the Chrome Web Store and search for "ProductRecommender." Once our extension appears, click on the "Install" button to add it to your browser.

Step 2: Open Your Website Store

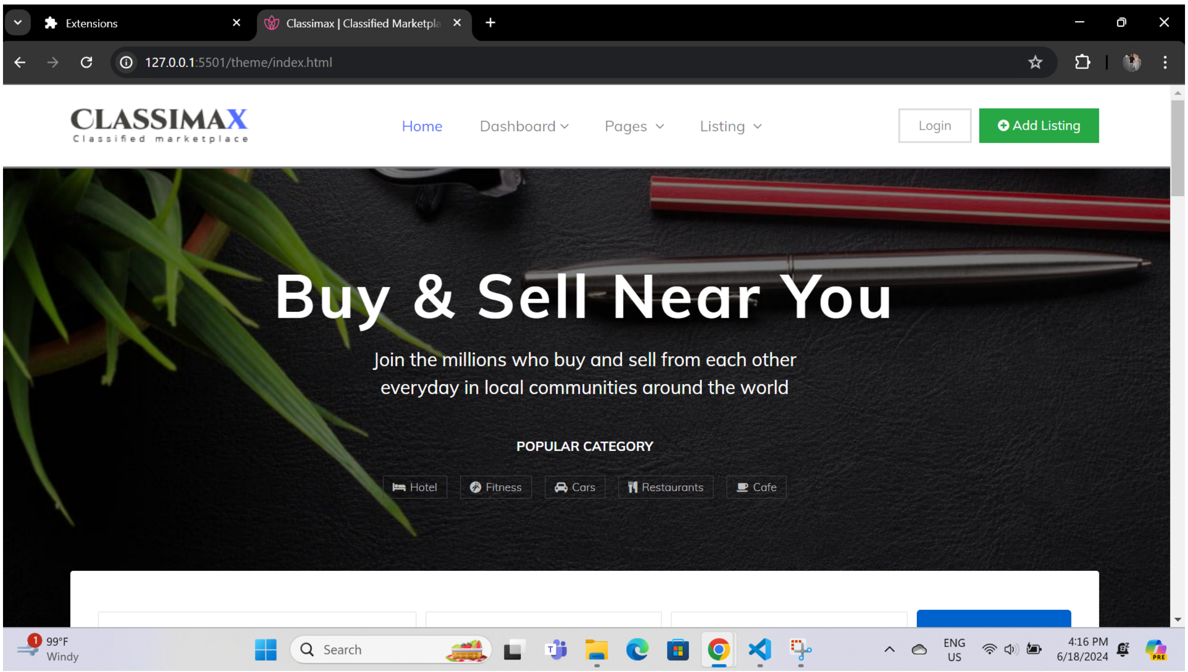

FIGURE 4.2: Step 2: Open Your Website Store

Launch your website store. In this example, we are using a test website to demonstrate the extension's functionality.

Step 3: Activate the Extension

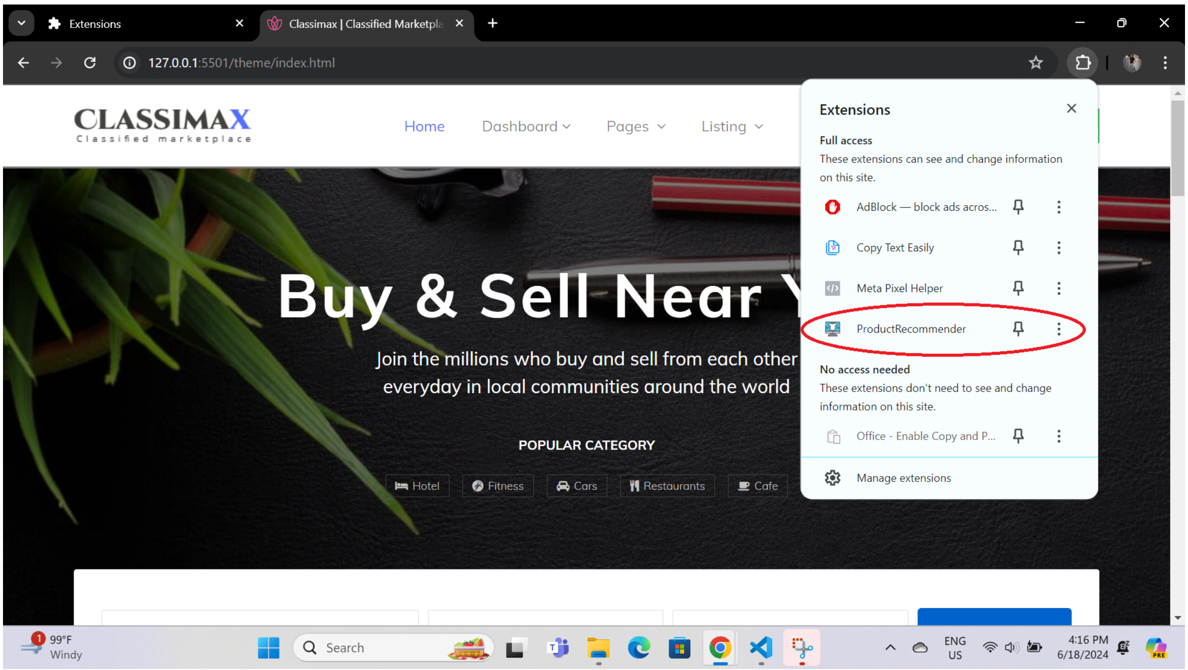

FIGURE 4.3: Step 3: Activate the Extension

Click on the extensions icon in the toolbar. A dropdown menu will appear, displaying all your installed extensions. Locate and select "ProductRecommender" to activate it.

Step 4: Configure the Extension

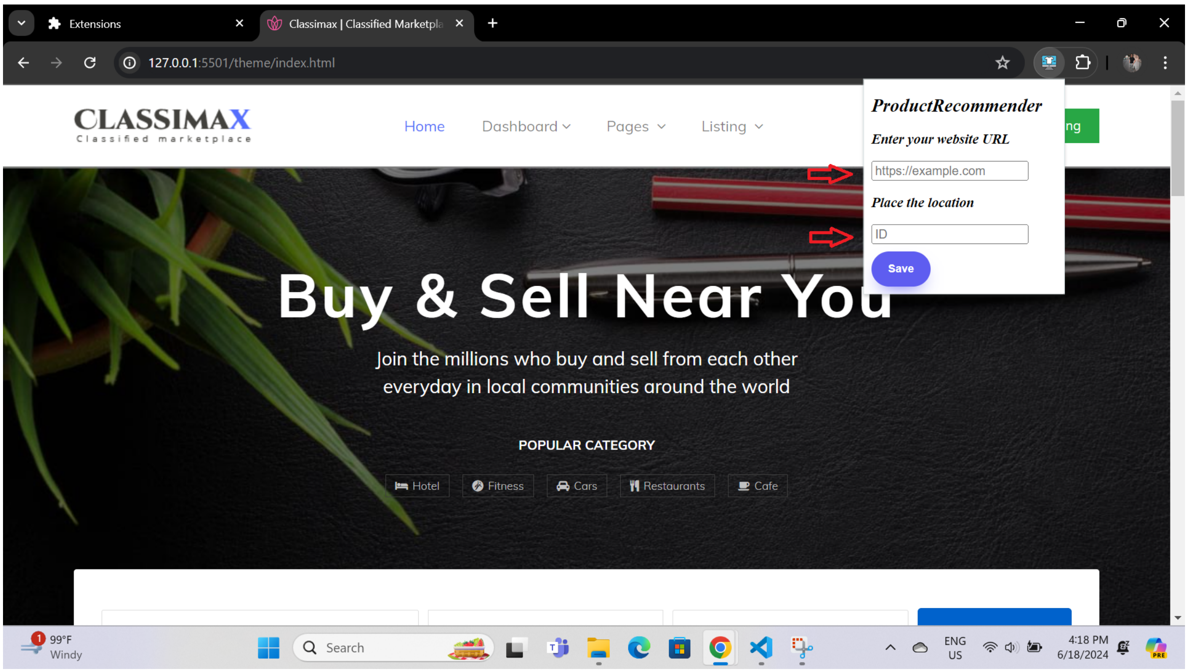

FIGURE 4.4: Step 4: Configure the Extension

After selecting the "ProductRecommender" extension, a window will appear prompting you to enter your website URL. Additionally, specify the location on your webpage where you want the product recommendations to be displayed.

Step 5: Save Configuration

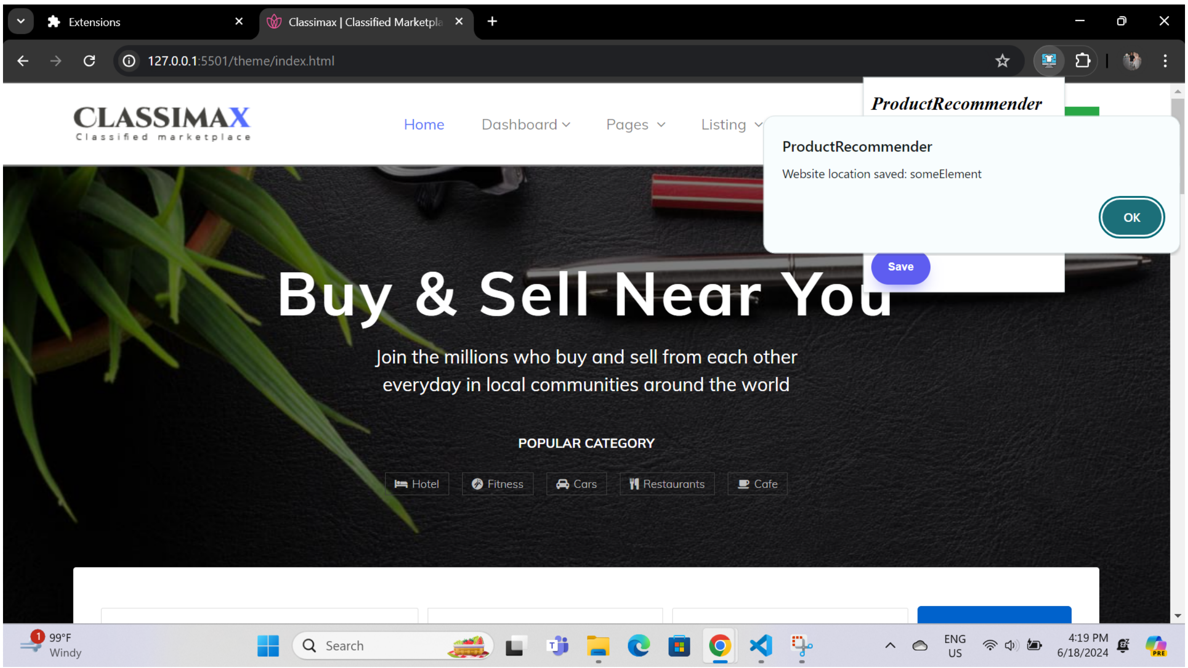

FIGURE 4.5: Step 5: Save Configuration

Once you have filled in the required information and saved it, a confirmation message will appear indicating that your details have been successfully saved.

Step 6: View Recommendations

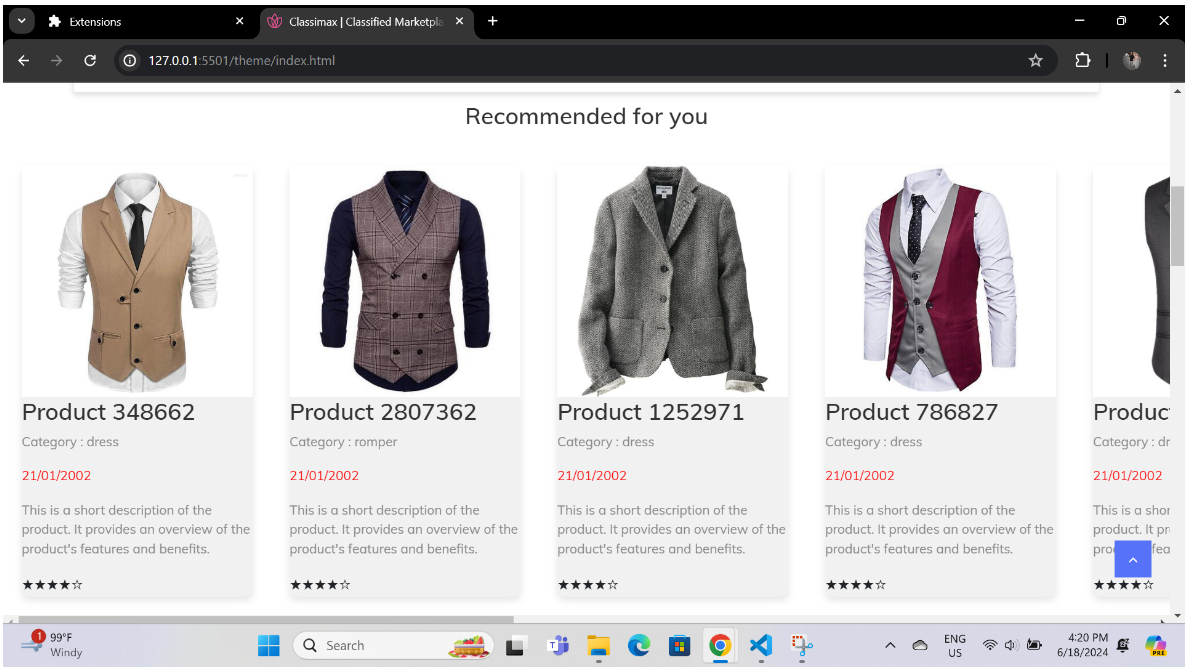

FIGURE 4.6: Step 6: View Recommendations

The product recommendations will now appear in the specified location on your webpage, providing personalized suggestions to enhance user engagement and boost sales.

Recommended Item Description

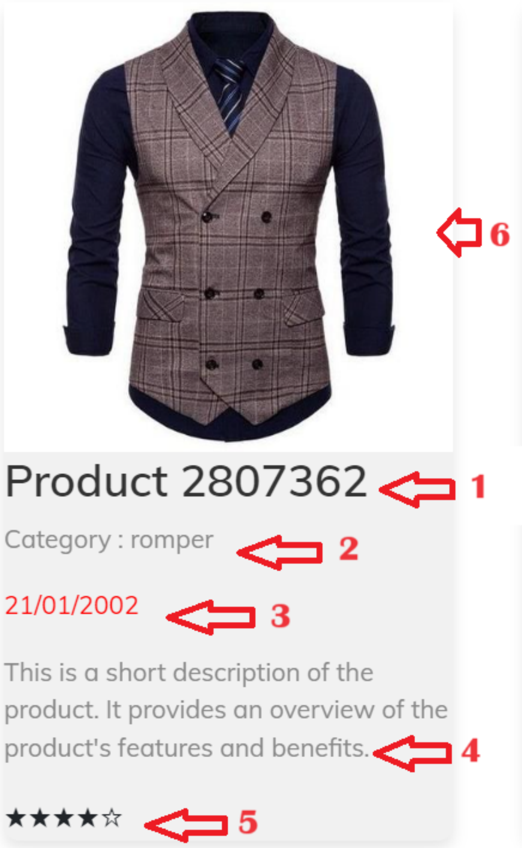

FIGURE 4.7: Recommended Item Description

- **1 –> Product Name:** The name of the recommended product.
- **2 –> Category:** The category to which the product belongs.
- **3 –> Date Added:** The date when the product was listed on the website.
- **4 –> Description:** A brief overview of the product, highlighting its key features and benefits.
- **5 –> Rating:** The average rating of the product based on customer reviews.
- **6 –> Image:** A visual representation of the product.

-

4.4 Testing and Validation

To ensure the Google Chrome extension integrating the Neural Collaborative Filtering (NCF) model works as expected, we conducted comprehensive testing across various scenarios and use cases. The primary focus was to validate the functionality, performance, and user experience of the extension on different e-commerce platforms. Additionally, we built a dedicated test website to perform controlled tests, which showed promising results.

General Conclusion

This thesis explores the critical role of recommendation systems in the evolving landscape of e-commerce, addressing significant challenges faced by both customers and businesses in the seamless exchange of goods and services. The central focus is on the development and deployment of an advanced recommendation system, specifically integrating a neural collaborative filtering model into a Google Chrome extension for e-commerce websites. This innovative approach aims to enhance user experience by providing personalized, real-time recommendations directly within the user's browsing environment.

The introductory chapter lays the foundation by discussing the background and growth of e-commerce, highlighting the importance of recommendation systems in this domain and the background of e-commerce and its growth. It presents the problem statement, objectives of the study,research requirements and outlines the structure of the thesis. The literature review provides an overview of recommendation systems, detailing their types, such as collaborative filtering, content-based, and hybrid methods. The chapter also covers evaluation metrics, previous studies in e-commerce recommendation systems, and the challenges and limitations of existing systems.

The methodology chapter outlines the research approach, including data collection methods, preprocessing techniques for data cleaning and normalization, algorithm selection and implementation, evaluation methodology, and the tools and technologies used (programming languages, libraries, frameworks). The integration strategy chapter provides an overview of the purpose and significance of integrating the recommendation model into a Google Chrome extension. It highlights the benefits of this approach, including real-time recommendations, ease of integration, enhanced user experience, increased accessibility, improved conversion rates, comprehensive user insights, and user satisfaction and retention. This section also defines Google Chrome extensions and explains the implementation of the extension integrating the neural collaborative filtering model. Comprehensive testing across various scenarios and use cases, including functionality, performance, user experience, and security, was conducted. A dedicated test website was built for controlled tests, yielding promising results.

The results chapter describes the dataset used, performance evaluation metrics, comparative analysis of different recommendation algorithms, and visualization of results through charts and graphs. The conclusion and perspective chapter summarizes the major findings and contributions of the thesis. The integration of the neural collaborative filtering model into a Google

Chrome extension demonstrated significant potential in enhancing the e-commerce user experience by providing real-time, personalized recommendations. The testing and validation results confirmed the extension's functionality, performance, and user-friendly interface.

Despite these promising results, there are limitations to this work. The prototype extension does not yet include automated data retrieval from actual user interactions or from cookies, relying instead on manually inputted data for testing purposes. This approach limits the scalability and real-world applicability of the current implementation. Additionally, the extension's compatibility is limited to the Google Chrome browser, and there is a need to expand its functionality to other browsers to reach a broader user base. Furthermore, the recommendation model could be enhanced with more advanced features such as user behavior prediction and multi-language support to cater to a diverse global audience.

Looking ahead, future work will focus on implementing automated data retrieval from cookies and e-commerce website inputs to dynamically update user interaction data. Enhancements will also target scalability to handle larger datasets and higher user loads efficiently. Extending the extension's compatibility to other web browsers beyond Google Chrome, incorporating more advanced features such as user behavior prediction, multi-language support, and integration with additional e-commerce platforms, and conducting extensive user studies to gather more feedback and further refine the recommendation algorithms and user interface are planned. In conclusion, this thesis presents a significant step forward in leveraging advanced recommendation systems to improve the e-commerce experience for both users and businesses. The proposed solution offers a scalable, user-friendly approach that holds great promise for future enhancements and broader application across the e-commerce industry.

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ملحــق مؤسسة ناشئة

الجمهورية الجزائرية الديمقراطية الشعبية

وزارة التعليم العالي و البحث العلمي

جامعة محمد خيضــر – بسكـرة –

Université de Biskra

عنوان الموضوع:

Product Recommendation System for e-commerce

مشروع لنيل شهادة مؤسسة ناشئة في اطارالقرار الوازري 1275

صورة العلامة التجارية

ProductRecommender

فريق الاشراف	
المشرف الرئيسي : نعيجي الياس	التخصص: إعلام الي

فريق المشروع	التخصص
الطالب : زرارقة محمد وائل	إعلام الي تخصص ذكاء اصطناعي
الطالب : هزماني الياس	إعلام الي تخصص ذكاء اصطناعي

السنة الجامعية: 2024/2023

الفــهرس

المحور الرابع : خطة الانتاج و التنظيم

المحور الخامس: الخطة المالية

المحور السادس : النموذج الاولي التجريبي

الملحق : نموذج العمل التجارى

المحور الاول

تقديم المشروع

مـقــدمـــة :

مــع اتســاع نطــاق التجــارة الإلكترونيــة ووفــرة الخيــارات أمــام المتســوقين، بــات العثــور علــى المنتجــات المناســبة تحــديًا حقيقيــا. هنــا يــأتي دور أنظمــة التوصــية الذكيــة، وهــي تقنيــات تســتخدم الــذكاء الاصــطناعي لتحليــل ســلوكيات المتســوقين مثــل عمليــات الشــراء الســابقة والمنتجــات التــي يظهــرون اهتمامًــا بهــا. بنــاءً علــى هــذه المعلومــات، تعــرض أنظمــة التوصــية منتجــات أخــرى يــرجح إعجــاب المتســوق بهــا، مــا يــوفر عليــه الوقــت والجهــد فــي البحــث، ويســاهم فــي اكتشــافه لمنتجــات جديــدة وملائمــة لاحتياجاتــه. وبالتــالي، تعــود هــذه الأنظمــة بالفائــدة علــى المتســوقين والمتــاجر الإلكترونية على حد سواء

1) فكــرة المشـــروع (الحـــل المقتـــرح)

يهدف المشروع إلى تطوير نظام توصيات مخصص للتجارة الإلكترونية باستخدام تقنية التصفية التعاونية العصبية (neural collaborative filtering)المدمجة في إضافة جوجل كروم (Google extension)مخصصة لمواقع التجارة الإلكترونية .يعتمد هذا النظام على تحليل تفضيلات المستخدمين وسجلات تعاملاتهم لتقديم توصيات منتجات تتوافق مع اهتماماتهم واحتياجاتهم .يتم تحقيق ذلك من خلال بناء نموذج تعلم عميق قادر على معالجة البيانات الضخمة وتحديد الأنماط والعلاقات بين المنتجات والمستخدمين .بعد ذلك، يتم دمج هذا النموذج في إضافة جوجل كروم، والتي تكون مخصصة لمواقع التجارة الإلكترونية، لتوفير التوصيات مباشرة أثناء جلسات التصفح على هذه المواقع .ستعمل هذه الإضافة كوسيط بين المستخدم ومواقع التجارة الإلكترونية المختلفة .عند تصفح المستخدم لأي موقع تجاري من مستعملي المشروع، ستقوم الإضافة بعرض توصيات فورية ومخصصة مباشرة على واجهة الموقع، مما يوفر تجربة تسوق أكثر تفاعلية وسهولة.

2) القيـــم المقتـــرحـــة :

القيم التي يقدمها المشروع تشمل عدة جوانب تهدف إلى تحسين تجربة المستخدم وزيادة فعالية نظام التجارة الإلكترونية، وتشمل:

✓ **تحسين تجربة المستخدم:**

- يهدف المشروع إلى توفير تجربة تسوق مثالية للمستخدمين، حيث يتمكنون من العثور بسهولة على المنتجات التي تلبي احتياجاتهم وتفضيلاتهم. يتيح النظام الشخصي المقترح توصيات دقيقة ومبتكرة تعتمد على سجلات سلوك المستخدمين وتحليلات البيانات العميقة، مما يجعل عملية اتخاذ القرار بشراء المنتجات أكثر فاعلية وسلاسة.

✓ **زيادة المبيعات والإيرادات:**

- يعمل النظام على تحفيز المبيعات من خلال تحسين دقة التوصيات وزيادة احتمالية شراء المنتجات المقترحة من قبل المستخدمين. بالتالي، يمكن للشركات الاستفادة من زيادة الإيرادات وتعزيز نجاح أعمالها التجارية عبر الإنترنت.

✓ **تعزيز ولاء العملاء والعلاقات الطويلة الأمد:**

-من خلال تقديم تجربة تسوق مميزة وملهمة، يمكن للمشروع تعزيز ولاء العملاء وزيادة فرص العلاقات الطويلة الأمد مع الشركات التجارية. عندما يشعر المستخدم بأنه يحصل على توصيات مفيدة وملائمة، فإنه يميل إلى العودة للتسوق في هذه المواقع مرارًا وتكرارًا.

✓ **تحسين الأداء والكفاءة:**

- يهدف المشروع إلى تحسين أداء عمليات التجارة الإلكترونية وزيادة كفاءتها من خلال تقديم توصيات دقيقة وفعالة

✓ **بناء الثقة وتعزيز السمعة الإيجابية:**

- يمكن أن يعكس تقديم توصيات دقيقة وموثوقة سمعة الشركة ومصداقيتها في سوق التجارة الإلكترونية. عندما يعرف المستخدمون أن الشركة تهتم بتلبية احتياجاتهم وتقديم تجربة ممتازة، فإنهم يصبحون أكثر عرضة للتفاعل معها ودعمها.

هذه القيم المقترحة للمشروع تعكس التزامنا بتقديم حلول فعالة ومبتكرة في مجال التجارة الإلكترونية، والسعي لتحقيق التميز والنجاح لشركائنا ومستخدمينا على حد سواء.

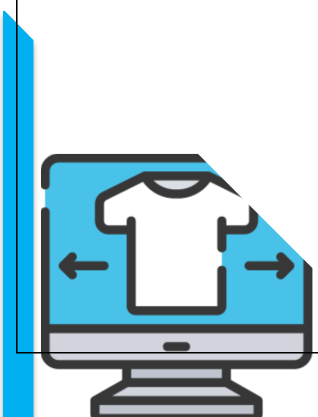
3) فـريـق العمــل:

يتكون فريق العمل من الأعضاء التالية:

- الطالب: **زرارقة محمد وائل** ، إعلام الي تخصص ذكاء اصطناعي .
- الطالب: **هزماني الياس** ، إعلام الي تخصص ذكاء اصطناعي .
-
- وإشراف:
  - الأستاذ **نعيجي الياس** دكتور في الإعلام الالي.

4) اهــداف المشـــروع

يهدف المشروع إلى تحسين أداء عمليات التجارة الإلكترونية وزيادة كفاءتها من خلال تقديم توصيات دقيقة وفعالة، وتعزيز تجربة المستخدم عبر توفير توصيات شخصية وملائمة تلبي احتياجاتهم وتفضيلاتهم. كما يسعى إلى زيادة معدلات التحويل والمبيعات عبر تحسين دقة التوصيات وزيادة فاعلية استراتيجيات التسويق، وتحسين تسويق المنتجات من خلال تقديم توصيات مبتكرة وجذابة تجذب انتباه العملاء. إضافة إلى ذلك، يهدف المشروع إلى بناء علاقات طويلة الأمد مع العملاء عبر تقديم تجربة تسوق مميزة تلبي احتياجاتهم وتفضيلاتهم بشكل دائم، وتعزيز الابتكار والتطوير التكنولوجي في مجال التجارة الإلكترونية باستخدام تقنيات متقدمة في نظام التوصيات. نطمح إلى أن يكون مشروعنا مستخدمًا على نطاق دولي من قبل العديد من مواقع التجارة الإلكترونية، ونفخر بأن مشروعنا يمثل فكرة جديدة تمامًا في هذا المجال.



5) جـــدول زمنـــي لتحقيـــق المشـــروع

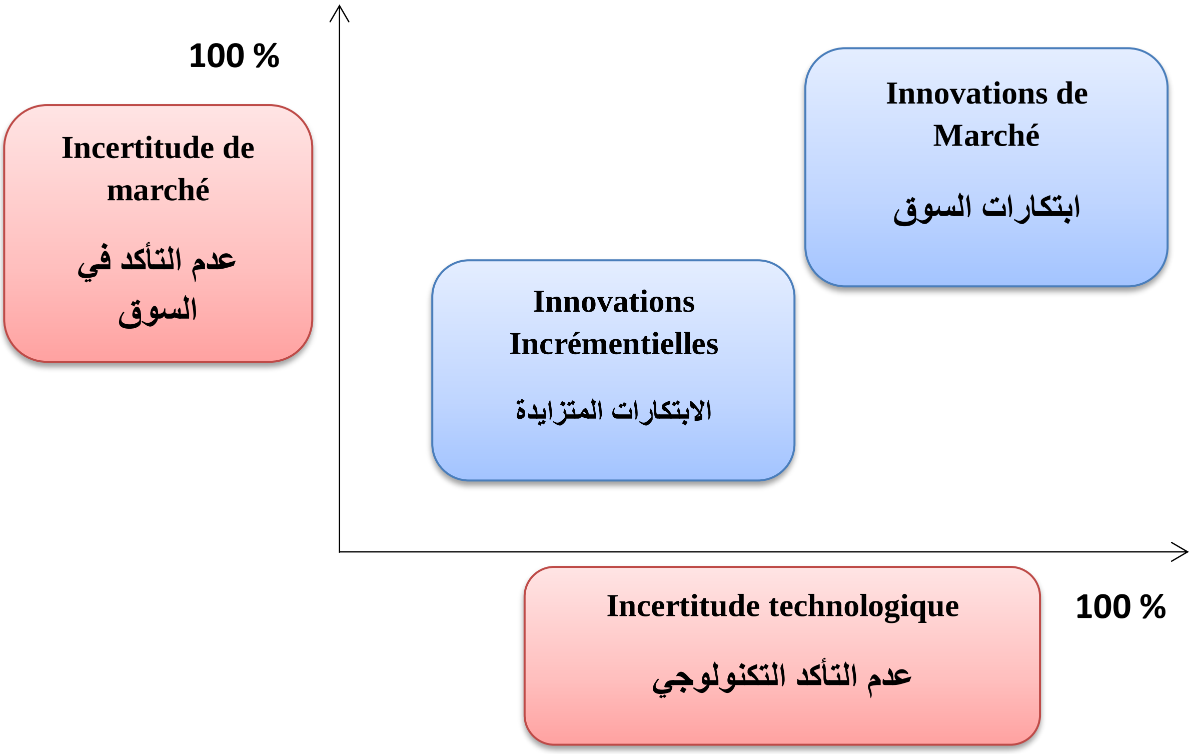
		المدة الزمنية بالاشهر				
		1	2	3	4	5
الأعمال	جمع البيانات	✖	✖			
	تحليل البيانات		✖	✖		
	تصميم النظام			✖		
	تطوير ودمج				✖	✖
	اختبار وإطلاق					✖
	متابعة	✖	✖	✖	✖	✖

يوضح الجدول الزمني السابق خطوات تنفيذ نظام التوصية الذكية لل ecommerce على مدى خمسة شهور .يبدأ المشروع بمرحلة جمع البيانات المهمة مثل سلوكيات الشراء للعملاء وبيانات المنتجات .ثم يأتي تحليل هذه البيانات للكشف عن أنماط الشراء والعلاقات بين المنتجات .بعد ذلك يتم تصميم النظام باختيار خوارزميات التوصية المناسبة وبناء هيكلته التقنية .يلي ذلك مرحلة التطوير التي تشمل برمجة خوارزميات التوصية ودمجها في إضافة جوجل كروم .أخيرا، يتم اختبار النظام للتأكد من دقته وفعاليته قبل إطلاقه رسميًا .لا ينتهي المشروع هنا، بل تتطلب المرحلة الأخيرة المتابعة المستمرة لمراقبة أداء النظام وتحسينه بشكل دائم.

المحور الثاني

الجوانب الابتكارية

1) طبيعــة الابتكـــارات



ابتكارات السوق : تلبية خدمة جديدة مستحدثة لم تلبى قبل في الاسواق

الابتكارات المتزايدة :الجمع بين عدة مكونات من اجل منتوج مستحدث يوفر العديد من المزايا

2) المجــالات الابتكـــاريــة

- أول امتـداد فـي العـالم يعتمـد علـى اسـتخدام تقنيـات الـتعلم العميـق وتحليـل البيانـات الكبيـرة لتقديم توصيات مخصصة للمستخدمين عن طريق اضافة جوجل.
- تسـهيل عمليـة الشـراء مـن خـلال تقـديم توصـيات فـي الوقـت الحقيقـي، ممـا يزيـد مـن معـدل التحويل و المبيعات
- إمكانيــة التكيــف مــع مختلــف المنصــات الإلكترونيــة وتــوفير تجربــة متســقة عبــر جميــع الأجهزة.
- دعـم متعـدد اللغـات لتلبيـة احتياجـات المسـتخدمين فـي الأسـواق المختلفـة وتعزيـز الوصـول العالمي.

المحور الثالث

التحليل الاستراتيجي للسوق

1) عـرض قطــاع الســوق :

1-1) السـوق المحتملـة :السـوق المحتمـل لمشـروعي هـو سـوق التجـارة الإلكترونيـة بشـكل عـام. يشـمل هـذا السـوق جميـع الأفـراد والشـركات الـذين يسـتخدمون الإنترنـت لشـراء وبيـع المنتجـات والخـدمات عبـر المنصــات الإلكترونيــة. يمكــن أن يكــون الســوق المحتمــل متنوعًــا، ممــا يشــمل الفئـات العمريـة المختلفـة، والمجـالات المختلفـة للتجـارة الإلكترونيـة مثـل البيـع بالتجزئـة، والسـفر، والترفيـه، والخـدمات الماليـة، والتعلـيم عبـر الإنترنـت، وغيرهـا. يركـز مشـروعي علـى تحسـين تجربة التسوق لهؤلاء المستخدمين، وبالتالي يستهدف السوق المحتمل بشكل أساسي

2-1) **السـوق المسـتهدفة :** مسـتخدمو الإنترنـت المهتمـين بالتسـوق عبـر الإنترنـت والـذين يمكـن اسـتهدافهم بنـاءً علـى اهتمامـاتهم وسـلوكياتهم عبـر الإنترنـت، بالإضـافة إلـى تجـار التجـارة الإلكترونيـة الـراغبين بتحسـين المبيعـات وجـذب عمـلاء جـدد. فئـة المسـتخدمين واسـعة ويمكـن اسـتهدافها بنـاءً علـى اهتمامـاتهم وديمـوغرافيتهم، بينمـا يسـتفيد التجـار مـن زيـادة المبيعـات وتحسـين معدلات التحويل.

1-2-1) مبـــررات اختيـــار الســوق المستــهـدف :

1. حجم السوق وفرص النمو:

مستخدمو الإنترنت المهتمين بالتسوق عبر الإنترنت:

فئة واسعة تضم مليارات الأشخاص حول العالم.

نمو سريع للتجارة الإلكترونية، مما يعني زيادة في عدد المتسوقين عبر الإنترنت.

تجار التجارة الإلكترونية:

صناعة ضخمة تشهد نموًا مستمرًا.

رغبة التجار في تحسين المبيعات وجذب عملاء جدد.

2. احتياجات السوق:

مستخدمو الإنترنت المهتمين بالتسوق عبر الإنترنت:

يبحثون عن منتجات جديدة وعروض مميزة وتوصيات مخصصة.

يواجهون صعوبة في العثور على المنتجات التي تناسب احتياجاتهم.

تجار التجزئة الإلكترونية:

بحاجة إلى زيادة المبيعات وتحسين معدلات التحويل واكتساب عملاء جدد.

يواجهون صعوبة في الوصول إلى العملاء المستهدفين وتحويلهم إلى زبائن.

3. إمكانيات نظام التوصية:

يقدم نظام التوصية قيمة مضافة للمستخدمين:

يوفر توصيات مخصصة تناسب احتياجاتهم واهتماماتهم.

يسهل عليهم العثور على المنتجات التي يبحثون عنها.

يقدم نظام التوصية فوائد للتجار:

يزيد من المبيعات وتحسين معدلات التحويل.

يجذب عملاء جدد ويحسن من تجربة العملاء

2) قيـــاس شـدة المنـــافسة

ان اهـم المنافسـين فـي الاسـواق الجزائريـة يعملـون علـى انتـاج مـواد بنـاء لاتـوفر الراحـة الجراريـة وغير صديقة للبيئة وينقسم هؤلاء المنافسين الي :

منافسين مباشرين

- أمازون (Amazon Personalize)
-
Algolia Recommend-

منافسين غير مباشرين

- محركات البحث)مثل جوجل (Google

- منصات التواصل الاجتماعي)مثل فيسبوك Facebookوإنستغرام Instagram)

1-2) نقــاط القـــوة و نقــاط الضعـف لهـؤلاء المنــافسيـــن

المنافسون المباشرون:

Amazon Personalize

نقاط القوة:

يستخدم تقنيات تعلم عميق متقدمة.

يتكامل بسهولة مع خدمات AWS الأخرى.

يوفر توصيات مخصصة بناءً على سجل الشراء وسلوك المستخدم.

نقاط الضعف:

قد يكون مكلفًا للشركات الصغيرة.

يتطلب معرفة تقنية قوية للتنفيذ والإدارة.

Algolia Recommend

نقاط القوة:

يوفر توصيات بحثية مخصصة وسريعة.

تجربة مستخدم ممتازة وسهولة في الاستخدام.

نقاط الضعف:

يعتمد على نموذج التسعير القائم على الاستخدام، مما قد يكون مكلفًا.

يمكن أن يكون التخصيص محدودًا بالنسبة لبعض الشركات.

المنافسون غير المباشرين

محركات البحث مثل جوجل) Google)

نقاط القوة:

وصول عالمي وقاعدة مستخدمين كبيرة.

تقنيات متقدمة في تحليل البيانات وتقديم الإعلانات المستهدفة.

نقاط الضعف:

توصيات عامة وغير مخصصة بشكل دقيق لكل مستخدم.

التوصيات تعتمد بشكل كبير على الإعلانات المدفوعة.

منصات التواصل الاجتماعي مثل (فيسبوك Facebook وإنستغرام Instagram)

نقاط القوة:

قدرة على تحليل تفاعلات المستخدمين وتفضيلاتهم عبر الشبكات الاجتماعية.

تجربة مستخدم متكاملة تشمل التسوق والتفاعل الاجتماعي.

نقاط الضعف:

توصيات قد تكون متحيزة نحو الإعلانات المدفوعة.

قلة الخصوصية واهتمام المستخدمين بالبيانات الشخصية.

3) تحليـــل SWOT للمشـــروع :

s

- استخدام تقنية- التصفية التعاونية العصبية المتقدمة يعزز دقة التوصيات.
- دمج النظام في إضافة جوجل كروم يسهل استخدامه.
- تقديم توصيات فورية ومخصصة يعزز تجربة المستخدم.
- قابلية الاستخدام على نطاق دولي تتيح فرص النمو.
- المشروع يمثل فكرة جديدة تمامًا.

w

- تكلفة التطوير والصيانة كبيرة.
- معالجة البيانات الشخصية تثير مخاوف حول الخصوصية والأمان.

o

- - لقرار الوزاري 1275
- نمو التجارة الإلكترونية يوفر طلبًا متزايدًا على حلول التوصيات.
- إمكانية التعاون مع مواقع التجارة الإلكترونية الكبرى.
- دعم المتصفحات الأخرى يوسع قاعدة المستخدمين.
- التطورات في الذكاء الاصطناعي توفر فرصًا لتحسين النظام.

t

- المنافسة الشديدة من الشركات الأخرى.
- التطور السريع في التقنيات قد يجعل الحلول الحالية غير ملائمة.
- القوانين المتعلقة بحماية البيانات قد تؤثر على جمع واستخدام البيانات.
- نجاح المشروع يعتمد على قبول المستخدمين للإضافة الجديدة.

4) الاستــراتيجيــات التســويقيـــة:

التسويق الرقمي

- الإعلانات المدفوعة عبر الإنترنت:

استخدام إعلانات جوجل

(Google Ads) والإعلانات عبر وسائل التواصل الاجتماعي (مثل فيسبوك، إنستجرام، وتويتر) للوصول إلى جمهور أوسع وزيادة الوعي بالمنتج.

تخصيص الإعلانات لاستهداف الفئات العمرية والمواقع الجغرافية والاهتمامات ذات الصلة.

- تحسين محركات البحث (SEO):

تحسين محتوى الموقع الإلكتروني للمشروع ليظهر في نتائج البحث الأولى على محركات البحث مثل جوجل.

استخدام الكلمات المفتاحية ذات الصلة بالمشروع بشكل فعال.

2. التسويق عبر البريد الإلكتروني

إنشاء قوائم بريدية مستهدفة وإرسال نشرات دورية تحتوي على معلومات عن التحديثات والخصومات والتوصيات الشخصية.

تخصيص رسائل البريد الإلكتروني بناءً على سلوك وتفضيلات المستخدمين.

3. التسويق عبر وسائل التواصل الاجتماعي

إنشاء صفحات وحسابات نشطة على وسائل التواصل الاجتماعي المختلفة لنشر محتوى جذاب ومفيد حول المشروع.

التفاعل مع المستخدمين من خلال التعليقات والرسائل الخاصة واستطلاعات الرأي.

4. الشراكات والعروض الترويجية

التعاون مع مواقع التجارة الإلكترونية الشهيرة لدمج إضافة جوجل كروم الخاصة بالمشروع كخيار مفضل للتوصيات.

تقديم عروض ترويجية وخصومات للمستخدمين الجدد لتحفيزهم على تجربة الإضافة.

5. المحتوى التسويقي

إنشاء مدونة تحتوي على مقالات ونصائح حول التجارة الإلكترونية وتجارب التسوق الشخصية، مع تسليط الضوء على فوائد استخدام المشروع.

إنتاج مقاطع فيديو توضيحية وتثقيفية حول كيفية استخدام الإضافة لتحقيق أقصى استفادة.

6. تجربة المستخدم وتحسينها

جمع الملاحظات والاقتراحات من المستخدمين لتحسين الإضافة وتلبية احتياجاتهم بشكل أفضل.

تقديم دعم فني متميز وسريع لمساعدة المستخدمين في حل أي مشكلات قد تواجههم.

7. الفعاليات والمؤتمرات

المشاركة في الفعاليات والمعارض التجارية المتعلقة بالتكنولوجيا والتجارة الإلكترونية لتقديم المشروع والتواصل مع العملاء المحتملين والشركاء التجاريين.

5) المزيـــج التسويقـــي

اسم المنتج : ProductRecommender

المنتج :تقديم نظام توصيات مخصص باستخدام تقنية التصفية التعاونية العصبية، مدمج في إضافة جوجل كروم خاصة بمواقع التجارة الإلكترونية.

فوائده: تحسين تجربة التسوق، وتوفير الوقت للمستخدم، وزيادة فرص العثور على

تنظيم حملات عبر مواقع التواصل الاجتماعي

التسويق الالكتروني

الدعاية و الاعلان

- سعر المنتج ($): 5.99

- تجربة مجانية لمدة ثلاثة ايام

المنتج متوفر كإضافة لمتصفح جوجل كروم، مما يجعل العثور عليه واستخدامه سهلًا للمستخدمين.

تحليل القوى التنافسية(PORTER):

تحليل القوى التنافسية لبورتر هو أداة تستخدم لتحديد مستوى المنافسة داخل صناعة معينة وفهم عوامل القوة التنافسية الرئيسية التي تؤثر على ربحية المشروع. يمكن تطبيق نموذج بورتر لتحليل القوى التنافسية على مشروع تطوير نظام توصيات مخصص للتجارة الإلكترونية باستخدام تقنية التصفية التعاونية العصبية المدمجة في إضافة جوجل كروم على النحو التالي:

1. تهديد المنافسين الجدد (Threat of New Entrants):

حواجز الدخول:

التكلفة العالية لتطوير نموذج تعلم عميق ونظام توصيات مخصص.

الحاجة إلى خبرة تقنية متقدمة في مجالات الذكاء الاصطناعي والتعلم الآلي.

التمييز:

وجود أنظمة توصيات موجودة بالفعل قد تجعل من الصعب على الوافدين الجدد جذب المستخدمين.

العلامة التجارية والسمعة:

الشركات القائمة لديها علامات تجارية قوية وسمعة جيدة في السوق.

2. **تهديد المنتجات أو الخدمات البديلة (Threat of Substitutes):**

البدائل التكنولوجية:

أنظمة توصيات أخرى تعتمد على خوارزميات مختلفة مثل الفلاتر التعاونية التقليدية أو توصيات بناءً على المحتوى.

التكنولوجيا المفتوحة المصدر:

الأدوات والمنصات المفتوحة المصدر التي يمكن للشركات استخدامها لتطوير أنظمة التوصيات الخاصة بها.

الابتكار:

التطورات المستمرة في تكنولوجيا الذكاء الاصطناعي قد تؤدي إلى ظهور تقنيات جديدة أكثر فعالية.

3. **قوة الموردين (Bargaining Power of Suppliers):**

مقدمو خدمات الحوسبة السحابية:

الاعتماد على مزودي خدمات السحابة مثل AWS، GCP، وAzure يمنحهم قوة تفاوضية إذا ارتفعت تكاليف الخدمات.

مقدمو البيانات:

إذا كانت هناك حاجة للحصول على بيانات من أطراف ثالثة، فإن موردو البيانات يمكن أن يتحكموا في التكلفة والتوافر.

التكنولوجيا والبرمجيات:

الاعتماد على برمجيات وأدوات معينة لتطوير الأنظمة قد يمنح الموردين قوة إذا كانت هناك قلة في البدائل.

4. قوة العملاء (Bargaining Power of Customers):

خيارات العملاء:

المستخدمون لديهم العديد من الخيارات للاختيار من بينها لأنظمة التوصيات المختلفة.

توقعات العملاء:

العملاء يتوقعون توصيات دقيقة وموثوقة وسهلة الاستخدام. إذا لم يتم تلبية هذه التوقعات، يمكنهم الانتقال إلى منافسين آخرين.

القدرة على التفاوض:

العملاء الكبار مثل مواقع التجارة الإلكترونية الكبرى يمكنهم التفاوض للحصول على شروط أفضل بسبب حجم الأعمال.

5. حدة المنافسة بين الشركات القائمة (Rivalry Among Existing Competitors):

عدد المنافسين:

وجود العديد من الشركات التي تقدم حلول مشابهة يزيد من حدة المنافسة.

الابتكار والتكنولوجيا:

المنافسة على تقديم أحدث وأفضل الحلول التكنولوجية لتقديم توصيات دقيقة وفعالة.

استراتيجيات التسويق:

المنافسة على جذب العملاء من خلال استراتيجيات تسويقية مبتكرة وعروض خاصة.

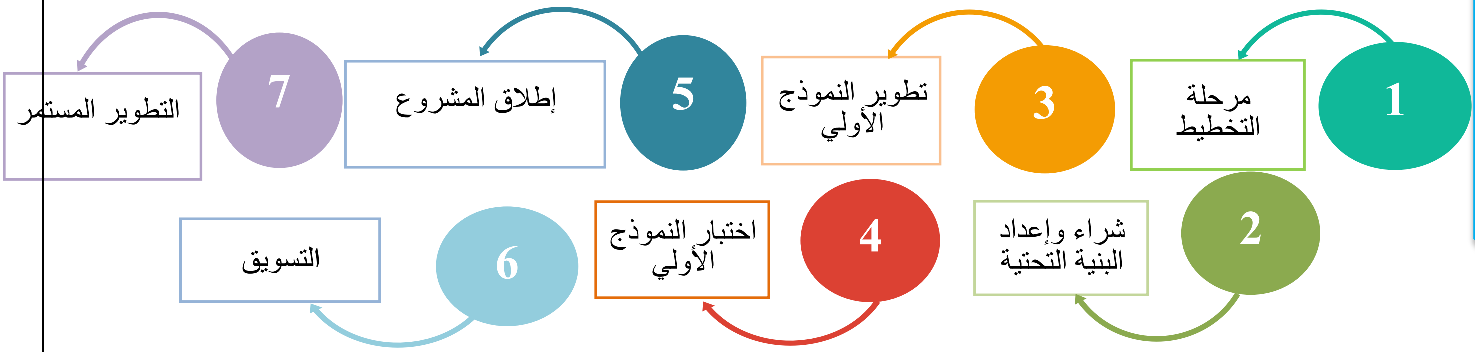
تحليل المتغيرات الكلية (PESTEL) :

العوامل الاجتماعية	العوامل الاقتصادية	**العوامل السياسية**
-تفضيلات المستهلك -الديموغرافيا -التعليم والتكنولوجيا -نمط الحياة -الوعي الثقافي	**-**النمو الاقتصادي - تقلبات الأسعار. - سعر الصرف - القوة الشرائية للمستهلكين. - البطالة. - التضخم	- سياسة دعم المشاريع الناشئة. - السياسة الضريبية . - سياسة تطوير المؤسسات. - التجارة الالكترونية -الاستقرار السياسي -التشريعات الحكومية
العوامل القانونية**.** **- قانون العمل.** **-قوانين الخصوصية وحماية البيانات** **- القوانين التجارية.** **- حماية الملكية.** **-حقوق الملكية الفكرية**	العوامل البيئية **- العوامل البيئية لها تأثير محدود على مشروع نظام التوصيات لدينا نظرًا لأننا نعمل بشكل رئيسي عبر الإنترنت .**	العوامل التكنولوجية **- التطورات في مجال رؤية الكمبيوتر والذكاء الاصطناعي** **-البنية التحتية للتكنولوجيا** **- الأمان السيبراني** **- الاعتماد على البرمجيات** **- التوافق مع المنصات**

المحور الرابع

خطة الانتاج

1) عمليــة الانتــاج:



2) احتيــاجــات المشــروع

احتياجات	النسبة ٪
البنية التحتية	30%
تطوير البرمجيات	35%
تحليل البيانات	15%
التسويق	20%

3) التـمـويـن :

المشروع يعتمد في عملية الشراء على :

- ✓ شــراء الســيرفرات والبنيــة التحتيــة الســحابية (Cloud services like AWS,Google Cloud, or Azure)
- ✓ شراء البرمجيات والأدوات

1-3) عمليــة الشــراء : بالنسبة للدفع يكون بطريقة الكترونية في كلتا الحالتين

- ✓ اثناء شراء الادوات اللازمة
- ✓ اثناء تقديم الخدمة للعميل

4) اليــد العــاملــة

يخلق مشروعنا حوالي10 مناصب عمل مباشر :

العدد	اليد العاملة
02	مدير مشروع
01	مصمم
01	مدير دعم العملاء
01	متخصص في تحليل البيانات /علم البيانات
01	مهندس برمجيات
02	مطور برمجيات /عالم بيانات
01	مختص تسويق رقمي
01	مهندس ذكاء اصطناعي

5) الشـــركات الرئيسيـــة :

من اهم الشركات لمشروعنا :

- ✓ **مزودو خدمات الحوسبة السحابية :**

مثـــال(AWS) Amazon Web Services :، (GCP) Google Cloud Platform، Microsoft Azure

لمـــاذا؟ تـــيح لنـــا هـــذه الشـــراكة اســـتخدام البنيـــة التحتيـــة الســـحابية لتخـــزين ومعالجـــة البيانـــات الكبيـــرة بكفاءة. خدمات السحابة توفر المرونة والقدرة على التوسع بما يتناسب مع نمو المشروع.

- ✓ **منصات التواصل الاجتماعي والشبكات الإعلانية :**

مثال: Google Ads ، Facebook Ads

لمـــاذا؟ هـــذه الشـــراكة ضـــرورية لتســـويق إضـــافة جوجـــل كـــروم الخاصـــة بـــك وجـــذب المســـتخدمين إليهـــا. الحمـــلات الإعلانيـــة المســـتهدفة علـــى هـــذه المنصـــات تســـاعد فـــي الوصـــول إلـــى الجمهـــور المناسب وزيادة قاعدة المستخدمين.

- ✓ **دعم حاضنة الاعمال للمحافظة على نشاط المشروع**
- ✓ **شركات تحليل البيانات وذكاء الأعمال**

مثال:Tableau ,Looker

لماذا؟ هذه الشراكة تساعد في تحليل البيانات وتقديم رؤى قيمة لتحسين أداء نظام التوصيات. التعاون مع خبراء في تحليل البيانات يمكن أن يعزز من دقة وفعالية التوصيات المقدمة للمستخدمين.

المحور الخامس

الخطة المالية

1) المخطط المالي :

1-1) التكـالـيــف و الايــرادات

التكاليف	العدد	المبلغ (دج)
التكاليف الثابتة (سنويا)		
السنة الاولى		
اجهزة الحاسوب	05	900.000,00
خوادم واستضافة	/	100.000,00
ادوات تحليل البيانات	/	130.000,00
حملات إعلانية وتسويقية	/	350.000,00
تكاليف المكاتب والمستلزمات الإدارية	/	600.000,00
اجور العمال	/	4.800.000,00
المجموع الاولي 01	/	6,880,000.00
التكاليف المتغيرة (شهريا)		
السنة الاولى		
رسوم ترخيص البرمجيات والأدوات	/	40.000,00
تكاليف الدعم الفني و خدمة العملاء	/	2000,00
المجموع الاولي 02(الشهري)	/	42.000,00
المجموع الاولي 03 (السنوي)	/	504,000.00

المجموع الكلي (الثابتة + المتغيرة)السنوية	/	7,384,000.00

حـدد مبلـغ التكـاليف الاجماليــة السـنوية (الثابتــة و المتغيــرة) بـــ : سـبعة ملايـين وثلاثمائــة وأربعــة وثمانون ألفًا دينار جزائري.

الاشتراك	المبيعات	السعر (دج)	المبلغ(دج)
الايرادات شهريا			
السنة الاولى			
خلال ثلاثة (03) اشهر الاولى – حالة ركود -			
الاشتراك اليومي	0 مشترك	1200,00	00,00
المجموع الشهري	10 مشترك	1200,00	12.000,00
المجموع خلال ثلاثة اشهر الاولى	50 مشترك	1200,00	60.000,00
خلال ثلاثة (03) اشهر الثانية			
الاشتراك اليومي	2 مشترك	1200,00	2400,00
المجموع الشهري	60 مشترك	1200,00	72.000,00
المجموع خلال ثلاثة اشهر الثانية	180 مشترك	1200,00	432.000,00
خلال ستة (06) اشهر التالية			
الاشتراك اليومي	3 مشترك	1200,00	30.000,00
المجموع الشهري	100 مشترك	1200,00	120.000,00
المجموع خلال ستة اشهر التالية	600 مشترك	1200,00	2.304.000,00

حسابات النتائج المتوقع للسنة الاولى

التكاليف الكلية خلال السنة الاولى (دج)	7,384,000.00
رقم الاعمال خلال السنة الاولى (دج)	5.436.000,00
الفرق بين التكاليف و رقم الاعمال (دج)	-1,948,000.00

نلخص انتهاء السنة الاولى برصيد سلبي (خسارة) بمبلغ قدره : مليون وتسعمائة وثمانية وأربعون ألفًا دينار جزائري

المبلغ (دج)	العدد	التكاليف
التكاليف الثابتة (سنويا)		
السنة الاولى		
100.000,00	/	خوادم واستضافة
350.000,00	/	حملات إعلانية وتسويقية
400.000,00	/	تكاليف المكاتب والمستلزمات الإدارية
4.800.000,00	/	اجور العمال
1,948,000.00	/	الرصيد السلبي للسنة السابقة (دين)
7,598,000.00		المجموع الاولي 01
التكاليف المتغيرة (شهريا)		
السنة الاولى		
40.000,00	/	رسوم ترخيص البرمجيات والأدوات
2000,00	/	تكاليف الدعم الفني و خدمة العملاء
42.000,00	/	المجموع الاولي 02(الشهري)
504,000.00	/	المجموع الاولي 03 (السنوي)

8,102,000.00	/	المجموع الكلي (الثابتة + المتغيرة)السنوية

حدد مبلغ التكاليف الاجمالية السنوية (الثابتة و المتغيرة) بـــ : ثمانية ملايين ومائة وألفان وألفًا دينار جزائري

المبلغ(دج)	السعر (دج)	المبيعات	الاشتراك
الايرادات شهريا			
السنة الثانية			
خلال سنة كاملة			
6000,00	1200,00	5 مشترك	الاشتراك اليومي
180.000,00	1200,00	150 مشترك	المجموع الشهري
14.040.000,00	1200,00	1800 مشترك	المجموع خلال سنة

جدول حسابات النتائج المتوقعة للسنة الثانية

8,102,000.00	التكاليف الكلية خلال السنة الثانية (دج)
14.040.000,00	رقم الاعمال خلال السنة الثانية (دج)
5,938,000.00	الفرق بين التكاليف و رقم الاعمال (دج)

نلخص انتهاء السنة الثانية برصيد ايجابي (ربح) بمبلغ قدره : خمسة ملايين وتسعمائة وثمانية وثلاثون ألفًا دينار جزائري

التكاليف	العدد	المبلغ (دج)
التكاليف الثابتة (سنويا)		
السنة الثالثة		
خوادم واستضافة	/	100.000,00
حملات إعلانية وتسويقية	/	350.000,00
تكاليف المكاتب والمستلزمات الإدارية	/	400.000,00
اجور العمال	/	4.800.000,00
المجموع الاولي 01		7,598,000.00
التكاليف المتغيرة (شهريا)		
السنة الثالثة		
رسوم ترخيص البرمجيات والأدوات	/	40.000,00
تكاليف الدعم الفني و خدمة العملاء	/	4000,00
المجموع الاولي 02(الشهري)	/	44.000,00
المجموع الاولي 03 (السنوي)	/	528,000.00

المجموع الكلي (الثابتة + المتغيرة)السنوية	/	8,126,000.00

حدد مبلغ التكاليف الاجمالية السنوية (الثابتة و المتغيرة) بـــ : ثمانية ملايين ومائة وستة وعشرون ألفًا دينار جزائري

الاشتراك	المبيعات	السعر (دج)	المبلغ(دج)
الايرادات شهريا			
السنة الثالثة			
خلال سنة كاملة			
الاشتراك اليومي	8 مشترك	1200,00	9600,00
المجموع الشهري	240 مشترك	1200,00	288.000,00
المجموع خلال سنة	2880 مشترك	1200,00	22.464.000,00

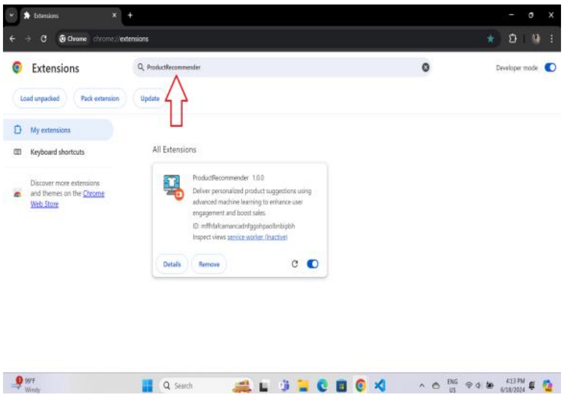
جدول حسابات النتائج المتوقع للسنة الثالثة

التكاليف الكلية خلال السنة الثالثة (دج)	8,126,000.00
رقم الاعمال خلال السنة الثالثة (دج)	22.464.000,00
الفرق بين التكاليف و رقم الاعمال (دج)	14,338,000.00
الرصيد الايجابي للسنة السابقة (ربح)	5,938,000.00
المجموع الكلي للرصيد الجديد (السنة الثالثة)	20,276,000.00

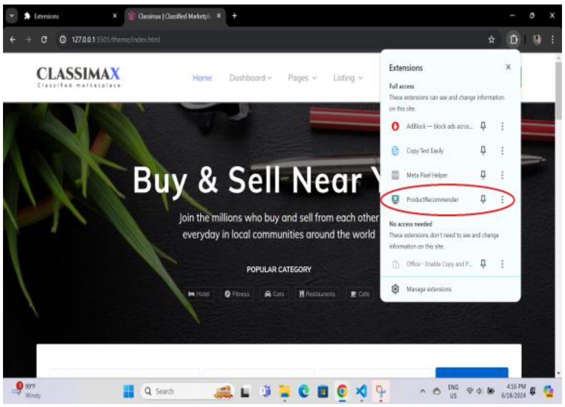
نلخص انتهاء السنة الثالثة برصيد ايجابي (ربح) بمبلغ قدره : عشرون مليونًا ومائتان وستة وسبعون ألفًا دينار جزائري

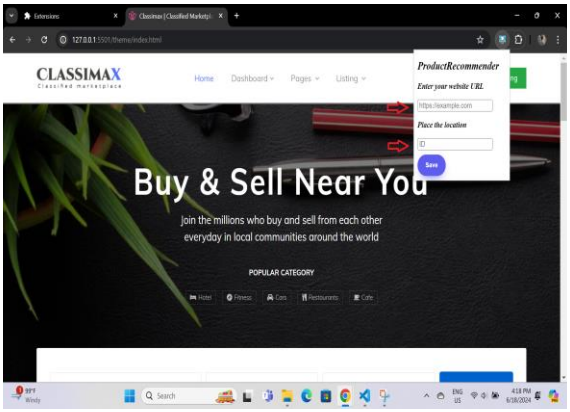
المحور السادس

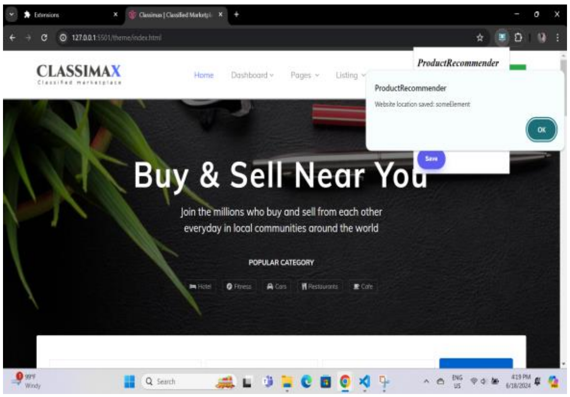
النموذج الاولي

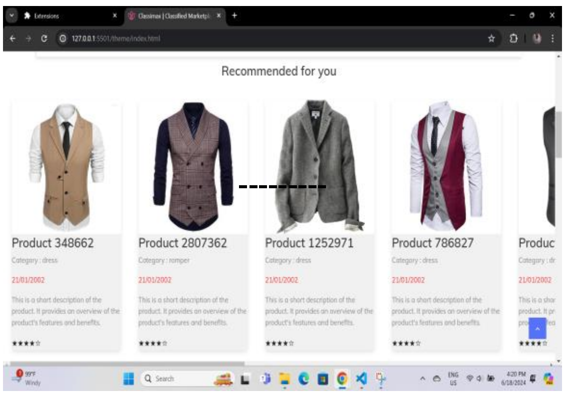

Extensions
ProductRecommender
Load unpacked
Pack extension
Update
Developer mode
My extensions
Keyboard shortcuts
All Extensions
ProductRecommender 1.0.0
Deliver personalized product suggestions using advanced machine learning to enhance user engagement and boost sales.
Details
Remove


CLASSIMAX
Home
Dashboard
Pages
Listing
Login
Add Listing
Buy & Sell Near You
Join the millions who buy and sell from each other
everyday in local communities around the world
POPULAR CATEGORY


CLASSIMAX
Extensions
Full access
These extensions can see and change information on this site.
ProductRecommender
No access needed
Manage extensions
Buy & Sell Near Y
Join the millions who buy and sell from each other
everyday in local communities around the world
POPULAR CATEGORY


CLASSIMAX
ProductRecommender
Enter your website URL
Place the location
Save
Buy & Sell Near You
Join the millions who buy and sell from each other
everyday in local communities around the world
POPULAR CATEGORY


CLASSIMAX
ProductRecommender
ProductRecommender
Website location saved: someElement
OK
Save
Buy & Sell Near You
Join the millions who buy and sell from each other
everyday in local communities around the world
POPULAR CATEGORY


Recommended for you
Product 348662
Product 2807362
Product 1252971
Product 786827
Produc

شرائح العملاء Customer Segments	العلاقة مع العملاء Customer Relationships	القيم المقترحة Value Proposition	الانشطة الرئيسية KeyActivities	الشركات الرئيسية KeyPartners
-مواقع التجارة الإلكترونية -مستخدمو مواقع التجارة الإلكترونية -المتاجر الإلكترونية الصغيرة والمتوسطة	- دعم فني على مدار الساعة -تحديثات مستمرة للميزات بناءً على ملاحظات العملاء -قنوات تواصل متعددة (بريد إلكتروني، دردشة مباشرة، وسائل التواصل الاجتماعي)	- تقديم توصيات منتجات مخصصة وفورية لتحسين تجربة التسوق عبر الإنترنت. -زيادة رضا العملاء وتحسين معدل التحويل في مواقع التجارة الإلكترونية. -سهولة التكامل والاستخدام مع إضافة جوجل كروم - قابلية التوسع في الأسواق العالمية -زيادة المبيعات والإيرادات	- تطوير وصيانة نظام التوصيات وإضافة جوجل كروم - جمع وتحليل بيانات المستخدمين - دعم العملاء والشركاء - التسويق والترويج للنظام -تحسين النماذج التنبؤية والتوصيات	-مستشاري الأمان والخصوصية -شركات التسويق الرقمي -مواقع التجارة الإلكترونية - مزودي خدمات السحابة والتخزين
	القنوات Channels		الموارد الرئيسية KeyRessou	
	-حملات التسويق الرقمي والإعلانات على وسائل التواصل الاجتماعي -الدعاية والاعلان -إضافة جوجل كروم - الشراكات مع مواقع التجارة الإلكترونية -المعارض والمؤتمرات		-الحواسيب و البرامج -فريق تطوير البرمجيات -بنية تحتية تقنية (خوادم، قواعد بيانات، أدوات تحليل) -فريق الدعم الفني والتسويق. -فريق تحليل البيانات - فريق الذكاء الاصطناعي والتعلم الآلي	

Structure Cost **هيكل التكاليف**	Streams Revenue **مصادر الايرادات**
-تكاليف تطوير وصيانة البرمجيات -تكاليف البنية التحتية التقنية (خوادم، تخزين، خدمات سحابية) -تكاليف الرواتب والأجور للفرق المختلفة -تكاليف التسويق والترويج -تكاليف الدعم الفني وخدمة العملاء	-رسوم اشتراك شهرية أو سنوية لمواقع التجارة الإلكترونية -إيرادات من الشراكات مع مواقع التجارة الإلكترونية -إعلانات مستهدفة بناءً على توصيات المنتجات

BMC