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Review Article

Recommendation Systems in Online Retail: A Comprehensive Survey of AI Techniques

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Abstract: Recommender systems play a vital role in providing pertinent content across diverse domains, such as entertainment, social networks, healthcare, education, travel, cuisine, and tourism. This review offers a thorough examination of cutting-edge recommender systems, as well as hybrid recommender systems. Hybrid models, combining different recommendation approaches, have gained prominence in enhancing system performance. The study classifies several models of hybridization and arranges the literature depending on the hybrid model and the applied machine learning methods in each study. Additionally, a systematic literature review examines the landscape of recommender systems over the last few years, emphasizing the quantitative aspects of research in this field. The review explores challenges, data mining techniques, recommendation strategies. It identifies common issues, such as addressing cold-start, accuracy, scalability and data sparsity, and highlights emerging challenges, including adapting to evolving user contexts and tastes.. Given the ongoing significance of hybrid recommenders, the review proposes exploring fresh possibilities such as utilizing parallel hybrid algorithms, and handling more extensive datasets, to address the evolving requirements of users.

Keywords: Artificial Intelligence, Collaborative Filtering, Recommendation System, Hybrid Recommendation System, Data Mining.

1. Introduction

In the ever-expanding landscape of the World Wide Web, the challenge of information overload is escalating with the exponential surge in digital data. This not only creates a dilemma for users during decision-making but also poses a difficulty for service providers aiming to offer customized and pertinent material based on individual preferences. To address these issues effectively, many e-commerce sites and service providers leverage Recommender Systems (RS), which have become integral in various domains such as entertainment, health, education, travel, food, and tourism. Derived from the Latin term "Recommendare," RS seeks to support or commend something as valuable or desirable, thereby enhancing decision-making by offering users personalized recommendations. This paper emphasizing the evolution of RS from the early Tapestry system[6] to contemporary applications like Amazon, Netflix, and LinkedIn. Through a thorough examination of recommendation techniques, encompassing Knowledge-based systems, Hybrid systems, Content-based filtering, and Collaborative filtering research categorizes diverse hybridization models according to user demography and community[1].The convergence of information from different sources highlights the significance of RS not only in the general online market but also in niche industries such as electronics equipment. Moreover, the paper offers a valuable survey of cutting-edge hybrid recommendation models, classifying current hybrid systems according to hybridization models, machine learning algorithms, and the suggested goods or services. This review's contributions include an in-depth examination of existing recommendation approaches as well as insights into hybrid recommendation models.

The primary achievements of this research include:
1. Offering a comprehensive summary of different types of recommendation methods.
2. Providing the overview of popular hybrid recommendation models available.
3. Dealing with various issues in recommendation systems.

2. Popular Recommendation Approaches

2.1. Collaberative Filtering

Collaborative filtering involves establishing connections between users[8-9]. The underlying principle is that if multiple individuals share common interests in a particular domain, it's probable that their preferences may also extend to analogous products or items in different categories additionally[3–4]. Collaborative filtering include features like friend suggestions, recommended posts, pages with similar content, and pokes on platforms like Twitter. These recommendations are tailored depending on variables including the quantity of shared connections, similar content preferences, or mutual group memberships. For instance, if two users share common connections, there's a chance they might know each other.

2.2. Content-based filtering (CBF)

Filtering use the depending on content principle of "Recommend more of what aligns with my preferences"[8]. These programs make product recommendations to users that closely resemble those they have previously enjoyed [3-4]. The features that two or more products have in common determine how comparable they are. Consider a scenario where a user is exploring articles on an online news platform. The system analyzes the user's reading patterns to identify the types of articles they prefer, subsequently recommending similar content under the suggested articles feature. Essentially, according to CBF systems, there's a good chance that a user who shows an affinity for one item in a given category will also be interested in another item in that same category.

2.3. Systems based on knowledge (KBS)

Knowledge-based systems operate on the principle of "Guide me to what suits my requirements"[8]. These systems generate recommendations by harnessing specific domain expertise or domain-specific knowledge[3–4]. The system receives needs from users and correlates them with its knowledge base to deliver the most pertinent recommendations. Imagine a scenario where individuals are searching for recipes on a cooking website. Users input their dietary preferences, such as desired ingredients, cuisine type, and dietary restrictions. The system utilizes its cooking expertise to recommend recipes aligning with the user's specified preferences, ensuring a tailored and suitable suggestion based on the user's unique requirements.

2.4. Systems of demographics

These systems tailor recommendations based on user demographic data, such as location, gender, and age[3–4]. Think about a streaming service that considers a user's age group and suggests content suitable for that demographic. For instance, for users in their twenties, the system may recommend trending movies, music, and TV shows that align with the preferences of that age group. Additionally, users can specify the category they are interested in, such as action, comedy, or drama, ensuring that the recommendations are finely tuned to their demographic and personal preferences.

2.5. Community-based systems (CBS)

Community-based systems operate on the principle of "Show me what my friends like, and I'll find what I might like"[8]. These systems factor in the interests and preferences of a user's social circle when generating recommendations. Unlike collaborative filtering, which considers suggestions from both anonymous and known users, community-based systems specifically focus on recommendations from the user's immediate network of acquaintances. Imagine a music streaming service that makes song recommendations based on a user's friends' listening preferences or a social media platform that recommends posts based on what similar connections have engaged with. By emphasizing recommendations from familiar connections, community-based systems enhance the personalization of suggestions, aligning more closely with the user's social preferences.

3. Hybrid Recommender System (HRS)

The best elements of two or more recommendation algorithms are efficiently combined by hybrid recommender systems to tackle the drawbacks of each method separately. Consider a music streaming service that integrates collaborative filtering with content-based strategies to improve user recommendations[1]. The system considers what the user has listening history and preferences, and the music choices of similar users to provide personalized suggestions. Imagine a user who enjoys rock and classical genres; the hybrid system would intelligently recommend a mix of rock and classical tracks that align with the user's diverse taste. By integrating the strengths of different recommendation approaches, hybrid systems aim to offer more accurate and tailored suggestions, providing a holistic and improved user experience.

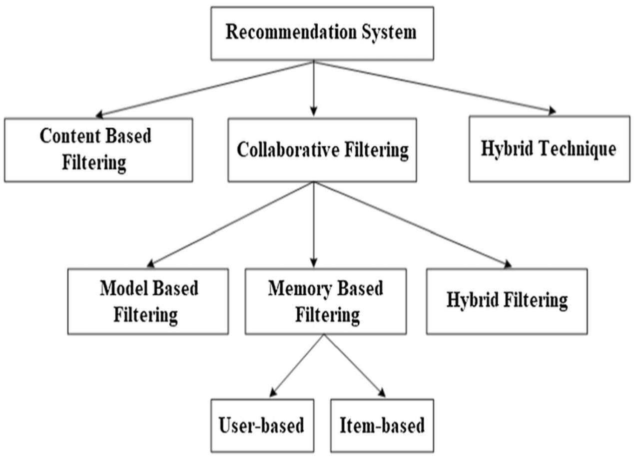

Figure 1. types of recommendation systems

Additional categorization of hybrid systems for recommendation includes:

3.1. Systems that are Hybrid but Monolithic

Dedicated recommendation modules in monolithic hybrid systems combine various recommendation strategies by preprocessing and incorporating information from a variety of sources [11]. The development of a monolithic hybrid system involves incorporating any algorithm capable of handling and preprocessing input data. This classification is further subdivided into hybrid systems with feature combination and augmentation. In Feature Augmentation, complex input data is seamlessly integrated into a single recommendation algorithm. Conversely, Feature Combination entails utilizing the results of one method as the starting point for a another algorithm. This modular integration of diverse recommendation strategies aims to improve the monolithic hybrid system's overall performance and flexibility.

3.2 Parallelized hybrid systems

Parallelized hybrid systems represent a fusion of multiple recommender systems operating simultaneously, employing hybridization mechanisms to amalgamate the outputs from these systems[1]. This category includes hybrid systems that switch, mix, and weigh data. By combining the weighted total of ranks from several recommendation techniques into one unique recommendation list, weighted systems provide suggestions. Within the framework of mixed hybrid recommender systems, user input results are combined from various suggestion systems into a single set of recommendations. Switching systems, conversely, prioritize the superiority of user preferences and suggestion results. For the user to have access to the most pertinent and appropriate results, these systems dynamically transition between recommendation methodologies based on their preferences and the effectiveness of the recommendation methods.

3.3. Hybrid systems with pipelines

Pipelined hybrid systems provide recommendations for users by means of a methodical, phased process in which several recommendation strategies are carefully sequenced one after the other. There are two divisions within this classification: Meta-level systems and Cascade systems[1]. The ideas of predecessor (antecedent) and successor (descendant) are used in cascade systems, where the output of the predecessor is modified by the successor to provide the final suggestions. Meta-level systems, on the other hand, build a model from the model as an input value for another recommendation algorithm after using it for one recommendation method. This structured arrangement of recommendation approaches in a pipeline ensures a step-by-step refinement process, ultimately enhancing the precision and relevance of the final recommendations provided to the user.

According to Robin Burke's work, hybrid systems exhibit a thorough classification into seven unique groups [11–12]:
Equilibrated: By merging scores from multiple recommendation approaches, this system delivers an enhanced and more influential weighted recommendation.
Switching: Dynamically selecting from various recommendation approaches, this system efficiently administers the chosen strategy for the final output.
Mixed: Integrating recommendations from various recommenders, this system offers a consolidated set of suggestions to the user.
Combination of Features: The elements of this system are smoothly integrated from various information bases, applying a single recommendation algorithm for cohesive output.
Feature Augmentation: In this approach, a single recommendation method computes an attribute or group of attributes, with the result serving as input for the subsequent approach in a sequential manner.

Cascade: Operating in a cascading manner, by using input from another recommender system, this approach improves recommendations made by a single recommender.

At the meta-level: Constructing a model created using just one suggestion method, this system utilizes the created model as input for another approach, thereby enriching the overall recommendation process.

Table 1. Existing Systems Based On Hybrid Model

Hybrid of	Model	Machine Learning Algorithm	Recommends
CF, CBF	Cascade	-	Websites
CF, CBF	Cascade	Clustering	Movies
CF, CBF	Feature Augmentation	Bayesian Network	Movies
CF, Context -based	Weighted, Mixed	-	Music
CF, CB F, KBS, Context-based	Feature Augmentation	Distance based re-ranking	e- Tourism
CF, CBF	Mixed	Multi-granular Fuzzy linguistic	Research resources
CF, CBF, DBS	Cascade	Boosted Similarity	Movies
CF, CBF	Weighted	Cosine similarity, Data Mining	Places of interest
CF, CBF	Mixed	Factorization Machine	Restaurants
CF, DBS	Mixed	Fuzzy Cosine, Fuzzy Jaccard	Movies
CF, CBF	Mixed	-	Movies
CF	Weighted	Hybrid Matrix factorization	Healthcare

The presented table[1] outlines a comprehensive overview of hybrid recommendation models and machine learning algorithms applied across various domains, including websites, movies, music, and e-tourism. The hybrid models often combine collaborative filtering (CF) and content-based filtering (CBF) techniques, utilizing approaches like cascade, clustering, context-based, and feature augmentation to enhance recommendation accuracy. The incorporation of diverse methodologies such as Bayesian networks, weighted and mixed strategies, and distance-based re-ranking reflects the versatility in designing these recommendation systems. Furthermore, the table showcases the application of hybrid matrix factorization, boosted similarity, and factorization machine methods, alongside distance-based techniques and fuzzy linguistic models. This amalgamation of algorithms caters to different domains such as movies, healthcare, and e-tourism, showcasing the adaptability and effectiveness of hybrid recommendation systems across a range of research resources and practical applications.

4. Machine Learning techniques in Recommendation System

Numerous techniques for machine learning and data mining employed in Recommendation Systems include[2]:

4.1 K-NN (K-Nearest Neighbours)

The machine learning algorithm KNN is utilized in collaborative filtering and other recommendation techniques where products are suggested according to the tastes of users who most closely resemble the target consumer. It considers the k-nearest neighbors to make recommendations.

4.2 Clustering

Clustering techniques group users or items with similar preferences into clusters. Recommendations are then made according to the inclinations of other users or objects in the same cluster.

4.3 Association Rules

Association rule mining identifies patterns in user behavior, such as items frequently purchased together. This technique is frequently employed in using collaborative filtering to offer suggestions depending on the historical behavior of users.

4.4 Fuzzy Logic

Fuzzy logic deals with uncertainty and imprecision in data. Fuzzy logic can be utilized in recommendation systems to control user preferences that are not strictly defined, enabling more flexible recommendations.

4.5 Matrix Manipulation

Matrix manipulation techniques, such as matrix factorization, are commonly used for collaborative filtration. Decomposing the user-item interaction matrix is a step in these techniques to capture latent features and make personalized recommendations.

Other: This category likely includes various other DM/ML techniques that are not explicitly listed. These could encompass diverse methods such as decision trees, neural networks, or hybrid models combining multiple techniques.

Table 2. DM/ML Techniques Used In Recommendation Systems

DM/ML Technique	Studies
K-NN	59
Clustering	34
Association rules	17
Fuzzy Logic	14
Matrix manipulation	9
other	19

As per the study conducted by G. Eason et al[2], The percentage of each technique used out of 152 recommendation systems is as follows:
Percentage of K-NN: (59 / 152) * 100 ≈ 38.82%
Percentage of Clustering: (34 / 152) * 100 ≈ 22.37%
Percentage of Association Rules: (17 / 152) * 100 ≈ 11.18%
Percentage of Fuzzy Logic: (14 / 152) * 100 ≈ 9.21%
Percentage of Matrix Manipulation: (9 / 152) * 100 ≈ 5.92%
Percentage of Other: (19 / 152) * 100 ≈ 12.50%
These percentages signify the weight of each technique regarding recommendation algorithms, in light of the provided studies.

5. Challenges

5.1. Cold-Start:

Tackling the cold start challenge in recommender systems[20], where new users and items lack sufficient data for accurate recommendations, a comprehensive solution is implemented. To overcome the user cold start, particularly when profiles are almost empty, some systems incorporate surveys during user profile creation, gathering valuable information to understand their preferences. Simultaneously, items facing a cold start, being new and unrated, benefit from hybrid filtering techniques. These methods find relationships that make up by applying association rule mining on item or user data to account for the absence of ratings. Moreover, feature extraction mathematical constructs enhance the understanding of user preferences[2], enabling more nuanced recommendations. The combined approach involves the strategic integration of different recommendation strategies, ensuring a robust solution to both user and item cold start challenges in recommender systems. By these strategies, we can solve the cold start problems and perform better in case of beginners.

5.2. Sparsity:

Overcoming the challenge of sparsity in recommender systems[20], particularly prevalent in large online shops with numerous users and items, demands a thoughtful solution. The sparsity issue arises when users have rated only a few items, making it challenging to accurately determine their interests and potentially associating them with the wrong user neighborhood. To address this, a strategic approach involves utilizing the limited existing ratings and specific item features to generate additional pseudo ratings, augmenting the available data. Experimentation with advanced techniques such as Matrix Factorization or Dimensionality Reduction proves beneficial in mitigating sparsity challenges[2]. By leveraging these methods, recommender systems can enhance the understanding of user preferences, alleviate the impact of sparse data, and provide more accurate and reliable recommendations in diverse and data-scarce environments.

5.3. Scalability:
Effectively tackling the scalability challenge in recommender systems[2], which arises When the quantity of products and users increases, requires a comprehensive solution. As the system demands more resources for processing information and generating recommendations, a strategic approach involves combining various types of filters within the recommender system and implementing physical improvements. Specifically, the resource-intensive task of identifying users with similar tastes and items with analogous preferences is optimized through the integration of diverse filters and enhancing the system's infrastructure[20]. Additionally, to streamline the recommendation process, parts of computational tasks can be executed offline, expediting the issuance of recommendations online. An innovative solution to enhance scalability involves compressing or reducing datasets using clustering techniques or alternative measures of similarity, ensuring efficient and resource-conscious operations in the face of increasing user and item volumes.

5.4. Accuracy:
To tackle the challenge a thorough approach to increasing a recommender system's accuracy entails the thoughtful integration of fuzzy logic or fuzzy clustering in tandem with Collaborative Filtering (CF). The challenge lies in accommodating imprecise user preferences, particularly in cases where ratings lack clarity[2]. Fuzzy Logic introduces flexibility, allowing the system to capture nuanced preferences with a degree of uncertainty. Furthermore, to further refine accuracy, the solution incorporates a hybrid approach including of CBF (content-based filtering) using mathematical structures or sophisticated probabilistic models like Bayesian Networks. This synergistic approach leverages both user-item interactions and item characteristics, providing a more precise and adaptive recommendation mechanism. By addressing the inherent challenges of imprecise preferences and incorporating advanced mathematical models, this solution significantly enhances the accuracy of the recommender system, guaranteeing users receive more relevant and customized recommendations. [20].

6. Related Work

Hu. Y et al[5] addresses collaborative filtering challenges in implicit feedback scenarios, where user preferences are inferred from implicit user actions. The authors propose a novel collaborative filtering algorithm that incorporates implicit feedback and demonstrates improved performance on real-world datasets.

Neural collaborative filtering, or NCF for short, is introduced by He. X. et al.[7] with an emphasis on the use of deep learning in recommendation systems. Network architectures and matrix factorization are combined in the model to capture complex user-item interactions. showcasing superior performance compared to traditional collaborative filtering methods.

Pazzani M.J et al[10] present a comprehensive overview of content-based recommendation systems, emphasizing the utilization of text mining techniques. The paper discusses the incorporation of item features and user profiles to enhance recommendation accuracy and user satisfaction. This survey delves into context-aware recommender systems: investigating the use of contextual data (e.g., time, location) to enhance recommendation accuracy. Adomavicius et al[13] analyse different approaches, challenges, and potential extensions for context-aware recommendation systems.

A thorough overview of hybrid recommender systems combine content-based and collaborative filtering techniques—is provided in the work [14]. The efficacy of hybrid models is evaluated by the author through an examination of various hybridization methods and the demonstration of experimental findings.

G. Adomavicius et al[15] provides an in-depth analysis of existing recommender systems, highlighting their strengths and limitations. The authors discuss possible extensions, including hybrid models, trust-aware recommendations, and the integration of contextual information.

Focusing on context-aware recommendation, Linas Baltrunas et al[16] introduces matrix factorization techniques to handle contextual information. The authors propose a model that incorporates both user preferences and contextual factors, enhancing the accuracy of recommendations in dynamic environments.

Addressing the challenges of multicriteria rating systems, Adomavicius et al[17] propose novel recommendation techniques. This study explores the integration of multiple criteria into the recommendation process, aiming to provide more personalized and relevant suggestions to users.

Robert M. Bell et al[18] reflects on the Netflix Prize challenge, a competition aimed at improving collaborative filtering algorithms. The authors discuss the lessons learned, including the importance of addressing scalability issues and the impact of ensemble methods on recommendation accuracy.

A thorough review of methods for recommending based on deep learning is provided in the work [19]. Shuai Zhang et al examine different deep learning models used for tasks involving recommendations discussing their strengths, challenges, and potential future directions in the field.

Yuanyuan Zhang et al[21] in This survey paper comprehensively analyzes how to incorporate temporal dynamics into recommendation systems for improved performance. It covers various methods for modeling temporal patterns and their impact on the effectiveness of recommendations

Jianlong Zhu et al[22] provides an overview of the application of graph neural networks (GNNs) in recommender systems. It explains different GNN architectures and their benefits for recommendation tasks, making it a valuable resource for researchers in this field.

Yaohua Liu et al[23] explores counterfactual recommendation approaches that leverage causal inference techniques. It explains how these methods provide more accurate and explainable recommendations by analyzing possible outcomes under different conditions.

Yifan Liu et al[24] proposes a novel ranking-based recommendation method that utilizes attention mechanisms to explain model predictions while promoting fairness. This leads to improved recommendation accuracy, transparency, and reduced bias compared to existing methods.

Jitao Yu et al[25] presents a comprehensive survey on context-aware recommendation systems, analyzing how they incorporate various contextual factors (e.g., user location, time, social network) to improve recommendation accuracy and user satisfaction.

7. Conclusion & Future Scope

This review examined the robust global recommendation systems, examining their various uses, current research directions, and the data mining methods such as KNN, clustering, association rule mining, and fuzzy logic that contribute to their effectiveness. Through the integration of diverse recommendation methodologies, such as collaborative filtering and content-based filtering, these models provide more precise and tailored recommendations in a range of industries, including healthcare and entertainment. Although major issues like data sparsity and cold start are addressed, there are plenty of prospects for further study. Unlocking even more potential in these systems will guarantee recommendations that are always appropriate for users in every subject. This can be achieved by investigating parallel hybrid algorithms for quicker processing, managing larger datasets to capture evolving user behavior, and adjusting to shifting preferences.

Conflict of Interest

The authors of this review paper, declares that we have no actual or potential conflicts of interest with any organizations, institutions, or individuals related to the subject matter of this paper. We have not received any financial or non-financial support from any parties directly or indirectly related to the content of this review. Our analysis and opinions are based solely on our independent and objective assessment of the available research and information.

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Author's Contribution

Author-1 Contributed to the literature review and manuscript editing for review paper. Author-2 Contributed to the literature review and conceptualization of research ideas. Author-3 Assisted in data interpretation, manuscript drafting, and provided critical revisions for research papers. Author-4 collected data, and contributed to data mining techniques and results based on research papers. Author-5 Supervised the research, provided guidance throughout the process.

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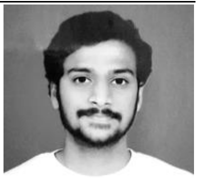

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