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REVIEW ARTICLE

A Survey on Recommendation System Techniques.

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ABSTRACT

The main objective of recommendation systems (RS) is to analyze user behavior and recommend important items or services that users might be interested in. Recommendation systems have grown in popularity in various domains such as information technology and e-commerce. They achieve this by customizing recommendations based on individual preferences, efficiently filtering options from a vast pool, and enabling users to discover content that matches their interests. To generate personalized suggestions, numerous recommendation techniques have been developed, including collaborative filtering, content-based filtering, knowledge-based recommendation systems, and others. In addition, hybrid recommendation systems have been proposed to address the limitations of individual methods by combining various techniques.. Our article provides an overview of diverse recommendation techniques, their fundamental approaches, challenges, solution and has equally looked at different solutions to these challenges faced by modern recommender systems. It also recommends promising avenues for future directions.

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INTRODUCTION

Recommendation systems (RSs) are programs that forecast a user's interest in an item based on associated data about the item and then recommend the most appropriate items (service or product) to clients (businesses or individuals (Jie et al., 2019). The goal of developing a recommender system is to reduce information overload by recovering the most relevant information and services from massive amounts of data, enabling personalized services (Mohammed and Chandrasekar, 2019). The most important feature of a recommender system is its ability to predict a user's preferences and interests by analyzing this user's actions and/or the actions of other users to generate personalized recommendations. (Lipi et al., 2016).

In recent years, much progress has been made in the field of artificial intelligence, particularly within the framework of machine learning. A variety of software systems are currently using Machine Learning-based techniques. The features provided in practical applications range from assisting the client in making decisions, such as a recommendation system, to completely autonomous decision making, such as an automated pricing algorithm (Cheng et al., 2019). A steady increase in such intelligent applications is expected in the coming years, as more types of data become available for use by modern machine learning algorithms, which may pose new challenges in the development of a recommender system (Nunes and Jannach, 2020).

Furthermore, recommender systems are used in many areas to reduce the burden of information overload, allowing clients to concentrate on critical information mainly based on their interests (Li et al., 2021). One area in which these types of systems would play a significant role is in assisting students in achieving their professional objectives by producing tailored career path and talent guidelines (Li and Sun, 2021). At the moment, there are multiple job posting websites that provide an extensive range of information and students are willing to devote hours searching for job that match what interests them. Simultaneously, current process recommendation systems are useful for remembering a user's field of interest, but fail to take into account their personal strength and competence which can generate more relevant career path recommendations for users (Alhijawi and Kilani, 2016).

According to Numnonda (2018), there are four different types of recommendation systems that are frequently used: content-based, collaborative filtering-based,

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knowledge-based, and hybrid-based. Every recommendation system type has advantages and disadvantages (Xiao et al., 2018). For instance, collaborative filtering-based recommenders may experience problems with cold start, scalability, and sparsity. While the capacity of a content-based recommenders system to broaden users' existing interests may be constrained (Zhang et al., 2019; Benouaret and Amer, 2020).

This article provides an overview of several recommendation techniques, their underlying approaches, problems, and solutions. It also looks at various answers to the problems that contemporary recommender systems face today and suggests potential prospects.

The remaining part of this paper is structured as follows: Section 2 offers a thorough analysis of ground-breaking developments in recommendation systems as well as a detailed analysis of previous and present state-of-the-art methodologies. The issues that recommendation systems encounter, like diversity scalability and sparsity, are covered in Section 3. It also discusses solutions to problems with contemporary recommendation systems. While Section 5 takes care of the conclusion, Section 4 offers directions for the future.

RECOMMENDATION SYSTEM

In order to provide personalized services, recommendation systems attempt to predict users' preferences for a specific product (Yi et al., 2019). The collaborative filtering-based, content filtering-based, knowledge-based, and hybrid recommender methods will all be covered in this section.

Content based Filtering Recommendation Systems

The fundamental idea behind content filtering based recommendation systems (RS) is to suggest products based on how similar they are to other products or clients (Lops et al., 2011). By analyzing the corresponding descriptions of each item, this algorithm determines as well as differentiates the major common characteristics of a specific client's preferred items. These preferences are then saved in the client's profile. The algorithm afterwards recommends items that are closely matched to the client's profile. Additionally, content-based recommendation systems have the ability to identify a client's unique interests and suggest unusual items that might not be of much interest to other clients. However, this approach requires a lot of domain-specific knowledge because item representations of features are somewhat manually designed. Additionally, content-based RS can only make recommendations based on the current interests of the clients.

Collaborative Filtering Recommendation Systems

Collaborative filtering (CF) based RS assist client in making choices based on the perspectives of others with similar interests (Elahi et al., 2016). CF recommendation systems recommend to other clients based on the behavior of a group of users (Al et al., 2018). User-based and item-based collaborative filtering techniques exist. In the user-based collaborative filtering method, users receive recommendations of products liked by other users (Rezaimehr and Dadkhah, 2021). In the item-based CF approach, the user receives recommendations of products that are comparable to those they have previously liked (Zhang et al., 2019). To determine the similarities between users or items, "Pearson correlation-based similarity is used, constrained Pearson correlation (CPC) based similarity, cosine-based similarity, or adjusted cosine based measures can be used" (Resnick et al., 1994) to assess the similarities between users or items. When determining the similarity between two items using the aforementioned metrics, only users who have rated both items are taken into account. If items with few ratings express a high level of similarity with other items, the outcome may have an effect on similarity accuracy. "By combining the adjusted cosine approach with the Jaccard metric as a weighting scheme, an enhanced item-based CF approach was presented to enhance similarity accuracy. The Jaccard metric was combined with the CPC as a weighting scheme to create a weighted CPC measure, which was then used to calculate user similarity (Shambour et al., 2011). Multi-criteria collaborative filtering was created to address the shortcomings of the single-rating approach (Nilashi et al., 2014).

Knowledge based Recommendation Systems

According to Shishehchi et al., (2012) and Aggarwal (2016), the fundamental idea behind knowledge-based RS is to suggest items to users based on their knowledge of users, items, and item relationships. There is no cold start problem for knowledge-based RSs because they don't need user ratings or history of purchases (Cabezas, 2017). Knowledge based RSs are ideal for complex domains with infrequently purchased products, such as cars and apartments (Tarus et al., 2018). However, acquiring the necessary domain knowledge may be an impediment for this recommendation technique (Dong et al., 2020).

Hybrid based Recommendation Systems.

By combining the advantages of various recommendation techniques, hybrid-based recommendation systems aim to overcome the "potential weaknesses of traditional recommendation systems" (Ribeiro et al., 2012). "Mixed, Weighted, feature, Switching, combination, cascade, feature augmentation, and meta-level methods are the seven basic hybrid recommendation techniques" (Ibrahim et al., 2021). The most popular approach to prevent sparsity, scalability, and cold-start issues is to combine CF recommendation methods with other recommendation methods (such as content-based or knowledge-based) (Hrnjica et al., 2020; Zagranovskaia and Mitura, 2021; George et al., 2019). By combining multiple approaches, hybrid systems have the potential to provide more accurate and diverse recommendations (Zhang et al., 2016; Hassan and

Hamada, 2016). Table 1 provides the summary of recommender systems techniques.

Table 1: Summary of the Modern Recommendation Systems Methods.

Recommendation Systems	Descriptive Key	Points Papers
Content based	Items are recommended based on their similarities.	Musto et al., 2016 Volkovs et al., 2017 Mittal et al. 2020
Collaborative Filtering based	Recommend items to some users based on the behavior of other users.	Zhang et al., 2016 Bobadilla et al., 2020 Bobadilla et al., 2020
Knowledge based	Recommend items to users based on the understanding of the users, the items, and the relationships between the items.	Dong et al., 2020 Gazdar et al., 2020 Alamdari et al., 2020
Hybrid based	Recommend items to users using more than one filtering method.	Hrnjica et al., 2020 Shokeen et al., 2020 Zagra & Mitura, 2021

Machine Learning (ML) for Recommender Systems

Machine learning, an aspect of artificial intelligence, empowers computers to learn from data, experience, and examples directly (Fumo, 2017). This approach enables computers to intelligently perform specific tasks and complex operations by learning from data and examples. "The phrase machine learning" was first used by Arthur Samuel to describe a branch of computer science that focuses on how computers can learn and educate themselves without the need for explicit programming" (Cheolsoo et al., 2018). Recent times, technologies for machine learning have advanced to a point where models can outperform humans in certain tasks, such as image recognition. Significant advancements have been made in the field of ML, particularly in recent years.

Machine learning is a crucial tool in this study due to its capability to make decisions or predictions based on vast amounts of data. Unlike static resume audits, machine learning models continuously adapt their output based on inputs and knowledge gained from previous data and experience. "Supervised learning, unsupervised learning, and reinforcement learning" are the three categories of ML (Fumo, 2017).

Predicting a target variable from a set of predictors is what Supervised Learning is all about. This method employs labeled data with a known target variable to create a function that can translate input variables into desired output. K-nearest neighbors (KNN), support vector machines (SVM), decision trees, logistic regression, and random forests are a few examples of supervised machine learning algorithms. On the other hand, unsupervised learning is employed when the data set consists of clusters and the target variables are unknown. Unsupervised learning algorithms, such as Apriori and K-means, seek to discover patterns and relationships in data that do not contain a specific target variable (Ray, 2017). Classification is a data mining technique commonly used in supervised learning that involves predicting the value of class attributes based on predictor values (Sharma et al., 2015).

"An unsupervised learning algorithm does not have a target or outcome variable to predict or estimate. It is widely used to segment customers into different groups for targeted interventions by clustering the population into these groups. Clustering, association rules, and dimensionality reduction are a few examples of unsupervised learning" (Smiti, 2020).
Another machine learning method that can be used for recommendations is reinforcement learning. In reinforcement learning, the computer is programmed to make particular judgment calls. It operates in the following manner: "The machine is exposed to a setting where it continuously trains itself using trial and error. To make precise business decisions, this machine attempts to learn from the past and attempts to gather the best knowledge it can. Following are a few instances of reinforcement learning: Process of Markov Decisions. With reinforcement learning, the learner decides which tasks to complete in order to enhance the outcome. The actions taken by the learner will have an effect on events and actions that happen later. Trial-and-error searching and delayed outcomes are the two main prerequisites for reinforcement learning (Dey, 2016).

CHALLENGES IN MODERN RECOMMENDATION SYSTEMS

i. Data Sparsity and Cold Start: Recommender systems frequently struggle with sparse data, especially for new or specialized products and users with scant prior interaction. (West et al., 2016) "Handling the cold start problem where there is insufficient data to make accurate recommendations remains a challenge" (West et al., 2016).

ii. Scalability: As datasets and user bases continue to grow, scalability becomes a challenge. Recommender systems need to efficiently handle large-scale datasets, real-time recommendations, and handle high user and item dimensions (Shokeen and Rana, 2020).
iii. Long-Tail Recommendations: Recommending items from the long tail (less popular or niche items) is crucial for diverse and personalized recommendations. However, it is challenging to capture user preferences and provide accurate recommendations for these less prominent items (Ricci et al., 2015).
iv. Explaining Recommendations: Explainability and transparency are important for building trust with users. Providing meaningful and understandable explanations for recommendation is a challenge, especially for complex models like deep learning approaches (Ricci et al., 2015).
v. Contextual Recommendations: Incorporating contextual information such as time, location, or user context can improve recommendation accuracy. However, effectively leveraging contextual data and adapting recommendations in real-time based on changing contexts remains a challenge (Kaminskas and Bridge, 2016).
vi. Diversity and Serendipity: Ensuring diverse recommendations that go beyond mainstream item is a challenge. Recommender systems often struggle to provide serendipitous recommendations that introduce users to new and unexpected items (He and Ke, 2021).
vii. Fairness and Bias: Recommender systems may inadvertently introduce biases, leading to unequal representation or discrimination. Ensuring fairness in recommendations and mitigating biases related to user demographics or historical data remains an ongoing challenge (Kaminskas and Bridge, 2016).
viii. Privacy and Security: Protecting user privacy while providing personalized recommendations is a challenge. Designing recommender systems that respect user privacy, handle sensitive data appropriately, and prevent unauthorized access is a crucial concern (Kaminskas and Bridge, 2016).
ix. User Engagement and Satisfaction: Measuring and optimizing user engagement and satisfaction beyond accuracy metrics is a challenge. Capturing user preferences, capturing evolving tastes, and incorporating diverse user feedback into the recommendation process are ongoing challenges (Kaminskas and Bridge, 2016).

SOLUTIONS TO CHALLENGES FACED BY MODERN RECOMMENDATION SYSTEMS

These solutions provide potential approaches to address the current challenges in recommender systems. The effectiveness of this solution may vary depending on the "specific application and context," according to Ge et al., (2010).

Here are some potential solutions to the open current problems and challenges in recommender systems:

i. Data Sparsity and Cold Start:
   - Hybrid approaches: these combine collaborative filtering and content-based techniques to address the cold start issue and reduce data sparsity.
   - Knowledge-based recommendations: Make recommendations for new or less popular items and users based on "domain" knowledge or metadata.

ii. Scalability:
   - Distributed computing: Utilize distributed systems and parallel computing techniques to handle large-scale datasets and perform real-time recommendations efficiently.
   - Model optimization: To lessen the computational complexity of recommendation algorithms, investigate model compression, dimensionality reduction, or approximation techniques.

iii. Long-Tail Recommendations:
   - Diversity promotion techniques: Introduce diversity-aware recommendation algorithms that actively promote less popular items and avoid over-representing popular ones.
   - Hybrid models: Combine popularity-based and personalized approaches to balance recommendations between popular and long-tail items.

iv. Explaining Recommendations:
   - Model interpretability: Develop explainable recommender systems that provide transparent explanations for recommendations, such as by leveraging rule-based models or providing feature-level explanations.
   - User interface design: Design intuitive and user-friendly interfaces that communicate recommendations and their rationale effectively to users.

v. Contextual Recommendations:
   - Context-aware algorithms: Develop recommendation models that incorporate contextual information explicitly, such as incorporating temporal or spatial into the recommendation process.
   - Dynamic adaptation: Always update recommendations based on changing contextual factors, leveraging real-time data and online learning techniques.

vi. Diversity and Serendipity:
   - Novelty-focused algorithms: Design algorithms that prioritize recommending novel and diverse items, encouraging users to explore different options.

- Serendipity enhancement techniques: Incorporate randomness or surprise factors into recommendation algorithms to introduce unexpected and delightful recommendations.

vii. Fairness and Bias:

- Develop recommendation models that explicitly address fairness considerations, mitigating biases related to user demographics or item popularity.
- Regularization techniques: Incorporate fairness constraints or regularization terms into recommendation models to promote equal representation and mitigate biases.

viii. Privacy and Security:

- Privacy-preserving techniques: Employ privacy-enhancing technologies such as differential privacy, federated learning, to protect user data while generating personalized recommendations.
- User control and transparency: Provide users with greater control over their data, explicit consent mechanisms, and transparent information about data usage and security measures.

ix. User Engagement and Satisfaction:

- Interactive recommendation interfaces: Develop interactive systems that allow users to provide feedback, refine preferences, and actively engage in the recommendation process.
  Multi-objective optimization: Incorporate multiple metrics beyond accuracy, such as novelty, diversity or serendipity into recommendation models to optimize user satisfaction.

FUTURE DIRECTIONS

According to Lu et al., (2018), here are some potential future directions for recommender systems:

i. Explainable Recommender Systems: Enhancing the transparency and interpretability of recommender systems is a growing area of research. Future directions may involve developing models and techniques that provide clear explanations for recommendations, enabling users to understand and trust the underlying recommendation process.

ii. Contextual and Multimodal Recommendations: Incorporating contextual information, such as time, location, or user context, can lead to more personalized recommendations. Additionally, exploring multimodal data sources like images, audio, or text can provide richer representations of items and users, enabling more diverse and accurate recommendations.

iii. Long-Term User Modeling: Modeling user preferences and behavior over longer periods can improve recommendation quality. Future directions may involve capturing and utilizing long-term user interests, preferences, and evolving behaviors to adapt recommendations to changing user needs.

iv. Trust and Fairness: Incorporating trustworthiness and fairness considerations into recommender systems is an emerging research area. Addressing biases, ensuring fair representation of diverse items and user groups, and considering the impact of recommendations on different stakeholders are important future directions.

v. Privacy-preserving strategies: Use technologies that protect user data while producing personalized recommendations, such as differential privacy and federated learning.

vi. Reinforcement Learning and Sequential Recommendations: Applying reinforcement learning techniques to optimize sequential recommendations can improve long-term user satisfaction. Future directions may involve exploring advanced reinforcement learning algorithms and approaches to model user dynamics and preferences in sequential decision-making scenarios.

vii. Interactive and Conversational Recommendations: Enabling interactive and conversational recommendation systems allows users to provide feedback, refine preferences, and have interactive dialogues with the system. Future directions may involve integrating natural language processing (NLP) techniques and dialog management to create more engaging and personalized recommendation experiences.

CONCLUSION

Recommendation systems are now widely used in a variety of web applications due to their recent surge in popularity. The goal of these systems is to offer users customized recommendations for online goods and services. To address various scenarios, various recommendation techniques have been developed, including content-based, collaborative filtering-based, knowledge-based, and hybrid approaches.

An extensive analysis of traditional and modern recommendation system approaches is given in this article. Explores the difficulties that contemporary recommendation systems face, such as scalability, sparsity, diversity, etc., and discusses solutions. It also suggests promising directions for the future.

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