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A Systematic Review of Recommendation Systems: Applications and Challenges

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Abstract: Recommendation system has emerged as one of the major and important research interests amongst researchers and scholars that is being used to find items of choice online by providing suggestions matching their interest. In this review paper we have tried to provide different recommendation systems being used, issues associated with them, and the tools and methodologies used for the retrieval of desired information. This paper's primary goal is to identify the current research direction in recommender systems. This work has produced a number of intriguing discoveries that will help scholars and researchers in evaluating and planning their future directions.

Keywords: *Recommender system; issues, challenges, filtering approach, filtering technique; information retrieval technique.*

1. Introduction

Recommendation systems are methods and techniques being used to offer recommendations for users[1]–[5]. There are different types of recommendations such as fashion[6], news[7], education [8], smart phones[9],movies[10], [11], banking [12], [13] tourism recommendations[14], [15]. Taking contextual information into account, the system provides recommendations based on user interest. There is massive amount of data being generated every day characterized by variety, volume, velocity, veracity, and value that has dramatically transformed many aspects of everyday life that includes interactions with social networks, healthcare services, e-commerce, education, energy etc. The massive data being generated must be processed appropriately in order to provide users with significant knowledge about their health, education, news, environment subsequently allowing them to adapt to changes on time. However, it is a huge challenge to process the data correctly that can be accessed by the users[16]. To overcome such a problem recommender system could effectively be used to provide maximum and accurate information required for personalized learning and usages[17]. Contextual information is one of the approaches that can effectively be used to make substantial recommendations in different fields. Still, issues like plentiful information, context redundancy, and data redundancy must be resolved in order to more generate effective recommendation systems[18].

User-related data being generated carries value and it is sensitive to phishing. There have been many researches wherein the researchers have tried to develop privacy-preserving recommendation systems but most of the research has overlooked the important aspect of privacy and security rather they have focused on developing algorithms for optimization of accuracy and scalability. Recommendation systems are vulnerable to external attacks by hackers who can inject or manipulate data used for training the models[19]. Emergence of cloud computing has made the safety of storage data much more difficult and challenging as the security and privacy can be compromised by phishers.

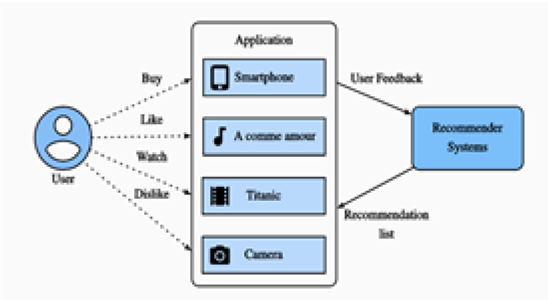

Fig 1 Architecture of a recommender system

Overall, recommender systems are a promising technology with many practical applications, and their continued development and improvement will play an important role in enhancing user experiences and driving innovation in various fields.

This review paper provides an overview of the most common types of recommender systems, including content-based filtering, collaborative filtering, and hybrid

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systems. It discusses the advantages and limitations of each approach, as well as the challenges associated with building effective and scalable recommender systems.

The paper also reviews recent advances in the field, such as deep learning and matrix factorization techniques, which have shown promising results in improving the accuracy and efficiency of recommender systems. Additionally, the paper discusses emerging research directions, such as explainable recommendation and personalized recommendation, which aim to enhance the interpretability and user-centricity of recommender systems.

Finally, the paper highlights the ethical and social implications of recommender systems, such as filter bubbles, bias, and privacy concerns, and discusses potential solutions and best practices for addressing these issues. Overall, this review paper provides a comprehensive and up-to-date overview of recommender systems, which can be useful for researchers, practitioners, and anyone interested in understanding the key concepts and challenges of this important field.

2. History of Recommender Systems

The 1990s created the groundwork for many of today's recommender systems. An experimental mail system named Tapestry introduced the idea of "Collaborative Filtering" by allowing users to create mail filtering criteria that, among other things, may be related to other people's opinions andbehaviours[20]. Later, in 1994, the GroupLens news filtering system was introduced with the goal of automating the Tapestry system's rule-based collaborative filtering process. One of the earliest systems was GroupLens, which relied on explicit ratings provided by a user community andused machine learning to forecast whether a user will find certain unseen messages appealing.

The World Wide Web expanded quickly in the 1990s, opening up a growing number of potential application areas for recommender systems. Many success stories involving the use of recommender systems in e-commerce were documented even before the decade concluded, with Amazon.com being one of the pioneers in the widespread adoption of recommendation technology. Nowadays, personalised recommendations are a common part of our online experiences, and numerous studies on the economic benefits of these recommendations have been published over time.

The original GroupLens system used a relatively straightforward nearest-neighbor method. Since then, though, a variety of machine learning techniques have been used or adapted for specific problems. Matrix factorization techniques, which were initially proposed to be utilised for collaborative filtering in the 1990s, predominated the field for a significant amount of time. The Netflix Prize (2006–2009), whose objective was to forecast movie ratings accurately, later accelerated research on the application of machine learning algorithms for rating prediction and item ranking. Research of a very similar sort is blooming today, 15 years after the Netflix Prize was established, this time propelled by deep learning's widespread adoption and success in numerous machine learning application fields.

These days, social networking websites (like Facebook, Twitter, etc.) have become a significant application platform for recommender systems. These well-known websites are regarded as the primary sources of information about people, making them an excellent choice for utilising cutting-edge methods for recommendations instead of the conventional ones in order to improve accuracy. The contextual information found in these social networking sites, such as time, place, and people's emotions, provides up a new channel for recommendations known as contextual Recommender System. Also, it offers a fantastic opportunity to add a dynamic quality to the recommendation. The impact of recommender systems on human behaviour, both individually and collectively, and the implications for businesses and societies call for more study. Since the intended effects of utilising a recommender system—and hence the pertinent performance metrics—largely depend not just on a certain domain or application, but even on the provider's business model, it is frequently crucial to understand the quirks of the particular application.

3. Different Types of Recommender Systems

3.1. Content Based Recommender System

Content-based filtering recommends items that are similar to the ones a user has previously liked or interacted with. It analyzes the attributes or features of items, such as genre, keywords, or metadata, and uses them to create a user profile or preference model. Then, it recommends items that have similar features to the ones that the user has already shown interest in.

One advantage of content-based filtering is that it can handle the cold start problem, where new items or users have little or no data available. However, it may suffer from the over-specialization problem, where it recommends only items that are too similar to the user's past behavior, leading to limited diversity and serendipity.

3.2. Collaborative filtering recommender system

Collaborative filtering recommends items based on the similarity between users' past behavior or ratings. It assumes that users who have similar preferences in the past are likely to have similar preferences in the future. There are two main types of collaborative filtering: user-based and item-based.

User-based collaborative filtering creates a similarity matrix between users based on their past ratings, and then recommends items that are highly rated by similar users. Item-based collaborative filtering creates a similarity matrix between items based on how frequently they are co-rated by users, and then recommends items that are similar to the ones that the user has already liked.

One advantage of collaborative filtering is that it can handle the sparsity problem, where users have rated only a small fraction of the available items. However, it may suffer from the scalability problem, where the computational cost of calculating the similarity matrix increases rapidly with the number of users and items.

There are various categories of CF such as:

3.2.1. Memory-based collaborative recommender system

The memory-based Collaborative Recommender System uses a similarity measure and a prediction calculation as its two primary phases. The memory-based Collaborative Recommender System is further divided into two components dependent on the method used to compute similarity.

- **Item-based Collaborative Recommender System:**

Similarity computation is performed on a set of items.

- **User-based Collaborative Recommender System:**

Similarity computation is performed based on the similarity values of users.

- **Model-based collaborative recommender system**

Different machine learning algorithms, including Bayesian networks, clustering, Markov decision processes, sparse factor analyses, dimensionality reduction techniques, and rule-based approaches, among others, are used in model-based Collaborative Recommender Systems to construct a model for the recommendation.

3.3. Demographic recommendation system

A demographic recommendation system is a type of recommendation system that makes recommendations based on demographic information about users, such as their age, gender, location, education level, and income.

The system works by analyzing demographic data and identifying patterns in user behavior and preferences. It then uses this information to suggest products or services that are likely to be of interest to users with similar demographic profiles.

For example, a demographic recommendation system used by an online retailer might analyze data from customers in a certain age group and location, and then recommend products that have been popular with other customers in that demographic group. Similarly, a movie streaming service might use demographic data to suggest movies that have been popular with users in a particular age or gender group.

However, it is important to note that demographic information is just one of many factors that can influence user preferences, and relying solely on demographic data may not provide accurate recommendations for all users. Therefore, it is often used in combination with other recommendation techniques, such as collaborative filtering or content-based filtering, to improve the accuracy and relevance of recommendations.

3.4. Hybrid recommender system

Hybrid recommender systems combine multiple recommendation approaches to improve their accuracy and coverage. For example, a hybrid system can combine content-based and collaborative filtering by using the content-based approach for new users or items, and the collaborative filtering approach for users or items with sufficient data.

Hybrid systems can also incorporate other information sources, such as demographic or social data, or use more advanced techniques such as deep learning or matrix factorization. One advantage of hybrid systems is their flexibility and adaptability to different domains and data sources. However, they may require more complex algorithms and infrastructure to integrate multiple approaches.

3.5. Knowledge-based recommender system

Knowledge-based recommender systems recommend items based on explicit rules or knowledge about the domain or the user's needs. For example, a knowledge-based system for travel recommendations can consider the user's travel budget, destination preferences, and travel dates to suggest the best options.

One advantage of knowledge-based systems is their transparency and explain-ability, as they can provide detailed and personalized explanations for each recommendation. However, they may require significant domain knowledge and expert input, which can be expensive and time-consuming to acquire.

Another type of Knowledge Based Recommender System, known as constraint-based Recommender System. A constraint-based recommender system is a type of recommendation system that considers user preferences and constraints to generate personalized recommendations.

In a constraint-based recommender system, users provide information about their preferences and constraints, which are used to generate recommendations that meet their specific requirements. The system then searches for items or products that satisfy these constraints and presents them as recommendations to the user.

For example, a constraint-based recommender system used by a travel agency might consider a user's preferred destination, budget, travel dates, and other constraints such as preferred modes of transportation or accommodation type. Based on this information, the system would recommend travel packages that meet the user's specific requirements.

Constraint-based recommender systems can be useful in situations where users have very specific requirements or constraints that must be met, such as when planning a trip or purchasing a high-end product. However, they may be less effective in cases where users have more general preferences or are open to exploring new options.

Overall, constraint-based recommender systems can be a useful tool for providing personalized recommendations that meet user's specific needs and preferences.

3.6. Context-aware recommender system

Context-aware recommender systems are a type of recommendation system that considers contextual information about the user and their environment in order to provide personalized recommendations.

Contextual information can include a wide range of factors, such as location, time of day, weather, device type, social context, and user activity. By analyzing this information, the system can generate recommendations that are more relevant and tailored to the user's current context.

For example, a context-aware recommender system used by a music streaming service might consider a user's location, time of day, and previous listening history to recommend songs or playlists that are appropriate for the user's current environment. Similarly, a context-aware recommender system used by a restaurant recommendation app might consider a user's location, time of day, and preferred cuisine to recommend nearby restaurants that match the user's current context and preferences.

Context-aware recommender systems can be particularly effective in situations where user preferences are highly influenced by contextual factors. For example, a user's music preferences may change depending on their location or mood, and a context-aware system can adapt to these changes and provide more relevant recommendations.

Overall, context-aware recommender systems can be a powerful tool for providing personalized recommendations that consider the user's current context and preferences. By leveraging contextual information, these systems can provide more accurate and relevant recommendations, leading to a better user experience.

4. Challenges associated with building effective and scalable recommender systems

Building effective and scalable recommender systems can be challenging due to several factors. In this article, we will discuss some of the most common challenges and how they can be addressed.

4.1. Data Sparsity and Cold Start

Recommender systems rely on data about user behavior, preferences, and feedback to make accurate recommendations. However, in many cases, the available data is sparse, meaning that most users have rated only a small fraction of the items. This can lead to inaccurate and biased recommendations, especially for new or unpopular items.

One solution to this problem is to use content-based filtering or hybrid approaches that can leverage the available item features or metadata to make recommendations even for users with little or no data. Another solution is to use active learning or user feedback to gather more data and improve the model over time.

4.2. Scalability and Performance

As the number of users and items grows, recommender systems can become computationally expensive and time-consuming to train and evaluate. This can limit the scalability and real-time performance of the system, leading to slower and less personalized recommendations.

To address this challenge, several techniques can be used, such as dimensionality reduction, model parallelism, and distributed computing. These techniques can reduce the computational cost and speed up the training and prediction time, enabling faster and more accurate recommendations.

4.3. Diversity and Serendipity

Recommender systems should not only provide accurate and relevant recommendations but also ensure diversity and serendipity, meaning that they should recommend items that the user has not seen before or that are outside their usual preferences.

One solution to this problem is to use diversity metrics, such as coverage or novelty, to evaluate the performance of the system and to balance accuracy and diversity. Another solution is to use hybrid approaches that can combine different recommendation techniques, such as collaborative filtering and content-based filtering, to improve diversity and coverage.

4.4. Privacy and Security

Recommender systems can collect and use sensitive data about users, such as their browsing history, purchase behavior, or social connections. This can raise privacy and security concerns, especially if the data is used for purposes that the user did not explicitly consent to.

To address these concerns, recommender systems should follow ethical and legal guidelines, such as data protection regulations or privacy policies. They should also provide transparent and explainable recommendations, meaning that the user should be able to understand how the recommendations are made and to control their data usage.

5. Improving the accuracy and efficiency of recommender systems

Improving the accuracy and efficiency of recommender systems is a crucial task to provide users with relevant and personalized recommendations in a timely manner. In this article, we will discuss some of the most effective techniques and strategies to improve the performance of recommender systems.

5.1. Collaborative Filtering

Collaborative filtering is one of the most popular techniques used in recommender systems. It works by analyzing the behavior and preferences of a group of users to find similar users or items and to make recommendations based on their past actions. This technique can be improved by using more advanced models, such as matrix factorization or deep learning, that can capture complex and non-linear relationships between users and items.

5.2. Content-based Filtering

Content-based filtering is another technique used in recommender systems. It works by analyzing the features and attributes of the items to find similar items and to make recommendations based on the user's preferences. This technique can be improved by using more advanced natural language processing or computer vision techniques to extract and represent the item features, such as text or images.

5.3. Hybrid Approaches

Hybrid approaches combine multiple recommendation techniques, such as collaborative filtering and content-based filtering, to improve the accuracy and coverage of the recommendations. This technique can be improved by using more sophisticated combination strategies, such as weighted or cascading models, that can better balance the strengths and weaknesses of the individual techniques.

5.4. Active Learning

Active learning is a technique used to improve the accuracy of recommender systems by actively selecting and requesting feedback from users on specific items or attributes. This technique can be improved by using more intelligent and personalized selection strategies, such as uncertainty sampling or diversity maximization, that can better balance exploration and exploitation of the user preferences.

5.5. Scalable Computing

Scalable computing is a technique used to improve the efficiency of recommender systems by using distributed or parallel computing architectures that can handle large amounts of data and computations. This technique can be improved by using more efficient and optimized algorithms, such as stochastic gradient descent or alternating least squares, that can exploit the distributed computing resources and reduce the communication overhead.

6. Explainable recommendation and personalized recommendation to enhance the interpretability and user-centricity of recommender systems.

6.1. Explainable Recommendation

Explainable recommendation aims to provide users with clear and understandable explanations for why certain recommendations are being made. This can help users to better understand the system and build trust in its recommendations.

- There are several ways to achieve explain-ability in a recommender system, including:
- Using clear and concise language in the recommendation interface
- Providing information about the input data used to generate the recommendations (e.g., item features or user feedback)
- Highlighting the key factors that influenced the recommendations
- Using visualization techniques to show the relationships between items or users

By providing explanations, users can better understand the reasoning behind the recommendations and make more informed decisions.

6.2. Personalized recommendation

Personalized recommendation aims to provide users with recommendations that are tailored to their specific needs and preferences. This can help to improve the user-centricity of the system, as users are more likely to engage with the recommendations when they are relevant to their interests.

- There are several ways to achieve personalization in a recommender system, including:
- Incorporating user feedback to improve the accuracy of the recommendations

- Using advanced machine learning techniques, such as deep learning, to better capture user preferences
- Combining multiple recommendation techniques, such as collaborative filtering and content-based filtering, to better balance the strengths and weaknesses of the individual techniques
- Using active learning techniques to actively seek feedback from users and improve the recommendations over time

By providing personalized recommendations, users are more likely to find items of interest and engage with the system, leading to higher user satisfaction and engagement.

7. Ethical and Social Implications of Recommender Systems

Recommender systems have become ubiquitous in many areas of our lives, from online shopping to social media. While these systems have the potential to provide valuable recommendations to users, they also raise a number of ethical and social concerns, including filter bubbles, bias, and privacy concerns.

7.1. Filter Bubbles

Filter bubbles occur when a recommender system only shows users content that reinforces their existing beliefs and opinions, leading to an increasingly narrow view of the world. This can lead to polarization and a lack of exposure to diverse viewpoints.

Potential solutions to this issue include:

- Providing users with a variety of content and recommendations, including those that challenge their beliefs
- Offering diverse sources of information and avoiding over-reliance on a single algorithm or source of data
- Encouraging users to actively seek out diverse viewpoints and engage with content that challenges their assumptions.

7.2. Bias

Recommender systems can perpetuate and even amplify existing biases in society, such as gender, racial, or socioeconomic biases. This can lead to unfair and discriminatory outcomes for certain groups.

Potential solutions to this issue include:

- Ensuring that the input data used to train the recommender system is diverse and representative of the population
- Regularly monitoring and auditing the system for bias and making adjustments as needed
- Incorporating ethical and social considerations into the development and deployment of the system.

7.3. Privacy Concerns

Recommender systems often rely on collecting and analyzing large amounts of user data, which can raise concerns about privacy and data security. Users may feel uncomfortable with the level of data collection and use by these systems.

Potential solutions to this issue include:

- Providing clear and transparent explanations of how user data is collected, stored, and used
- Giving users control over their data, including the ability to delete or limit access to their data
- Adhering to data protection regulations and best practices, such as the GDPR in the European Union or HIPAA in the United States.

8. Blockchain-based Recommender System (Emerging Technology)

A blockchain-based recommender system (BRS) is an emerging technology that combines the benefits of blockchain with the power of recommendation systems. Here is a high-level architecture for a blockchain-based recommender system:

8.1. Data Collection and Preprocessing:

The first step in building a BRS is to collect and preprocess the data. This includes gathering data from various sources, cleaning and normalizing it, and converting it into a format that can be used by the system.

8.2. Decentralized Knowledge Graph:

The preprocessed data is then fed into a decentralized knowledge graph. The decentralized knowledge graph is constructed by aggregating the data from various sources into a single graph. This graph can be used to represent the relationships between different entities, such as users, items, and attributes. The knowledge graph is decentralized and maintained by a network of nodes.

The main components of a deep recommender system based on a decentralized knowledge graph:

8.2.1. Data Collection and Preprocessing:

The first step in building a deep recommender system is to collect and preprocess the data. This involves gathering data from various sources and cleaning, normalizing, and transforming it into a format that can be used by the system.

8.2.2. Decentralized Knowledge Graph Construction:

The decentralized knowledge graph is constructed by aggregating the preprocessed data from various sources into a single graph. This graph can be used to represent the relationships between different entities, such as users, items, and attributes.

8.2.3. Embedding Learning:

The next step is to use embedding learning techniques to transform the entities and relationships in the knowledge graph into a low-dimensional vector space. This makes it easier to perform computations and comparisons between different entities.

8.2.4. Deep Learning:

Once the entities and relationships have been embedded, deep learning techniques can be used to train the recommender system. This involves building a neural network that can learn to predict the ratings or preferences of users for different items based on the embeddings in the knowledge graph.

8.2.5. Recommendation Generation:

Finally, the trained neural network can be used to generate recommendations for users. This involves feeding the user's profile into the system and using the learned embeddings to find similar items or users in the knowledge graph. The system can then generate a list of recommendations based on these similarities.

8.3. Smart Contracts:

The smart contract is a self-executing contract that resides on the blockchain network. The smart contract is used to define the rules and logic of the BRS. The smart contract can be used to specify the criteria for recommendation generation, reward distribution, and other aspects of the system.

8.4. Consensus Mechanism:

The consensus mechanism is used to maintain the integrity and security of the BRS. It ensures that the nodes in the network agree on the state of the knowledge graph and the transactions that occur on the network. This can be achieved through a variety of consensus mechanisms, such as proof of work (PoW), proof of stake (PoS), or delegated proof of stake (DPoS).

8.5. Recommendation Generation:

Once the knowledge graph is constructed and the smart contract is deployed, the recommendation generation process can begin. The system generates recommendations based on the relationships between different entities in the knowledge graph. The system can also use machine learning algorithms to generate more accurate and personalized recommendations.

8.6. Reward Distribution:

The reward distribution mechanism is used to incentivize users to participate in the BRS. The rewards can be in the form of tokens, which can be used to access premium features or services, or to trade on the open market. The rewards can be distributed automatically through the smart contract, based on predefined rules and criteria.

9. Information retrieval techniques in Recommender Systems

Unbounded amounts of data have been pushed into the digital world from a variety of sources. The interaction amongst the participants has heightened the situation. The Recommender System must examine all potential areas of dealing in order to collect and analyze informative data in order to comprehend people's preferences and tastes in order to provide a successful and fruitful recommendation. Every Recommender System uses a few information retrieval strategies to complete this task. The following list includes some of the most well-liked information retrieval methods applied in Recommender Systems.

9.1 An entity (a computer) can learn artificially through machine learning without explicit programming. Many algorithms are used, including logistic regression, decision trees, association rule learning, clustering, Bayesian networks, support vector machines, etc.

9.1. Machine Learning

An entity (a machine) can learn artificially through machine learning without explicit programming. Many algorithms are used, including logistic regression, decision tree, association rule learning, cluster, Bayesian networks, support vector machines, etc.

9.2. Logistic Regression

Logistic regression is a popular technique used in information retrieval for recommender systems. It is a statistical method that is used to predict the probability of a binary outcome based on one or more predictor variables. In the context of recommender systems, logistic regression is used to predict the probability that a user will be interested in a particular item, given information about that item and the user's preferences.

In logistic regression for recommender systems, the input data consists of a set of user-item pairs, where each user-item pair is represented by a set of features that describe the user, the item, and their interaction. These features could include things like user demographics, item attributes, and user-item interaction history.

The goal of logistic regression is to learn a set of weights for each feature that maximizes the likelihood of predicting the correct binary outcome (e.g., whether or not the user will like the item). The output of the logistic regression model is a probability score between 0 and 1, which can be interpreted as the likelihood that the user will be interested in the item.Logistic regression is often used in combination with other techniques, such as collaborative filtering and matrix factorization, to improve the accuracy of recommender systems. By combining these different techniques, recommender systems can provide more personalized recommendations that are tailored to the specific needs and preferences of each individual user.

9.3. Decision Tree

Decision trees are another popular technique used in information retrieval for recommender systems. Decision trees are a type of supervised learning algorithm that is used to make predictions based on a set of rules derived from the input data.

In the context of recommender systems, decision trees are used to predict the probability that a user will be interested in a particular item, given information about that item and the user's preferences. The input data for a decision tree in recommender systems consists of a set of user-item pairs, where each user-item pair is represented by a set of features that describe the user, the item, and their interaction.

The goal of a decision tree in recommender systems is to learn a set of rules that can be used to predict whether or not a user will be interested in a particular item. These rules are represented as a tree structure, where each node in the tree represents a decision based on a particular feature, and each branch represents a possible outcome of that decision.

To build a decision tree for recommender systems, the algorithm recursively partitions the input data into subsets based on the values of the different features, and then selects the feature that best separates the data into the most homogeneous subsets. The algorithm continues to recursively partition the data until it reaches a stopping criterion, such as a maximum depth or a minimum number of samples per leaf.

Once the decision tree is built, it can be used to predict the probability that a user will be interested in a particular item by following the path from the root of the tree to the appropriate leaf node based on the values of the input features. The probability score is then calculated as the fraction of training samples in the leaf node that are positive (i.e., the user is interested in the item).

Decision trees can be combined with other techniques, such as ensemble methods like Random Forest or Gradient Boosting, to improve the accuracy of recommender systems. By combining these different techniques, recommender systems can provide more personalized recommendations that are tailored to the specific needs and preferences of each individual user.

9.4. Association Rule Learning

Association rule learning is another popular technique used in information retrieval for recommender systems. It is a type of unsupervised learning algorithm that is used to discover interesting patterns or associations between different items or attributes in a dataset.

In the context of recommender systems, association rule learning is used to discover relationships between different items that are frequently purchased or consumed together by users. These relationships can then be used to make recommendations for related items that the user may be interested in.

The input data for association rule learning in recommender systems consists of a set of user-item pairs, where each user-item pair is represented by a set of features that describe the user, the item, and their interaction. The goal of association rule learning is to discover frequent itemsets, which are sets of items that are frequently purchased or consumed together by users.

Association rule learning algorithms work by first identifying all frequent itemsets in the dataset. They then use these frequent itemsets to generate association rules, which are statements of the form "if A, then B", where A and B are itemsets. The support of an association rule is the proportion of transactions in the dataset that contain both A and B, while the confidence of an association rule is the proportion of transactions that contain A that also contain B.

Once the association rules have been generated, they can be used to make recommendations for related items that the user may be interested in. For example, if a user frequently purchases items A and B together, and there is a high-confidence association rule that says "if a user purchases item A, then they are likely to purchase item C", then the system can recommend item C to the user.

Association rule learning can be combined with other techniques, such as collaborative filtering and content-based filtering, to improve the accuracy of recommender systems. By combining these different techniques, recommender systems can provide more personalized recommendations that are tailored to the specific needs and preferences of each individual user.

9.5. Cluster Analysis

Cluster analysis is another popular technique used in information retrieval for recommender systems. It is a type of unsupervised learning algorithm that is used to group similar items or users together based on their attributes or behaviors.

In the context of recommender systems, cluster analysis is used to group users or items together based on their similarities in preferences, behavior, or attributes. These clusters can then be used to make recommendations for items that are likely to be of interest to users based on the preferences of other users in the same cluster.

The input data for cluster analysis in recommender systems consists of a set of user-item pairs, where each user-item pair is represented by a set of features that describe the user, the item, and their interaction. The goal of cluster analysis is to group similar users or items together based on their features or behaviour.

There are several different types of clustering algorithms that can be used in recommender systems, including hierarchical clustering, k-means clustering, and density-based clustering. Each of these algorithms works differently, but the general idea is to group similar users or items together in a way that maximizes the similarity within each cluster and minimizes the similarity between different clusters.

Once the clusters have been identified, they can be used to make recommendations for items that are likely to be of interest to users in the same cluster. For example, if there is a cluster of users who all have similar preferences for certain types of items, the system can recommend items that are popular among other users in the same cluster.

Cluster analysis can be combined with other techniques, such as collaborative filtering and content-based filtering, to improve the accuracy of recommender systems. By combining these different techniques, recommender systems can provide more personalized recommendations that are tailored to the specific needs and preferences of each individual user.

9.6. Bayesian network

A Bayesian network is a graphical model that represents the relationships between variables in a probabilistic way. In the context of recommender systems, a Bayesian network can be used to model the relationships between users, items, and their features, and to make recommendations based on this model.

A typical Bayesian network for information retrieval in recommender systems might look like the following:

In this network, the variables are represented by nodes, and the relationships between them are represented by directed edges. The nodes represent:

U: the set of users

I: the set of items

F: the set of features of the items

R: the set of ratings given by users to items

The edges represent the dependencies between the variables. For example, the rating R(i,u) given by user u to item i depends on the user's preferences and the item's features, as well as the interaction between the user and the item. The conditional probabilities associated with the edges can be learned from the data using Bayesian inference or maximum likelihood estimation.

Once the network is trained on historical data, it can be used to make recommendations by computing the probability distribution over items given a user's preferences and the features of the items. This is done using Bayesian inference, which involves computing the posterior distribution over items given the evidence provided by the user's preferences and the item features. The items with the highest posterior probability are then recommended to the user.

9.7. Support Vector Machine

Support Vector Machines (SVMs) are a popular machine learning algorithm used in information retrieval and recommendation systems. SVMs are effective at classifying data by finding the optimal hyperplane that maximally separates different classes of data points.

In the context of recommendation systems, SVMs can be used to predict the relevance of items to a particular user based on their preferences and past behavior. The SVM model is trained on a dataset of user-item interactions, with the aim of predicting whether a user will like a particular item or not.The SVM algorithm works by mapping the input data to a higher-dimensional space using a kernel function, such as the radial basis function or polynomial kernel. In this higher-dimensional space, the SVM tries to find the optimal hyperplane that maximally separates the positive and negative examples. Once this hyperplane is found, the SVM can use it to predict the relevance of new items to a user based on their preferences.

One advantage of using SVMs in recommendation systems is their ability to handle high-dimensional and sparse data. They can also handle nonlinear relationships between features, which is important for capturing complex user-item interactions. Additionally, SVMs can be easily extended to handle multiple classes and can be trained incrementally, allowing the model to adapt to new user-item interactions over time.

9.8. Latent Dirichlet allocation

Latent Dirichlet Allocation (LDA) is a popular topic modeling technique that can be applied to information retrieval and recommendation systems. LDA is a probabilistic generative model that can identify the underlying topics in a corpus of text data, even if those topics are not explicitly labeled or known in advance.

In the context of recommendation systems, LDA can be used to identify the latent topics that are most relevant to a user's preferences and interests. The LDA model is trained on a dataset of user-item interactions, with the aim of identifying the underlying topics that are most associated with the items that the user has shown an interest in. Once the topics have been identified, the system can recommend items that are most closely related to those topics.

The LDA algorithm works by representing each document (in this case, each user-item interaction) as a mixture of latent topics. The model then assigns each word in the document to a particular topic based on the probability of that word appearing in the topic. The process is repeated for each document, and the resulting topic distribution is used to identify the most relevant topics for each user.

One advantage of using LDA in recommendation systems is its ability to identify the underlying topics in large and complex datasets. LDA can handle high-dimensional and sparse data, making it ideal for applications with large vocabularies and long documents. Additionally, LDA can be easily extended to handle additional features such as user demographics or item attributes, which can further improve the accuracy of the recommendation system.

9.9. TF-IDF

Term Frequency-Inverse Document Frequency (TF-IDF) is a popular technique used in information retrieval and recommendation systems to measure the relevance of a document to a particular query or user. TF-IDF is a numerical statistic that reflects how important a word is to a document in a corpus, by giving more weight to words that are rare in the corpus but appear frequently in a particular document.

In the context of recommendation systems, TF-IDF can be used to identify the most important features or characteristics of items that are most relevant to a user's preferences. The TF-IDF model is trained on a dataset of user-item interactions, with the aim of identifying the words or features that are most associated with the items that the user has shown an interest in. Once the most relevant features have been identified, the system can recommend items that have similar features.

The TF-IDF algorithm works by computing the term frequency (TF) and inverse document frequency (IDF) for each word in a document. The term frequency is the number of times a word appears in a document, while the inverse document frequency is a measure of how rare the word is in the corpus. The product of these two values yields the TF-IDF score for each word. The TF-IDF scores for all words in a document are then summed to obtain a vector representation of the document.

One advantage of using TF-IDF in recommendation systems is its simplicity and ease of implementation. TF-IDF is a lightweight algorithm that can handle large and sparse datasets with ease. Additionally, TF-IDF can be easily extended to handle additional features such as user demographics or item attributes, which can further improve the accuracy of the recommendation system.

9.10. Deep Learning

Deep learning techniques have gained popularity in recent years for information retrieval and recommendation systems due to their ability to automatically learn complex patterns and relationships from large and diverse datasets. Deep learning techniques can be used to model user-item interactions and make personalized recommendations based on the learned patterns.

Some of the commonly used deep learning techniques for recommendation systems are:

9.10.1. Neural Collaborative Filtering (NCF):

NCF is a deep learning technique that uses neural networks to learn the user-item interactions and generate recommendations. NCF uses a combination of user and item embeddings, which are learned through a neural network, to predict the relevance of an item to a user.

9.10.2. Deep Autoencoder:

Deep autoencoders are used to learn the latent representations of user-item interactions. Autoencoders compress the input data into a low-dimensional representation and then reconstruct the original data from the compressed representation. The learned latent representation can be used to predict the relevance of an item to a user.

9.10.3. Recurrent Neural Networks (RNNs):

RNNs are commonly used for modeling the sequential nature of user-item interactions. RNNs can capture the temporal dependencies between user interactions and use them to make personalized recommendations.

9.10.4. Convolutional Neural Networks (CNNs):

CNNs are used to extract features from user-item interaction data. CNNs can be used to learn the spatial and temporal relationships between features and can be used to predict the relevance of an item to a user.

9.10.5. Graph Neural Networks (GNNs):

GNNs are used to model the interactions between users and items as a graph. GNNs can capture the complex relationships between users and items and can be used to make personalized recommendations based on the learned graph structure.

Deep learning techniques can handle large and diverse datasets and can learn complex patterns and relationships in the data. However, deep learning techniques require a large amount of training data and are computationally expensive to train. Additionally, deep learning techniques require careful tuning of hyperparameters and can be prone to overfitting. Therefore, deep learning techniques are often used in combination with other techniques such as TF-IDF or LDA to improve the accuracy and effectiveness of recommendation systems.

10. Applications of Recommender Systems

10.1. E-commerce

Recommender systems have become an essential component of many e-commerce platforms. They help users discover products that they might be interested in and improve the overall user experience. Here are some common applications of recommender systems in e-commerce:

10.1.1. Product recommendations:

Recommender systems can suggest products to users based on their browsing and purchase history. These recommendations can be personalized to the user's preferences and interests, and can be shown on the website, in emails, or in mobile apps.

10.1.2. Cross-selling and upselling:

Recommender systems can suggest related or complementary products to users, increasing the chances of cross-selling and upselling. For example, if a user is buying a camera, the system might suggest a tripod or a camera bag.

10.1.3. Personalization:

Recommender systems can personalize the user experience by showing content and products that are tailored to the user's interests and preferences. This can improve engagement and increase the likelihood of a purchase.

10.1.4. Search recommendations:

Recommender systems can suggest search terms to users based on their browsing history or past searches. This can help users find what they are looking for more easily and quickly.

10.1.5. Content recommendations:

Recommender systems can suggest content to users, such as articles, videos, or blog posts, based on their interests and preferences. This can increase engagement and keep users on the platform longer.

Overall, recommender systems can help e-commerce platforms increase customer satisfaction, improve retention, and ultimately drive more sales.

10.2. Retail Sector

Recommender systems have numerous applications in the retail sector, where they can improve customer engagement, loyalty, and sales. Here are some common applications of recommender systems in the retail sector:

10.2.1. Personalized recommendations:

Recommender systems can suggest products to customers based on their purchase history, browsing behavior, and other data. These recommendations can be personalized to the customer's interests and preferences, making the shopping experience more enjoyable and increasing the chances of a purchase.

10.2.2. Product bundling:

Recommender systems can suggest product bundles that are commonly purchased together, increasing the chances of cross-selling and upselling.

10.2.3. Inventory management:

Recommender systems can help retailers manage their inventory more effectively by suggesting which products to order based on historical sales data and predicted demand.

10.2.4. Dynamic pricing:

Recommender systems can help retailers adjust their prices dynamically based on supply and demand, as well as other factors such as weather and events.

10.2.5. Customer retention:

Recommender systems can help retailers retain customers by suggesting products that are relevant and interesting to them. This can increase loyalty and reduce the likelihood of customers shopping with competitors.

Overall, recommender systems can help retailers improve the customer experience, increase sales, and manage their inventory and pricing more effectively.

10.3. Media

Recommender systems have a wide range of applications in the media industry, where they can help users discover new content that matches their interests and preferences. Here are some common applications of recommender systems in media:

10.3.1. Content recommendations:

Recommender systems can suggest movies, TV shows, music, and other types of media to users based on their viewing and listening history. These recommendations can be personalized to the user's interests and can help them discover new content that they might enjoy.

10.3.2. Personalization:

Recommender systems can personalize the user experience by showing content that is tailored to their interests and preferences. This can improve engagement and reduce churn rates.

10.3.3. Search recommendations:

Recommender systems can suggest search terms to users based on their browsing history or past searches. This can help users find what they are looking for more easily and quickly.

10.3.4. Advertisement targeting:

Recommender systems can help media companies target advertisements more effectively by analyzing user data and showing ads that are relevant and interesting to them.

10.3.5. Content distribution:

Recommender systems can help media companies distribute their content more effectively by suggesting which platforms and channels to use based on user data and engagement metrics.

Overall, recommender systems can help media companies increase user engagement, reduce churn rates, and improve their advertising and content distribution strategies.

10.4. Banking

Recommender systems have a growing number of applications in the banking industry, where they can help financial institutions provide personalized services to their customers and improve the customer experience. Here are some common applications of recommender systems in banking:

10.4.1. Personalized product recommendations:

Recommender systems can suggest financial products and services to customers based on their financial goals, risk tolerance, and other factors. This can help customers make informed decisions about their finances and improve their financial well-being.

10.4.2. Cross-selling and upselling:

Recommender systems can suggest related or complementary products and services to customers, increasing the chances of cross-selling and upselling. For example, if a customer is applying for a mortgage, the system might suggest related insurance products.

10.4.3. Fraud detection:

Recommender systems can help detect fraudulent transactions by analyzing user data and identifying suspicious patterns.

10.4.4. Cross-selling and upselling:

Customer service:

Recommender systems can help customer service representatives provide more personalized and relevant advice to customers, improving the customer experience.

10.4.5. Risk management:

Recommender systems can help banks manage risk by analyzing customer data and identifying potential risks and opportunities.

Overall, recommender systems can help banks improve customer engagement, increase sales, reduce fraud, and manage risk more effectively.

10.5. Telecom

Recommender systems have a wide range of applications in the telecom industry, where they can help telecommunications companies provide personalized services to their customers and improve the customer experience. Here are some common applications of recommender systems in telecom:

Personalized service recommendations: Recommender systems can suggest telecommunications services to customers based on their usage patterns, preferences, and other factors. This can help customers make informed decisions about their telecommunications services and improve their overall experience.

10.6.1. Cross-selling and upselling:

Recommender systems can suggest related or complementary services to customers, increasing the chances of cross-selling and upselling. For example, if a customer is signing up for a mobile phone plan, the system might suggest related services such as internet or TV packages.

10.6.2. Customer retention:

Recommender systems can help telecommunications companies retain customers by suggesting personalized offers and promotions based on their usage patterns and preferences.

10.6.3. Network optimization:

Recommender systems can help telecommunications companies optimize their network by analyzing user data and identifying potential issues or opportunities.

10.6.4. Marketing and advertising:

Recommender systems can help telecommunications companies target marketing and advertising more effectively by analyzing user data and showing ads that are relevant and interesting to them.

Overall, recommender systems can help telecommunications companies improve customer engagement, increase sales, retain customers, optimize their network, and improve their marketing and advertising strategies.

10.7. *Cinema*

Recommender systems have several applications in the cinema industry, where they can help moviegoers discover new movies and improve the movie-going experience. Here are some common applications of recommender systems in cinema:

10.7.1. Movie recommendations:

Recommender systems can suggest movies to moviegoers based on their viewing history and preferences. These recommendations can help moviegoers discover new movies that they might enjoy.

10.7.2. Personalization:

Recommender systems can personalize the movie-going experience by showing trailers, promotions, and other content that is tailored to the moviegoer's interests and preferences.

10.7.3. Targeted marketing:

Recommender systems can help cinemas target their marketing and advertising more effectively by analyzing user data and showing ads that are relevant and interesting to their audience.

10.7.4. Dynamic pricing:

Recommender systems can help cinemas adjust their pricing dynamically based on demand, availability, and other factors.

10.7.5. Movie scheduling:

Recommender systems can help cinemas schedule their movies more effectively by analyzing user data and identifying popular movies and times.

Overall, recommender systems can help cinemas improve the movie-going experience for their customers by suggesting relevant and interesting movies, personalizing the experience, and optimizing their pricing and scheduling strategies.

10.8. *Healthcare*

Recommender systems have several applications in the healthcare industry, where they can help healthcare providers and patients make informed decisions and improve healthcare outcomes. Here are some common applications of recommender systems in healthcare:

10.8.1. Personalized treatment recommendations:

Recommender systems can suggest treatment options to healthcare providers based on patient data, including medical history, symptoms, and genetic information. These recommendations can help healthcare providers make more informed decisions and improve patient outcomes.

10.8.2. Medication recommendations:

Recommender systems can suggest medications to healthcare providers based on patient data and clinical guidelines. These recommendations can help healthcare providers choose the most appropriate medication for their patients and reduce the risk of adverse effects.

10.8.3. Clinical trial matching:

Recommender systems can help match patients with clinical trials based on their medical history, symptoms, and other factors. This can help patients access new treatments and therapies that may not be widely available.

10.8.4. Disease prevention:

Recommender systems can suggest preventive measures and lifestyle changes to patients based on their medical history and risk factors. These recommendations can help patients reduce their risk of developing certain diseases.

10.8.5. Patient engagement:

Recommender systems can help engage patients by suggesting educational materials, self-care tips, and other resources that are tailored to their needs and preferences.

Overall, recommender systems can help healthcare providers and patients make more informed decisions, improve patient outcomes, and promote preventive care and patient engagement.

10.9. *Fashion*

Recommender systems have several applications in the fashion industry, where they can help shoppers discover new styles, improve their shopping experience, and increase sales for retailers. Here are some common applications of recommender systems in fashion:

10.9.1. Personalized product recommendations:

Recommender systems can suggest clothing items and accessories to shoppers based on their browsing history, purchase history, and preferences. These recommendations can help shoppers discover new styles that they might not have considered otherwise.

10.9.2. Outfit recommendations:

Recommender systems can suggest complete outfits to shoppers based on their individual items and preferences. These recommendations can help shoppers put together stylish and coordinated outfits.

10.9.3. Styling advice:

Recommender systems can provide styling advice to shoppers, suggesting items that will complement their body shape, skin tone, and personal style.

10.9.4. Inventory management:

Recommender systems can help retailers manage their inventory by analyzing customer data and identifying popular styles and sizes. This can help retailers optimize their inventory and avoid stockouts.

10.9.5. Targeted marketing:

Recommender systems can help retailers target their marketing and advertising more effectively by analyzing user data and showing ads that are relevant and interesting to their audience.

Overall, recommender systems can help fashion retailers increase sales, improve the shopping experience for their customers, and stay competitive in a crowded market by providing personalized recommendations and styling advice.

10.10. *Education and Career*

Recommender systems have several applications in education and career, where they can help students and job seekers make informed decisions and improve their outcomes. Here are some common applications of recommender systems in education and career:

10.10.1. Course and program recommendations:

Recommender systems can suggest courses and educational programs to students based on their academic history, interests, and career goals. These recommendations can help students make informed decisions about their education and career paths.

10.10.2. Career path recommendations:

Recommender systems can suggest career paths to students and job seekers based on their skills, interests, and experience. These recommendations can help job seekers make informed decisions about their career trajectories.

10.10.3. Job recommendations:

Recommender systems can suggest job openings to job seekers based on their skills, experience, and career goals. These recommendations can help job seekers find relevant job opportunities and increase their chances of being hired.

10.10.4. Learning resources:

Recommender systems can suggest learning resources to students and job seekers based on their interests and skill gaps. These resources can include online courses, books, videos, and other materials that can help them acquire new skills and knowledge.

10.10.5.Mentor matching:

Recommender systems can match students and job seekers with mentors based on their interests, experience, and career goals. These mentors can provide guidance and advice to help them achieve their goals.

Overall, recommender systems can help students and job seekers make more informed decisions, improve their outcomes, and stay competitive in a rapidly changing job market.

10.11. *Agriculture*

Recommender systems have several applications in agriculture, where they can help farmers make data-driven decisions and improve crop yields. Here are some common applications of recommender systems in agriculture:

10.11.1. Crop recommendations:

Recommender systems can suggest the most appropriate crops to grow based on soil data, climate conditions, and other environmental factors. These recommendations can help farmers optimize their crop yields and reduce waste.

10.11.2. Fertilizer recommendations:

Recommender systems can suggest the most appropriate fertilizers to use based on soil data and crop requirements. These recommendations can help farmers reduce the use of harmful chemicals and optimize their fertilizer use.

10.11.3. Pest management recommendations:

Recommender systems can suggest the most appropriate pest management strategies based on crop data and environmental conditions. These recommendations can help farmers prevent and control pests more effectively.

10.11.4. Weather forecasting:

Recommender systems can provide accurate weather forecasts to farmers, helping them make informed decisions about planting, harvesting, and other farm activities.

10.11.5. Equipment recommendations:

Recommender systems can suggest the most appropriate equipment and machinery to use based on farm size, crop type, and other factors. These recommendations can help farmers optimize their equipment use and reduce costs.

Overall, recommender systems can help farmers make more informed decisions, improve crop yields, and reduce waste and costs. They can also help promote sustainable farming practices by reducing the use of harmful chemicals and optimizing resource use.

10.12. *Real Estate*

Recommender systems have several applications in real estate, where they can help buyers and sellers make informed decisions and improve the buying and selling process. Here are some common applications of recommender systems in real estate:

10.12.1. Property recommendations:

Recommender systems can suggest properties to buyers based on their preferences, budget, and location. These recommendations can help buyers find properties that meet their needs and preferences more easily.

10.12.2. Pricing recommendations:

Recommender systems can suggest the most appropriate price range for a property based on market data, location, and other factors. These recommendations can help sellers set the right price for their property and improve their chances of selling it quickly.

10.12.3.Investment recommendations:

Recommender systems can suggest investment properties to buyers based on their investment goals, budget, and other factors. These recommendations can help investors make informed decisions and maximize their returns.

10.12.4.Agent recommendations:

Recommender systems can suggest real estate agents to buyers and sellers based on their experience, location, and other factors. These recommendations can help buyers and sellers find the right agent to work with and improve their overall experience.

10.12.5.Mortgage recommendations:

Recommender systems can suggest mortgage options to buyers based on their financial situation and credit history. These recommendations can help buyers find the best mortgage options and improve their chances of being approved.

Overall, recommender systems can help buyers and sellers make more informed decisions, improve the buying and selling process, and stay competitive in a crowded real estate market.

11. Literature Review

Recommender systems provide personalized suggestions as output or that have the effect of assisting the user in making individualized product selections from a product overloaded market. Throughout their recommendation process,Recommender systems carry out a number of fundamental functions, including (1) predicting unknown ratings and (2) generating a list of the items that are suggested.

Khan et al.[21] have a hybrid collaborative filtering model that incorporates matrix factorization, a convolutional neural network, and w2v for e-commerce applications.Word2vec (semantics) and CNN (context) are integrated into the PMF via the CMF-HRS to collect the content details of both item and user documents.The best dense vector representation for rating predictions and item recommendation has been built using w2v and CNN using both user and item contents. In addition to item textual information, the model also learns latent characteristics for both entities from customer evaluations. CNN along with w2v enable user/item contents feature extractions wherein feature locality information is captured as well. The proposed model outperforms the other models and can be used to any dataset enriched with both implicit and explicit feedback of users and items.

Aparicio et al.[22] have studied the effects of gamification and reputation on the likelihood of repeat purchases in e-commerce. The regular use of game components in non-gaming contexts is referred to as gamification. The researchers have described an empirical study (data from a survey) that was conducted in a real-world e-commerce environment. Data analysis has been done using the SEM/PLS technique. Findings show that trust has a beneficial effect on e-commerce intention, buy frequency, and repurchase intention. E-commerce platform usability and ease of use have an impact on use intentions.

Guo et al.[23] have proposed a prior ratings for recommender systems for e-commerce in virtual reality (VR). Prior ratings capture users' opinions on items that come through virtual product experiences, often prior to purchase, by utilising the successful interactions between users and virtual products depicted in a mediated environment.The researchers have shown that even a small number of prior ratings benefits the recommender systems.

Ahn et al.[24]introduced the PIP collaborative filtering a new heuristic similarity measure, which is a popular tool for automatic product recommendations in online shops. In order to address the shortcomings of conventional similarity and distance measures under new user cold-start settings, the PIP measure has been created using domain-specific interpretation of user evaluations on goods and items. For completeness, PIP has been evaluated using three publicly available datasets, where it has demonstrated higher performance under cold-start settings for new users.

Scholz et al.[25] have proposed Multi-attribute value theory (MAVT)-based recommender systems to deal with issues encountered with existing recommender systems that includes cold-start problem and changing preferences. According to the results, their suggested method performs better in terms of recommendation accuracy than TRADEOFF and CONJOINT and at least as well as SWING, better in terms of cognitive load than SWING and TRADEOFF and at least as well as CONJOINT, and participants are faster with this method than with any other method. It may be concluded that this approach may be a viable choice for assisting consumers’ decision-making during e-commerce buying chores.

Castro-schez et al.[26] have proposed an adaptive recommender system that is based on fuzzy logic for B2C e-commerce portals called e-Zoco. It is a dynamical hierarchical cataloguing system that uses a collection of variables to categorise and describe different product kinds. Secondly, it is a service for choosing products that can handle ambiguous and imprecise search preferences and delivers a group of results grouped according to their possible relevance to the user.

Karthik et al.[27] have proposed a fuzzy recommendation system for e-commerce that uses sentiment analysis and ontology to forecast buyer interests. They have used a state-of-the-art algorithm for estimating the sentiment score of the product with the corresponding end user.The suggested fuzzy rules and ontology-based recommendation system makes recommendations that are more accurate and forecast dynamically based on the search context by using ontology alignment. The suggested recommendation system performs better than the current product recommendation systems in terms of prediction accuracy of the pertinent goods for target consumers and in the time required to deliver such suggestions, according to testing data.

Pratama et al.[28] have used collaborative filtering for the offline retail industry for product recommendations. They have used four years' worth of purchase transaction data to infer indirectly what customers thought about particular goods they had bought. In order to generate product suggestions for clients and determine the optimal approach, the authors have used two Collaborative Filtering approaches. The outcome demonstrates that the Memory-based method (k-NN Algorithm) outperforms the Model-based method (SVD Matrix Factorization). Another observation is that the performance of the recommendation system will improve when more data training is employed. Customer segmentation using k-Means Clustering has been used to address the problem of data scalability. The outcome suggests that this is not essential because it did not increase the accuracy of the models. A proposed business procedure is then used to implement the recommendation system's findings for a particular offline retailer shop.

Herce-Zelaya et al.[29] have proposed a new method that uses data from social media and random decision forests to solve the cold start problem in recommender systems. The authors have used a method for classifying people based on their behaviour using social media data, and then generating predictions based on that classification using machine learning tools like classification trees and random forests. As the system would use this information to generate user profiles, which will be the input for the engine of recommender systems, the user would not have to actively supply any sort of data expressly other than their social media source, thereby reducing the cold start problem. The proposed approach has been tested in a setting where movie recommendations are made, and the predictions made have yielded results that are more than adequate. As a consequence, the recommendations created are, on average, quite excellent since they exceed other new user cold-start algorithms. It can be concluded that the proposed algorithm (BSSB-RS) is an ideal asset in cold-start scenarios because it makes use of the data collected from social media, turning it into a very valuable data source and improving the quality and precision in the decision-making process while also offering a much more accurate recommendation of items.

Vedavathi et al.[8]have proposed recommendation methods to select appropriate courses for students by the use of social media. The deep flamingo search reinforcement learning (DFSRL) based recommendation system, the clustering process, and the development of learner profiles are the foundations of the suggested technique. During the clustering method, the two factors productivity and motivation have been employed. Fuzzy logic has been used to categoris esentiments into positive, negative, or neutral categories using a semantic similarity-based approach.The accuracy (98%), precision (91%), recall (89%) and F-score (90%) of the proposed system are higher.

Papakyriakopoulos et al.[30]have quantitatively demonstrated that hyperactive users have a significant role in the political discourse by applying a geometric topic modelling algorithm (GTM) to German users' political comments and parties' posts and by analysing commenting and liking activities. These users become opinion leaders and have an agenda-setting effect, which results in the creation of an alternate perception of public opinion. The authors have also demonstrated how hyperactive users have a significant impact on some types of recommender systems. The authors have showed that models deliver varied advice to users, whether accounting for or disregarding hyperactive behaviour both in the input dataset and in the approach used by training collaborative filtering and deep learning recommendation algorithms on simulated political networks.

Wu et al.[31] have used multi-sourced data (such as social networks, item contents, and user feedbacks) to forecast user ratings of products and generate recommendations. The proposed system provides a compound recommendation engine for social media systems. For this, the authors have expanded Collaborative Topic Regression to simultaneously integrate social trust ensemble, topic modelling, and probabilistic matrix factorization. The authors havehypothesised that the users' decisions to adopt an item are influenced by both their preferences and the favours of trusted friends.The authors have provided related methods for learning the latent components of users and things, as well as other characteristics that need to be approximated.The Lastfm and Delicious datasets used in the empirical studies demonstrate that the proposed CTRSTE model is more accurate and reliable than the state-of-the-art approaches for producing suggestions. The outcomes of experiments also provide some insightful information that can help guide the creation of recommender systems in social media.

Hernándezet al.[13] have proposed CEBRA (CasE-Based

Reasoning Application), a case-based reasoning system tailored for commercial banking, into a virtual agent-driven Fog Computing architecture. The authors have presented the model of this architecture, described its life cycle, and have made suggestions for improvements by incorporating a number of techniques in the retrieve and reuse phases, such as the extraction of interests listed by users on their social network profiles and collaborative filtering systems. To assess CEBRA, a thorough case study has been conducted, and a dataset of 60,000 instances has been created. As a consequence, the recommendation algorithm and a REST interface for its use have been included in the presentation of the recommender system.

Hernández-Nieves et al.[12] have used a novel Fog Computing solution for Fintech industry. In order to give tailored client services and make product recommendations for a financial company, it incorporates predictive systems.In order to develop contextual recommendation systems and set up a Case Based Reasoning in the Cloud layer to increase the system's overall efficiency over time, the proposed architecture incorporates Fog nodes where data is processed by light intelligent agents. The recommendation system, which serves as the foundation of the architecture for financial products like mortgages, loans, retirement plans, etc., has been created using a hybrid recommendation technique that combines collaborative filtering and content-based filtering. The proposed FOBA architecture gives the chance to enhance customer service in the bank's physical channels while simultaneously generating technology support to enhance office managers' capacity for problem-solving, enabling staff to take on a more adaptable and flexible role. Moreover, it permits the development of the financial services model in offices while the procedures that underpin it adopt a one-stop shopping strategy.

Bouni et al.[32] have deep reinforcement learning tools as efficient recommender systems for smart agriculture. They have utilized Deep Reinforcement Learning, Naïve Bayes, KNN, decision tree (DT), and random forest-based classifiers. DRL and random forest outperform the other classifiers in terms of precision. The proposed recommender system takes different environmental attributes such as different micronutrients required for the growth of crops like nitrogen, potassium, Sulphur etc. along with temperature, humidity, rainfall etc., and the recommender system is able to predict what is the most suitable crop the farmer can plant so that the crop survives in the given climatic conditions.

Santosh Kumar et al.[33] have proposed a recommender system based on Apriori algorithm that can predict and recommend the consumption of different agricultural products. The proposed recommender system is able to make predictions and recommendations based upon the purchase history of customers and product recommendations of their peers. The cumulative prediction by proposed recommender system can assist farmers in planning and cultivating crops for any season, ensuring that no items generated by farmers are wasted.

Banerjee et al.[34] have proposed a fuzzy logic-based crop recommender system for the assistance of rural farmers of West Bengal. The model proposed is intended to deal with eight major crops (paddy, Jute, potato, tobacco, wheat, seasumum, mustard, green gram) that are cultivated in West Bengal. The researchers created separate fuzzy rule bases for each crop in order to speed up the processing. Diversified datasets have been used to validate the performance of the model attaining an accuracy of approximately 92.14% exceeding similar existing systems.

Kuanr et al.[35] have proposed TSARS (Tree Similarity Algorithm Recommender System) algorithm that recommends seeds, pesticides, fertilizers, and equipment based on farming needs and location preference of the farmer. Tree data structure is used to store the information of the database users. Compared to other recommender systems, the proposed system is more time efficient. The efficiency of the model has been assessed by using precision accuracy and positive predictive values.

Kamatchi et al.[36] have used a predictive analysis to determine the best crop that can be grown according to the local weather conditions. Furthermore, they have used a hybrid recommender system that uses case-based reasoning to improve the model's success ratio. The proposed hybrid system combines the collaborative filtering approach and case-based reasoning. The proposed model uses the district level agricultural data in order to analyse and predict the future climatic conditions and subsequently proposing the crops based on those climatic conditions. The precision and recall values are 80% and 73%, 88% and 79%, 90% and 93% for collaborative filtering, case-based reasoning and hybrid recommendation respectively.

Peters et al.[37] have proposed an AI recommender system coupled with machine learning to retrieve prior user choices enormous volume of data while accounting for variations in weather and management decisions that are typical of agricultural systems. The objective of the proposed model is to optimise the use of data relevant to agricultural problems, enhance the efficiency of the scientific workforce, and improve the accuracy of estimations of the amount of food produced.

Ren et al.[38] have created a hybrid collaborative filtering algorithm in order to offer search keywords to clinicians for a given patient. The model is based on the data retrieved from the patient's visit to clinics and the searches they conduct online. For the recommendations, the model employs search terms that are commonly co-occurring with the ICD codes recorded for the patient and secondly highly relevant to the most recent search terms. The model, Hybrid Collaborative Filtering Method for Healthcare uses most recent ICD codes allocated to the patients. ICD codes other than the previous one is processed by Co-occurrence Pattern based HCFMH. Extensive experiments have been conducted in order to evaluate the proposed model. The HCFMH model outperforms the baseline methods in terms of recommendation quality.

Ochoa et al.[39] have proposed LONN (Logic Operator Neuronal Network), a medical recommender system that works on continuous-valued logic and multi-criteria decision operators, using neural networks. The methodology is transparent as the model outcomes emulate logical decision processes based on the hierarchy of relevant physiological parameters, and secondly the proposed model is more resistant to cyber-attacks compared to conventional deep learning methods as it drastically reduces the number of trainable parameters. The proposed LONN model has shown an accuracy of approximately 75% though 8% less accurate than conventional deep learning models. The loss in accuracy is compensated as it is transparent and more secure making it less vulnerable to cyber-attacks. Prediction of personalised treatments using the proposed model is optimum compared to other models.

Wang et al.[40] have proposed more robust XAI (explainable AI) to make AI applications more transparent and efficient for hospital recommendation. The researchers have applied some of the simplest cross-domain tools and techniques in order to improve the explanations of the AI applications (fuzzy mixed integer-nonlinear programming (FMINLP)-ordered weighted average (OWA) method, BPN-RSM, LSTM, fuzzy linear regression (FLR)-fuzzy intersection (FI)). Results show that explainability of all the four AI based clinic recommendation methods improved after applying cross-domain tools and techniques.

Barrera et al.[41] have proposed an efficient recommender system that uses natural language processing approaches and deep-learning techniques and recommends occupational hygiene services. The models used are item-based collaborative filtering and a deep learning-based recommender system called Extended Neural Matrix Factorization (Extended-NeuMF). The later model consists of two components such as a generalized matrix factorization (GMF) and a multilayer perceptron (MLP). The result shows that model-based CF outperforms memory-based CF in forecasting the top relevant acquisitions. This means that based on company and activity metadata, it is feasible to generalise company preferences for acquiring occupational hygiene services. Better prediction performance is achieved by combining these models. When the area under the ROC curve (AUC) for GMF, IVW, MLP, and the Extended NeuMFare calculated, the results are 0.87, 0.84, 0.82, and 0.80, respectively.

Ali et al.[42] have proposed a hybrid recommender system (a multi-stage recommender system)that delivers recommendations for both physical activity and diet in order to satisfy a user's health needs in a holistic manner. The model provides not only physical activity-based recommendations, and diet recommendations but also educational suggestions to a particular target user group. Furthermore, the authors have considered customization features of the recommender system. The proposed model is capable of offering instructional advice to the user base via an expert-in-the-loop technique. A multi-factor menu-set recommendation is also tailored to the consumers' unique nutritional requirements. The suggested strategy integrates several aspects of wellness support systems in a holistic manner to give a more comprehensive therapy to the users' particular requirements.

Sahoo et al.[43] a proposed DeepReco a deep learning based (Restricted Boltzmann Machine (RBM)-Convolutional Neural Network (CNN) deep learning method) health recommender system by using collaborative filtering. The healthcare dataset used for this study includes discrete ratings ranging from 1 to 5 for 10,000 patients from 500 hospitals. This dataset is divided into 75:25 training and test data segments. While assessing the findings, a 10-fold cross-validation approach is utilised. The authors have used Tensor Flow and Python to implement the suggested CRBM model. When the Root Square Mean Error (RSME) and Mean Absolute Error (MAE) values are considered, the proposed deep learning method (RBM-CNN) produces less error than existing models. The proposed model gives an opportunity for the healthcare industry to transition from a traditional approach to a more personal paradigm in this era of tele-health environment.

Stefanidis et al.[44] have proposed a Protein AI advisor, a kind of knowledge-based recommendation tool using expert validated meals in order to have healthy diets. The architecture of the proposed advisor incorporates a qualitative layer for validating ingredient suitability and a quantitative layer for meal planning. The first layer has been implemented as an expert system for fuzzy inference based on an ontology of rules given by nutritional experts on the other hand, second layer has been implemented as an optimization method to generate everyday meal plans based upon target nutrient values. The efficiency and effectiveness of the advisor has been validated through extensive experiments to make it work as a robust meal recommender. 3000 virtual user profiles have been used to evaluate the performance of the AI advisor. The result shows a very high precision and recall for recommending healthy ingredients, on the other hand meal plan generator has achieved an accuracy of 92% for nutrient recommendations.

12. Conclusion

Deciding from among a variety of possibilities and in light of the enormous amount of internet material is always going to be difficult and complicated though online Recommender Systemshelp us to overcome this difficulty. Effective information retrieval and filtering processes are used by Recommender Systems to perform their duties effectively and accurately. Several suggestion approaches and tactics have been put out as a result of the extensive study that has been done in the last ten years to achieve these goals. This paper provides a summary of the many recommendation techniques utilised in Recommender Systems, including knowledge-based, content-based, collaborative, demographic, hybrid, and context-aware recommendation. Limited content analysis, over-specialization, cold start, sparsity, scalability, synonymyproblem is just a few of the issues encountered while building and implementingRecommender Systems. IoT, AI, and cognitive computing technologies have given recommender Systems a new vigour. We are confident that there will be many fresh and creative directions for Recommender Systems research in the near future.

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