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A Review of Recommender System Algorithms in Social Networks and Their Challenges

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ABSTRACT

With the exponential growth of online information, the ability of websites to effectively respond to user needs and guide visitors toward relevant content has become a decisive factor in the success of digital platforms and the sustainability of online businesses. Consequently, developing intelligent systems capable of understanding and adapting to user preferences has become increasingly essential. Such systems should not only learn users' behavioral patterns but also dynamically filter irrelevant content while recommending information that aligns with their specific interests and contextual needs. Web personalization systems serve this purpose by providing users with individualized experiences, eliminating the need for explicit queries, and presenting recommendations that enhance engagement and satisfaction. Within this framework, recommender systems play a pivotal role by employing advanced computational models such as machine learning, data mining, and deep neural networks to analyze user data and predict preferences with high accuracy. The integration of these systems contributes to improving user retention, increasing website efficiency, and fostering long-term user loyalty. Hence, recommender systems are considered a cornerstone technology in modern information retrieval and digital personalization strategies.

1. INTRODUCTION

In the era of digital connectivity, social networks have emerged as pivotal platforms for information sharing, user interaction, and content dissemination, leading to an exponential growth in data volume and complexity [1]. Recommender systems (RS) in social networks address the challenge of information overload by leveraging algorithms to provide personalized suggestions, such as friends, content, or products, thereby enhancing user engagement and satisfaction [2]. Traditional RS algorithms, including content-based filtering and collaborative filtering, have been adapted to incorporate social dimensions like trust relationships, homophily, and influence propagation, resulting in more accurate and context-aware recommendations [3].

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Key algorithms in this domain include memory-based approaches, such as neighborhood-based collaborative filtering augmented with social ties (e.g., trust-aware methods like TidalTrust and TrustWalker), and model-based techniques, including matrix factorization models that integrate social regularization (e.g., SoRec and SocialMF) to model user-item interactions alongside social networks [3]. Emerging deep learning-based algorithms, such as autoencoders and neural collaborative filtering, have also shown promise in capturing non-linear patterns in social data, though their application remains nascent [4].

Despite these advancements, RS in social networks face significant challenges, including data sparsity due to incomplete user profiles and interactions, cold-start problems for new users or items, privacy risks from sharing social data, scalability issues with large-scale networks, and vulnerability to shilling attacks or bias amplification [5]. This review synthesizes existing literature on these algorithms and challenges, highlighting open research directions to foster more robust and ethical systems.

2. RECOMMENDER SYSTEMS

Recommender systems are tools that help users discover and select items of interest. Naturally, these systems cannot generate meaningful recommendations without sufficient and accurate information about users and the items in question. Therefore, a primary objective of recommender systems is to collect diverse information regarding user preferences and available items. There are various sources and methods for collecting such information. One approach is explicit data collection, in which users directly indicate their preferences. Another approach is implicit data collection, which is more challenging; the system must infer user preferences by monitoring and analyzing their behaviors and activities. In addition to explicit and implicit information, some systems utilize users' personal demographic data, known as Demographic Information, on which certain recommender systems are based.

Humans tend to collaborate and exchange information with strangers more than other species, forming communities that collectively create a global network. Sociality allows individuals to specialize in certain activities, creating interdependencies that arise from fulfilling needs and other desires. Consequently, individuals can be considered as "floating atoms" in markets where goods and services are exchanged. Upon closer examination, however, people tend to associate themselves with various groups and communities such as families, neighborhoods, religious organizations, workplaces, and sometimes virtual communities. A social network is a social structure composed of individuals or organizations, with nodes representing the actors and connections representing specific types of relationships, such as friendship, kinship, or shared interests.

Social network analysis (SNA) involves mapping and measuring relationships and collaborations among individuals, groups, organizations, or any entities capable of processing information and knowledge. Research in social networks draws on fields such as sociology, anthropology, psychology, communications, information technology, and economics. Recently, mathematical modeling of human behavior in social networks has gained significant attention due to applications in marketing and politics. Social networks are commonly represented as graphs, where nodes correspond to actors and edges indicate relationships between them. Depending on whether relationships are one-way or bidirectional, the corresponding graph may be directed or undirected. If the strength of relationships varies among individuals, the graph is weighted, with each edge reflecting the strength of the connection. Real-world social networks are highly dynamic, continuously evolving as new individuals join and form new connections [22].

With the explosive growth of the internet and the vast volume of information available online, there is an increasing need for systems that can recommend the most relevant web pages or products to users. Recommender systems perform this task by employing specific algorithms to identify items such as data, information, or products that closely match a user's preferences.

Recommender systems are generally categorized into three main types: content-based, knowledge-based, and collaborative filtering. A fourth category, hybrid recommender systems, combines elements of the first three approaches.

The web serves as a crucial communication tool and an information retrieval resource, growing in a decentralized and often chaotic manner. This growth has produced vast volumes of interlinked documents that lack coherent organization. Locating relevant and necessary knowledge from among countless web pages can be time-consuming and challenging. The emergence of web-based services, such as e-commerce and online learning, has fundamentally altered how the internet is used, transforming websites into commercial platforms and intensifying competition. Consequently, providing additional services tailored to individual user preferences and needs has become essential for maintaining customer engagement [22].

An intelligent system capable of learning user interests, automatically filtering irrelevant content, and recommending relevant information in a timely manner is therefore indispensable. Web personalization has emerged as a popular approach for customizing web environments. Using personalization technologies, user-specific services are provided based on individual preferences and priorities without explicit requests. Web personalization involves a set of operations that organize the web experience for individual users or groups of users, generating dynamic recommendations based on user behavior patterns [23]. In essence, the system adapts to each user, responding to requests according to their interests and needs.

The benefits of web personalization include:

- Reducing information overload and transforming websites into more user-friendly environments.
- Delivering desired information to users at the right time and in the most suitable manner, improving navigation and engagement.
- In e-commerce, providing mechanisms to better understand customer needs, anticipate future preferences, and enhance customer retention.

Web personalization systems are widely applied in e-commerce, targeted advertising, and search engines. Recommender systems are a prime example of such personalized web services. Web mining techniques have been extensively used to implement web personalization. One type, usage mining, involves constructing web recommender systems by analyzing server log files and applying data mining techniques such as association rule mining, sequential pattern mining, and clustering to extract user navigation patterns and provide personalized future recommendations. Despite various proposed methods for web personalization, many still lack sufficient accuracy and coverage [22].

2.1. Principles of Recommender Systems

Designing and implementing an effective recommender system requires careful consideration of several key aspects. These aspects include:

- **Type of data available in the system:** Depending on the system's application, various types of information may be present, such as user ratings on items, personal user information, item-related content, social network connections, and user location data. Naturally, the type of available data must be a primary consideration during the design of a recommender system [24].
- **Filtering algorithm used:** The main objective of a recommender system is to rank system items according to their relevance to user preferences so that higher-ranked items are presented to users first. Several algorithms have been proposed for this purpose, the most prominent of which include:
    - Collaborative Filtering
    - Content-based Filtering
    - Social-based Filtering
    - Knowledge-based Filtering
    - Context-aware Filtering
    - Hybrid Filtering [4]
- **System modeling approach:** Currently, two main strategies are used to implement recommender systems. One approach relies directly on the system's existing data, known as **memory-based**. The other, slightly

more sophisticated approach, involves using a model within the system, referred to as **model-based**, which may utilize algorithms such as genetic algorithms, neural networks, or fuzzy logic.

- **Recommendation technique employed:** Various techniques can be used to implement the core of a recommender system. Examples include genetic algorithms, neural networks, Bayesian networks, probabilistic methods, or harmony search algorithms.
- **Expected scalability of the system:** The system should be designed to handle growth in users, items, and interactions efficiently.
- **Desired performance:** The system's performance should be evaluated in terms of memory usage and response time.
- **Quality of recommendations:** The quality of the recommendations depends on the system's application domain and business context. For instance, some systems may prioritize presenting the latest items, whereas others aim to cover 2A2Qa2QAQ2QAA a broad set of items. Generally, recommender systems strive to optimize three key factors in their outputs: **novelty, accuracy, and coverage**.

3. FILTERING METHODS AND ALGORITHMS

Undoubtedly, the core component of recommender systems is their filtering algorithm and approach. In the following, we discuss the most commonly used strategies in this domain.

3.1. Collaborative Filtering Algorithm

One of the most important and widely used filtering methods in recommender systems is Collaborative Filtering (CF), which also serves as the foundation for many other approaches. The operation of this algorithm mirrors how we make decisions in daily life. For instance, we often choose a product that is favored by many others (e.g., a product with higher ratings in e-commerce platforms). Therefore, in Collaborative Filtering, the primary focus is on others' experiences rather than the individual's own preferences.

In this method, users must first participate in the system by providing ratings for various items. These ratings can also be implicit, detected by the system. For example, an implicit rating could be inferred from the frequency of downloads: items that are downloaded more frequently are likely more popular and thus receive higher implicit ratings.

It is important to note that in this approach, the system ranks items based on their ratings and recommends the highest-rated items to users. Consequently, if the system is newly launched or if a new item is added, there may not be enough information to accurately rate and rank items. This is a major issue known as the cold-start problem. Another challenge faced by CF systems is data sparsity, meaning that although information exists in the system, it is scattered, making it difficult to accurately determine which items are more favorable [25].

3.1.1. Cold-Start Problem and Data Sparsity

As mentioned, one of the most significant challenges in CF-based recommender systems is the cold-start problem, which arises when the system lacks sufficient information to provide recommendations. This situation may occur due to one of the following reasons:

1. **System initialization:** When the recommender system starts, it is recommended to encourage users to rate items using appropriate methods and only begin recommending once sufficient data has been collected.
2. **New user entry:** The primary challenge for CF systems occurs when a new user joins the system. In this case, while sufficient information about items may exist, the new user has not rated any items yet, making conventional CF methods ineffective. To address this issue, CF is often combined with other approaches (e.g., **Content-Based Filtering**) to create a hybrid system.

3. **Introduction of new items:** Newly added items generally have no ratings and therefore do not appear in recommendation lists, remaining invisible to users. This lack of exposure can prevent these items from ever receiving ratings. However, this problem is less critical in recommender systems, as other methods and tools can be used to present new items to users and collect ratings [25].

Due to the cold-start and data sparsity issues, CF systems are often employed in combination with other methods to leverage their advantages while mitigating their drawbacks. For example, implementing Collaborative Tagging within a CF-based system has been suggested to better capture user preferences and categorize items according to user interests.

Another approach to addressing these challenges is the use of clustering techniques, typically applied to solve the cold-start problem. Items, users, or both can be clustered to improve recommendation accuracy and system performance.

To tackle data sparsity, dimensionality reduction techniques are commonly employed. In addition, Latent Semantic Indexing (LSI) and Singular Value Decomposition (SVD) are also used. Although SVD produces excellent results, it has a high computational overhead and is better suited for offline applications with minimal changes in information.

3.2. K-Nearest Neighbors (KNN) Algorithm

The most commonly used algorithm in the CF approach is the K-Nearest Neighbors (KNN) algorithm. This algorithm can be implemented using two different approaches. The first approach takes a user-to-user perspective. Algorithms following this perspective generally include three steps:

Step 1: Based on a similarity measure (e.g., Mean, Pearson Correlation, Cosine, or Squared Difference), $k$neighbors are selected for user a. These neighbors are the users who are most similar to user a.

Step 2: For all items in the system, a quantitative measure is calculated to predict whether item $i$will be liked by user a. This measure is derived using various methods (e.g., average ratings, weighted sum) based on the ratings that user a's neighbors have assigned to item i.

Step 3: Based on Step 2, the top Nitems with the highest predicted values are recommended to the user.

The main advantages of this algorithm are its simplicity and the relatively high accuracy of its results. However, it has two fundamental limitations: low scalability and vulnerability to data sparsity. When a new user is added to the system, similarity measures and prediction values must be recalculated. As the number of users grows, this creates a substantial computational overhead.

To address the scalability issue, another version of the algorithm with a item-to-item perspective has been proposed, which significantly reduces the scalability problem. This version also involves three main steps:

Step 1: Based on similarity measures, $q$neighbors are determined for each item i.

Step 2: If user $a$has not yet rated item i, the predicted rating is calculated based on the ratings that the user has given to the neighboring items of i.

Step 3: Items with the highest predicted values are recommended to user a[25].

3.2.1. Similarity Measurement

The core of CF-based recommender systems is the determination of similarity between users and items to establish neighborhood relationships. This requires an appropriate similarity metric. In traditional methods, similarity was determined based on ratings: if two users rated the same item, the system inferred similarity between these users. Similarly, for items, if the same users rated two items, the system assumed a similarity between these items.

In addition to this basic metric, other measures are also employed to determine similarity between users and items. Some of these measures include: Mean Square Difference, Adjusted Cosine, Cosine, Pearson Correlation, and Constrained Correlation.

3.3. Demographic Filtering Method

Demographic information such as age, gender, nationality, and so on falls under the category of demographic data. Systems using this method operate on the assumption that users with similar demographic traits (e.g., belonging to the same age group) are likely to have similar preferences and interests.

3.4. Content-Based Filtering Method

In contrast to the previous approach, where recommendations are based on others' experiences, Content-Based Filtering (CBF) relies primarily on the user's own information and preferences. Recommendations are made by analyzing the user's past choices and experiences. Typically, this method requires analyzing both the user's data and the attributes of items in the system to determine the similarity between users and items (as well as between items themselves).

In content-based systems, items recommended to the user are those most similar to items the user has previously chosen. A critical aspect of such systems is the selection of an appropriate similarity metric.

Despite its advantages, Content-Based Filtering has several challenges and limitations:

- **Difficulty in data extraction:** The method aims to find similarities between items based on their attributes and content. In certain domains (such as music, video, or blogs), this can be very complex and challenging. Automated methods for feature extraction are often required.
- **Overspecialization problem:** Over the system's lifecycle, recommendations tend to focus only on items similar to those the user has previously selected. This can prevent items that may actually interest the user but differ from previously chosen items from ever being recommended.
- **Lack of user feedback:** Typically, content-based systems do not gather explicit feedback from users. For instance, users may not rate items (unlike in CF systems), making it difficult to evaluate the accuracy of recommendations.

Due to these limitations, Content-Based Filtering is often used in combination with other approaches. For example, a successful hybrid approach integrates CBF with social networks. In such systems, in addition to ratings, information from social media such as comments, blogs, friendships, likes, and followers is used to enhance the quality and accuracy of recommendations [25].

3.4.1. Steps of Content-Based Filtering (CBF)

The Content-Based Filtering method involves three main steps:

- **Feature extraction for items:** For a CBF system to function effectively, item features must first be extracted. Most features are explicitly associated with items in the system, so extracting these is generally straightforward. However, some features depend on the domain of the system and require specific extraction techniques. For example, in systems where items are textual documents, classic information retrieval methods such as term frequency (TF), inverse document frequency (IDF), and document length are used to extract relevant features.
- **Comparing item features with user preferences:** Once item features are determined, analyses are conducted to measure how well items in the system align with user interests. This is typically done using exploratory methods or clustering algorithms.
- **Recommending items that best match user preferences:** Items most similar to the user's interests are suggested.

A current trend in CBF systems is to combine them with social networks, utilizing information such as comments, tags, and social sharing. The most well-known of these are tag-based recommender systems. Work in this area is divided into two categories: developing tag-based recommender systems and using tags to enhance recommendations [6].

3.4.2. User Grouping

CBF systems require extensive processing and analysis, which can limit their efficiency. One effective solution to improve performance is user grouping, where recommendations are provided to the entire group rather than individual users. While this approach does not improve accuracy or recommendation quality, it significantly reduces computational overhead.

3.5. Social-Based Filtering

With the expansion of social networks, researchers began using data from these networks such as followers, trust, blogs, comments, friends, followers, and tags in recommender systems. These data can be collected explicitly or implicitly. Studies have shown that using such information improves recommendation quality and reduces data sparsity.

Research in social-based recommender systems (RS) falls into two categories. One group focuses on using social network data to enhance existing RS, demonstrating positive impacts. The other group develops entirely new recommender systems based solely on social filtering, independent of traditional methods, leveraging the potential of social networks.

3.5.1. Trust and Credibility

Among social network data, trust and credibility are particularly important. Trust measures a user's reliability among peers and can significantly influence recommendations. For example, the higher a user's trust, the greater the weight of their ratings on items. Two methods exist to determine user trust:

1. Using information explicitly provided by the user.
2. Using implicit information and user relationships present in social networks.

Suggested mechanisms in the literature include trust propagation mechanisms, Follow the Leader, trust networks, and similarity measures based on individual attributes.

For items, credibility is the key metric. It can be determined explicitly from user ratings or implicitly by analyzing user interactions with the item.

3.5.2. Use of Tags

In most social recommender systems, users can assign tags to items, forming triplets of <user, item, tag>, which create folksonomies. The high potential of tags as metadata has led to the development of tag-based recommender systems. Additionally, in hybrid systems, tags are often used to enhance recommendation quality.

3.6. Context-Aware Filtering

The rise of Web3 and the Internet of Things (IoT) has led to a new generation of recommender systems. In such environments, devices and sensors collect information about user conditions. This data can be used in context-aware recommender systems, emphasizing information such as time, location, security camera feeds, RFID, wireless sensor networks, as well as health parameters, shopping, and eating habits. This information can be collected explicitly or through data mining techniques.

3.7. Location-Based Recommender Systems

One of the most successful recent RS types is location-based recommender systems, commonly implemented in mobile applications. These systems provide suggestions within a specific domain based on the user's current location.

Some of these systems are hybridized with CF systems. In such approaches, items are rated using traditional CF methods, but the user's geographical location is considered during recommendation. This introduces complexity; as the user's location changes, previously recommended items may no longer be relevant. For example, a user may rate a restaurant near their workplace positively. If they later return home, should the same restaurant be recommended? While CF identifies it as preferred, its distant location may make it irrelevant.

3.8. Knowledge-Based Recommender Systems

Knowledge-based recommender systems (KBS) represent a new generation of RS that rely on knowledge about users and items. These systems provide recommendations based on interpretation and inference of user preferences and needs, theoretically offering higher accuracy and quality than other methods. Implementing such systems requires a knowledge-based infrastructure.

One application domain in KBS is Workflow, based on the users-roles-tasks model, which defines each user's roles and responsibilities. Another area of research involves peer-to-peer networks, where system knowledge about items and users is distributed among peers.

4. EXISTING APPROACHES IN RECOMMENDER SYSTEMS

Recommender systems can be categorized based on the type of data they use and the methods applied to analyze that data. According to [source], four main approaches are relevant to our study:

- Graph-based recommender systems
- User profile-based recommender systems
- Collaborative filtering-based recommender systems
- Hybrid recommender systems

4.1. Graph-Based Recommender Systems

In graph-based recommender systems, the inherent structural characteristics of a network are used to determine similarity among nodes. The goal of such systems is to identify active and influential individuals in social networks through social graph analysis.

Link prediction is a well-known problem in social networks with many applications. A major application is designing recommender systems based on graph topology. Link prediction aims to forecast new links at time $t + 1$based on a snapshot of the graph at time t. The snapshot at $t + 1$could be taken after a week, a month, a year, or several years. Algorithms for link prediction, often referred to as node similarity-based algorithms, can be divided into **local** and **global** approaches:

- **Local similarity measures** (e.g., FAOF, Jaccard coefficient, Adamic/Adar coefficient) primarily focus on the local structure of nodes and do not consider paths of varying lengths in the network, generally limiting analysis to paths of length two, which reduces accuracy in identifying neighboring friends.
- **Global algorithms** (e.g., Katz index, SimRank, PageRank) consider the overall network path structure, which is computationally intensive for large networks. Traversing the graph globally also leads to loss of local structural information.
- Some hybrid algorithms (e.g., FriendLink) combine both approaches, allowing connections through paths of varying lengths. This extends the local neighborhood horizon, improving both the accuracy and speed of link prediction.

4.2. Content-Based Recommender Systems

Content-based algorithms recommend items (objects or users) with higher priority based on item descriptions and user profile attributes (e.g., age, gender). In such systems, user features are used to calculate similarity between users. Features can be extracted from various sources such as registration information, location, and user interests. Several similarity metrics exist, primarily using categorical data. The simplest metric returns 1 if two items match and 0 otherwise. More complex metrics provide nonzero similarity scores for non-identical items and return 1 for identical values.

4.3. Collaborative Filtering-Based Recommender Systems

In these systems, new items are suggested to a user based on previous transactions and the preferences of similar users. User-based collaborative filtering models the social process of friend recommendation in social networks. Extensive data about user behaviors, activities, and preferences are collected and analyzed to predict similar users.

Collaborative filtering algorithms are generally classified into memory-based and model-based algorithms. Memory-based algorithms use the entire user-item database directly, while model-based algorithms first create a ranking model and then make predictions.

4.4. Hybrid Recommender Systems

Hybrid systems combine more than one approach to leverage the strengths of each method. For example, graph-based algorithms may be combined with content-based methods, or collaborative filtering methods may be combined with content-based techniques. The aim is to improve system performance by utilizing the advantages of multiple approaches. Some studies also integrate evolutionary algorithms (e.g., genetic algorithms, ant colony optimization) with other methods to create hybrid recommender systems.

5. CONCLUSION

Recommender systems have a wide range of applications and offer significant benefits:

Application areas of recommender systems:

- **E-commerce:** For suggesting products and services.
- **Enterprise intranets:** To find experts or individuals with experience in similar scenarios, often within organizations.
- **Digital libraries:** To locate books, articles, and other resources.
- **Medical applications:** For choosing appropriate doctors (considering location, disease type, time, etc.), selecting medications, and more.
- **Customer relationship management (CRM):** Helps establish effective communication between consumers and producers, offering solutions to product-related issues.

Key benefits of recommender systems:

- **Based on real, live data:** Recommendations rely on actual user activity and preferences rather than guesswork.
- **Excellent for discovering new areas:** Systems can introduce users to content they might never find otherwise, expanding their exploration horizons efficiently.
- **Personalized suggestions:** Recommendations are tailored to individual traits, similar to trusting close friends' advice. Unlike early Web 1.0 random suggestions, modern recommender systems offer more reliable guidance.

- **Always up-to-date:** By leveraging collective intelligence from thousands of users, one can stay informed about the latest trends and developments in areas of interest.
- **Reduced organizational maintenance costs:** Users' preferences help shape content, reducing the need for centralized content management and lowering organizational costs compared to traditional websites.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

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