International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 11, Issue 10, October 2022)

Recommender Systems (RSS) and Their Applications: A Survey

Karishma Kushwaha[1], Saurabh Sharma[2]

Department of Computer Science & Engineering Global Nature Care Sangathan's Group of Institutions, India

***Abstract--* With the expansion of the Internet, gleaning valuable information from the vast amount of online data has become considerably more challenging. Mechanisms for effective information filtering are required due to the massive amount of data. In a vast space of potential possibilities, recommender systems have the effect of directing users in a personalised fashion to attractive objects. Software tools and methods called recommender systems (RSs) make suggestions for products that would be useful to a user. In this essay, we will examine three distinct recommender system methodologies that can be used to various e-commerce websites: collaborative filtering (CF), content-based filtering, and hybrid recommender systems. We quickly outline each type's advantages and disadvantages before highlighting some of the ways Recommender Systems (RSs) are used in various fields.**

***Keywords--* Recommender systems, Collaborative filtering, Content-based filtering, Hybrid recommender systems, information filtering..**

I. INTRODUCTION

A subtype of information filtering system called recommender systems aims to forecast the "rating" or "preferred" that a user would assign to a given item [1]. In recent years, recommender systems have proliferated and are used in a wide range of applications. The most often used ones are generally products on e-commerce websites and books, research articles, movies, music, news, search queries, and social tags. In order to help people sort through the available books, articles, web pages, movies, music, restaurants, jokes, grocery items, and other information to identify the most interesting and useful information for them, recommender systems support and supplement this natural social process. Online stores frequently employ recommender systems because they increase consumer convenience and business advantages. By making purchases just a few clicks away or rewarding loyal customers with discounts and other incentives, it converts surfers into purchasers, cross-sells items that are suggested on the checkout page, and increases user loyalty. The operating environment for e-commerce recommendation algorithms is frequently difficult, especially for major online retailers like eBay and Amazon.

A recommender system that offers quick and accurate recommendations would typically pique customers' interest and help businesses. Collaborative filtering (CF), content-based filtering, and hybrid recommender systems are the typical methods used by recommender systems to generate a list of recommendations. RSs are largely targeted at people who don't have enough professional or personal expertise to evaluate the voluminous array of viable alternatives that, for instance, a website might provide [2].

II. TASKS OF A RECOMMENDER SYSTEM

Eleven common tasks that a recommender system can help implement are listed by Herlocker: [3]

- *Locate some useful items:* a featured list of the top-ranked products that the user's search criteria revealed.
- *Gather all useful items:* a list of all the things from the item database that meet all the user-specified conditions.
- *Text annotation:* a list of products that are suggested based on the user's preferences over the long term and the current environment. The user's long-term viewing patterns can be used to recommend a certain TV show on a particular channel.
- *Suggest a sequence:* a list of the item being searched for together with some similar items that might be interesting to the user but are not necessarily relevant to the search parameters.
- *Suggest a bundle:* a collection of related products that can cooperate to better serve the needs of the user. Typically, when you purchase a camera, you may also think about purchasing a memory card, a pouch, and other accessories to complete the purchase.
- *Just browsing:* The recommender system's job is to help users who browse merely for leisure find items within the scope that they will find interesting during that particular browsing session.
- *Locate a reliable recommender:* Some people have reservations about the system's recommendations. The recommender system's job is to then give the user a chance to evaluate the system's performance.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 11, Issue 10, October 2022)

- *To enhance the profile:* The user's explicit preferences and general likes and dislikes can be inputted into the system.
- *Express yourself:* While some users don't care much about suggestions, it's crucial for them to be able to share their thoughts on a particular product. Such inputs can be sent to the system in the comment box, and the satisfaction it generates can be used to encourage users to buy the linked item.
- *Help others:* Because they believe doing so will benefit the community, some consumers could be even more inclined to provide a thorough review or rating of the product. And that can serve as a powerful motivator for other prospective buyers to make a decision.
- *Influencing others:* Some users may have a disproportionate amount of influence, attempting to persuade other users to buy or not buy the product. This group includes even malicious users.

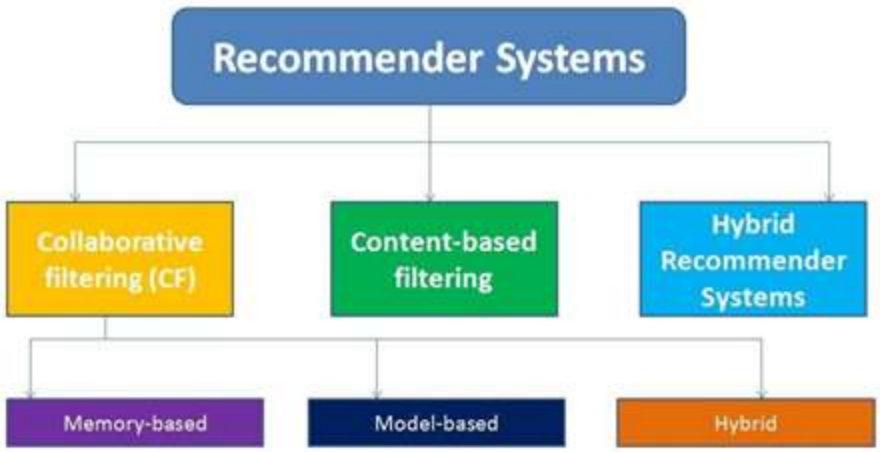

Fig. 1. Different types of Recommender systems

III. COLLABORATIVE FILTERING

The process of filtering information or patterns utilising methods that entail cooperation amongst various agents, viewpoints, data sources, etc. is known as collaborative filtering. [4] Collaborative filtering applications involve enormous data volumes. Many different types of data have been subjected to collaborative filtering techniques, including financial data, which is used by institutions that integrate a variety of financial sources, monitoring and sensing data, which is used in mineral exploration, environmental sensing over wide areas, or data collected by numerous sensors, as well as data from electronic commerce and web applications where the emphasis is on user data. By pooling the preferences or tastes of numerous users, collaborative filtering can be used to make predictions about a user's interests automatically.

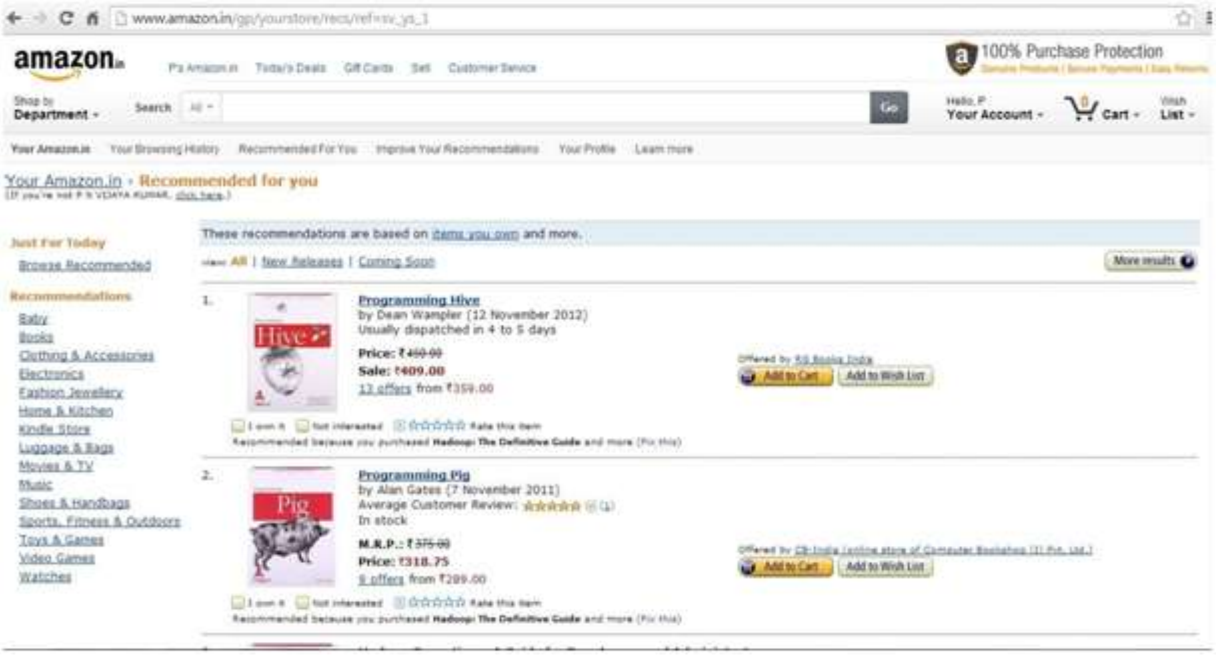

Fig. 2. Amazon recommends products to customers by customizing Collaborative filtering (CF) systems.

According to the collaborative filtering approach, if two people X and Y share the same view on a subject, X is more likely to share Y's opinion on subject "a" than the opinion of a person chosen at random. For instance, given a partial list of a user's preferences, a collaborative filtering recommendation system for laptop tastes may offer predictions about which laptop brand the user should choose (likes or dislikes).

A collaborative filtering system's typical procedure is as follows:

- A user can express their preferences by rating system content (such as articles, movies, or books). The user's interest in the respective domain can be roughly represented by these ratings.
- The system compares these users' evaluations to those of other users to identify those with the most comparable tastes.
- Based on similar users, the system suggests products that this user should evaluate highly but hasn't done so yet.

A. Types of collaborative filtering

a) Memory-based: To determine how similar users or things are, this technique employs user rating information. This is used to formulate suggestions.

This was the early mechanism, and many commercial systems still employ it. It works well and is simple to apply. Neighborhood-based CF and item-based/user-based top-N recommendations are typical instances of this system [5]. Neighbor-based CF (item-based/user-based CF methods with Pearson/vector cosine correlation) and item-based/user-based top-N recommendations are the representative methodologies.

Advantages:

- easy implementation
- new data can be added easily and incrementally
- need not consider the content of the items being recommended
- scale well with co-rated items

Shortcomings:

- are dependent on human ratings
- performance decrease when data are sparse
- cannot recommend for new users and items
- have limited scalability for large datasets

b) Model-based: Data mining and machine learning methods are used to create models by looking for patterns in training data. These are employed to forecast actual data. Model-based CF algorithms are widely used.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 11, Issue 10, October 2022)

This strategy aims to find latent characteristics that account for observed ratings in a more comprehensive manner. [6] These include Markov decision process-based models, Bayesian networks, clustering models, latent semantic models such as singular value decomposition, probabilistic latent semantic analysis, multiple multiplicative factors, and latent Dirichlet allocation, among others [7].

Advantages:

- better address the sparsity, scalability and other problems
- improve prediction performance
- give an intuitive rationale for recommendations

Shortcomings:

- expensive model-building
- have trade-off between prediction performance and scalability
- lose useful information for dimensionality reduction techniques

c) Hybrid recommenders: Applications that combine the memory-based and model-based CF methods are numerous. These get around the drawbacks of native CF methods. The performance of predictions is enhanced. Importantly, it resolves CF issues such sparsity and information loss. Most commercial recommender systems are typically hybrid, like the one for Google News [7].

Advantages:

- overcome limitations of CF and content-based or other recommenders
- improve prediction performance
- overcome CF problems such as sparsity and gray sheep

Shortcomings:

- have increased complexity and expense for implementation,
- need external information that usually not available

IV. Content-Based Filtering

The description of the item and the user's preference profile serve as the foundation for content-based filtering techniques [8]. These algorithms strive to suggest products that are comparable to those that a user has previously enjoyed or is now looking at. The user's prior ratings of various potential goods are specifically compared, and the best-matching things are then recommended. Research on information filtering and retrieval is the basis of this strategy. These techniques essentially make use of an item profile that describes the object within the system. Based on a weighted vector of item attributes, the system develops a content-based profile of each user. A number of methods can be used to compute the weights from individually rated content vectors, which represent the relevance of each characteristic to the user. In order to estimate the likelihood that the user will like the item, simple approaches simply use the average values of the rated item vector. More sophisticated approaches, however, use machine learning techniques like Bayesian Classifiers, cluster analysis, decision trees, and artificial neural networks.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 11, Issue 10, October 2022)

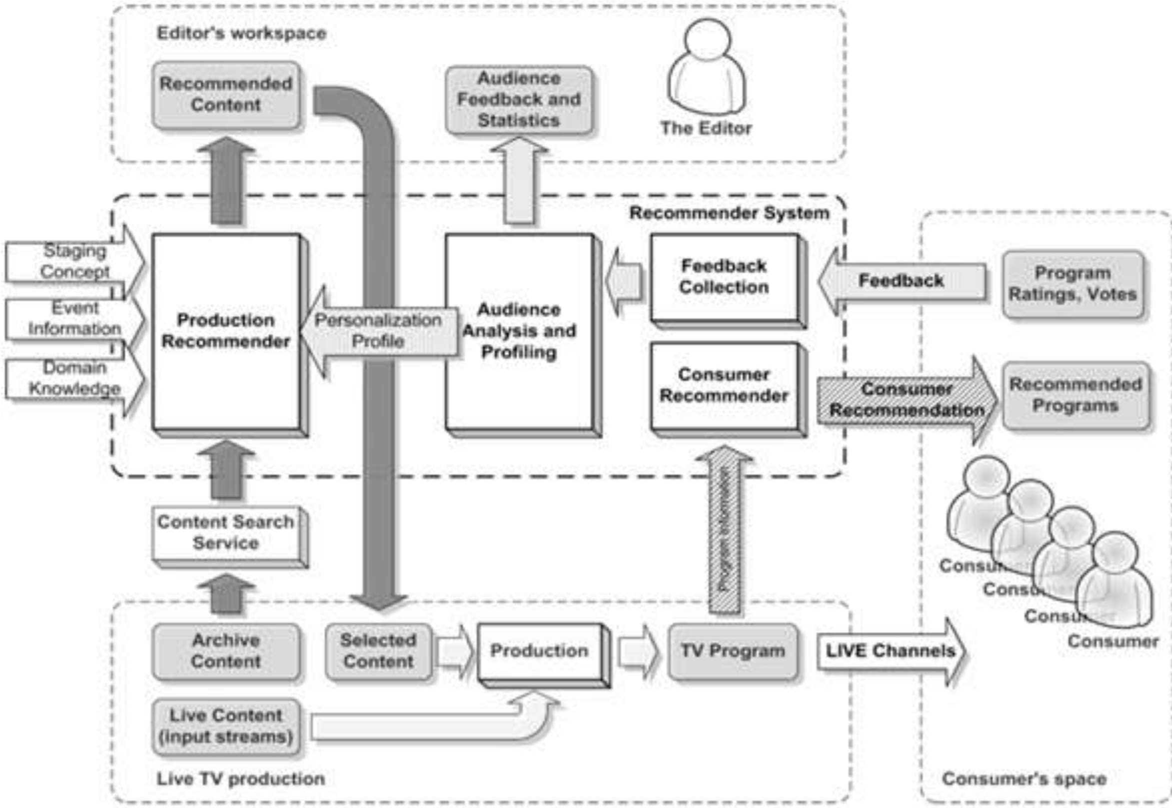

Fig. 3. Content recommender for the TV production, which includes Recommender GUI, and provides content search and personalization functionalities

Advantages: [9]

- User Independence - To create her own profile, content-based recommenders entirely rely on ratings from active users. Instead, collaborative filtering techniques rely on user ratings to identify the "nearest neighbours" of the active user, or people who share their likes since they assigned the same items comparable scores. Then, only the products that are most popular among the active user's neighbours will be suggested.
- Transparency - By explicitly presenting the content characteristics or descriptions that led to a particular item appearing in the list of recommendations, the recommender system's workings can be explained. To determine whether to trust a recommendation, one should look at such characteristics. Collaborative systems, on the other hand, are opaque because the sole justification for an item recommendation is that unidentified individuals with similar likes loved it.
- New Item - Content-based recommenders are able to suggest products that have not yet been given a user rating. Since they do not only rely on user preferences to create suggestions, they are not affected by the first-rater problem that plagues collaborative recommenders. Therefore, the system would be unable to propose the new item until a sizable number of people have given it a rating.
- The ability of the system to recognise user preferences from activities related to one content source and apply them to other content kinds is a critical problem with content-based filtering.
- Content-based recommenders lack a built-in mechanism for discovering unexpected items. The user will be recommended items that are comparable to those already rated by the algorithm because it only suggests items with high ratings when they match the user profile. Serendipity problem is another name for this flaw, which refers to the tendency of content-based systems to generate recommendations with just a little amount of originality.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 11, Issue 10, October 2022)

V. Hybrid Recommender Systems

Collaborative filtering and content-based filtering are the foundation of hybrid recommender systems. These get around the drawbacks of native CF methods. The performance of predictions is enhanced. Importantly, it resolves CF issues such sparsity and information loss. Numerous methods have been suggested for integrating two or more fundamental recommender system concepts to develop a new hybrid system [10]. They are costly to implement and have increasing complexity [11]. Most commercial recommender systems are typically hybrid, like the one for Google News [12].

Advantages:

- The hybrid approach tries to overcome the limitations of the other approaches and combine the advantages of the other approaches by using two or more approaches.

Disadvantages:

- As they combine two or more approaches to give better recommender system with increased complexity, they areexpensive to implement.

VI. Applications Of Recommender Systems

The most common recommender systems applications include:

- *Entertainment* - recommendations for movies, music, and IPTV.
- *Content* - personalized newspapers, recommendation for documents, recommendations of Web pages, e-learningapplications, and e-mail filters.
- *E-commerce* - recommendations for consumers of products to buy such as books, cameras, PCs etc.
- *Services* - recommendations of travel services, recommendation of experts for consultation, recommendation of houses to rent, or matchmaking services.

VII. Conclusion And Future Scope

The three recommender systems each have benefits and drawbacks when it comes to doing their job.

The majority of each approach's shortcomings can be complemented by the other. In order to prevent consumers from growing weary of seeing the same items in the recommendation list, a good recommender system should occasionally be able to offer constructive and pertinent recommendations as well as alternate suggestions. Future recommendation systems should be dynamic and allow for real-time profile updates. This implies the requirement for a significant amount of computational power, network bandwidth, etc., along with the synchronisation of numerous profiles. Due to the relatively high memory computational complexity of current methods and methodologies, significant system processing times and data latency result. Therefore, one of the development focuses will be on novel algorithms and techniques that might lessen memory computational complexity and finally remove synchronisation issues.

REFERENCES

[1] Francesco Ricci and Lior Rokach and Bracha Shapira, Introduction to Recommender Systems Handbook, Springer, pages 1-35, 2011,

[2] Resnick, P., Varian, H.R., Recommender systems. Communications of the ACM 40(3), Pages 56–58, 1997.

[3] Herlocker, J.L.; Konstan, J.A.; Terveen, L.G.; Riedl, J.T., Evaluating collaborative filtering recommender systems. ACM Transaction on InformationSystems 22(1), Pages 5–53, 2004,

[4] Terveen, Loren; Hill, Will, "Beyond Recommender Systems: Helping People Help Each Other". Addison-Wesley. Page 6, 2001.

[5] An integrated approach to TV Recommendations by Red Bee Media.

[6] Factor in the Neighbors: Scalable and Accurate Collaborative Filtering.

[7] Xiaoyuan Su, Taghi M. Khoshgoftaar, A survey of collaborative filtering techniques, Advances in Artificial Intelligence archive, 2009.

[8] Peter, Brusilovsky, the Adaptive Web. ISBN 978-3-540-72078-2., Page. 325, 2007.

[9] Pasquale Lops, Marco de Gemmis, Giovanni Semeraro, Content-based Recommender Systems: State of the Art and Trends, Recommender Systems Handbook, Springer, Pages 73-105, 2011.

[10] Burke, R.: Hybrid web recommender systems. In: The AdaptiveWeb, Springer Berlin / Heidelberg, Pages. 377–408, 2007.

[11] Kernel Mapping Recommender System Algorithms, www.sciencedirect.com/science/article/pii/S0020025512002587.

[12] Google News Personalization: Scalable Online Collaborative Filtering.