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A Review Paper on Recommender System for Higher Education

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Abstract:

A Recommender System is an artificial intelligence technique that helps consumers or clients in taking up decision based on their past preferences or choices. It is being used today in several sector including online shopping, healthcare, video surfing, reading books online, course, college or university selection for higher studies by student, and many more such recommender system are trained in a way to identify and capture the user preferences, past decision and characteristics of product and people using data accumulated through their interaction. In order to pre train such system, machine learning and deep learning are techniques which are widely used today. This paper majorly focuses on basics of recommender system and its type including the study of several machine and deep learning techniques which are implemented in the past by researchers across the world. This paper focuses on diverse techniques used in course selection for students moving towards higher education and the scope of the paper is limited to all those who are moved to recommender system for their better understanding and quick knowledge on the major work carried out the date.

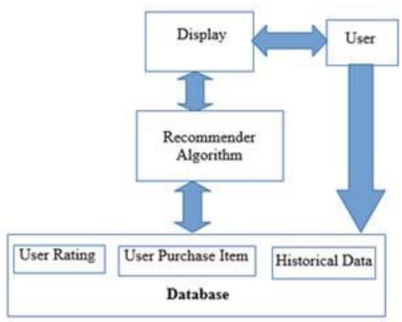
Keywords: Recommender System, Higher Education,Collaborative Filtering, Content Based Filtering, Knowledge Base, Hybrid, Machine Learning.

I. Introduction:

A great amount of internet information may now be accessed more quickly thanks to recent technological breakthroughs and the popularity of online services. For a variety of online services and products, users can write reviews, comments, and ratings. The problem of online data overload is a by-product of pervasive computing's recent advances. The act of locating pertinent and helpful stuff on the internet is made more difficult by this data deluge. However, the recent development of a number of methods with less computational demands can direct visitors to the pertinent content in a lot easier and quicker way. As a result, the creation of recommender systems has recently attracted a lot of interest. Generally speaking, recommender systems serve as tools for information filtration, providing consumers with pertinent and personalised content or information. The main goal of recommender systems is to minimise the user's time and effort spent searching for pertinent information online.

Recommender Systems are software applications created specifically to propose to users the next activity to partake in, based on a range of variables including preferences and the user's past. In other words, these programmes or systems assist users in selecting options that they find appealing. Generally speaking, the goal of all recommender systems is to produce useful recommendations for consumers for products that might be of interest. In order to arrange each element in a set of related characteristics, recommender systems must be able to determine which features consumers favour. To meet customer needs, recommender systems are widely employed in a variety of industries, including tourism, e-commerce, TV programming, movies, music, and education. The technology of today's recommender systems falls under the category of AI applications.

How does the Recommender System work?



Recommendation System Process

Higher education institutions today face a number of difficulties, including a competitive educational market, decreased government financing, rising student enrolment, and a variety of academic specialisations. Education administrators must continue to provide necessary and effective student support services, such as curriculum support, learning support, and career counselling, in spite of all these problems [3]. Since there are now a significantly greater number of courses included in the framework of smart education, the issue of choosing the appropriate courses is now having a big impact on how current learners learn [4]. Numerous students worldwide struggle to select the best university or college courses, according to certain academics' findings [5].

The recommender systems can be used to assist students in choosing courses that match their skills and interests. These help students save time by offering knowledgeable counsel through their knowledge base component. Knowing the needs of the students can help them learn more, gain experience, and improve their chances of succeeding [6]. This study focuses on recommender systems, which are used in education to help students who struggle to choose the right courses.

Recommender Systems are information search tools that have been suggested to address the issue of information overload and assist users in making decisions or maintaining their knowledge on a certain subject [7]. In the past, contemporary recommender systems first emerged in the final decade of the 20th century and have since demonstrated their value in addressing content personalisation and information overload in the current big-data environment [1]. Based on web usage statistics, recommender systems can be utilised for web recommendations. Recently, intelligent systems have been developed that appropriately utilise the combined contents and even the structural data of the useful data. In terms of user problems with web page recommendations, websites have been established and have produced better outcomes [8].

In the past, contemporary recommender systems first emerged in the final decade of the 20th century and have since demonstrated their value in addressing content personalisation and information overload in the current big-data environment [1]. Based on web usage statistics, recommender systems can be utilised for web recommendations. Recently, intelligent systems have been developed that appropriately utilise the combined contents and even the structural data of the useful data. Websites have been created and have produced better results when it comes to the user's problems with web page recommendations [8].

News Recommender Systems (NRS) on online news websites offer readers personalised reading recommendations [9]. Users can also receive movie recommendations via online recommender systems like "MovieLens," which is a movie recommendation system. The user is prompted to rate various films they have already seen after joining the website, and the ratings are subsequently used to recommend new films to the user [10]. By using mobile application recommender systems to guide them in choosing the best and most reliable mobile applications, mobile users can now prevent information overload [11]. Most of the time, some employees have trouble selecting the appropriate positions. In order to recommend workers to the appropriate jobs, several researchers have taken into account the aforesaid challenge of matching a user with a job [12]. Due to the abundance of sources for banking products, RS helps the banking industry by fostering customer loyalty and sparing the banks the cost of recruiting new clients for each product [13]. However, firms or system builders interested in using recommender systems must select the best strategy from a variety of options [7].

II. Literature Review:

Non-personalized recommendation systems are automatic as suggested by J. Ben Schafer, Joseph Konstan, and John[40] as they don't recognise users from one session to the next and don't depend on physical storage because their recommendations aren't dependent on consumers. According to a text classification surveyby Mladenic[41], the system searches for related things using its algorithm in the technique of content-based filtering, and then builds a model based on user interest. The recommendation is generated by this model.

A recommender model for online shoppers with a crude set association rule was put forth by Wang et. Al. [42]. The program calculated the likely behavioural variations of online shoppers and gave e-commerce platforms recommendations for product categories. A movie recommendation system based on user feedback gathered from microblogs andsocial networks has been represented in the paper by Walek, 2020[40]. It used the sentiment-aware association rule mining technique to provide recommendations based on previous knowledge of common program patterns, similarity between program metadata, and program view logs. A recommender system for social media platforms has been created by combining the Social Matrix Factorization (SMF) and Collaborative Topic Regression (CTR) techniques. The user ratings of the goods for creating recommendations could be calculated using the model. It gathered data from several sources, including item attributes, social networks, feedback, etc., to improve the recommendation quality. Adeniyi et al. [45] presented a research of automated web-usage data mining and created a recommender system for recognizing the visitor's or client's clickstream data that was evaluated both in real-time and online.

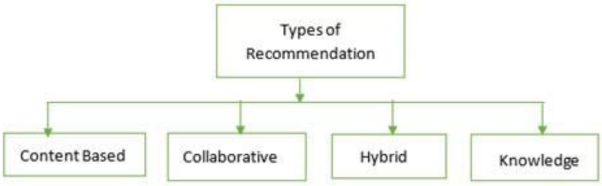
In 2020, Han et al. [15] suggested a Beetle Antennae Search (BAS)-based Internet of Things (IoT)-based cancer rehabilitation recommendation system. By using the objective function as the recurrence time, it offered the patients a solution to the issue of the ideal dietary program. A tree model-based recommender system for tailored adverts in online broadcasting has been presented by Kang et [43]. In order to reduce the overhead of preference prediction, recommendations were generated in real-time by taking into account user preferences and employing a hash map together with tree attributes. A random forest and convolutional neural network (CNN) based image-based service recommendation model for online shopping has been implemented by Ullah et al [36].

For the model to attain an accurate prediction rate, JPEG coefficients were utilized. A new hybrid recommender model using a many-objective evolutionary algorithm (MaOEA) was proposed by Cai et al. [12]. The novelty, diversity, and accuracy of recommendations were successfully optimized by the suggested method. A hybrid multi-criteria recommendation system based on a student's academic performance, interests, and choice of courses has been put into place by Esteban et al.[34] The system, designed to aid university students, was created using a Genetic Algorithm (GA). In order to improve system performance and the accuracy of the recommendations, it merged information about courses and students. By taking use of the idea of trust in a patient-doctor interaction, Mondal et. al.[29]. have developed a multilayer, graph data model-based doctor recommendation system. The suggested system performed well in real-world scenarios.

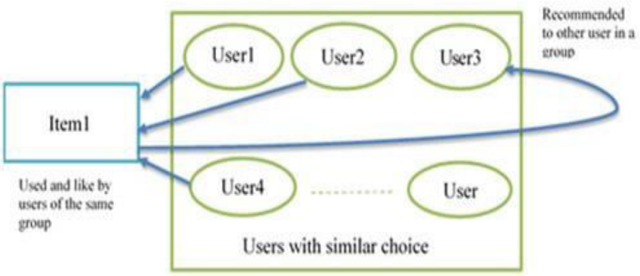
A personality-based product suggesting model has been created by Dhelim et al. [14] in 2023 using user interest mining and meta route discovery approaches. When compared to session-based and deep learning models, this model performed better. In order to solve the sparsity problem of recommender systems, Bhalse et al. [8] suggested a web-based collaborative filtering-based movie recommendation system that makes use of Singular Value Decomposition (SVD), collaborative filtering, and cosine similarity (CS). By taking into account the plot details of the movies, it offered a list of recommendations. Similarly, to address both the cold-start and sparsity issues A dynamic goods recommendation system built on reinforcement learning was suggested by Ke et al. [10]. On real-time applications, the suggested system was able to learn from the reduced entropy loss error. A movie recommender model using Feed-forward Neural Networks (FNN) has been presented by Chen et al. [11] and combines several techniques, including user interest with category-level representation, neighbour-assisted representation, user interest with latent representation, and item-level representation.

III. Types and Applications of Recommender Systems:

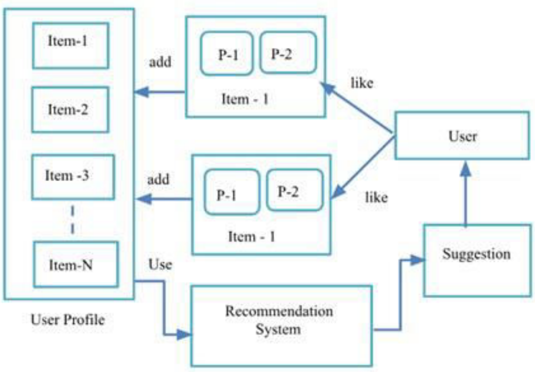
Recommender Systems are typically categorised based on the techniques they employ. Four basic broad categories have been used to organise these techniques. For their prediction process, the fundamental models use two different sorts of data: 1) User-item interactions, such as ratings or user behaviour, and 2) Users-items attribute information, such as textual profiles or pertinent keywords [45]. Additionally, there are two categories into which Techniques in Recommender Systems are graded: memory-based and model-based algorithms. Memory-based algorithms operate in this way on the entire user-item rating matrix. In contrast, rating data are used to train a model that is then utilised to provide recommendations in model-based procedures [45]. Following is a brief discussion of the various sorts of recommendation approaches or methods:



1. **Collaborative Filtering:** Collaborative Filtering is one of the often employed recommendation techniques. By locating people with like interests, it deals with making product recommendations to target users. This strategy tries to make it easier for users to find suggestions from people or organisations who share their tastes or behaviours. Collaborative filtering is a technique in recommender systems, according to G. Gupta and R. Katarya[22], in which the recommendations are dependent on the user's neighbours. This technique makes use of the idea of matrix factorization, in which a matrix contains the users, items, and the ratings provided by the items with various types of users. These methods are employed in a variety of e-commerce platforms and offer a better content suggestion (item suggestion) experience than other methods[21].

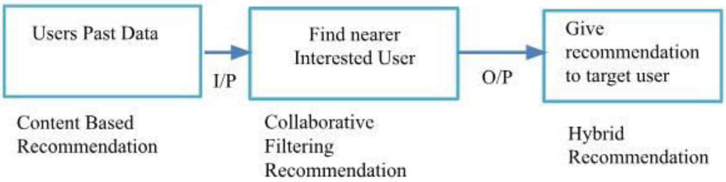


2. **Content Based Methods:** Users are given recommendations for products using this content-based method based on past data [41]. For instance, the technique first learns the things the user has searched for and purchased in the past to propose relevant items before offering them to the user. This strategy uses the potent attribute of rating. It is more likely to be used in the informational, commercial, and educational sectors.



3. **Knowledge Based Method:** These recommender methods assist users in selecting the best products while making purchases of goods with complex item domains due to the many qualities they have[46]. A specific automobile model, engine type, or interior house design may be the sole features that the user is interested in. It can be difficult to obtain reviews you can rely on for a recommendation in some company scenarios where products are not purchased frequently due to their high prices. Given that they are effective in cold-start scenarios, these techniques can be applied.

4. **Hybrid recommender methods:** These methods work by bringing together the strengths of different types of recommender systems [40]. The objective is to create recommender systems with techniques that are more efficient and effective in performance.



There are many areas today where recommender system is used to obtain better performance and analytical statistics of the presumed area. The usually observed area of recommender systems are E-commerce, Education, Entertainment, Health, Social Media and Tourism.Discussing the various applications of RS is out of scope of this paper. Here, implementation of Recommendation System in e-learning and course selection for higher education only have been focused. Recommender systems have a wide range of applications in higher education. Recommender Systems (RS) in e-learning: With the proliferation of online learning resources, RS can be used in e-learning to provide learners with appropriate content. In order to make it simple for students, readers, and researchers to locate the right books in accordance with their faculties and book categories, library service RS can be utilized on the websites of universities that house education libraries. Field of publications and research RS: Our daily lives are profoundly impacted by new ideas. Certain designers have developed systems for recommending publications to authors, suggesting appropriate journals and conferences. Faculty Recommender Systems (FRS): These systems can be used in higher education institutions to suggest faculty members to students, staff, lecturers and employees in the university.

IV. Diverse Approaches used in Recommender System:

Usually the type and qualities of the data as well as the functionality of the learning algorithms determine how effective and efficient a machine learning solution could be. To efficiently create data-driven systems, machine learning methods can be used in conjunction with classification analysis, regression, data clustering, feature engineering and dimensionality reduction, association rule learning, or reinforcement learning. Furthermore, as part of a larger family of machine learning techniques, artificial neural networks, which are known to be capable of intelligent data analysis, are the source of deep learning [47]. It is therefore difficult to choose an appropriate learning algorithm that fits the intended application in a given domain.

1. **K-Nearest neighbour:** The K-Nearest Neighbour (KNN) is a machine learning technique that uses the labels of nearby data points to estimate the class of a given data point[45]. All of the data points that are accessible are stored, and any new data is categorized using similarity metrics with the previously recorded data. Classifying data points according to the classification of their nearby points is a popular application of the technique.

2. **Decision Tree:** The decision tree is a guided learning technique in machine learning. A decision tree is a type of tree-structured classifier that uses internal nodes to represent a data set's attributes, branches to represent the decision rules, and leaf nodes to reflect the decision's outcomes[48]. A visual depiction of every possible resolution to a problem depending on a particular choice condition is offered by the decision tree.

3. **The supervised machine learning method** known as "linear regression" is used to forecast a continuous target variable using one or more input features. The least squares approach is used to find the best-fitting line through the data points, presuming a linear connection between the input features and the goal variable. The basic goal of linear regression is to identify the straight line that most accurately depicts the connection between the input and output variables [46].

4. **Apriori Association:** Association rules are employed to illustrate the connection between the data components. Creating association rules often involves two distinct steps: To locate all frequently occurring item sets in a database, minimum support is first applied. Second, rules are formed using the minimum confidence constraint and these frequent item sets. Apriori association rule is employed to extract recurring patterns from a database. Support and confidence are the standard metrics used to assess an association rule's quality. Encouragement of the association rule in the database is alike the percentage of transactions that contain XUY which is represented by X->Y. The ratio of the number of transactions containing XUY to the number of

transactions containing X determines the association rule's confidence level, which is X->Y[49].

5. **K-Means Clustering:** Finding groups of objects so that the items in one group are similar to one other and distinct from the objects in another group is known as clustering [8]. One of the most significant unsupervised learning strategies is clustering. A sort of unsupervised algorithm called the simple K-means algorithm moves items across the cluster set until the desired set is reached. As long as the number of clusters is known beforehand, this approach can be used to classify the data collection. The nature of this algorithm is iterative[40].

6. **Classification based AD Tree:** Data mining tasks like classification involve mapping the data into predefined groups and classes. Another name for it is supervised learning. A machine learning technique for classification that generalizes decision trees is called an alternating decision tree (ADTree). A decision tree with alternating branches has two nodes. A predicate condition is specified by decision nodes. A single number is present in prediction nodes. Prediction nodes are always both the roots and leaves of an ADTree. An ADTree classifies an instance by summing all traversed prediction nodes and by following all paths for which all decision nodes are true [45].

Conclusion:

These days, every industry is getting digital, and daily data usage from cellphones and social media is rising. It is difficult for any of us to arrange the information and make sense of it. Large volumes of heterogeneous data are handled by recommender systems, which also do crucial microanalysis, provide context for the data, and help customers and companies make decisions based on user-specific preferences. There are primarily four types of recommender systems that analyse data using various machine learning algorithms and provide recommendations to users and businesses. One of the many areas in which the recommender system is helpful is education. We shall demonstrate in the future how a recommender system aids in selecting a course for higher education.

References:

1. Aggarwal, C. C. (2016). Recommender systems. *Springer*.
2. Aguilar, J. a.-D. (2017). A general framework for intelligent recommender systems. *Applied computing and informatics*, 147-160.

3. Aguilar, J. S.-D.-G.-E. (2018). Learning analytics tasks as services in smart classrooms. *Universal Access in the Information Society*, 693-709.
4. Alhijawi, B. a. (2022). Survey on the objectives of recommender systems: measures, solutions, evaluation methodology, and new perspectives. *ACM Computing Surveys*, 1-38.
5. Ali, S. a. (2022). Enabling recommendation system architecture in virtualized environment for e-learning. *Egyptian Informatics Journal*, 33-45.
6. Amane, M. a. (2022). ERSDO: E-learning recommender system based on dynamic ontology. *Education and Information Technologies*, 7549-7561.
7. Beel, J. a. (2016). Paper recommender systems: a literature survey. *International Journal on Digital Libraries*, 305-338.
8. Bhalse, N. a. (2021). Algorithm for movie recommendation system using collaborative filtering. *Elsevier*.
9. Castells, P. a. (2021). Novelty and diversity in recommender systems. *Recommender systems handbook*, 603-646.
10. Chen, G. K.-L.-C. (2021). Cross-platform dynamic goods recommendation system based on reinforcement learning and social
11. Aggarwal, C. C. (2016). Recommender systems. *Springer*.
12. Chen, X. C. (2020). A hybrid recommendation system with many-objective evolutionary algorithm. *Expert Systems with Applications*, 113648.
13. Chung, S. K. (2020). Tree-Based Real-Time Advertisement Recommendation System in Online Broadcasting. *IEEE Access*.
14. Dhelim, S. a. (2023). A hybrid personality-aware recommendation system based on personality traits and types models. *Journal of Ambient Intelligence and Humanized Computing*, 12775-12788.
15. Fan, Q. a. (2021). Beetle antenna strategy based grey wolf optimization. *Expert Systems with Applications*, 113882.
16. Havas, S. a. (2022). A courses recommendation system based on graph clustering and ant colony optimization in MOOC environment. *2022 9th International and the 15th National Conference on E-Learning and E-Teaching (ICeLeT)*, 1-7.
17. Himeur, Y. a. (2022). Blockchain-based recommender systems: Applications, challenges and future opportunities. *Computer Science Review*, 100439.
18. Huang, Z. Q. (2019). Exploring multi-objective exercise recommendations in online education systems. *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, 1261-1270.
19. J. Ben Schafer, J. K. (1999). Recommender Systems in E-Commerce. *Proceedings of the 1st ACM conference on Electronic commerce*.
20. Jannach, D. Z. (2012). Recommender Systems in Computer Science and Information Systems – A Landscape of Research. *Lecture Notes in Business Information Processing, Springer, Berlin, Heidelberg*.

21. Jiang, L. a. (3023-3034). A trust-based collaborative filtering algorithm for E-commerce recommendation system. *Journal of ambient intelligence and humanized computing*, 2019.
22. Katarya, G. G. (2019). Recommendation Analysis on Item-based and User-Based Collaborative Filtering. *International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 1-4.
23. Ko, H. a. (2022). A survey of recommendation systems: recommendation models, techniques, and application fields. *Electronics*, 141.
24. Lee, S. a. (2022). Deep learning based recommender system using cross convolutional filters. *Information Sciences*, 112--122.
25. Lu, J. a. (2015). Recommender system application developments: a survey. *Decision support systems*, 12-32.
26. Mikhaylov, A. a. (2022). Integrated decision recommendation system using iteration-enhanced collaborative filtering, golden cut bipolar for analyzing the risk-based oil market spillovers. *Computational Economics*, 1-34.
27. Milano, S. a. (2020). Recommender systems and their ethical challenges. *AI & Society*, 957-967.
28. Mladenic, D. (1999). Text-learning and related intelligent agents: a survey. *IEEE Intelligent Systems and their Applications*, 44-54.
29. Mondal, S. a. (2020). Building a trust-based doctor recommendation system on top of multilayer graph database. *Journal of Biomedical Informatics*, 103549.
30. orsomme, R. a. (2019). Content-Based Course Recommender System for Liberal Arts Education. *International educational data mining society*.
31. Nabizadeh, A. H. (2020). Learning path personalization and recommendation methods: A survey of the state-of-the-art. *Expert Systems with Applications*, 113596.
32. Peška, L. T. (2019). Swarm intelligence techniques in recommender systems-A review of recent research. *(Swarm intelligence techniques in recommender systems-A review of recent research. Swarm and Evolutionary Computation*, 201-219.
33. Renjith, S. a. (2020). An extensive study on the evolution of context-aware personalized travel recommender systems. *Information Processing & Management*, 102078.
34. Romero, A. E. (2020). Helping university students to choose elective courses by using a hybrid multi-criteria recommendation system with genetic optimization. *Knowledge-Based Systems*, 105385.
35. Telikani, A. a. (2020). A survey of evolutionary computation for association rule mining. *Information Sciences*, 318-352.
36. Ullah, F. a. (2020). Image-Based Service Recommendation System: A JPEG-Coefficient RFs Approach. *IEEE Access*, 3308-3318.

37. Varga, E. a. (2019). Recommender systems. Practical data science with python 3: synthesizing actionable insights from data, 317-339.
38. Verachtert, R. a. (2022). Are we forgetting something? Correctly evaluate a recommender system with an optimal training window. Proceedings of the Perspectives on the Evaluation of Recommender Systems Workshop, 3228.
39. Vijayakumar, V. a. (2019). Effective knowledge based recommender system for tailored multiple point of interest recommendation. International Journal of Web Portals (IJWP), 1-18.
40. Walek, B. a. (2020). A hybrid recommender system for recommending relevant movies using an expert system. Expert Systems with Applications, 113452.
41. Wang, D. a. (2018). A Content-Based Recommender System for Computer Science Publications. Knowledge-Based Systems.
42. Wang, X. C. (2023). An integrated model for crude oil forecasting: Causality assessment and technical efficiency. Energy Economics, 106467.
43. Wu, P. a.-H. (2022). On the opportunity of causal learning in recommendation systems: Foundation, estimation, prediction and challenges. arXiv preprint arXiv:2201.06716.
44. Yan, L. a. (2020). An ensemble prediction model for potential student recommendation using machine learning. Symmetry, 728.
45. Yongquan, D. A. (2016) Automated web usage data mining and recommendation system using K-Nearest Neighbor (KNN) classification method. Applied Computing and Informatics, 90-108.
46. Yu, J. a. (2023). Self-supervised learning for recommender systems: A survey IEEE Transactions on Knowledge and Data Engineering
47. Zhang, F. a. (2016) Fast algorithms to evaluate collaborative filtering recommender systems Knowledge-Based Systems, 96-103
48. Zhang, S. a. (2020). Evaluating conversational recommender systems via user simulation Proceedings of the 26th acmsigkdd international conference on knowledge discovery \& data mining, 1512-1520
49. Zhu, J. a. (2022). Bars: Towards open benchmarking for recommender systems.Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval, 2912-2923