NATURALISTA CAMPANO
ISSN: 1827-7160
Volume 28 Issue 1, 2024

E-Learning Recommendation System and Classification Techniques - A Survey

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Abstract: eLearning has brought about significant transformations in the way students receive education where systems recommend essential elements. "E-learning task recommenders" refer to recommendations of learning activities to students based on their completed assignments. Collaboration and content-based filters are two examples of the many techniques and algorithms that may be used to create recommendation systems. The goal of this research project is to present a comprehensive overview of recommender systems, covering challenges and strategies used. For reliable results, this research proposes to combine content-based and collaborative filters. The review examines several approaches to recommendation system creation, with a primary focus on techniques for course recommendation systems. Online course recommendation systems aim to improve learning experiences by helping students locate courses that align with their interests, hone their skills, and expand their knowledge in a targeted and efficient manner. This study gives valuable information on online course recommenders that may tremendously aid in defining future advances for researchers, instructors, and practitioners working in the field of online education.

1. Introduction

People enjoy advantages of Internet growth, but face challenges in information overloads which makes it difficult to sort required information in massive volumes of accessible data [1]. Recommendation systems have drawn the attention of researchers because they provide effective solutions to issues of information overloads.

Growth of online information resources has been phenomenal in recent years. The usage of recommendation algorithms have proven to be helpful strategies for reducing information overloads [2]. Users often receive a plethora of things including e-learning resources where personalisation is an essential strategy for facilitating better user experiences [3]. E-learning websites, amongst many other online domains are dependent on technologies [4]. Over the years, eLearning has been established with the help of teaching principles. In an attempt to promote eLearning, a large number of institutions, universities, businesses, and organisations throughout the world offer students online courses, online degrees, and online certifications. This paper examines challenges associated with eLearning Recommendations which can provide learners with correct and relevant information where one of the challenges of e-learning is information overloads [5]. Students should be able to access common e-learning portal shown in Figure 1.

Recommendation systems are the most widely utilised and popular implementations of e-learning, e-movie, and e-music industries. Two techniques are usually applied in order for an e-learning recommendation system to produce recommendations that are useful: collaborative and content-based filtering [6]. Collaborative filtering is a recommendation strategy that examines users' similarities in browsing the internet and then generates recommendations based on commonalities [7]. Collaborative filters examine patterns in user behaviours and similarities to suggest items that people like, whereas content-based techniques use the objects or contents as the main focus and examine their characteristics to forecast the next helpful item.

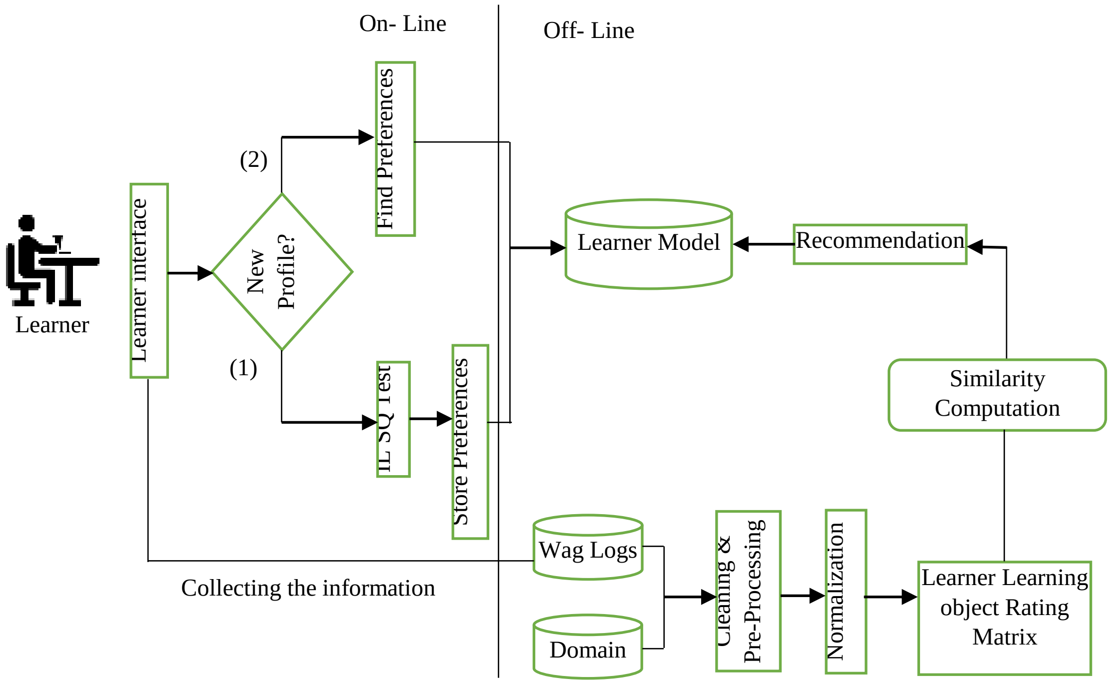

Figure 1. Architecture diagram for the E-Learning Recommendation System

Data sparsity, cold-start problems, and the inherent diversity of learners and courses are among the topics that were studied [8]. Additionally, ethical concerns about privacy, fairness, and transparency in course suggestions are explored, highlighting significances of recommendations. This survey presents potential strategies and approaches to deal with aforesaid issues [9] and examine context-aware and social recommendation approaches with active learning that can effectively deal with shortcomings of conventional algorithmic recommendations [10].

The study also addresses integration of auxiliary data sources including student profiles and social networks for better suggestions. In summary, reports highlight recent developments, outline future research areas for e-learning recommenders and summarize main findings. The statement underscores the necessity of more investigations and creativity to develop more personalised and efficient recommenders that cater to the requirements of virtual students.

2. Literature Review

Vedavathi and Anil Kumar [11] suggested a user preference-based efficient e-learning recommendation (EELR) based on hybrid optimisation algorithm (HOA) where improved whale optimisation (IWO) algorithm and deep recurrent neural network (DRNN) are used. The various types of e-learners are first ranked using DRNN according to these groups, and customers can get course suggestions from the group's suggestion. Following that, the configurations that the IWO computation regularly monitors are mined in order to evaluate the behaviour and preferences of the learners. Instead of having students efficiently search for material, recommender systems provide them recommendations for their requirements. Thus, assessments of frequently seen information serve as the foundation for e-learning strategies. The recommended system will be put into practice and tested in several e-learning entries against the preferences of the customer over an unclear amount of time. Its competency in terms of accuracy with traditional recommendation systems will be demonstrated. This approach can improve students' learning effectiveness by helping them comprehend guidelines and structures of educational processes. The results of the observations show that the recommended method improves the capacity to advise an asset to a single customer, which comes from a variety of sources.

Das and Al Akour [12] recommended customised, dynamic, and continuing guidelines for online education platforms. This study suggested information for online learners through three main stages: (a) data collections; (b) feature extractions; and (c) data classifications. Initially, local data collections were done using Ekhool learning programme. Next, feature extraction techniques such as Principle Component Analysis (PCA) and t-

Distributed Stochastic Neighbour Embedding (t-SNE) were employed to choose most relevant features. To increase membership limitations, Fuzzy Logic Classifiers that enhanced by the Rider Optimisation Algorithm (ROA) were included in this work. The performance study demonstrated that, when examining several performance measures, the recommended technique was superior.

Shahbazi and Byun [13] suggested using virtual and intelligent agents to make recommendations. These agents need accesses to users' preferences and personal information for providing relevant content and search results based on users' browsing histories. We employed methods for semantic analysis and Natural Language Processing (NLP) to suggest courses to tutors and e-learners. Moreover, machine learning (ML) performance analyses enhance user rating outcomes in e-learning environments. Clustering approaches are used by systems to automatically learn once and then assess these learned features. Their suggested system and simulation results exhibited reduced errors when compared to other suggested schemas. Offering the user a comfortable platform to select and suggest courses is one of the approach's successes. Similarly, promoting same products and initiatives were avoided by examining user preferences and improve recommendation engine's performances while presenting users with highly relevant contents based on their profiles. The proposed method exhibited better prediction accuracies when compared to hybrid filtering, self-organization systems, and ensemble models. Balasamy and Athiyappagounder [14] proposed to assist students by suggesting relevant learning contents using recommendations built from data mining and deep learning (DL) methods. Their content matrices improved recommendations when logistic regression and DL techniques classified suggestions. Their experiments show that when compared to Chi Squared, SA, PSO, and ICA techniques, deep neural network (DNN) recommendations performed better in terms of accuracy, recall, and f measure values than logistic regression based recommendations.

Hafsa et al [15] gave an evolutionary method to resolve the Mandarine Academy Recommendation System (MACRE) issue that is based on the Pareto ranking concept. First, we formulated the goals as an optimisation problem, including similarity, diversity, novelty, RMSE, and nDCG@5. Subsequently, the performances of many algorithms (NSGA II, NSGAIII, IBEA, SPEA2, and MOEAD) were tested under various scenarios. The work offered improvements to user experiences and interfaces after detailed statistical study of real-world user interactions while highlighting shortcomings of key graphical challenges that prevented them learning effectively. The study initially identified many themes and subsequently in production modes yielded encouraging outcomes. The study recommended usage of bespoke mutation operators which performed better than typical swap mutations. On training the model, outcomes were provided for end users using multi-criteria decisions employing pseudo weights.

El Youbi El Idrissi et al [16] proposed use of auto encoders for feature extractions, data reconstructions, and dimensionality reduction in collaborative filtering based e-learning recommendations to learn and anticipate student preferences. Based on the obtained values of root-mean-square error (RMSE) and mean absolute error (MAE), their model performed better in their experimental results than other models based on K-nearest neighbour (KNN), singular value decomposition (SVD), singular value decomposition plus plus (SVD++), and non-negative matrix factorization (NMF).

Li et al [17] proposed content-based hybrid algorithm with improved collaborative filters. Their user feature rating matrices took the role of conventional user item rating matrices by merging user rating with items' features. User sets were processed using K-means clustering (KMC) for suggestions. Traditional collaborative filtering algorithmic issue of data sparsity could be resolved by this enhanced method. By comparing projects' attributes with users' profiles in score matrices, the study could also anticipate interests in new projects and thus overcoming "cold start" issues using created push lists for new projects. The results of their experiments indicated that their modified algorithm offered higher calibre of suggestions and addressed bottlenecks related to data sparsity, cold starts, and online recommender speeds.

Joshi and Gupta [18] used a model built using genetic algorithm (GA) and KMC methods. This study used KMC to monitor user activities and GA as a search engine to locate needed resources in the database. They study also evaluated their schema for for efficacy. Their projected results demonstrated that their proposed technique hastened computations and increased recommendation accuracy. Their findings demonstrated that their method was appropriate for use in application development for next generations.

Antony Rosewelt and ArokiaRenjit [19] suggested novel content recommendations that made use of enhanced Bidirectional Encoder Representations from Transformers (BERT) technique known as the Robustly optimized BERT Pretrained Approach (RoBERTa) and a recently proposed semantic fuzzy optimality aware hummingbirds optimization technique to determine more appropriate contents for e-learners based on their interests and learning capacities. In this work, each study material's semantic similarity score is calculated. The more significant and pertinent terms located pertinent study resources subsequently determined by hummingbirds' optimisation procedures, which consider fuzzy optimality results as inputs. Lastly, RoBERTa was employed to classify most relevant, unnecessary, and helpful documents from the local repository, online database, and accessible datasets. Experimental of their recommended methodologies showed that their schema outperformed current systems in terms of precision, recall, f1-measure, and prediction accuracy values.

Houshmand-Nanehkaran et al [20] used continuous genetic algorithm (CGA) in fuzzy-genetic collaborative filtering (FGCF) approach to optimise fuzzy similarities for item recommendations. This method first converts the user's crisp evaluations into fuzzy ratings before computing the fuzzy similarities. The evolutionary algorithm receives similarity values, fine-tunes them, and applies them to fuzzy prediction. This implies dual instances of this fuzzy system are in operation. Their experimental results on Movielens 100 K, Movielens 1 M, and RecSys datasets demonstrated quality improvements and accuracy of suggestions by FGCF in collaborative filtering, while also reducing time and space complexities. FGCF solved issue of users with several rating scales and prevented data sparsity by careful selections of neighbours. However, it could not overcome cold-start issues.

Vellaichamy and Kalimuthu [21] suggested hybrid Collaborative Movie Recommender system that reduced scalability issues and enhanced clustering. When Fuzzy C Means clustering (FCM) and Bat optimisations were integrated, their recommendation quality improved. FCM divided consumers into many groups by clustering while the Bat Algorithm determined starting positions of clusters. Lastly, films were recommended for targeted users.. The proposed method was evaluated using the Movie Lens dataset where results showed that their recommended algorithm provided suggestions with greater MAE, accuracy, and recall values when compared to other approaches.

Dien et al [22] offered deep matrix decompositions as extensions of regular matrix decompositions and suggest learning materials according to the needs and skills of students. We assessed the suggested model on two experimental datasets: one containing five datasets of user-generated learning materials to provide intelligent suggestions for aiding learners, and the other containing a dataset of learning outcomes for university students to recommend courses. The study results are promising when compared to a few baselines. It is expected that large datasets would fit well with this study.

Fraihat, and Shambour [23] suggested semantic recommender e-learning framework for assisting students to locate and select learning objectives (LO) that are relevant to their areas of interests. The suggested method made use of intra/ extra-semantic connections between student requirements and LO to provide learners with customised recommendations. By using concepts, reasoning strategies, and semantic relationships found in domain ontology's, semantic recommendation systems broaden the scopes of query words. The recommended strategy improves learning outcomes by reducing the amount of time and effort required to select relevant learning objectives.

Le [24] improved generalisation to provide a meta-learning framework for collaborative filters used in recommendation systems. The proposed framework, MetaRec, incorporated and unified major popular models in recommendation systems and expanded their capabilities further to perform well with minimal data and customisable setups. The MetaRec framework architecture was evaluated empirically on many recommendation benchmark datasets using variety of evaluation criteria where notable gains in prediction performances when tackling collaborative filtering problem using meta-learning were discovered.

Chaudhary and Gupta [25] Pre-processing and prediction are the two distinct phases of the suggested ML technique. The initial part of the procedure entails looking through multiple e-learning platforms URL tailored for computer science courses. Following the completion of the pre-processing of the information, a specific topic is chosen by reading the text of the examined URLs and using their keywords. Predicting query-specific connections on e-learning systems is the next step. The study's suggested Intelligent E-learning through Web (IEW) primarily included content mining, lexical analyses, categorizations, and ML based predictions.

Table 1: Comparison Table for E-Learning Recommendation System with Existing Methods

Author	Methods	Merits	Demerits
Vedavathi and Anil Kumar [2021]	Hybrid Optimization Algorithm (HOA)	It improves learning efficiency for pupils in a more precise and proficient manner than the conventional recommender structure.	A specific type of data separation architecture called the Customised Suggestion Model is utilised to identify numerous articles that are relevant to e-learners.
Das and Al Akour [2020]	Membership optimized Fuzzy Logic classifier	By optimising, it raises the membership limitations.	It is a real, non-trivial issue..
Shahbazi and Byun [2022]	ML and Knowledge Discovery Methods	To deliver material that is extremely relevant to the user profile circumstance.	The correct material and accurate information based on search results, quality, and these resources..
Balasamy and Athiyappagounder [2022]	Deep Neural Network	It is being utilised more and more in e-learning platforms and information systems.	The extraction of data mining rules and their classification has been driven by the necessity to obtain this sort of knowledge.
Hafsa et al [2022]	Evolutionary Algorithm	Priorities must be chosen in a user-friendly interface; graphical interfaces increase readability, usability, and interaction availability.	Need to improve the scalability.
El Youbi El Idrissi et al [2023]	Autoencoders	It improves data dimension reduction, filtering, feature extraction, and data reconstruction.	To increase the quality of the recommendations, hybrid filtering was integrated with additional deep-learning techniques including self-organizing maps (SOMs) and generative adversarial networks (GANs).
Li et al [2021]	Hybrid Algorithm	Better recommendation quality may be ensured by addressing the issues causing data sparsity, cold start, and online recommendation to become performance bottlenecks.	Rules' quality is challenging and cannot be updated on the fly. The system will get harder and harder to administer as the number of regulations rises.
Joshi and Gupta [2020]	GA And KMC Algorithm	Lowering the effort required to explore the data, identify patterns, and assist in making decisions, creating forecasts, and learning about certain topics.	It aimed to understand end users' requirements and create a precise and useful e-learning recommendation system.
Antony Rosewelt and ArokiaRenjit [2020]	Semantic Fuzzy Humming Birds Optimization and RoBERTa	The fuzzy optimality and semantic similarity score improve the feature optimisation procedure.	The DL method and the new lightweight feature optimizer need to be improved.
Houshmand-Nanehkaran et al [2022]	Continuous Genetic Algorithm (CGA)	In less time, to deliver a list of the top products for recommendation.	The problem of users' different rating scales must be addressed, however the cold start cannot be fixed.
Vellaichamy and	Hybrid	In addition to having	Traditional CF algorithms have

Kalimuthu [2017]	Collaborative Movie Recommender System	forecast accuracy, the algorithm can offer trustworthy and customised movie recommendations.	two key issues: data sparsity and scalability.
Dien et al [2022]	Deep Matrix Factorization	It decreased in dimensions and expanded the conventional matrix factorization for learning resource suggestions.	Chilly condition The recommender system is the centre of the problem, and the meta data tackle problem is brought up.
Fraihat, and Shambour [2015]	Semantic Recommender System	It gives learners personalised suggestions by using the intra- and extra-semantic links between LO and their requirements.	Its main objective will be to verify the efficacy and calibre of suggestions.
Le [2020]	Meta-Learning Framework	It expands on the easily configured and effectively run on little data.	Improvements are required for fixed learning rates, derivative costs, and training instability.
Chaudhary and Gupta [2019]	ML Approach	It provides the best forecast accuracy.	Scalability and sparsity concerns must be resolved.

Recommendation System
In an increasingly digitised age, people have access to a wealth of information and alternatives, which may make decision-making challenging. Personalised recommendation systems have developed as effective ways to handle this challenge in the suggestion stages by helping users navigate through enormous amounts of material and make well-informed judgements.

A recommendation system, also known as a recommender system, is a software algorithm or process that anticipates and makes suggestions about things of interest to users based on their preferences, behaviour, and contextual data [26]. One of the several businesses that heavily utilises these technologies is online education. A few more are e-commerce, social networking, music streaming services, and other things. By assisting consumers in locating intriguing and pertinent items, recommendation engines seek to improve user experience.
Recommendation systems employ complex algorithms and user data to provide personalised suggestions based on the user's needs, interests, and preferences (Figure 2). They have not only transformed online shopping but also simplified the process of consuming personalised content, leading to higher levels of customer satisfaction and engagement. Recommendation systems help students choose courses that fit their interests, skill levels, and learning goals by guiding them through the vast array of educational possibilities that are accessible to them in the context of online learning. It is expected that recommendation systems will become increasingly sophisticated as technology advances. Accuracy, adaptability, and precision of these systems will rise as machine learning, artificial intelligence, and natural language processing advance.

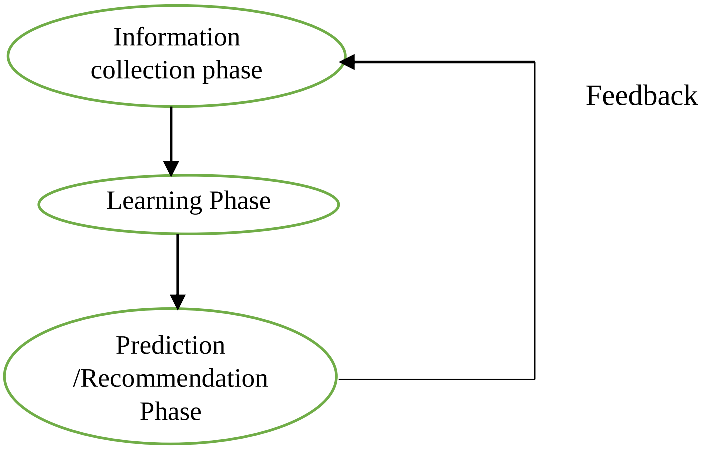

Figure 2. Recommendation Phases

Types of Recommendation Systems

Recommendation systems may be divided into three primary categories: collaborative filtering, content-based filtering, and hybrid approaches. The diagrammatic form of the recommendation system's classification is displayed in Figure 3.

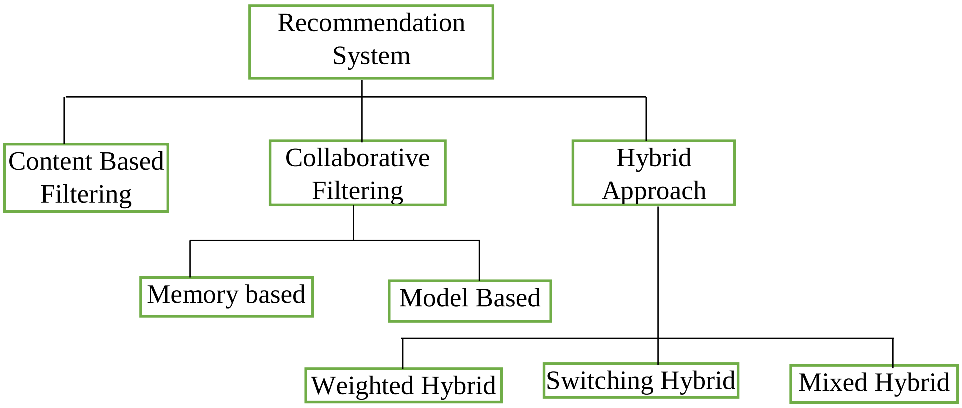

Figure 3.Classification of Recommendation Techniques

Content- Based Filtering

Content-based (CB) recommenders suggest products based on comparative products that customers have previously enjoyed. The following are the main ideas of CB RSs: 1. the suggested things are found by using the item specs. To identify these characteristics, the item description that a particular user prefers should be examined and shown in Figure 4.

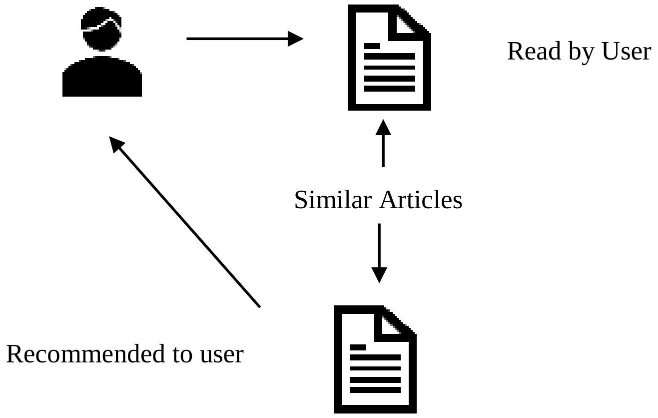

Figure 4. Content Based Filtering

2. The user profile and each item's specs are compared. Products that bear a strong resemblance to the user's profile will eventually be suggested. CB generates suggestions using two methods. The first method, which produces suggestions, makes use of information retrieval techniques like Cosine similarity metrics. The second method generates suggestions using ML techniques.

Collaborative Filtering

Random Signs (RS) and Collaborative Filtering (CF) aim to help users make decisions by providing recommendations from other users who have similar interests. Item-based and user-based techniques are the two categories of CF approaches. In the former, products that are loved by users who are similar to the person making the recommendation will be made. Users will receive item-based recommendations in Figure 5, which is based on the products that piqued their interest.

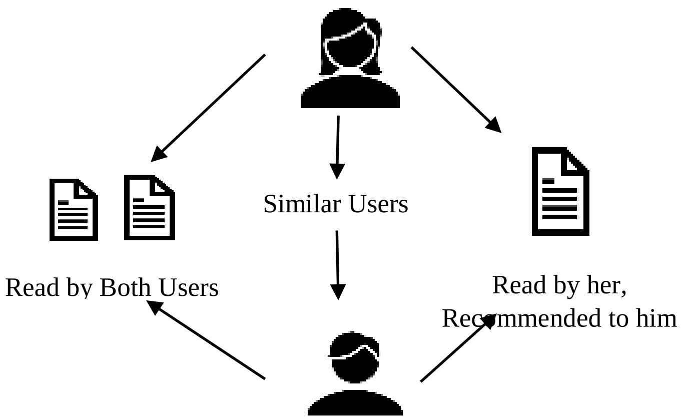

Figure 5. Collaborative Filtering

The similarity of people or things may be determined using three different methods: Pearson correlation-based, Cosine-based, and Adjusted Cosine-based. The similarity of suggested things is calculated with the participation of users who assessed both items, improving the accuracy of the result. The combination of the Jaccard metric with the Adjusted Cosine resulted in improved item based CF that enhanced similarity computational accuracies.

Hybrid Filtering

In order to overcome the shortcomings of conventional RS approaches and attain greater efficiency, the hybrid RS methodology, as shown in Figure 6, combines two or more recommendation techniques.

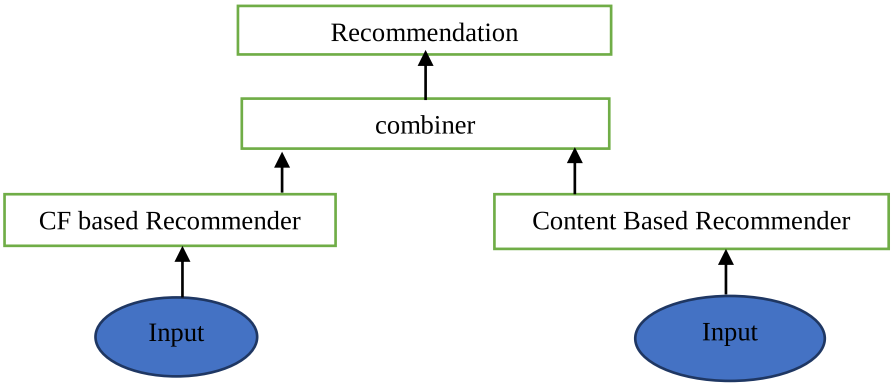

Figure 6. Hybrid Filtering

To construct hybrid techniques, seven basic combination procedures are used: Argumentation, Meta-level, Mixed, Weighted, Switching, Feature Combination, and Cascade. The most popular hybrid RSs make an effort to address scalability and cold start problems.

Table 2: Advantages and Disadvantages Comparison Table with different filtering approaches

	Collaborative Filtering	**Content Based Filtering**	**Hybrid recommendation**
Advantages	1) CF methods just use ratings rather than item and user profiles. 2) CF methods rely on the experiences of others. 3) CF techniques produce suggestions that are specific to each user since they consider the experiences of others.	CBF will assess every item and user profile independently before to providing a suggestion. 2) CBF will offer suggestions in accordance with the item's characteristics.	1) To overcome these limitations, hybrid recommendation blends content-based and collaborative filtering algorithms.
Disadvantages	A cold start issue arises	1) If there is insufficient	It is difficult since it combines

	when a new user enters in and finds that their history is empty. 2) The CF approach requires a large volume of data in order to produce precise suggestions. 3) CF techniques grow slower while handling large volumes of data.	information in the item and user profiles, the CBF suggestion will be inaccurate. 2) CBF suffers from synonymity, which occurs when two distinct terms with different spellings are treated as separate words.	two different approaches to work as a single system.

3. Conclusion

The study's conclusion is that the recommendation systems for e-learning have shed light on the many approaches and techniques used in the e-learning industry to provide customised suggestions.

After a large number of research articles and studies were analysed, some noteworthy results and trends emerged. To begin with, e-learning recommendation systems have mostly relied on content-based filters to find relevant suggestions based on user profiles and item attributes. By analysing user preferences, keywords, and course content, suggestions may be tailored to each individual's needs and preferences.

Second, collaborative filtering has proven to be effective in gathering user preferences by leveraging the collective knowledge of users who share similarities with one another. Collaborative filtering algorithms identify people with similar course likes and behaviours, which promotes serendipitous discovery and enhances user experience. The algorithms produce recommendations based on these encounters.

Hybrid recommendation systems, which incorporate a number of techniques including content-based and collaborative filtering, have also attracted attention. By combining the best features of each method, these hybrid methods aim to address the limitations of individual approaches and generate more accurate and diversified suggestions. By merging several recommendation algorithms, hybrid systems can address problems like data sparsity and the cold-start issue and perhaps increase suggestion quality.

The poll has also shown how important it is that contextual factors be taken into account by e-learning recommendation systems. Learning goals, course information, and user demographics may all be included to recommendations to increase their relevance and personalisation. Context-aware recommendation systems provide recommendations that are adaptable and tailored to each user's circumstances.

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