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A Survey of recommendation systems for online courses

Sakshi Amrutkar[a], Tanaya Peshave[b], Vikram Ramwani[c]

[a]**Department of Electronics and Telecommunication, Pune Institute of Computer Technology, Pune, India**
[b]**Department of Electronics and Telecommunication, Pune Institute of Computer Technology, Pune, India**
[c]**Department of Electronics and Telecommunication, Pune Institute of Computer Technology, Pune, India**

A B S T R A C T

There is a constant growth in online learning platforms across the internet. It becomes extremely difficult for one to choose a specific online course or learning material from such a huge data pool. Hence, Recommendation system plays a vital role in e-learning platforms. A well-built recommendation system provides personalized online learning resources to users. Numerous approaches and algorithms are out there for recommendation system like Content-based filtering technique and Collaborative-filtering technique. This survey aims to present a comprehensive overview of Recommendation Systems along with their challenges and algorithms used. A hybrid approach refers to combination of Content-based and Collaborative-filtering. By combining these two techniques accurate results can be observed in the system. The survey studies number of approaches used to build a recommendation system but mainly focuses on the approaches used to build a course recommendation system. A recommendation system for online courses is a software algorithm or mechanism designed to suggest relevant and personalized course options to learners based on their preferences, needs, and previous learning behavior. The primary goal of a recommendation system for online courses is to enhance the learning experience by helping learners discover courses that align with their interests, improve their skills, and expand their knowledge in a targeted and efficient manner. By analyzing and understanding user preferences, the system aims to alleviate the overwhelming abundance of available courses and provide tailored recommendations that are more likely to meet the learner's needs. This survey serves as a valuable resource for researchers, educators, and practitioners in the online education domain, providing insights into the current state-of-the-art in recommendation systems for online courses and guiding future developments in this important area.

Keywords: Content-based filtering, Collaborative filtering, Hybrid recommendation system, Machine learning, Deep learning, Survey.

1. Introduction

Ecommerce, Social media platforms, retail sites all of these businesses boost their economy by targeting users with advertisement and personalized cookies. This user centric mechanism used solely relies on recommendation/ recommender system. Recommendation system is an application of machine learning which predicts the users' preferences/ likes and dislikes. This is achieved by gathering huge amount of data related to user activities and classify those activities into negative and positive experiences. Social media sites and streaming platforms like YouTube, Instagram, Netflix increase their audience by suggesting content the user prefers. But not only social media, recommendation systems also play a significant role in e-learning/ online courses platforms. Today, the main issue learners face is that they are not provided tailored access to information. To overcome this issue recommendation systems are used to provides well curated choices to learners from substantial data. The main advantage of recommendation system for online courses is that it reduces the time and efforts of students/learners in finding the courses they'll benefit from.

The rapid growth of online education has led to an increasing demand for effective recommendation systems that can assist learners in selecting suitable online courses. Various recommendation systems have been developed to assist learners in selecting courses based on their interests and past behaviors. This survey paper focuses on hybrid course recommendation systems, which combine different recommendation approaches to provide more accurate and diverse recommendations.

This survey aims to provide a comprehensive overview of recommendation systems for online courses, highlighting their methodologies, challenges, and potential solutions. The survey begins by presenting an introduction to the importance of recommendation systems in the context of online education. It outlines the benefits of personalized course recommendations, such as enhancing learner engagement, improving learning outcomes, and facilitating efficient course discovery. Next, the survey explores various recommendation techniques employed in online course platforms. Content-based filtering, collaborative filtering, and hybrid approaches are discussed, along with their strengths and limitations. Additionally, recent advancements in deep learning-based recommendation models are examined, emphasizing their potential to capture complex user preferences and provide accurate recommendations. The survey then delves into the challenges faced by recommendation systems in the online course domain. Issues such as cold-start problems, data sparsity, and the inherent diversity of courses and learners are analyzed. Moreover, ethical considerations related to privacy, fairness, and transparency in course recommendations are addressed, recognizing the need for responsible recommendation practices.

To overcome these challenges, the survey presents potential solutions and strategies. Techniques such as context-aware recommendation, social recommendation, and active learning are discussed, showcasing their effectiveness in addressing the limitations of traditional recommendation approaches. Additionally, the survey explores the integration of auxiliary data sources, such as social networks and learner profiles, to enhance recommendation accuracy.

Lastly, the survey concludes by summarizing the key findings, highlighting emerging trends, and identifying future research directions in the field of recommendation systems for online courses. It emphasizes the need for continued exploration and innovation to create more personalized and effective recommendation systems that cater to the diverse needs of online learners.

This survey serves as a valuable resource for researchers, educators, and practitioners in the online education domain, providing insights into the current state-of-the-art in recommendation systems for online courses and guiding future developments in this important area.

1.1. Recommendation System

In our increasingly digital world, the overwhelming amount of information and choices available to individuals can make decision-making a daunting task. Recommendation systems have emerged as powerful tools to address this challenge by providing personalized suggestions that help users navigate through vast amounts of content and make informed choices.

A recommendation system, also known as a recommender system, is a software algorithm or mechanism designed to predict and suggest items of interest to users based on their preferences, behavior, and contextual information. These systems are widely employed in various domains, including e-commerce, social media, music streaming platforms, and, of course, online courses. The primary objective of recommendation systems is to improve user experience by assisting individuals in discovering relevant and appealing items they may not have encountered otherwise. By leveraging user data and employing sophisticated algorithms, recommendation systems strive to deliver personalized recommendations that align with users' interests, needs, and preferences. Recommendation systems have revolutionized the way we discover and consume content. They have not only transformed the online shopping experience but also facilitated personalized content consumption, fostering user engagement and satisfaction. In the context of online courses, recommendation systems help learners navigate through a vast array of educational offerings, enabling them to find courses that align with their interests, learning goals, and skill levels. As technology continues to evolve, recommendation systems are expected to become even more sophisticated. Advancements in machine learning, artificial intelligence, and natural language processing will further enhance the accuracy, personalization, and adaptability of these systems. The future holds great potential for recommendation systems to continue shaping our digital experiences by delivering tailored and relevant suggestions, making our decision-making processes more efficient and enjoyable.

1.2. Types of recommendation systems

Recommendation systems are broadly classified into three different types – Content based filtering, Collaborative filtering and Hybrid method. The diagrammatic representation of classification of recommendation system is given in the Fig. 1.

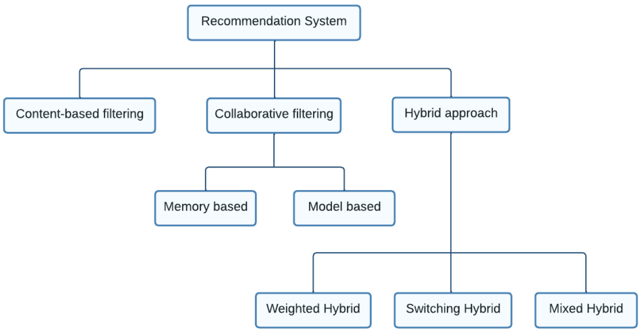

Fig. 1 – Classification of Recommendation System

1.2.1. Content based filtering technique

Content-based filtering is a recommendation technique employed by recommendation systems to suggest items to users based on the characteristics and attributes of those items. In the context of online courses, content-based filtering focuses on the features of the courses themselves to generate personalized course recommendations. The underlying principle of content-based filtering is to analyze the content, metadata, or other descriptive information associated with each item (in this case, courses) and match them to the user's preferences. The system learns about the user's interests by examining their previous interactions, such as courses they have enrolled in, completed, or rated. Based on this information, the system identifies courses with similar content or attributes to those the user has shown interest in and recommends them. Content-based filtering offers several advantages. It can provide recommendations even in scenarios with limited or sparse user data since it primarily relies on the features of the items themselves. It can also address the "cold-start" problem by suggesting courses to new users based on their stated preferences or characteristics. Furthermore, content-based filtering can offer diversity in recommendations by suggesting courses that may not be popular among other users but are highly relevant to the individual's interests. However, content-based filtering also has limitations. It tends to recommend similar items, potentially leading to a lack of novelty or exposure to new courses outside the user's established preferences. Additionally, it may not capture the evolving interests or changing preferences of users over time, as it primarily relies on historical data. Fig 2 describes the process of content-based filtering approach.

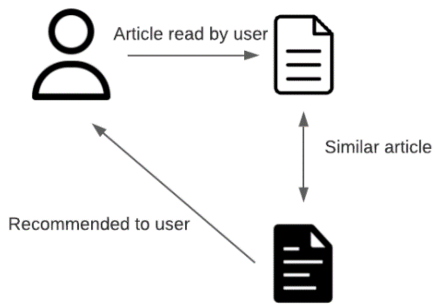

Fig. 2 – Content based filtering

1.2.2. Collaborative filtering technique

Collaborative filtering is a popular recommendation technique used by recommendation systems to suggest items to users based on the preferences and behaviors of similar users. It relies on the idea that users with similar tastes and preferences in the past are likely to have similar preferences in the future. In the context of online courses, collaborative filtering analyzes the historical interactions and feedback of users to identify patterns and make recommendations. The system identifies users who have shown similar interests or preferences in courses and leverages their data to suggest relevant courses to a target user. Collaborative filtering has several advantages. It can provide serendipitous recommendations by suggesting items that users may not have discovered on their own. It is capable of capturing evolving user preferences and adapting to changes over time. Additionally, collaborative filtering can handle the "cold-start" problem, where new users or items have limited or no historical data, by relying on the preferences of similar users or items. Collaborative filtering also has its limitations. It requires a significant amount of user data to identify reliable patterns and similarities, which can be challenging in scenarios with sparse data. It can also lead to the "popularity bias" issue, where popular items are recommended more frequently, potentially overlooking niche or personalized recommendations. Furthermore, collaborative filtering struggles when dealing with new or rare items that have limited user interactions. Collaborative filtering has been widely adopted in recommendation systems, powering personalized suggestions in various domains, including online courses. By analyzing user behavior and leveraging the wisdom of the crowd, collaborative filtering helps learners discover relevant and appealing courses based on the preferences of users with similar interests and learning trajectories. Fig 3 represents the working of collaborative filtering technique.

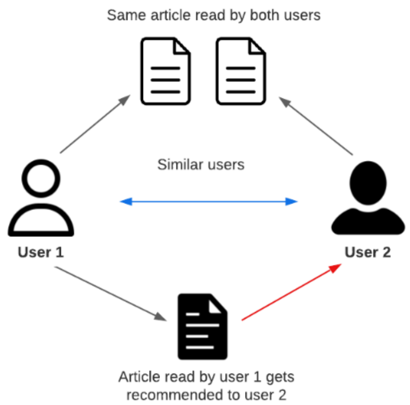

Fig. 3 – Collaborative filtering

Further classification of collaborative filtering is the memory based and model based collaborative filtering.

- Memory based – Memory based collaborative filtering heavily relies on the user interaction data such as the likes, dislikes, comments, ratings etc. It focuses on finding similar items for recommendation using simple distance/similarity measures like Cosine similarity, Pearson correlation, Euclidean distance etc.
- Model based – Model based collaborative filtering technique on the other hand tries to “guess” the user reaction (likes or ratings) to a product. This helps predicting if the user will like an item or not using the minimal user-item interaction data. This approach utilizes several machine learning or deep learning algorithms to create a user-item matrix for calculating missing values (user reactions).

1.2.3. Hybrid technique

A hybrid recommendation system is an approach that combines multiple recommendation techniques or models to overcome the limitations of individual methods and provide more accurate and diverse recommendations. It mainly combines the Content based filtering and Collaborative filtering technique to provide accurate results. Hybrid recommendation systems offer several benefits, including improved accuracy, increased recommendation diversity, and enhanced coverage of user preferences. By combining multiple techniques, these systems can mitigate the limitations of individual approaches, leverage different data sources, and provide more effective and personalized recommendations to users. The selection and design of a hybrid recommendation system depend on various factors, such as the available data, the specific domain or application, and the target user characteristics. Experimentation and evaluation of different hybrid approaches are essential to identify the most suitable techniques and optimize the recommendation performance for the given context. Hybrid recommendation system is divided into three categories –

- Weighted hybrid - The weighted hybrid approach assigns different weights to recommendations generated by different techniques. Each recommendation technique contributes to the final recommendation based on its effectiveness and performance for a particular user or item. The weights can be determined using machine learning techniques or user feedback. This approach allows the system to dynamically adjust the influence of each technique based on its reliability and relevance.
- Switching hybrid - In the switching hybrid approach, the system selects and switches between different recommendation techniques based on certain conditions or user contexts. For example, it may use content-based filtering for users with limited interaction data and switch to collaborative filtering once sufficient data is available. This approach adapts the recommendation strategy based on the specific characteristics of users or items, optimizing the recommendations accordingly.
- Mixed hybrid – For a large number of recommendation mixed hybrid technique is preferred. A mixed hybrid recommender is a type of hybrid recommendation system that combines multiple recommendation techniques or models at different stages of the recommendation process. Unlike other hybrid approaches that integrate techniques or models into a single unified framework, a mixed hybrid recommender involves using different techniques separately and then merging their recommendations at the end.

1.3. Course recommendation systems

A course recommendation system uses the metadata of courses along with the user attributes. Among pool of online course platforms a recommendation system makes it easier for the user to choose the course well suited for them. There are several approaches proposed for building a recommendation system for online courses. A web-based recommendation for online courses plays and important role as it creates a user profile using the user interaction data with the courses and recommend courses using rule-based filtering method [1]. Collaborative filtering is vital in building the recommendation system. Most of the implementation heavily relies on the collaborative filtering technique [2].

Recommendations become more accurate for the users when entire user journey is recorded. By recording the users' cognitive level and creating a knowledge structure, recommendations matching the user cognitive level can be made. This method helps in providing course recommendation to the user based on their intellectual level.

When it comes to similar courses based on the skill set, content-based filtering technique is preferred. By identifying the knowledge gad courses can be recommended to the users based on content-based filtering technique [3].

2. Literature review

2.1. Research based on content-based filtering technique

Content based recommendations are made by taking features of the items with which user has interacted in the past as demonstrated in Fig 1.

Pazzani provides an overview of content-based filtering techniques and discusses their application in building recommender systems. It covers topics such as feature selection, user profiles, and evaluation methods for content-based recommendation systems [5]. Bansal presents a content-based recommendation approach that combines content-based filtering with collaborative filtering. It introduces a method to learn the optimal combination of both approaches using matrix factorization and demonstrates its effectiveness through experiments. But it has more focus on content-based filtering approach [6]. Li-Tung Weng focuses on using item taxonomies (hierarchical categorization) in content-based recommendation systems. It investigates how incorporating the hierarchical structure of item taxonomies can enhance the recommendation accuracy and diversity, and presents experimental results to support the findings [7]. Saman suggested a web-based recommendation system that uses OWL (web ontology language) rules and ontologies. The technique for making recommendations was rule filtering. Semantic Based System and Rule Based System are the two subsystems that make up their suggested recommendation system design. Observer, Learner profile, Recommendation storage, and User interface are the modules for each subsystem [8]. Marco de Gemmis proposes an ontology-based item categorization approach for content-based recommendation systems. It leverages domain-specific ontologies to enhance the representation and matching of item features, leading to more accurate and meaningful recommendations [9]. Bagher suggested a content-based movie recommendation system that forecasts the most popular films based on temporal user preferences captured in user modelling. The propsed approach offers a user-centered framework that applies a Dirichlet Process Mixture Model to the content attributes of rated films (for each user) in order to infer user preferences and generate an appropriate suggestion list [10].

2.2. Research based on collaborative filtering technique

Utilising the preferences and behaviours of related users or objects as suggested in Fig 2, collaborative filtering is a technique used in recommendation systems to deliver personalised recommendations. It is predicated on the idea that users who have shared tastes or preferences in the past are probably to continue to do so.

Rubén analyzes user interactions, such as reading history, preferences, ratings, and reviews, so that the system can understand user interests and make tailored recommendations for books or related content [11]. The application of a recommendation system based on user interaction data to intelligent electronic books aims to enhance the reading experience, introduce users to new books, and help them discover relevant content tailored to their interests. Raghad offers a collaborative recommender system that suggests online courses for students based on how similar their course histories are. The suggested solution makes use of data mining techniques to identify trends between courses. They made clusters of students based on the course selection by students which results in high accuracy results. They used combination of association rules and clustering algorithms [12]. Rahul developed a novel method that, using a naive Bayes classifier, first chooses pertinent contextual variables based on the reviewers' ratings and contextual information for a class of items. Singular Value Decomposition (SVD) is then used to extract the most significant features related to each entity after the pertinent contextual variables have been extracted. The recommendation system uses this data to analyse the user's contextual information and recommend to him entities that pique his interest [13]. J. Bobadilla suggested that while calculating the recommendations, individuals with more information should be given more weight than users with less expertise (for instance, those who performed better on various exams). To do this, they developed some new equations at the heart of memory-based collaborative filtering, which expand the existing equations to gather and process data pertaining to each user's scores in a variable number of level assessments [14].

2.3. Research based on deep learning techniques used in e-learning recommendation system

When it comes to build recommendation system for a large dataset, deep learning technique outperforms the machine learning algorithms. Deep learning techniques are also preferred while building a real time recommendation system. When a new user is introduced to the system it faces a “cold start issue” which can be tackled by deep learning algorithms.

Jian Wei proposed a system to tackle the cold start problem faced in building recommender system. It uses the combination of tightly coupled collaborative filtering system with deep learning techniques. It focuses on both complete cold start and incomplete cold start problem [15]. Faizan Ahemad addressed the soft item cold start issue by building a graph-based recommender system. They used weighted averaging algorithm to simplify training of large dataset and bigger graphs [16]. Another graph based approach was proposed by Thomas Kipf which is graph convolution matrix completion. It works on autoencoders, which means it build upon the data which is already present. This helps in building profile for a new user which has no prior data for reference [17]. Xiangnan He used the neural networks to improve the collaborative filtering approach. They mainly focused on replacing the process of finding inner product in matrix factorization by neural networks. This improves the predictability of user ratings for the unrated items [18].

2.4. Research based on hybrid approach

Robin Burke provides a comprehensive survey of hybrid recommender systems, discussing different hybridization techniques and evaluating their performance. It explores combinations of collaborative filtering, content-based filtering, and other methods to create hybrid systems [19]. Xinxi Wang proposes a hybrid recommendation system for music, combining collaborative filtering and deep learning. It integrates user-item collaborative filtering with a deep neural network to capture complex user preferences and improve recommendation accuracy [20]. S. S. Devi proposes a hybrid recommendation system for movie recommendations, combining collaborative filtering, content-based filtering, and demographic information. It leverages user ratings, movie attributes, and user demographics to provide personalized movie recommendations [21].

3. Conclusion

In conclusion, the survey on recommendation systems for online courses has shed light on the diverse approaches and techniques used to provide personalized recommendations in the e-learning domain. Through the examination of various research papers and studies, several key findings and trends have emerged.

Firstly, content-based filtering has been widely utilized in online course recommendation systems, leveraging item attributes and user profiles to generate relevant recommendations. The analysis of course content, keywords, and user preferences helps tailor recommendations based on individual needs and interests.

Secondly, collaborative filtering has proven to be effective in capturing user preferences by leveraging the collective wisdom of similar users. By identifying users with similar course preferences and behaviors, collaborative filtering algorithms generate recommendations based on their interactions, fostering serendipitous discovery and enhancing the user experience.

Moreover, hybrid recommendation systems, combining multiple techniques such as content-based and collaborative filtering, have gained attention. These hybrid approaches aim to leverage the strengths of different methods to overcome their limitations and provide more accurate and diverse recommendations. By integrating various recommendation techniques, hybrid systems can enhance the recommendation quality and address challenges like the cold-start problem and data sparsity. The survey has also highlighted the importance of considering contextual factors in recommendation systems for online courses. Incorporating information such as user demographics, learning objectives, and course metadata can enhance the relevance and personalization of recommendations. Context-aware recommendation systems enable adaptive and tailored suggestions that align with specific user needs and circumstances.

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