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ARBEITSWELT PLUS

AI-BASED RECOMMENDATION SYSTEM FOR INDUSTRIAL TRAINING

KI-BASIERTE EMPFEHLUNGSSYSTEME FÜR DIE INDUSTRIELLE AUSBILDUNG

Mechanisms, challenges and opportunities of recommendation systems in e-learning and in web-based training

Mechanismen, Herausforderungen und Chancen von Empfehlungssystemen im E-Learning und in der webbasierten Ausbildung

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WORKING PAPER #9

Fraunhofer IOSB-INA

ÜBER DAS KOMPETENZZENTRUM ARBEITSWELT.PLUS

Wie wird Künstliche Intelligenz die Arbeitswelt verändern? Wie gelingt es, Veränderungen der Arbeitswelt gemeinsam zu gestalten? Und wie können Beschäftigte auf den Wandel eigentlich vorbereitet werden? Antworten auf diese Fragen liefern wir als Kompetenzzentrum Arbeitswelt.Plus.

Unserem gemeinsamen Leitmotiv **Mensch. Industrie. Morgen.** entsprechend entwickeln Hochschulen und Unternehmen aus OstWestfalenLippe im Kompetenzzentrum gemeinsam mit der IG Metall Ansätze für die Einführung von Künstlicher Intelligenz in der Arbeitswelt, beispielsweise im Hinblick auf die Arbeitsplatzgestaltung und die Qualifizierung von Mitarbeiter:innen.

ÜBER DIE WORKING-PAPER-REIHE

Damit die Ausprägung der künftigen Arbeitswelt nicht allein technologisch geprägt wird, braucht es eine **ganzheitliche Gestaltung**. Deshalb führt das Kompetenzzentrum Arbeitswelt.Plus Erkenntnisse der Arbeitsforschung im Kontext von KI-Anwendungen zusammen und entwickelt daraus passende Lösungen für mittelständische Unternehmen.

Mit dieser **Working-Paper-Reihe** geben wir Einblicke in die laufende Forschung der Wissenschaftler:innen des Kompetenzzentrums und möchten gleichzeitig einen Beitrag zur Diskussion rund um aktuelle Themen aus den Feldern Künstliche Intelligenz und Arbeitsforschung leisten.

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ABSTRACT

Recommendation systems have become a main part of e-learning, reshaping the landscape of digital education. In an era marked by the proliferation of online courses, diverse learning materials, and users with varying needs, these systems offer a dynamic solution.

This paper explores recommendation techniques and their role in e-learning and web-based training, delving into their mechanisms, challenges, and opportunities. Moreover, future directions of these systems in e-learning, including the integration of artificial intelligent and emerging technologies, and the quest for transparency and privacy are highlighted.

Additionally, a case study is discussed which focuses on providing a recommendation system in order to offer optimal courses for the employees of Weidmüller Interface GmbH & Co. KG.

Empfehlungssysteme sind zu einem wichtigen Bestandteil des E-Learnings geworden und haben die Landschaft der digitalen Bildung neu gestaltet. In einer Zeit, die durch die Verbreitung von Online-Kursen, vielfältigen Lernmaterialien und Nutzern mit unterschiedlichen Bedürfnissen gekennzeichnet ist, bieten diese Systeme eine dynamische Lösung.

In diesem Beitrag werden Empfehlungstechniken und ihre Rolle im E-Learning und in der webbasierten Ausbildung untersucht, wobei ihre Mechanismen, Herausforderungen und Möglichkeiten näher beleuchtet werden. Darüber hinaus werden künftige Richtungen dieser Systeme im E-Learning, einschließlich der Integration von künstlicher Intelligenz und neuen Technologien, sowie das Streben nach Transparenz und Datenschutz beleuchtet.

Zusätzlich wird eine Fallstudie diskutiert, die sich auf die Bereitstellung eines Empfehlungssystems konzentriert, um optimale Kurse für die Mitarbeiter der Weidmüller Interface GmbH & Co. KG.

1 Introduction

During the last few years and the global pandemic, the appeal for online shopping and entertainment raised, resulting in increasing the demand for personalized services. With the growth of the e-commerce industry, the need for recommendation systems expands as well. Recommendation systems retrieve and filter the data through content and similar profiles increases [1]. These systems are mainly employed within the e-commerce domain for predicting what users want by analysing their gathered data and information on past preferences. For example, websites, such as Amazon, YouTube, Netflix, or Facebook apply recommendation systems to allow the user suggestions for products, videos, movies, or friends that users may not know and could be of their interest [2].

In the context of industrial organizations, continuous training proves its advantages for creating and maintaining the skill profile for employees. As the skills and expertise of employees influence the effectiveness and productivity of the workforce [3]. Therefore, employees should be supported to select the suitable training course that matches their working path. However, the process of selecting suitable training can become problematic since there is usually a variety of trainings and presentation methods within an organization. As an example, training courses can be related to management, quality, domain-specific, or soft skills. These training courses may be presented in different ways such as web-based training (WBT), classroom, or external trainings. In some cases, there are mandatory trainings for employees to take which enable them to reach the level or skill required for a specific task or project. In addition, employees are able to voluntarily choose any training courses that they are interested in.

Consequently, it is important to assist employees in order to select the proper training course. This can be achieved by employing recommendation systems. In this paper, a recommendation system for selecting the proper web-based training course is proposed.

The paper is organized as follows. Section 2 gives an overview of recommendation systems for e-learning applications and the challenges regarding these methods. Section 3 reviews the related work. A case study is presented in Section 4. The future direction of recommendation systems in e-learning is given in Section 5. Finally, the paper includes a conclusion and an outlook in Section 6.

2 Recommendation Techniques

A recommendation system is an information filtering algorithm that supports a user by suggesting content or products which might interesting for that particular user [4].

In order to bring users and relevant content together, recommendation systems collect user information which can be explicit or implicit. Explicit data is gathered from users' direct action that indicates their preferences (e.g., ranking or rating given by users). Implicit data is obtained by monitoring the users' behavior (e.g., applications downloaded, the most viewed products, taken courses) [5].

Overall, recommendation systems are divided mainly into three types (Fig. 1) [6,7]: Collaborative filtering, Content-based, and Hybrid approaches.

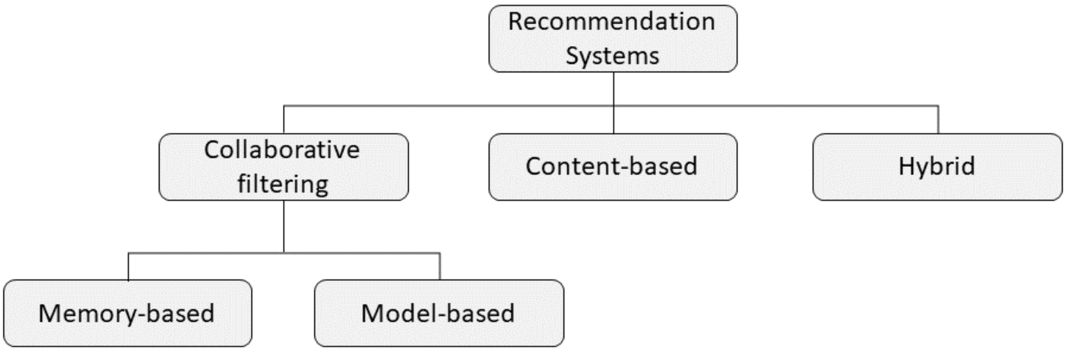

Figure 1:Types of recommendation systems.

Collaborative filtering. Collaborative filtering recommends items based on the preferences and behaviours of similar users [5]. It assumes that users who have similar preferences in the past will have similar preferences in the future. Collaborative filtering techniques build a user-item matrix based on user preferences for items. In order to make recommendations, these methods calculate similarities between users' profiles to detect and match users with relevant interests [8]. Users with similar preferences build a group called neighbourhood. A user receives recommendations for those items that were positively rated by users in his/her neighbourhood [8].

There are two main approaches to collaborative filtering: Model-based and Memory-based. As their name says, model-based approaches involve a model for training and computing similarities. Memory-based approaches are a type of collaborative filtering method that relies on the direct computation of similarities between users or items and is divided into user-based and item-based methods. User-based collaborative filtering finds users with similar tastes and recommends items liked by those similar users. Item-based collaborative filtering identifies similar items based on user ratings and recommends items that are similar to the ones the user has liked.

Collaborative filtering methods provide two types of outcomes: Recommendations and predictions. Recommendation outcomes are a list of top N items, while prediction outputs are presented by a predicted score of item i for the user u, $(p_{i,u})$.

Content-based. Content-based filtering recommends items to users based on the features or characteristics of the items themselves [9]. It analyses the attributes or content of the items a user has previously liked or interacted with and suggests similar items. Such systems prepare the item profile based on the contents of available courses. After that, a user profile with the user's historical record will be made (a combination of item profile that the user has taken in the past). Finally, the similarity between user and item profiles will be calculated and recommendations will be made, accordingly [10].

Hybrid approaches. Hybrid recommendation systems combine multiple techniques, such as collaborative filtering and content-based filtering, to provide more accurate and diverse recommendations. By leveraging the strengths of different approaches, hybrid systems can overcome some of the limitations of individual techniques and provide improved recommendations [11, 12].

2.1 Challenges of Recommendation Systems

Recommendation systems face various challenges that affect their effectiveness and user satisfaction. These key challenges are:

- Cold-start: The cold-start problem refers to situations with insufficient data or information about new users or items. In such cases, it becomes challenging to provide accurate recommendations as the system lacks the necessary user preferences or item characteristics. Techniques like content-based filtering or hybrid approaches are often used to address this problem and make initial recommendations based on available data or user attributes [13, 14].
- Data Sparsity: It occurs when users have limited interactions or ratings for items, resulting in sparse user-item interaction matrices. This leads to the problem of finding reliable similarity measures which can affect the accuracy of collaborative filtering techniques. Matrix factorization-based methods, such as singular value decomposition (SVD) or matrix completion techniques can overcome this limitation [13, 15].
- Scalability: Increasing the number of users and items in a recommendation system results in the growth of computational complexity since computing pairwise similarities between users or items becomes time-consuming. Methods such as approximation techniques, distributed computing frameworks, or matrix factorization algorithms like alternating least squares (ALS) can address this problem [16].
- Diversity and Serendipity: Over-recommending popular or similar items is another issue that is due to a lack of diversity in recommendations. To tackle this challenge, techniques like diversity-aware recommendation algorithms, novelty-based approaches, or incorporating exploration-exploitation trade-offs can be employed to offer diverse and unexpected recommendations [17].

The aforementioned challenges may vary depending on the specific application domain, dataset characteristics, and user requirements.

3 Related Work

Recommendation systems belong to the category of information filtering systems that predict and suggest relevant items or topics to users based on their preferences, behavior, and characteristics. During the last decade, the use of recommendation systems has increased in diverse areas [5]; such as movie recommendation [18,19], music [20] television [21], books [22], and e-commerce [23] among others.

In the e-learning and training context, recommendation systems deliver personalized recommendations for learning materials based on users' learning interests and paths in online learning systems [24].

Several approaches include a content-based approach for recommendation systems. A content-based approach using correlation analysis is employed in [25] to group learning courses. This method defines three categories according to a rule-based model for obtaining learning objects for each group and optimizing the learning path. Shu et al. [26] applied a content-based recommendation system with a semantic-based approach. They employed convolutional neural networks (CNN) to recommend the right course for students.

A content-based system applying a multi-layer graph modeling technique is employed in [27] for citation recommendation. This approach results in a high computational complexity due to the large graph size. Nevertheless, the authors solve this problem, by conducting a three-layered interactive clustering approach.

In [28], a decision tree and a clustering algorithm are employed, first to classify learners into three groups of beginner, intermediate, and master, and then to recommend the right materials to them.

Collaborative filtering is the most common recommendation technique [8]. Liu [29] designed a collaborative filtering approach using the influence of e-learning group behavior. A similar approach is used in [30] for teaching strategy recommendations by analysing the facial expression in e-learning for students.

Sequential pattern mining was employed in the work of [31] to predict the learning style of users. In [32], a technique is applied to develop a score model in order to gather users' feedback, weigh the learning materials, and to suggest the proper object to the user.

El-Bishouty et al. [33] included a collaborative filtering approach using a k-mean algorithm to extract the learning sequence. After that, the learning sequences were mapped to learning objects according to the style of users.

Several approaches [34-37] employed model-based factorization matrices for the recommendation task. Nevertheless, these straightforward approaches do not consider context with models. Genetic algorithms were used in [38, 39] to generate an optimized learning path for users.

Hybrid approaches consider user preference, background, interests, and memory capacity to store information that overcomes problems such as cold start [40]. Benhamdi et al. [41] considered the multi-dimensional similarity of users' prior knowledge, interests, time spent on tests, and memory capacity using a correlation matrix (see also [42]). An artificial neural network, decision tree, logistic regression, and support vector machine were included in [43] to predict the problems that students may struggle with in further subjects.

Although hybrid approaches combine the advantages of both content-based and collaborative filtering methods to overcome their problems, they are still memory and time-consuming.

4 Case Study - Model-based Recommendation System

In this section, a case study is presented which is part of a project within the Arbeitswelt.Plus [44] project, which deals with issues such as artificial intelligence (AI) in the workplace.

The purpose of this case study is to provide a recommendation system for the training department of Weidmüller Interface GmbH & Co. KG [45], which is a company, in the field of electrical connection technology and electronics. The proposed recommendation system must offer three optimal courses to the employees.

As stated, selecting proper courses for the employees may become a challenging task due to e.g. diversity of the courses and required skills. In order to recommend suitable courses to employees of Weidmüller an approach is proposed, which is illustrated in Fig. 2.

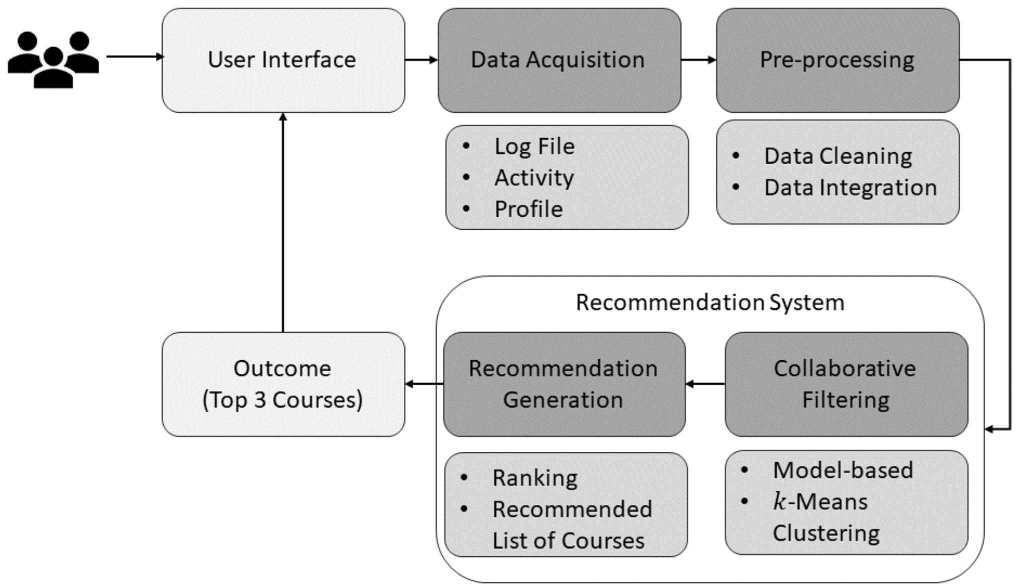

Figure 2:Steps of the proposed recommendation system

The first step is to collect relevant information from users to generate a user profile. A user profile usually includes personal information associated with the user such as gender, job title, taken courses, user activity, interests, and preferences. These data can be gathered from the user interface which users work with to view requested web pages, materials, and courses, or to provide feedback for certain tasks or courses. Weidmüller has a Learning-Management-System (LMS) which provides various courses and web-based training materials to employees.

The collected data can be implicit, explicit, or a combination of both. The data in this study are implicit and gathered from the training-related past data from Weidmüller employees who took courses between the years 2018 and 2023. The data contained job title, user ID, country where the employee works, employment date, the name and the ID of the taken courses, the date of taken courses, and courses' category. The name, age, and gender of the employees are not included. These data contained around fifteen thousand entries and 3206 distinct training courses. Three categories of courses namely; Human Recourse development, Product and Application, and Sales skills are considered.

In the second step, the data must be cleaned of redundant and unnecessary information. This step is vital since it affects the results of the recommendation algorithm. The accuracy and success of recommendation systems depend largely on the relevance and efficiency of the data.

Entries without information were deleted from the data. Additionally, several inconsistencies in the data are removed. For instance, job titles were saved in various manners, e.g. similar jobs having different naming, synonyms, German and English titles, complete job titles, or acronyms. Consequently, only the job title, user ID, name, and the ID of the taken courses are considered as test cases in this study.

After cleaning the data, in the third step, the data is filtered using collaborative filtering. A collaborative filtering method uses a list of N users $U = \{u_1, u_2, \dots, u_N\}$, and M courses $C = \{c_1, c_2, \dots, c_M\}$ to which generates an $N \times M$ user-course matrix.

Since the collected data in this study are implicit, the user ratings were not available. Consequently, a model-based approach is considered, aiming to build an offline model by applying machine learning and data mining techniques. Examples of such methods are Singular Value Decomposition (SVD), Matrix Completion technique, Latent Semantic methods, and Regression and Clustering.

In this study, a clustering method is applied to analyse the user-course matrix and recommend the top three courses. Clustering algorithms partition the data into a set of sub-clusters in order to discover meaningful groups within the data [8,46]. After defining the clusters, based on the information in a cluster, recommendations for individual users can be made.

A good clustering method will produce high-quality clusters in which the intra-cluster similarity is high, while the inter-cluster similarity is low. In some clustering approaches, a user can have partial participation in different clusters [47]. K-means and Self-Organizing Map (SOM) are the most applied clustering methods [8].

The K -means method is also employed in this study. This approach partitions the data into K clusters. In order to detect the number of clusters, the elbow method is used in this study. The elbow method calculates the within-cluster sum of squares (WCSS) for every value of K. It iterates continuously for K =1 to $K = p$ (in this study $p = 20$). By plotting the number of K clusters versus their WCSS value, the optimal value for K (number of clusters) can be determined. In such a graph, $K = 1$ has the highest value of the WCSS, but with increasing K, the value of WCSS decreases. Consequently, for K the value will be chosen where the graph starts to look like a straight line.

After clustering the data, the courses in each cluster are ranked according to the three most taken courses in each cluster. Next, these courses are recommended to the individual user. It should be noted that only the courses that were not taken by the user are suggested. Thus, if one of the recommended courses was already done by the user, the algorithm recommends the next optimal course.

Various offline tests are performed to measure the performance of this approach. Since user ratings for the taken courses were not available in this study, statistical evaluation methods such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Correlation are not applied.

Nevertheless, the accuracy of the results is analysed by precision metric. Precision represents the fraction of recommended items that are relevant to the user and is given by

$$Precision = \frac{Correctly\ recommended\ courses}{Total\ recommended\ courses}.$$

The data set is divided into test and train data with a five-fold cross-validation method. The precision rate was 100% ($Precision \cdot$ 100%) in the majority of the tests. The precision rate was 30% or 60% when the user took all the relevant courses in his/her cluster. Thus, there was no course left in the cluster to recommend it to the user.

Moreover, the first online tests, performed by Weidmüller employees proved the accuracy of this approach. Further studies are planned to evaluate the results of this method and recommendation systems generally. These studies will focus on the change in learning behaviour or the effects of the recommendation systems on the learning path of users.

In this study, a straightforward approach is proposed, which fits to the features of the tested data. Nevertheless, to improve the results of this method, other criteria such as employees' age, year of employment, or country of employment can be considered as well. Moreover, considering the rating given for each course after participation can also increase the efficiency and performance of this method.

5 Future Directions

E-learning and web-based training are more flexible and accessible in comparison to old-fashioned training and therefore have gained significant growth in popularity during the last decade. Hence, their development is essential in order to meet the needs of users and fulfill their new requirements. Some of the key points regarding the development of web-based training and e-learning are explained below.

- **Adaptability and flexibility.** Adaptive and drift-aware recommendation systems play a vital role in enhancing the e-learning experience by providing personalized and real-time recommendations to users. Drift-aware recommendation systems are designed to handle changes in users' preferences and content availability over time. These systems continuously monitor user interactions and adapt the recommendations to interests or trending topics. For example, if a user's preferences change from one subject to another, the system can adjust recommendations accordingly [48, 49].
- **Real-time Feedback.** One of the main limitations of the existing recommendation systems is the inability to provide real-time feedback. While recommendation systems leverage context information and historical data to make predictions and offer in-time recommendations, they struggle to adaptively model and respond to changes in the user's profile and provide real-time recommendations. Reinforcement learning techniques, employed recently [50], are promising methods due to their interaction with users in order to track users' interests.
- **Multi-Modal Recommendations.** As, content becomes multi-modal (e.g., combining text, images, audio, video), recommendation systems are needed to incorporate these different data types into their models to provide more comprehensive recommendations.
- **Explainability and Transparency.** Users are becoming more concerned about how and why recommendations are made. Future recommendation systems will need to provide transparent and interpretable explanations for their recommendations. Visualization or interactive strategies can be applied to explain the recommendation process to users.

6 Conclusion and Outlook

Recommendation systems in e-learning have emerged as a critical component in enhancing the online learning experience. These systems leverage data analytics and machine learning techniques to provide users with personalized and relevant content recommendations. By continuously analysing user behaviour, tracking progress, and adapting to evolving interests, recommendation systems empower learners to discover and engage with the most suitable courses, modules, and resources.

In this paper, different types of recommendation systems and their limitations and benefits, along with the challenges regarding these systems are explained. Also, several works are described regarding recommendation systems for education and e-learning. The future direction of these systems in e-learning is discussed. For instance, in order to meet the needs of learners, these systems must become more adaptive and flexible, as described in Sec. 5.

A case study is discussed with the training-related past data gathered from the employees of Weidmüller Interface GmbH & Co. KG. [45]. The aim of the study is to recommend the top three optimal courses to the employees. Consequently, a recommendation system with a model-based collaborative filtering approach is applied. The K-Means clustering method divides the employees into the number of K clusters based on the past training courses done by employees. Finally, the top three courses taken in each cluster are recommended to the specific user in the cluster. The performance of the proposed method is analysed by precision metric. Additionally, interviews and tests are planned to be performed by the employees in order to evaluate this method.

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