Recommendation System for Adapting Learning Objects: Using the K-means Clustering Algorithm

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Abstract. This article examines the use of recommendation systems to personalize educational content according to learners' preferences and learning styles. Utilizing K-means clustering algorithms, the study aims to improve the effectiveness and engagement of e-learning environments. By integrating learning style models and adaptive evaluation methods, it addresses the diversity of learners' needs. The research highlights the benefits of personalized learning, enhanced engagement, and support for diverse learning styles through recommendation systems. It also discusses the application of K-means clustering for more accurate recommendations. Despite progress, significant gaps remain in initializing learning styles and developing adaptive techniques.

Keywords: Recommendation Systems, Adaptive Learning, K-means Clustering, learning object, learning Style.

Introduction

Adapting learning objects to learning styles has become essential to maximize the effectiveness of e-learning environments. Learners have unique preferences and ways of assimilating knowledge, necessitating the personalization of learning pathways to address this diversity. Learning style models offer a theoretical framework for understanding these differences and developing tailored pedagogical strategies.
This article explores how recommendation systems can be used to adapt learning objects to learner profiles. Using advanced algorithms like K-means clustering, these systems analyze learner interactions and preferences to suggest personalized educational content. This approach aims to create more engaging and effective learning environments that can meet the specific needs of each learner.

1 Learning Style Models and Adaptive System Evaluation

Learning style models offer a framework for classifying learners' preferences and learning strategies, while the evaluation of adaptive systems measures their effectiveness in adapting educational content. The following table presents a compilation of learning

M. Khaldi et al. (eds.), Proceedings of the E-Learning and Smart Engineering Systems (ELSES 2024), Atlantis Highlights in Social Sciences, Education and Humanities 36,
https://doi.org/10.2991/978-2-38476-408-2_35

style models used in Adaptive Learning Environments, along with associated measurement tools and evaluations conducted on these systems [1]. This information is crucial to understanding how different adaptive educational systems address the diversity of learners' learning styles. Each entry in the table details the specific model used, the type of measurement tool employed, the dimensions covered by the system, and the results of empirical evaluations, if any.

The provided references allow access to the studies and research that have contributed to evaluating the effectiveness and relevance of these approaches in the modern educational context. This synthesis aims to offer an overview of current practices in the field of adaptive education, facilitating a deeper understanding of the methodologies employed to personalize the learning experience based on individual learners' preferences.

Table 1. Exploring Previous Adaptive Learning System Models

System	Learning Style Model Used	Style Measurement Tool	Covered Dimensions	Evaluation
Arthur	[2] (auditory, visual, and tactile) by (Sarasin 1998)	Determined by the system	Visual-Interactive, Auditory-Textual, Auditory-Lecture, Text-Based Presentations	An empirical study with 89 participants was conducted .
SACS	VARK [3]	VARK Questionnaire or self-reported by learner	VARK	No formal evaluation specified
AES-CS	Dependent or independent of Witkin's field [4]	GEFT Test (Witkin et al. 1971)	Dependent/Independent of the field	No formal evaluation specified
iWeaver	[5]	Building Excellence Inventory (Rundle and Dunn 2000)	Global, analytical, impulsive, reflective, visual, auditory, kinesthetic	Sixty-three learners participated in a conducted workshop
INSPIRE	[6]	Honey and Mumford Questionnaire (1992)	Reflector-activist	A study involving twenty-three participants was carried out
AHA!	[7]	LAG-XLS generic adaptive language	Active-Reflective, Verbalizer-Imager, Global-Analytic, Field Dependent-Field Independent	An empirical study with thirty-four participants was conducted
CS383	Various dimensions of FSLSM [8]	ILS (Felder and Soloman 1996)	Sensing-intuitive, visual-verbal, sequential-global	No formal experimental research has been performed for the evaluation; only informal evaluations have been conducted.
ILASH	[10]	ILS (Felder and Soloman 1996)	Global/sequential dimension	An empirical study with twenty-two participants was conducted

2 Utilization of Recommendation Systems

Recommendation systems (RS) are essential software tools that filter information according to users' personalized preferences. Used in various fields such as online commerce, multimedia content dissemination, and education, these systems leverage sophisticated algorithms to analyze users' preferences and behaviors to propose products, services, or content likely to interest them. By helping manage information overload, recommendation systems offer users relevant recommendations from a vast amount of available data.

These systems have proven effective in various sectors, notably e-commerce platforms like Amazon, audio and video streaming services like Netflix, and social networks like Facebook. For example, according to Dalia (2014), recommendations account for two-thirds of rented movies on Netflix, 38% of news on Google News, and 35% of purchases on Amazon.com. Recommendation systems represent an advanced form of information filtering aimed at presenting items likely to interest the user. They aim to suggest the most appropriate items for individual users by forecasting their interest based on information about the items, users, and their interactions. These systems primarily seek to alleviate information overload by filtering out the most pertinent data and services from extensive datasets, thus delivering tailored recommendations. A key aspect of recommendation systems is their capability to predict user preferences and interests by examining both individual behaviors and interactions among users to create personalized suggestions.In the educational context, recommendation systems can adapt learning objects to the individual needs and learning styles of learners. They play a crucial role in pedagogical adaptation by offering several benefits:

- Personalization of Learning: By analyzing learners' interactions and preferences, RS can suggest adapted educational resources such as articles, videos, exercises, or online courses.
- Improvement of Engagement: By proposing relevant and adapted content, these systems can increase learners' engagement by making learning more interesting and motivating.
- Support for Diverse Learning Styles: By taking into account different learning styles, RS can offer educational experiences that better match individual preferences, thereby facilitating better understanding and retention of knowledge.

Thus, recommendation systems do more than filter information; they transform the user experience by providing relevant and personalized suggestions, thereby contributing to a more effective and engaging interaction with available content.

3 Clustering with the K-means Algorithm in Recommendation Systems

Traditional recommendation algorithms face several challenges in today's online learning systems. To implement effective recommendation techniques in e-learning, these obstacles must be addressed. This research proposes a new enhanced collaborative filtering (ECF) algorithm and an enhanced content-based filtering (ECBF) algorithm. These algorithms integrate multidimensional attributes of learning objects (LO), learner profiles (learning styles), and learners' rating information to tackle the cold start problem and data sparsity issue. The K-means clustering technique is employed to group learners with similar preferences and learning objects based on their profiles, resulting in more effective recommendations.

Various recommendation methods based on partitioning clustering algorithms have been suggested, as detailed in Table 2. The K-means clustering algorithm has been utilized to improve computational efficiency, particularly in the quality and accuracy of recommendations. The algorithm relies on partitioning clustering methods and has numerous applications, especially in personalized learning, with the AHA! learning system being a notable example. The AHA! learning system creates clusters that correspond to each learner's model, consolidating relevant data into an XML file where each cluster's centroid is recorded. Essentially, a typical user is represented by a centroid within a cluster.

The K-means algorithm has also been used to study the impact of human characteristics on learners' performance while listening to music. Moreover, K-means has been applied to construct the neighborhood by considering the user's distance to various cluster centers as a pre-selection step for neighbors. The successful implementation of this straightforward and effective clustering technology has outperformed KNN-based collaborative filtering (CF) methods.

Table 2. Summary of Research on Personalized Learning Recommendation Systems Employing Clustering Algorithms

Research	Technique	Findings
Best combination of machine learning algorithms for course recommendation system in e-learning [11]	Classification & association rule (Apriori algorithm) & clustering (K-means)	The combination of K-means clustering, ADTree classification, and the Apriori association rule algorithm outperforms both the ADTree and Apriori Rule when used individually.
Combination of machine learning algorithms for recommendation of courses in e-learning system based on historical data [12]	Clustering (K-means) & association rule (Apriori algorithm)	K-means clustering in conjunction with the Apriori association algorithm provides the most effective results for improving the accuracy of course recommendations
Multi-agent system for knowledge-based recommendation of learning objects [13]	Clustering (K-means) & knowledge-based (ontology)	Improvement of learning objects recommendation using K-means clustering according to learners' prior knowledge

A novel algorithm for dynamic student profile adaptation based on learning styles [14]	Clustering (K-means) cosine similarity metrics & Pearson correlation	Improvement of learning objects recommendation accuracy
Application of implicit and explicit attribute based collaborative filtering and bide for learning resource recommendation [15]	Clustering (K-means) Bi-Directional based frequent closed sequence mining	Results show more accurate learning objects recommendation according to real-time updated contextual information

The K-means clustering algorithm is a widely used and straightforward partitioning technique for grouping data. In standard K-means clustering, the process begins with the random selection of K initial cluster centroids, where K represents the desired number of clusters. Distance metrics, such as the Euclidean distance, are employed to measure the similarity between data points and cluster centroids. Each data point is then assigned to the cluster whose centroid is closest. Afterward, the centroids are recalculated as the mean of all points in each cluster. This process of reassigning points and updating centroids continues iteratively until there are no further changes in the cluster assignments.

Traditional K-means focuses on minimizing the Euclidean distance through a least squares approach. However, using alternative distance functions can sometimes prevent the algorithm from converging. The algorithm follows these main steps:

1. Randomly select K points from the dataset to serve as the initial centroids.
2. Form K clusters by assigning each data point to the nearest centroid using the Euclidean distance formula.
3. Update each centroid by computing the average position of all points in its cluster.
4. Continue reassigning points and updating centroids until there are no changes in the clusters.

To enhance the effectiveness of recommendation systems, K-means clustering can be used offline to partition the data into clusters of similar items, allowing the system to focus on the most relevant data for recommendations. Its key benefits include its simplicity and efficiency, making it well-suited for clustering large datasets. The following section will explore the similarity metrics commonly applied in e-learning recommendation systems.

4 Conclusion

This article has reviewed existing literature on adaptive recommendation systems for e-learning. It identified the benefits, challenges, and theories associated with this concept, as well as three key aspects such as learning styles, recommendation algorithms, and clustering in e-learning systems. Our article highlighted significant research gaps, particularly the initialization of learners' learning styles and recommendation techniques based on learners' adaptive profiles. Despite existing efforts, no comprehensive solution has yet been found to address these challenges simultaneously.

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