A Survey on Personalized Learning Course Recommendations with Bert and Collaborative Filtering

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ABSTRACT:

E-learning is the general term for an electronic learning environment that is based on formalized instruction and makes use of electronic resources. Whether learning happens in conventional classrooms or somewhere else entirely, integrating computers and the Internet is a keystone of this strategy. A network-enabled transfer of knowledge and skills that may be used to deliver education to a variety of audiences concurrently or at different times is what defines e-learning. E-learning was first viewed with skepticism since it was seen to lack human connection, but it has since developed, and e-learning websites are now an essential part of the learning process. Dynamic recommendation algorithms are now used by e-learning websites to improve user experience. These platforms use cutting-edge algorithms to overcome the drawbacks of conventional systems and enable more efficient learning. Using the in the current systems To overcome this, a dynamic recommendation system is suggested that combines cutting-edge methods such as BERT to better comprehend user preferences and queries, as well as recurrent neural networks (RNNs) to increase prediction performance. To improve prediction tasks, RNNs, a kind of neural network, are added to the recommendation system. The proposed e-learning system uses RNNs for dynamic sequence modeling and BERT for natural language comprehension to provide users with more effective and personalized learning experiences that dynamically adjust to their preferences. This strategy overcomes the drawbacks of earlier systems and demonstrates how e-learning technology is constantly evolving.

Keywords: recurrent neural networks (RNNs), BERT, e-learning

INTRODUCTION:

E-LEARNING:

Electronic learning, or e-learning for short, is a method of teaching that uses digital and electronic resources to make it easier for students to learn new things. It includes a wide variety of teaching strategies that are made available via digital platforms like computers, mobile devices, and the Internet. E-learning offers greater flexibility than traditional classroom-based education about scheduling, location, and learning speed. This technique promotes a globalized and accessible approach to education by enabling students to access instructional materials from almost anywhere. Multimedia components, interactive activities, and dynamic evaluations are common in e-learning systems, which increase the interactivity and engagement of the learning process. As technology has advanced, e-learning has emerged as a significant and essential part of modern education, providing a flexible and adaptive way to learn about a wide range of topics and disciplines.

COLLABORATIVE FILTERING:

The collaborative aspect of collaborative filtering algorithms involves the recommendation of items (the filtering component) based on user preference data (the collaborative part). Using the similarity of user preference behavior, recommender algorithms are trained to anticipate future interactions based on past interactions between users and goods. These recommender systems create a model based on historical user behavior, such as previously purchased things, ratings for those items, and judgments made by other users that are similar to their own. The theory goes that if a group of individuals have previously made similar decisions and purchases—for example, choosing a movie—there's a good chance they'll agree on more choices in the future. For instance, if a collaborative filtering recommender recognizes that you and another user have similar movie tastes, it may suggest a film to you that it already knows the other user likes.

LITERATURE SURVEY:

[1] Enabling recommendation system architecture in a virtualized environment for e-learning E-learning platforms help enhance the knowledge and abilities of the core members of the academic community, including teachers, students, support personnel, and people looking for up-to-date information about different universities. Even with all the advantages of an online learning platform, users still have to deal with certain difficulties and complications, such as choosing the right courses and learning resources according to their needs and preferences. Therefore, it is their primary duty to give high-quality materials during the training phases. It is well known that several problems arise because service providers do not offer adequate online assistance. To improve the abilities and knowledge of learners, a system that can thoughtfully suggest courses while taking into account a range of perspectives must be developed. This study suggests an architecture that uses virtual agents to create semantic suggestions based on user preferences and requirements, helping academics find relevant courses in real-world settings. The experimental and statistical findings demonstrate that, in contrast to current methods, the virtualized agent-based recommendation system enhanced user learning abilities and simplified the process of choosing a course based on the interests and preferences of the user.

[2] An Efficient Approach of Product Recommendation System Using NLP Technique The advent of digital globalization and online shopping has led to a growing demand for a dependable and effective system that facilitates the discovery of appropriate products by customers and website visitors. At the moment, when a visitor visits several websites, the product that was searched for is displayed. A system that can suggest things that are similar to the products that are searched for is what we require. If the product is not accessible, the product that was looked for is insufficient, or the customer would want to browse through several comparable items, this will assist them in finding a different product. Companies might benefit financially from an effective recommendation system as well. Customers are reported to be 35% more inclined to purchase a product if they feel the recommendation meets their needs.

[3] An e-commerce recommendation algorithm based on link prediction The majority of recommendation algorithms used in e-commerce are built on top of a user-item bipartite graph network (BGN). Nevertheless, the accuracy and diversity of this type of recommendation system are seriously lacking. This paper proposes a unique method for e-commerce recommendation based on BGN link prediction. To begin with, the distance formula was used to import all of the user-item data and determine how similar the attributes were. After that, the BGN was projected into a single-mode network (SMN), which improved the efficiency of the BGN's link extraction process. The possible connections were therefore inferred using similarity. It was demonstrated through tests on actual e-commerce datasets that our system outperforms other common recommendation algorithms in terms of accuracy and coverage.

[4] **Adaptive Personalized Recommendation System Using Learning Automata and Item Clustering** Based on user preferences that are documented in each user's unique profile—the personalized recommender systems offer services relevant to the user. As a result, the suggestion process is more successful the more accurate and thorough each user profile is. While traditional research does not consistently track these changes, people's interests do shift throughout time. Creating an effective user model to monitor users' interests is crucial in these situations. In the present work, we propose an algorithm to generate user profiling based on learning automata. We grouped the things because there were a lot of them and their features were similar. This method assigns the active user to a learning automaton. Based on user feedback, the learning automaton modifies the user interest level in each cluster. The internal state of the learning automaton converges towards the user's true interests in the item clusters as the number of user interactions with the system rises. The experimental findings show that in terms of precision, recall, RMSE, and MAE, our algorithm performs better than the compared methods. Furthermore, the suggested technique performs acceptably for new users.

[5] Advanced Recommendation Systems Through Deep Learning For a long time, recommendation systems have helped businesses thrive, particularly e-commerce businesses. Systems for making recommendations have been implemented in a number of consumer goods markets to provide consumers enhanced user experiences, such as customisation. Successful applications of recommendation systems include movie recommendation (Netflix reported that 80% of movies viewed by users were suggested by the platform's recommendation engine), e-commerce, restaurant reservations, YouTube video recommendations (which generated 60% of the platform's video clicks), book recommendations, etc. The main variables employed in the creation of a recommendation engine include temporal and spatial data, item attributes, historical interactions between users and items, and user preferences. categorised recommendation strategies for collaborative filtering, hybrid recommender systems, and content-based recommender systems according to the kind of incoming data. Users receive recommendations from content-based recommendation systems that are comparable to their previously favoured option. In contrast to content-based recommendations, collaborative filtering recommendations highlight products that users with similar tastes have already purchased, while hybrid models combine the best features of both of the aforementioned models.

[6] Improving Recommender Systems via a Dual Training Error based Correction Approach We suggest a Dual (user and item) Training Error based Correction strategy (DTEC) to enhance the prediction performance of recommender systems. The Synthetic Coordinate Recommendation system (SCoR) (Papadakis, Panagiotakis, and Fragopoulou, 2017) as well as three other cutting-edge systems are subjected to the suggested methodology. First, suggestions for users and things are given via a recommender system. After the recommender system is first run, we add a second stage that enhances its predictions by accounting for the error in the training set between users and items as well as their similarity. These adjustments can be made from the perspectives of the item and the user, and in the end, a dual system that effectively incorporates both adjustments is suggested. In order to enhance the rating predictions on the test set, DTEC computes a model that reduces the recommendation error in the training set to zero. Any model-based recommender system with positive training error can use the suggested DTEC technique, which could improve recommendation accuracy. The experimental findings on four well-known, real-world datasets show the effectiveness and excellent performance of DTEC.

[7] ChoseAmobile: A Web-based Recommendation System for Mobile Phone Products New forms of shopping were made possible by the tools and technologies that the information and communication technologies brought to the sector of electronic commerce. The user base is moving away from traditional in-store buying and towards online e-commerce sites as a result of the introduction of e-commerce platforms. Because so many e-commerce sites have similar brands and products, it can be challenging for users to determine which site is delivering the greatest prices and accurate specifications. In this work, we describe a recommendation system called choseAmobile that gives the user appropriate recommendations based on certain metrics and product reviews as auxiliary data. To provide accurate and current results, the system constantly scans and evaluates the data sources to identify whether updates have been made. The system's viability and effectiveness have been demonstrated by the trial results, leading to improved suggestions for choosing a mobile phone, particularly for inexperienced users.

[8] E-Learning Course Recommender System Using Collaborative Filtering Models In pandemic scenarios, e-learning is a highly sought-after choice for students. The user must choose the ideal course for them from the many options accessible on e-learning platforms. Recommender systems are therefore crucial in helping users make better automated course selections. Using their preferences as a guide, it helps consumers choose the choice they want. The recommendation mechanism of this system can be implemented by machine intelligence (MI) based methods. This method can determine the most popular items among users based on their past usage and preferences. This paper proposes a recommender system for e-learning course suggestion utilising the collaborative filtering method. The work focuses on MI-based models, including neural network-based collaborative filtering (NCF) models, K-nearest neighbour (KNN), and Singular Value Decomposition (SVD). For analysis, a dataset of one lakh Coursera course reviews was obtained from Kaggle. The suggested work can assist students in choosing the online courses that best suit their interests. Python is used in the implementation of this work. Metrics like mean absolute error (MAE), average reciprocal hit ranking (ARHR), and hit rate (HR) are used to assess how well these models perform. The findings show that, in comparison to other models, KNN performs better in terms of greater HR and ARHR and lower MAE values.

[9] Machine Learning based recommendation systems for E-Learning The ever-expanding selection of online learning resources available to students is making it increasingly challenging to find particular information in data pools. Personalised systems use recommendation engines and adaptive e-learning to try to cut through this complexity. There has been advancement in the latter, which are often based on machine learning techniques and algorithms. Nevertheless, issues with accuracy, scalability, cold start, data scarcity, and time consumption still exist. We give an overview of recommendation systems in the context of e-learning in this article, breaking them down into four main categories: knowledge-based, content-based, collaborative filtering, and hybrid systems. We created a taxonomy that takes into consideration the elements needed to create a successful recommendation system. It was discovered that datasets, algorithms, evaluation, valuation, and output are essential elements of machine learning techniques. By offering a much-needed summary of the present status of research and lingering obstacles, this study significantly advances the area.

[10] Pointer-based item-to-item collaborative filtering recommendation system using a machine learning model With the introduction of digital marketing, businesses may now offer customised product recommendations to their clientele. They stay ahead of the competition thanks to this procedure. An item-based recommendation system, sometimes referred to as item-item collaborative filtering, is one method of item recommendation. At the moment, ratings ranging from 1 to 5 are the only factors used to propose items; comments are not taken into consideration. Customers or users share their opinions regarding goods and services in this context. In this paper, a machine learning model system with a product rating system based on 0, 2, and 4 is proposed. 2 is neutral, 4 is positive, and 0 is negative. This will be added to the current review system, which manages user reviews and comments without interfering with it. To run the internal work, we have constructed this model using the Sci-kit Learning, Pandas, and Keras libraries. For Yelp datasets of companies across 11 metropolitan regions in four nations, the suggested approach improves prediction with 79% Accuracy, combined with a Mean Absolute Error (MAE) of 21%, Precision at 79%, Recall at 80%, and F1-Score at 79%. Our model demonstrates the benefit of scalability and how businesses may transform their recommender systems to draw in more clients and boost revenue. In order to assess the suggested similarity algorithm's correctness and performance in terms of Root Mean Square Error (RSME), Precision, and Recall, it was also compared to conventional algorithms. The experiment's findings demonstrate that the similarity recommendation algorithm outperforms the traditional approach and improves suggestion.

CONCLUSION:

In conclusion , the wide range of benefits offered by different personalized e-learning algorithms emphasizes how complex it is to customize instructional materials for specific students. When viewed as individual properties, each algorithm contributes special advantages to the fields of personalized learning and course recommendation. An extensive analysis of these algorithms demonstrates a range of advantages, from improving learner engagement to tailoring information delivery to individual preferences and learning styles. Combining these algorithmic qualities offers a viable way to greatly increase the effectiveness of course recommendation systems. A more sophisticated and successful strategy for individualized learning can be developed by educators and developers by comprehending and utilizing the advantages of various algorithms. A more customized response to the various requirements and preferences of learners is made possible by the range of algorithmic solutions available, which eventually leads to an improved learning environment. Furthermore, the use of these algorithms is consistent with the larger movement in educational technology to incorporate artificial intelligence (AI). It is clear from the findings of this study that there is room for significant improvement in the effectiveness of course suggestions. A more responsive and efficient educational ecology is facilitated by the personalized deployment of different algorithms in conjunction with a detailed understanding of student demands. These results offer a strong basis for future research and development, indicating ongoing progress in the effort to maximize the effectiveness and efficiency of course suggestions in e-learning environments as we map out the future of personalized education.

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