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USING NEURAL COLLABORATIVE FILTERING TO PERSONALIZE ONLINE LEARNING CONTENT

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Abstract

Personalization of learning is a strategy used to determine the characteristics of learners so they can learn effectively. There are many approaches that can be taken to personalize learning. This system for personalizing learning content in the form of recommendations for online learning content was built using the Neural Collaborative Filtering method and utilizes a collection of implicit feedback data taken from student activity records when interacting with online learning content as reference data to produce recommendations. The design of a learning content personalization system in the form of recommendations on online learning content for students using the Neural Collaborative Filtering method has been successfully built and can run well in online learning content. The literature study approach was used to conduct the research. Data and relevant information were gathered through a review of the literature using Neural Collaborative Filtering to personalize online learning content. This research discusses traditional methods in personalizing online learning content, Neural Collaborative Filtering, relevant previous research, and the implementation of Neural Collaborative Filtering in online learning content.

Keywords: Neural Collaborative Filtering, online learning content

INTRODUCTION

One way to improve student happiness, motivation, and interest in studying is to provide relevant learning materials. On the other hand, this frequently results in students ignoring some learning content since it is

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challenging to find curriculum that meets the requirements and interests of every student. The online teaching and learning sessions that have been carried out so far include lecturers providing learning content in the form of material slides, meetings with Google Meet and assignments which must be accessed by all students in online learning content (Curtin & Sarju, 2021). Apart from that, lecturers also provide alternative learning content that students can learn, such as additional material, learning video links, and discussion forums in online learning content. This alternative learning content is provided by the lecturer so that students can still obtain reliable sources of learning content that are in accordance with what is taught by the lecturer. However, not all alternative learning content is appropriate to what every student needs. This is certainly a weakness in online teaching and learning sessions in online learning content. For this reason, lecturers hope that there is a system in online learning content that can provide suggestions or recommendations for appropriate learning content for each student, so that the learning content provided in online learning content can suit their needs and interests when studying. According to Lee et al (2018), the use of personalized tools in the form of recommendations has been proven to increase students' interest, understanding and success in learning. Personalization itself is a form of refinement of customization that is carried out automatically by the system.

Data on system requirements that are easier to interpret and incorporate into software can be generated by recommendation systems. Combining different recommendation techniques results in a recommendation based on Fermat points that is more thorough. Education has never been averse to new technology and has finally moved to make use of the Internet. With time, the use of information and communication technologies in teaching and learning has given rise to a field of study and practice known as technology-enhanced learning. There needs to be a recommendation system to help students determine topics according to their abilities or understanding of learning.

The online learning recommendation system is designed as a basic concept using the Using Case-Based Reasoning (CBR) Model, but special studies are needed so that the completeness and accuracy of the data becomes complex by implementing the use of the Neural Collaborative Filtering (NCF) algorithm, which will later be implemented as the basic concept of the system online learning recommendations built by a team of educators. This research is really needed so that the research results can be used later and is a new technology in improving online learning content and application models implementing the use of the Neural Collaborative Filtering algorithm (He et al, 2017). This research takes several previous research references including journals related to this research. Different recommendation systems function on two levels. Initially, a ranked list of learning objects is generated based on how well the source repository indicates their quality and how well they correspond to the query. Subsequently, the social media characteristics are employed to demonstrate to educators how the learning objects on the list have been misused in other classes.

Broadly speaking, two techniques for making recommendations are Content Based Filtering and Neural Collaborative Filtering. The recommendations made by Content Based Filtering are based on the item's description; if there are more products that need to be recommended, the algorithm will take longer to extract them all. The Neural Collaborative Filtering approach generates recommendations based on the relationship between people who enjoy a given item, in contrast to the Content Based Filtering method. For instance, the algorithm will suggest item X if user A enjoys items X and Y and user B likes item Y. This is how it enhances the performance of recommendations (Murad et al, 2020).

Generally, in the Neural Collaborative Filtering method, the user's interest in an item can be represented by the size of the rating given by the user to the item. In general, obtaining rating data consists of two ways, namely explicitly and implicitly. In this research, the rating data collection was collected implicitly, where the rating data was obtained from students' activities when interacting with online learning content.

According to Zou et al (2020), this implicit method of collecting rating data is a smart method, because students will not realize that their activities are being used as rating data. Based on the background explained above, the author tries to design a learning content personalization system in the form of online learning content recommendations for students using the Neural Collaborative Filtering method, based on the learning content they have previously accessed. Rating data is collected implicitly (implicit feedback) based on student activities when accessing online learning content. Thus, it is hoped that this personalization system can provide suggestions or recommendations for learning content that suits students' needs and interests. On the other hand, if online learning content is able to provide a personalized approach as needed by students, then factors such as cost and time for developing an e-learning system will certainly be more effective.

RESEARCH METHOD

Qualitative research employing a literature study methodology is the research methodology adopted. Using Neural Collaborative Filtering to tailor online learning content, literature study is a data collection strategy that involves searching books, journals, scientific works, encyclopedias, the internet, publications from agencies, and other related sources for relevant information. The process of gathering data for this study involves looking for and creating sources from a variety of sources, such as books, journals, and completed research (Mardalis, 1999 in Mirzaqon, 2017). To bolster the claims and concepts, library materials gathered from a variety of references are critically examined and need to be thoroughly explored.

The researcher identifies the issue to be studied then looks for reading materials in journals or books that contain discussions and theories about the topic to be researched. This research aims to find out how to use Neural Collaborative Filtering to personalize online learning content.

RESULT AND DISCUSSION

Traditional Methods in Personalizing Learning Content

In learning activities, basically each learner has different characteristics, needs and preferences. In terms of speed and ability, there are learners who are quickly able to capture and process information, but there are also learners who are slow. According to Taylor et al (2021), in terms of format preferences for learning materials, there are students who like materials in the form of text, audio or video. In terms of comfort, there are differences, there are students who are comfortable and concentrate on studying during the day, but there are also students who are more comfortable and concentrate when studying at night. Unfortunately, these fundamental learner differences cannot be accommodated in conventional learning. In conventional learning, educators provide the same treatment to students. This makes students uncomfortable, stressed, and unable to perform at their best in learning. In the end, there are students who succeed in achieving the learning objectives by getting good grades, but there are also students who fail and have to repeat.

The concept of personalizing learning experiences has been around for a while in the field of education, and in the Web 4.0 age, it is beginning to gain traction. According to Garrido & Morales (2014), personalization in education is a special approach that is predicated on the needs, interests, and talents of each individual student. Up until now, the goal of education's teaching and learning strategies has always been to make them accessible to all. Textbooks still contain broad material, and the general education system is still built on a teaching and learning concept. Nonetheless, it's critical to first determine each person's strengths and shortcomings in order to attain the maximum level of efficacy in teaching.

Personalization of learning is a strategy used to determine the characteristics of learners so they can learn effectively. There are many approaches that can be taken to personalize learning. In terms of the process of identifying learner characteristics, many researchers use different factors such as learning style, motivation, knowledge ability, and other factors. From a technical perspective, there are several approaches used by researchers, including using data mining, web semantics, and predefined rules. Personalization of learning can take three forms. First, personalization of the learning flow is personalization in the form of providing recommendations for learning steps that suit learning preferences in studying the material. Second, personalization of the learning media interface is personalization that is more focused on changing the appearance of the learning media such as font type, font size, menu layout, colors and background images. Third, personalization of learning content is personalization in the form of providing learning content that suits the needs and preferences of learners (Ghazali et al, 2015).

Research on the traits, skills, shortcomings, and qualifications of each individual forms the foundation of personalized learning experiences. Personalized approaches will therefore save you time by avoiding the need to study unrelated content that is out of context for your experience and skill level. Students will attain results faster and finish learning objectives in less time if they concentrate on the necessary content understanding (A. Qaffas et al, 2020).

We have total influence over the learning process when we receive a personalized learning experience. When paired with contemporary technology, personalization of the learning process grants students autonomy, enabling them to select courses and acquire knowledge according to their own objectives and passions. The knowledge that emerges from the filtering process will be far more engaging, satisfying the needs of the learner and accelerating their rate of information retention as well as their capacity for interaction.

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Three-quarters of schools that tried with individualized learning experienced very positive results in terms of student test performance, according to study done in the United States by the Gates Foundation. In particular, students' average mathematics scores increased from below the national average to above the national average following the implementation of individualized strategies for mathematics teaching and learning.

In addition to the Gates Foundation study, numerous other studies demonstrate how customization in education can enhance learning outcomes by altering the way that students are approached. By giving students content that is more tailored to their requirements, personalization promotes engagement with academic material and enhances learning results.

The implementation of a learn-to-earn model in online education will contribute to the exciting transformation of the learning process into an exhilarating voyage of knowledge discovery, as the education sector makes enormous gains in personalizing the learner experience. All game objects, characters, and assets are owned by learners through the Learn-to-earn feature in the form of NFTs, which they can use to accrue reward points as they learn. The same as in the actual world, users can invest in, purchase, sell, hold, swap, and trade NFTs. Learn to Earn has the power to revolutionize the educational process by removing the biggest obstacle that a lot of students encounter: a lack of motivation. You may learn, invest, create wealth for yourself, and transform your recently gained knowledge into priceless assets with Learn to Earn (Blazheska et al, 2017).

One could argue that teaching students how to get something can inspire them to work harder and more conscientiously, as well as to devote more time and energy to their studies.

Neural Collaborative Filtering

The development of the internet has driven the pace of development of online services that can be accessed easily by the general public, such as e-commerce, music subscription services and social media. This development was also followed by the development of data generated from user activities (Bai et al, 2017). This data is considered very valuable because after processing it, a pattern can be drawn from the user and this can drive business speed. Because this pattern can be predicted, artificial intelligence emerged which is called a recommendation system.

In simple terms, the way this recommendation system works is divided into 2 mechanisms. In the first, the system recommends items or films to users based on items they have used or purchased before. The implementation of this system is by using weighted rating or matrix factorization. Second, the system recommends items based on similarities to other items, such as similarity in item type. This type of implementation can be done using the similarity function. However, this simple recommendation system has several weaknesses, one of which is the condition when the user has never purchased an item at all or is called a cold-start (Chen et al, 2019).

To overcome these weaknesses, a new recommendation system was created called Neural Collaborative Filtering. This system is implemented using a deep neural network which consists of an input layer, an embedding layer, a collaborative filtering layer, and an output layer. The combination of each of these layers represents a simple neural collaborative filtering framework. The user and item vector represents each interaction of each user and item. Vectors u and I are generic input vector representations so that vector u can be replaced with a feature vector if no user has ever interacted with the item. This also overcomes the shortcomings of previous recommendation systems, namely the cold-start problem.

One of the methods used to create recommender systems is neural collaborative filtering, which has shown to produce very good outcomes. The most significant component of this algorithm is the product ratings, which are derived from the majority of buyers who expressly rate the product. The system's analysis of this data, as demonstrated by an illustration from a scale of zero to five that shows the least preferred to most preferred assessment from the customer's perspective, leads to the conclusion that the system gives returns to customers. It is feasible to perform statistical computations using this data, and the results show which products are superior received a positive review from clients (He et al, 2018). A database that is collected from users is used by Neural Collaborative Filtering. To generate predictions for the recommender system, this data consists of two primary components: items and users.

Neural Collaborative Filtering is a technique in recommendation systems that is popularly used today. Many studies discuss this technique because of its several advantages, such as: producing serendipity (unexpected) items, according to market trends, easy to implement and allows it to be applied in several domains. The way this technique works is by utilizing data on the community by looking for similarities between users, namely assuming that users who have similar preferences in the past are likely to have the same preferences in the future. Basically, we will be more confident in recommendations from people who have the same preferences as us, this is the basis used by collaborative filtering in generating recommendation items (Guo & Yan, 2020).

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A multi-layer representation of user interactions with items denoted by yui is used in Neural Collaborative Filtering. Implicit information gleaned from readers' and users' interactions with the news is used as news data. A yui value of one indicates that the user and the object are interacting, but it does not imply that user u likes item i. Similarly, a result of 0 does not necessarily indicate that user u dislikes item i; rather, it may indicate that the user interacts with item i despite being unaware of its existence. The output of one layer will become the input of the next layer. In neural collaborative filtering, two latent vector features are used, namely user latent vector and item latent vector. It can be transformed by converting it into a binary sparse vector with one hot encoding, where u and i are the user and item, respectively, and are represented by a variable. It is evident that the embedding layer serves as the input layer in the neural collaborative architecture. A multi-layer neural architecture known as the collaborative filtering layer incorporates user and item embedding in order to map latent vectors and generate anticipated values from the outcomes. Neural collaborative filtering allows for the customization of each layer to look for latent patterns derived from interactions between users and items. The final dimension that determines the capability model is symbolized by yui by minimizing the pointwise loss of ŷui with the target value yui (Rendle et al, 2020).

Relevant Previous Research

This research takes several previous research references including journals related to this research. Different recommendation systems function on two levels. Initially, a rating list of Learning Objects is generated based on how well the source repository indicates their quality and how well they correspond to the query. Furthermore, teachers can see how the mentioned Learning Objects have been utilized unfairly in other courses by using the socially created features. Pratama, Mustaqiem, Minarni (2021) conducted research by developing an application for submitting thesis titles online using the Winnowing Algorithm.

The recommendation system can provide recommendations for acceptance of the proposed title based on a comparison of the percentage of similarity with the acceptable percentage limit of similarity that has been determined in the system. Mawanta, Gunawan, Wanayumini (2021) conducted research by testing the similarity of final assignment title sentences using the cosine similarity method and TFIDF weighting with an average time result of 0.12117 in minutes.

Andakke (2021) conducted research to produce a thesis title bank information system, adaptation of research and development (Research and Development) with the ADDIE development model, it is known that the test results used the ISO 9126 standard with 4 characteristics, namely functionality

(100%), reliability (100 %) no errors were found and by using white-box testing no logical errors were found. The research was carried out by developing a recommendation system using Neural Collaborative Filtering where later students were asked to choose the courses they were interested in along with their grades. After obtaining the required data, the recommendation system will process the data and then display the title and abstract of the publication that best suits the entered data.

Implementation of Neural Collaborative Filtering in Online Learning Content

Ling, G., Yang, H., King, I., & Lyu, M. R. (2012) stated that the system for personalizing learning content in the form of recommendations for online learning content was built using the Neural Collaborative Filtering method and utilizing a collection of implicit feedback data taken from student activity records when interacting with online learning content as reference data to produce recommendations. The following is an explanation of the workflow of the personalization system implemented in this research.

1. Pre-processing

   At this stage, student activity logs are taken from the online learning content database implicitly. Each implicit feedback attribute is calculated with the COUNT() function by grouping the ID of each student and the ID of each learning content they have accessed, thus producing a rating value. Based on research conducted by Wimmer et al., it was concluded that the rating scale 1-10 is the best scale and can describe the widest differences, so the rating values that have been obtained are then normalized so that the rating values remain in the range 1-10. Where 10 indicates that students are very interested in certain learning content. The rating value will be 0 if a learning content has never been accessed by students.
2. Neural Collaborative Filtering

   The next stage is to look for learning content that is similar to each other, using one of the Neural Collaborative Filtering models, namely kNN. The result of this stage is a similarity value which shows how similar the learning content is to each other. First, calculate similarity based-distance using the Euclidean formula. This formula is used to calculate the similarity value between learning content u and v which has received a rating value from students l. Second, calculate the predicted value of learning content ratings for students using the weighted sum technique. If students have accessed certain learning content, then the predicted value is empty. The system will only calculate and display predictions of learning content that has never been accessed by students. The following is the weighted sum technique used. For each learning content that is similar to m3, a calculation is carried out as in the example above and produces a predicted value for the learning content rating. The design of a learning content personalization system in the form of recommendations on online learning content for students using the Neural Collaborative Filtering method has been successfully built and can run well in online learning content. Based on the results of the Mean Absolute Error (MAE) test, it was concluded that the personalization system which had been built using the Neural Collaborative Filtering method had the best level of accuracy during the 5th test at a sparsity level of 10% with the lowest average MAE value of 0.4514 and based on the results of User Acceptance calculations. Test (UAT), it was concluded that this personalization system was well accepted by 82.67% of students when viewed from three aspects, namely the Display Aspect, User Aspect, and System Interaction Aspect (Alfian Fathurrahman et al, 2022).

CONCLUSION

Personalization of learning is a strategy used to determine the characteristics of learners so they can learn effectively. There are many approaches that can be taken to personalize learning. In terms of the process of identifying learner characteristics, many researchers use different factors such as learning style, motivation, knowledge ability, and other factors. Research on the traits, skills, shortcomings, and qualifications of each individual forms the foundation of personalized learning experiences. Personalized approaches will therefore save you time by avoiding the need to study unrelated content that is out of context for your experience and skill level.

This system for personalizing learning content in the form of recommendations for online learning content was built using the Neural Collaborative Filtering method and utilizes a collection of implicit feedback data taken from student activity records when interacting with online learning content as reference data to produce recommendations. The design of a learning content personalization system in the form of recommendations on online learning content for students using the Neural Collaborative Filtering method has been successfully built and can run well in online learning content.

REFERENCES

A. Qaffas, A., Kaabi, K., Shadiev, R., & Essalmi, F. (2020). Towards an optimal personalization strategy in MOOCs. *Smart Learning Environments*, *7*(1), 14.

Andakke I. Pengembangan Sistem Informasi Bank Judul Skripsi Terintegrasi Sistem Pengajuan Judul Pada Jurusan Pendidikan Teknik Elektro Fakultas Teknik Universitas Negeri Makassar (Doctoral dissertation, Universitas Negeri Makassar).

Bai, T., Wen, J. R., Zhang, J., & Zhao, W. X. (2017, November). A neural collaborative filtering model with interaction-based neighborhood. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management* (pp. 1979-1982).

Blazheska-Tabakovska, N., Ivanovic, M., Klasnja-Milicevic, A., & Ivkovic, J. (2017). Comparison of E-learning personalization systems: Protus and PLeMSys. *International Journal of Emerging Technologies in Learning (iJET)*, *12*(1), 57-70.

Chen, W., Cai, F., Chen, H., & Rijke, M. D. (2019). Joint neural collaborative filtering for recommender systems. *ACM Transactions on Information Systems (TOIS)*, *37*(4), 1-30.

Curtin, A. L., & Sarju, J. P. (2021). Students as partners: Co-creation of online learning to deliver high quality, personalized content. In *Advances in Online Chemistry Education* (pp. 135-163). American Chemical Society.

Er-Radi, H., Aammou, S., & Jdidou, A. (2023). PERSONALIZED LEARNING THROUGH ADAPTIVE CONTENT MODIFICATION: EXPLORING THE IMPACT OF CONTENT DIFFICULTY ADJUSTMENT ON LEARNER PERFORMANCE. *Conhecimento & Diversidade*, *15*(39), 263-275.

Garrido, A., & Morales, L. (2014). E-learning and intelligent planning: Improving content personalization. *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje*, *9*(1), 1-7.

Ghazali, A. S. M., Noor, S. F. M., & Saad, S. (2015, August). Review of personalized learning approaches and methods in e-learning environment. In *2015 International Conference on Electrical Engineering and Informatics (ICEEI)* (pp. 624-627). IEEE.

Guo, Y., & Yan, Z. (2020). Recommended system: attentive neural collaborative filtering. *IEEE access*, *8*, 125953-125960.

He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017, April). Neural collaborative filtering. In *Proceedings of the 26th international conference on world wide web* (pp. 173-182).

He, X., Du, X., Wang, X., Tian, F., Tang, J., & Chua, T. S. (2018). Outer product-based neural collaborative filtering. *arXiv preprint arXiv:1808.03912*.

Lee, D. H., Cho, S. H., & Kim, Y. (2018). A design and development of the learning contents management based on the personalized online learning. *International Journal on Advanced Science, Engineering and Information Technology*, *8*(4), 1321-1326.

Ling, G., Yang, H., King, I., & Lyu, M. R. (2012, June). Online learning for collaborative filtering. In *The 2012 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE.

Mawanta I, Gunawan TS, Wanayumini W. Uji Kemiripan Kalimat Judul Tugas Akhir dengan Metode Cosine *Similarity* dan Pembobotan TFIDF. JURNAL MEDIA INFORMATIKA BUDIDARMA. 2021 Apr 25;5(2):726-38.

Mirzaqon. T, A dan Budi Purwoko. (2017). Studi Kepustakaan Mengenai Landasan Teori dan Praktik Konseling Expressive Writing. Jurnal BK Unesa, 8 (1).

Alfian Fathurrahman., Kusuma Ayu L., Dawam D. (2022). Penerapan Metode Collaborative Filtering untuk Personalized Learning Content pada Learning Management System (LMS). JURIKOM (Jurnal Riset Komputer), Vol. 9 No. 2.

Murad, D. F., Heryadi, Y., Isa, S. M., & Budiharto, W. (2020). Personalization of study material based on predicted final grades using multi-criteria user-collaborative filtering recommender system. *Education and Information Technologies*, *25*(6), 5655-5668.

Pratama NP, Mustaqiem M, Minarni M. Pengembangan Sistem Informasi Pengelolaan Judul Skripsi dan Tugas Akhir dengan Fitur Deteksi Kemiripan Menggunakan Algoritma Winnowing. TIN: Terapan Informatika Nusantara. 2021 Oct 15;2(5):271-8.

Rendle, S., Krichene, W., Zhang, L., & Anderson, J. (2020, September). Neural collaborative filtering vs. matrix factorization revisited. In *Proceedings of the 14th ACM Conference on Recommender Systems* (pp. 240-248).

Taylor, D. L., Yeung, M., & Bashet, A. Z. (2021). Personalized and adaptive learning. *Innovative learning environments in STEM higher education: Opportunities, Challenges, and Looking Forward*, 17-34.

Wang, X., He, X., Wang, M., Feng, F., & Chua, T. S. (2019, July). Neural graph collaborative filtering. In *Proceedings of the 42nd international ACM SIGIR conference on Research and development in Information Retrieval* (pp. 165-174).

Zou, L., Xia, L., Gu, Y., Zhao, X., Liu, W., Huang, J. X., & Yin, D. (2020, July). Neural interactive collaborative filtering. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 749-758).