ISSN 2228-9860 eISSN 1906-9642 CODEN: ITJEA8

International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies

http://TuEngr.com

Deep Learning for MOOCs Course Recommendation Systems: State of the Art Survey

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Paper ID: 12A11Q
Volume 12 Issue 11
Received 25 June 2021
Received in revised form 25 August 2021
Accepted 28 August 2021
Available online 08 September 2021

Keywords:
Recommendation system; MOOC; Deep Learning method; Literature Review; Deep course recommendation system; Personalized learning.

Abstract

The integration of the resources of massive open online courses (MOOCs) for the learning process is crucial. The power of the Internet and big data analysis technology brings the ultimate benefits for learners. With the help of the recommendation systems (RSs), the complexity in finding the needed learning materials is limited. MOOCs-based RSs provide suggested quality of courses to learners. Recently Deep Learning techniques have evolved to enhance MOOC's course recommendation results. This survey investigated different deep learning techniques in MOOCs for course recommendation due to the high performance and significant performance of these special types of neural network algorithms. This survey contributes to the field of MOOCs recommendation systems by overviewing the current research trends and the use of different deep learning models with MOOCs recommendation systems. Literature in the utilization of deep course recommendation systems is promising and outperforms the traditional recommendation techniques.

Disciplinary: Information Technology, Education.

Cite This Article:

Alahmadi, D., Alruwaili, F. (2021). Deep Learning for MOOCs Course Recommendation Systems: State of the Art Survey. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies, 12*(11), 12A11Q, 1-9. http://TUENGR.COM/V12/12A11Q.pdf DOI: 10.14456/ITJEMAST.2021.227

1 Introduction

Massive open online courses (MOOCs) have spread all over the world due to the course's variety and easy access to the platforms such as Udacity, Coursera, and edX. Therefore, many education systems and learners are attracted to MOOCs. Notably, with the increased demand for distance learning, tremendous amounts of the offered courses information overwhelmed learners and confused them to find the right course that matches their need. The exponential growth of courses information reduces the effectiveness of the learning decisions; therefore, recommendation systems solutions are used to improve the quality of course selections [1].

1.1 Recommender Systems

Traditional recommendation methods are applied successfully in different areas such as e-commerce, news, movies and books and e-learning, to detect users' feedback that represents users' preferences. In the literature, there are three fundamental categories of techniques in Recommender Systems [2]:

- Collaborative Filtering: this technique is widely used and it is basically based on the historically collected data and building common history between similar users.
- Content-based: this technique uses the content collected from the users' preferences profile, item information and profile. For instance, in the context of book recommendation systems, it collects books content information like author, title, ratings, etc. Then, it applies comparison with the user's book preferences profile.
- Hybrid Filtering Approach: It is a combination of different approaches and techniques. Basically, it uses features from collaborative and content-based filtering. This is to discover broader suggestions and overcome any upcoming limitations.

Other methods such as Knowledge-dependent Recommendation and Demographic Recommendation as they are based on information from users preferences history are explained next.

1.2 MOOCs Recommender Systems

This section highlights recent trends in the utilization of RSs on MOOCs platforms. Generally speaking, RSs provide solutions to the several problems faced by learners in MOOCs, for instance, choosing courses among numerous options, predicting the full path of learning, predicting learning style, course dropout.

For example, Radoiu [3], which integrated the user attributes, user behavior, and item attributes in the MOOCs platform in order to suggest courses. In a different context, Kardan et al. [4], analyzed the social network to lead learners in order to match the relevant information in MOOCs platforms. Abhinav et al. [5] presented a framework of hybrid recommendation systems to address the cold start problem. Several predictive models have been combined to provide efficient course recommendations for learners. While other studies such as Xiao Li et al. [6] have relied on analysis of the user preferences and behavior besides the demographics data to enhance recommendations accuracy. Additionally, Huang & Lu [7] present a content-based model in MOOCs for intelligent education, which contributed to the development of user profiling. They have used User Interest Analysis on the MOOCs page to create a user profile and provide recommendations that match the user's activity log. Zhang et al. [8] developed a recommendations model based on content analysis for learners and educational courses, called (MOOCRC), to predict the scores of learners using deep belief networks (DBNs) in MOOC environments.

In the era of social media, natural language processing techniques (NLP) were applied to study the users' behavior on Online Social Networks (OSN) to provide them with recommendations that improve their decision-making process. Dai et al. [9] also have a contribution in this field by using the available personal data on LinkedIn pages. Customized recommendations were suggested to learners based on their preferences focusing on the job market demands. In addition to that, [10] used data taken from two well-known social networks, LinkedIn and Twitter, to provide users with recommendations that largely correspond to their written information in both LinkedIn and Twitter. This study proved to be highly effective in recommendation systems. The last research was for Kumalasari & Susanto [11], in which they collected data from professional profiles in LinkedIn for IT professionals to be used as a reference for the skills that will be presented later as a recommendation for students and job seekers.

These methods are recently replaced by the neural recommendation models based on deep learning techniques [12-13]. This paper aims to investigate the literature and answer this question: what is the state of the art of deep learning utilization in MOOCs course recommendations? The primary contributions of this article are to (1) summarize the main deep learning existing recent works for course MOOCs recommendations, and (2) underline datasets that are experimented with to train and test deep learning models.

2 Methodology

This section illustrates the methodology and the process of retrieving and searching the existing studies on MOOCs course recommendations using deep learning.

Review procedure was employed [12] with the following steps:

2.1 Determining the Topic of the Research

In terms of the paper gathering, the following popular scientific databases were accessed: ACM Digital Library (https://dl.acm.org), IEEEXplore (https://ieeexplore.ieee.org). Springer (https://www.springer.com), ScienceDirect (https://www.sciencedirect.com). Regarding the searched terms, in this survey, the keywords that were used to retrieve the papers are "deep learning" AND "MOOCs course recommendation".

2.2 Studies Retrieving Exclusion and Inclusion Criteria

A number of papers were extracted, duplicates and papers on unrelated topics are removed manually. Duration explored is from 2018-June 2021. In this paper, to be very concise in our investigation, topics such as the teaching style predictions, gamification or tag prediction in MOOCs platforms are excluded. The main scope of this research is to study the role of deep learning in improving the course recommendations in MOOCs platforms. To achieve a clear insight into the experiments applied in this domain, this survey gives the community a comprehensive understanding of the efforts that have been done in the fields.

2.3 Evaluation of the Quality of the Studies

To reach high quality of collected studies, the review focused on the well-known database and high citation number. However, deep learning algorithms have emerged as a rising trend solution in the literature and a large number of new papers published it in the last few years. For this reason, the citation number is noticed as not high.

2.4 Analysis of the Data

The extracted papers are filtered gradually to meet the review aim. Hundreds of papers result, however, thorough filtering steps starting from searching database engines until arrive at the final required papers are shown in Figure 1.

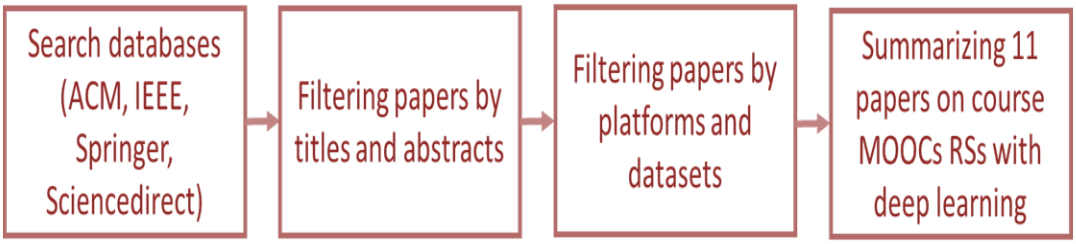

Figure 1: Literature review filtering process.

The final set contained in total 11 papers were extracted likely to contribute to MOOCs course recommendations with deep learning techniques. Figure 2 summarizes the number of studies per year. Over the years from 2018-June 2021. Three papers until the first half of 2021, more publications are expected by the end of the year.

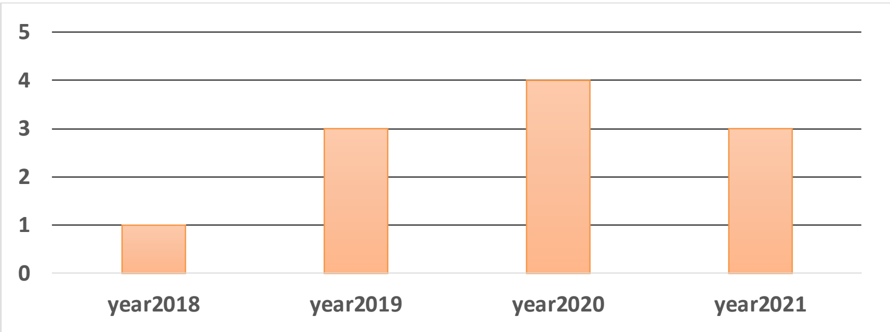

Figure 2: Number of papers per year

2.5 Report of the Results

In this section, the resulting papers are introduced, and the focus is twofold: main aim and problem solved.

In this respect, [14] aimed to detect the changes in users' choices, they tried to enhance recommendations by understanding the user profile interactions. Authors' solutions overcome limitations in the literature of ignoring users' dynamic interests and interaction behavior. They used the dataset: XuetangX (http://www.xuetangx.com). Another study [15] proposed a Top-N personalized Recommendation with Graph Neural Network (TP-GNN) in MOOCs. The models explore two types of aggregation functions to track the user's session sequence and then to use an attention mechanism to develop the final item profiles. The study tried to improve the problem in the previous studies of neglecting the implicit representation and recency of the items. The validation on a real-world course dataset showed the significant effect of TP-GNN. In addition, the system is gained positive feedback from the participants, which demonstrates the model efficiency in predicting learners' courses.

On the other side, efforts in [16] predicted future interest trajectories of students based on the forum thread. This is done by integration of two key operations: (1) Update and (2) Projection. First operation models the interdependency between the interaction of student and thread using well-known Recurrent Neural Networks when the student posts on the thread. The second operation predicts future courses of students and threads. For students, the projection operation understands the drift in their taste caused by the change in the course topic they study. The projection operation for threads shows how different posts are changing in courses levels for student-based to the thread structure. The study utilized the discussion forums to leverage interaction among forums to help in allocating informative discussion course forums considering the drift in learners' interest. With the same context of using discussion threads, [17] proposed a novel neural network framework for session-based thread recommendation (STR-SA) It recommended threads to a learner based on the threads clicked by the student in the visited session. The model learns the similarities between threads based on self-attention mechanisms. Moreover, the model detects the latest-visited session and thread as the current desire for learners. The model alleviated the problem of the massive amount of information of threads in different courses forums that confuses learners. In addition, [18] applies the item-based filtering technique with Bayesian Personalized Ranking for course recommendation problems. The solution is based on Bayesian Personalized Ranking and develops a novel neural network model, called Bayesian Personalized Ranking Network (BPRN). The model studies the pairwise course desires for each user extracted from learner-enrolled courses. The approach improves the solution of traditional item-based recommendation methods to be shifted from pointwise to pairwise course ratings. In terms of rating prediction, authors in [19] predicted the top-n courses with corresponding ratings from learner behaviors and learning. Using attention-based convolutional neural networks (CNN) to predict the user course ratings. They could enhance decisions of the next course among a number of choices.

To improve the formal education institutions, [20] presented a system that can recommend courses from MOOCs. Thus, to reduce the cost of course designing and course production in the formal platforms. Also, MOOCs include well interesting courses that can improve the quality of learning that can easily engage students. Deep Learning is also implemented in [21] for big data analysis. MOOCs recommendation approach is modelled with multilayer perceptron architecture with 7 hidden layers. The work developed a solution that adapted the changes in courses opportunities in data over these platforms. [22] proposed HCRDL: A Hybridized Approach for Course Recommendation Using Deep Learning. The approach integrates Recurrent Neural

Networks, long short-term memory (LSTM), N-Gram, and Jaccard similarity to increase accuracy against the available models. Courses are provided for learners based on their queries and interests. The effort aimed to reduce the complexity of finding the appropriate course. In [23], the study presented a personalized recommendation system based on Deep Reinforcement Learning that provides learners with a set of courses that match their profile, needs, and competencies. Features such as price, duration, complexity, and level are used to alleviate the difficulty in multi-criteria decision-making among a variety of courses.

In the case of learners' hidden patterns, [24] discovers a personalized learning full-path recommendation model based on neural networks. To accomplish this, two phases are combined. First, clustering a group of similar learners. Second, long short-term memory (LSTM) to predict the suitable full paths of courses. Table 1 summarizes the finding from literature review.

Table 1. Finding of the literature review.

Study	Model	Dataset	Description
[14]	Dynamic Attention and hierarchical Reinforcement Learning (DARL)	XuetangX	Focusing on the student dynamic interests and taste changes
[15]	Top-N personalized Recommendation with Graph Neural Network (TP-GNN)	XuetangX	Using Graph Neural network to learn the user's session sequence interactions
[16]	Learning future trajectories of students	Datasets from Coursera of three courses, Machine Learning, Algorithms, and English Composition in 2012	Predicting future interest courses of students based on the forum threads
[17]	Session-based thread recommendation (STR-SA)	General three course-forum datasets	Using session-based to predict course threads
[18]	Bayesian Personalized Ranking Network (BPRN)	XuetangX	Using pairwise course ratings to predict top-n courses
[19]	Attention-based convolutional neural networks (CNN)	no dataset and real experiment only prototype and Architecture of the solution	Focusing on learner behaviors and learning to predict top-n course ratings
[20]	Deep Recommender System for MOOCs	Randomly 250 courses from several MOOCs platforms (Coursera, edx.) in different fields.	Predicting courses from MOOCs for formal institutions to reduce the cost of designing new courses
[21]	(MOOCs) Recommendation Modeling using Deep Learning	Dataset from Harvard and MIT, in edX platform in 2012-2013	Focusing on the changes in courses opportunities in data over these platforms
[22]	HCRDL: A Hybridized Approach for Course Recommendation Using Deep Learning	Coursera dataset	Using learners queries and interests to predict similar courses
[23]	Deep Reinforcement Learning for Personalized Recommendation of Distance Learning	Set of real students and 100 courses from not specified e-learning platforms.	Using user profile and course profile features such as price, duration, complexity and level
[24]	Personalized learning full-path recommendation model based on LSTM neural networks	Dataset on learners' access to the courses from Edx open datasets.	Predicting suitable courses for a whole learning path

3 Results and Discussion

In total, 11 papers were found likely to contribute to MOOCs course recommendation using deep learning. The list of papers, their aims, methods, dataset, and description were given in Table 1. In general, the review results were analyzed in terms of the use of deep learning which indicated that attention are growing during the last three years. This is because of the high performance of deep learning models that outperform the traditional recommendation systems techniques.

Regarding datasets for studies experiments, a set of benchmark datasets are used. From the previous discussion of the literature, the validation process in [14-15] and [18] is based on the use of use XuetangX as an emerging benchmark dataset. While Coursera dataset is used in [16-20-22] and edX dataset is applied in [20-21] and [24]. The rest of the study built their own dataset from different MOOCs platforms not clearly indicated.

In terms of forum threads utilization, two efforts were presented in [16-17] to predict the next desirable courses. In [16] focused on the thread posts and analyzed the content. On the other side in [17] studied the clicks and behavior in thread sessions visited by learners.

Using context information, such as session-based recommendation is clearly implemented in the approaches of [15, 17]. Studies employed the implicit data of clicked session, time and recency to provide course recommendations.

Different deep learning methods are implemented in the collected papers. Popular deep learning models such as Deep Reinforcement Learning were integrated into the solution of [14] and [23], while Convolutional Neural Networks are used in [19] and Recurrent Neural Network is applied in [16] and [22]. A set of newly implemented deep neural networks are developed in combination with other techniques such as ranking algorithms in [18] and with big data analysis techniques in [21] and Graph Neural Network is tested in [15]. long short-term memory (LSTM) is a type of Recurrent Neural Network that is also developed in [22, 24] combined with a clustering algorithm.

4 Conclusion

In this paper, a literature review on MOOCs course Recommendation Systems was investigated, and the findings were presented. The main conclusion is that MOOCs recommendation approaches using deep learning are a promising solution for courses recommendations. The studies demonstrated that deep learning has been increasingly embedded in different types and solutions. This paper aims to contribute to the literature by underlining the studies about MOOCs course recommendations using deep learning and providing a set of reviewed papers along with a comparison of aims and models for future studies in the field.

Further review studies can be established to cover a broader set of inclusion, exclusion criteria, and duration. Furthermore, a variety of academic journals from more databases can be investigated in the next step for a literature review of MOOCs and deep learning.

5 Availability of Data and Material

Data can be made available by contacting the corresponding author.

6 References

[1] Zhang, H., Huang, T., Lv, Z., Liu, S. Y. & Zhou, Z. MCRS: A course recommendation system for MOOCs. Multimed. Tools Appl. 77, 7051-7069 (2018).

[2] Xing, W. & Du, D. Dropout Prediction in MOOCs: Using Deep Learning for Personalized Intervention. J. Educ. Comput. Res. 57, 547-570 (2019).

[3] Rădoiu, D. Organization and Constraints of a Recommender System for Moocs. Sci. Bull. Univ. Tîrgu Mureş 11, 2286-3184 (2014).

[4] Kardan, A. A., Narimani, A. & Ataiefard, F. A Hybrid Approach for Thread Recommendation in MOOC Forums. Waset.Org 11, 2175-2181 (2017).

[5] Abhinav, K., Subramanian, V., Dubey, A., Bhat, P. & Venkat, A. D. LeCoRe: A Framework for Modeling Learner's preference. Educ. Data Min. Conf. (2018).

[6] Li, X., Wang, T., Wang, H. & Tang, J. Understanding User Interests Acquisition in Personalized Online Course Recommendation. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) 11268 LNCS, 230-242 (2018).

[7] Huang, R. & Lu, R. Research on Content-based MOOC Recommender Model. 2018 5th Int. Conf. Syst. Informatics, ICSAI 2018 676-681 (2019) doi: 10.1109/ICSAI.2018.8599503.

[8] Zhang, H., Huang, T., Lv, Z., Liu, S. & Yang, H. MOOCRC: A Highly Accurate Resource Recommendation Model for Use in MOOC Environments. Mob. Networks Appl. 24, 34-46 (2019).

[9] Dai, K., Vilas, A. F. & Redondo, R. P. D. A New MOOCs' Recommendation Framework based on LinkedIn Data. 13-19 (2017) doi:10.1007/978-981-10-2419-1.

[10] Pourheidari, V., Mollashahi, E. S., Vassileva, J. & Deters, R. Recommender System based on Extracted Data from Different Social Media. A Study of Twitter and LinkedIn. 2018 IEEE 9th Annu. Inf. Technol. Electron. Mob. Commun. Conf. IEMCON 2018 215-222 (2019) doi:10.1109/IEMCON.2018.8614793.

[11] Kumalasari, L. D. & Susanto, A. Recommendation System of Information Technology Jobs using Collaborative Filtering Method Based on LinkedIn Skills Endorsement. 5, 35-39 (2020).

[12] Ricci, F., Rokach, L., Shapira, B. & Kantor, P. B. Recommender Systems Handbook. Journal of Chemical Information and Modeling vol. 53 (Springer US, 1989).

[13] Aher, S. B. & Lobo, L. M. R. J. Combination of machine learning algorithms for recommendation of courses in E-Learning System based on historical data. Knowledge-Based Syst. 51, 1-14 (2013).

[14] Lin, Y. et al. Adaptive course recommendation in MOOCs. Knowledge-Based Syst. 224, 107085 (2021).

[15] Wang, J., Xie, H., Wang, F. L., Lee, L.-K. & Au, O. T. S. Top-N personalized recommendation with graph neural networks in MOOCs. Comput. Educ. Artif. Intell. 2, 100010 (2021).

[16] Pandey, S., Lan, A., Karypis, G. & Srivastava, J. Learning Student Interest Trajectory for MOOC Thread Recommendation. IEEE Int. Conf. Data Min. Work. ICDMW 2020-Novem, 400-407 (2020).

[17] Zhang, M., Liu, S. & Wang, Y. STR-SA: Session-based thread recommendation for online course forum with self-attention. IEEE Glob. Eng. Educ. Conf. EDUCON 2020-April, 374-381 (2020).

[18] Li, X. et al. Improving Deep Item-Based Collaborative Filtering with Bayesian Personalized Ranking for MOOC Course Recommendation. in Knowledge Science, Engineering and Management (eds. Li, G. et al.) 247-258 (Springer International Publishing, 2020).

[19] Wang, J., Xie, H., Au, O. T. S., Zou, D. & Wang, F. L. Attention-Based CNN for Personalized Course Recommendations for MOOC Learners. Proc. - 2020 Int. Symp. Educ. Technol. ISET 2020 180-184 (2020) doi:10.1109/ISET49818.2020.00047.

[20] Mrhar, K. & Abik, M. Toward a Deep Recommender System for MOOCs Platforms. in Proceedings of the 2019 3rd International Conference on Advances in Artificial Intelligence 173-177 (Association for Computing Machinery, 2019). doi:10.1145/3369114.3369157.

[21] Sakboonyarat, S. & Tantatsanawong, P. Massive Open Online Courses (MOOCs) Recommendation Modeling using Deep Learning. in 2019 23rd International Computer Science and Engineering Conference (ICSEC) 275-280 (2019). doi:10.1109/ICSEC47112.2019.8974770.

[22] Roopak, N., Deepak, G. & Santhanavijayan, A. HCRDL: A Hybridized Approach for Course Recommendation Using Deep Learning. in Intelligent Systems Design and Applications (eds. Abraham, A. et al.) 1105-1113 (Springer International Publishing, 2021).

[23] Agrebi, M., Sendi, M. & Abed, M. Deep Reinforcement Learning for Personalized Recommendation of Distance Learning. in New Knowledge in Information Systems and Technologies (eds. Rocha, Á., Adeli, H., Reis, L. P. & Costanzo, S.) 597-606 (Springer International Publishing, 2019).

[24] Zhou, Y., Huang, C., Hu, Q., Zhu, J. & Tang, Y. Personalized learning full-path recommendation model based on LSTM neural networks. Inf. Sci. (Ny). 444, 135-152 (2018).

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