A Brief Survey of Deep Learning Approaches for Learning Analytics on MOOCs

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Abstract. Massive Open Online Course (MOOC) systems have become prevalent in recent years and draw more attention, a.o., due to the coronavirus pandemic's impact. However, there is a well-known higher chance of dropout from MOOCs than from conventional off-line courses. Researchers have implemented extensive methods to explore the reasons behind learner attrition or lack of interest to apply timely interventions. The recent success of neural networks has revolutionised extensive Learning Analytics (LA) tasks. More recently, the associated deep learning techniques are increasingly deployed to address the dropout prediction problem. This survey gives a timely and succinct overview of *deep learning techniques for MOOCs' learning analytics*. We mainly analyse the trends of feature processing and the model design in dropout prediction, respectively. Moreover, the recent incremental improvements over existing deep learning techniques and the commonly used public data sets have been presented. Finally, the paper proposes three future research directions in the field: *knowledge graphs with learning analytics, comprehensive social network analysis, composite behavioural analysis.*

Keywords: MOOCs · Deep Learning· Dropout Prediction · Learning Analytics.

1 Introduction

Although Massive Open Online Courses (MOOCs) have been deemed as a popular choice of online education [22], the low completion rate (7-10% on average) has become a primary concern [4, 8, 26]. To address the problem, researchers are interested in exploring why students drop out, by applying different approaches.

Concomitantly, deep learning is a major sub-domain of machine learning and has consistently obtained higher accuracy, compared with conventional statistical linear regression, including for student dropout prediction [6, 29].

Several previous papers surveyed the current progress of learning analytics in MOOCs [12, 41, 48], but none of them considered the application of deep learning in the area. In this paper, we specifically focus on analysing deep learning in MOOCs, by differentiating deep learning from classical machine learning. Extensive studies [40, 54, 56, 57, 61, 62] have investigated the dropout problem.

In this paper, a brief, timely overview of deep learning techniques that have been used to tackle the dropout problem, is presented. This study aims to help researchers understand the trends of using deep learning in MOOCs better and gain future research insights. The main contributions of this study are:

1. First presentation of a succinct and timely overview of the application of deep learning in MOOC dropout prediction.
2. Summarising the trends of feature processing and development of applied deep learning models for MOOCs, for informing research and implementation decisions of the community.
3. Identifying the recent improvements of existing deep learning techniques in the area and informing on the publicly available data for experimentation.
4. Discussing and highlighting of three possible future research directions: knowledge graph with learning analytics, comprehensive social network analysis and composite behavioural analysis.

2 Method

This paper surveys recent literature, to outline and clarify the progress of deep learning approaches to learning analytics, mainly regarding student dropout prediction. Extensive databases, including Springer Link, Association for Computing Machinery (ACM)and IEEE Xplore have been searched, by indexing keywords in titles, such as "MOOC dropout prediction", "deep learning in learning analytics", "application of deep learning in MOOC dropout prediction" and "MOOC dropout prediction using deep learning", and we found 570 papers published from 2015 to 2020. We only focused on primary research articles, surveys, evaluations or reviews were excluded. Papers that mainly used conventional machine learning for dropout prediction [19, 36] deep learning for other tasks e.g., grade prediction [17], learner interactions [15] or other purposes [33] rather than dropout prediction were also ruled out. We next examined the whole text of the 41 remaining papers to understand the content and focus of deep learning in MOOC dropout prediction. Furthermore, we analysed and evaluated the trends and improvements of deep learning on the topic of dropout prediction.

3 Deep Learning in Learning Analytics of MOOCs

As explained in Section 1, extensive studies [40, 54, 56, 57, 61, 62] have investigated the dropout problem. However, most of them only adopt the basic Recurrent Neural Networks (RNN) to process the sequential data. However, other advanced deep learning methods, such as Convolutional Neural Networks (CNN), Graph Neural Networks (GNN) and other deep learning models present promising alternatives. They are, however, less applied to dropout prediction in MOOCs, as analysed below.

Considering the temporal activities of students, existing dropout prediction researches in MOOCs mainly use RNN networks to obtain the temporal student behavioural information contained in the whole sequence [51]. Driven by the success in other prediction areas addressed before, CNN networks have started to be applied in learning analytics. CNN is a multi-layer neural network to extract features locally and could avoid the complex feature extraction. Currently, the main predictive features of existing dropout prediction studies using deep learning could be divided into *learning activity-based prediction* and *comment analysis on discussion forums*. We also present other *recent improvements* over existing deep learning techniques deployed in MOOC prediction.

3.1 Learning Activity-based Prediction

In the **learning activity-based prediction** field, we categorise the research into the development of the feature process and model selection. Studies [7, 14, 31] treated learning activities as features, which generally include *number of learning sessions*, *video viewing and clickstream*, *quiz attempt*, *forum views and posts*, *page views* and so on. However, those features generally require manual processing by RNN models that are not flexible and time-consuming.

To address this problem, [51] proposed a ConRec Network model consisting of CNN and RNN, to automatically extract features from raw records, as CNN networks performs well at automatic feature extraction from raw input [16]. Despite the success of feature processing, the ConRec model is not outperforming the conventional feature engineering method. [39] then used a two-dimensional CNN directly, to learn the best features from the raw click-stream data, to reduce the complexity of feature extraction; they reached 86.75% dropout forecast accuracy.

Recently, [26] reported novel progress of applying RNN directly to raw log-line level click-stream data with no feature engineering, which was inspired by the success of one popular variant of RNN models, the Long Short-Term Memory (LSTM) Networks, on anomaly detection using raw texts [63]. They combined Gated Recurrent Unit (GRU-RNN) and dropout layers to solve long-term temporal dependencies and over-fitting, which could be further extended to other large-scale data sets.

To conclude, reducing the complexity of feature selection and processing is an important trend in the research area and both CNN and RNN methods could achieve the goal, although the former is more intuitive and robust for raw click-stream data [26].

From the **model perspective**, some researches use fundamental deep learning models, such as Feedforward neural networks (FFNN), which do not consider the connections among nodes within the same layer, and thus represent the simplest type of artificial neural network [43]. For instance, [3] used FFNN in a dropout prediction study, but their results could not identify the dropout students early enough [56].

Due to the temporal nature of attrition in MOOCs, the most popular models used for the dropout prediction are RNNs, as they are based on the temporal prediction mechanism with trace data. However, RNN models generally suffer from long-term dependency on learning behaviours in these studies, leading to limited prediction performance. Additionally, all these studies [9, 14, 44, 50] stress more temporal characteristics, but neglect the fact that students are likely to exhibit similar learning patterns during a period.

Based on the above findings, [53] proposed a novel CNN model for dropout prediction, to capture the local correlation among the learning features, as a feature matrix. These studies mainly treat all the automatic extracted features equally, but fail in considering the relative influence of different features on the outcome of dropout prediction.

Addressing the problem, [65] developed a FWTS-CNN model to consider both feature weights and learning time series, by ranking the filtered key features. This idea is akin to the widely applied attention mechanism in deep learning introduced by [47], and improved accuracy by 2% compared to using CNN alone. [38] also reported 1.75% AUC (area under the curve) improvement by integrating an attention embedding of learners' behaviours. We refer the reader elsewhere [60] for more details on the attention mechanism.

3.2 Comment Analysis

Apart from the conventional predictors of learning, the analysis of informative comments and posts could provide an understanding of learners' satisfaction and attitudes [13]. This has become a current research hotspot in the area. For example, [59] found a positive correlation between the students' confusion posts in forums and dropout. [7] found a positive relation by applying an FFNN model to examine sentiments of the forum posts data to predict the student attrition in MOOCs in the following week, with an accuracy of 88%. [55] also found a negative correlation between participation in forums and dropout rate.

However, these existing studies simply explore the positive and negative emotions [32], while learners could have more complex achievement emotions, such as confusion, boredom, shame, which could affect the learning outcome [37]. A deeper understanding of the reasons of how students think and feel regarding the course could help to timely identify students at risk and help improve their engagement [21].

3.3 Recent Improvements

Several recent works made incremental improvements over existing deep learning techniques deployed in MOOC prediction. [24] incorporated a graph convolutional network (GCN), to consider more latent features of learners, such as social interaction with others and courses, as well as learners' embeddings (representations) for prediction. GCN is proposed by [25] to capture both global structural and local patterns by treating inputs as a graph. As graphs can be irregular, arbitrary, non-Euclidean in structure and contain rich values, they are arguably capable of representing the knowledge among entities (students and courses) in the real world [46, 64]. Additionally, most existing work focuses on performance prediction based on predefined fixed order of learning activities (videos, readings and assessment) while the conventional sequential models are unable to be implemented when there are online question pools where students could select which question to answer [30]. As nodes (entities) in graphs can be order-invariant, the student-interaction-question could be represented by a graph neural network (GNN) model; [30] proposed a novel method, R^{2}GCN, to fully model the knowledge evolution of students and predict their performance in interactive online question pools. The idea of representing the online learning system as a graph to leverage students' relations, activities and courses could be extended further. Additionally, most studies mainly utilise the post-hoc prediction structures, while required features are not entirely knowable for predictive models in incomplete courses [23]. Addressing the problem, [23] proposed a new algorithm based on knowledge distillation, which only requires a few basic features, but still reaches promising forecasting results.

3.4 Dataset Summary

Popular MOOC platforms are EdX, FutureLearn, Udemy, Coursera, Khan Academy, Canvas and other open online study channels. Researchers collected data from those platforms or use public datasets summarised as in Table 1, below.

Table 1. MOOC data set summary

Datasets	Category	Source	Citation
Standford MOOCPosts	Forum Discussion	[2]	[52]
Act-Mooc	Social Network	[27]	[58]
KDDCup 2015	Learning Analytics	[31]	[5, 51]
OULAD	Learning Analytics	[28]	[20, 24]
HarvardX Person	Learning Analytics	[34]	[23, 45]
Coursera Forums	Forum Discussion	[42]	[18]

4 Future Directions

Though deep learning techniques have proven their power for dropout prediction in MOOCs, there is still room for improvement, due to the complexity of learner behaviours and sentiments. As most studies only focus on prediction based on students' learning behaviors or other interaction activities, respectively, we suggest three future directions including more features using deep learning models, based on our review and the literature gaps it exposed.

- **Knowledge Graphs with Learning Analytics** As aforementioned, graphs can be flexible and expressive. Knowledge graphs (KGs) are graphs that consist of facts and relations among entities [49], and have been applied to MOOCs [11] to represent the online learning resources across several platforms and to represent the relations between students and courses [24]. In fact, these techniques could be implemented to account for more demographic information of learners, such as age, gender, nationality, working experience, educational background, disability, socio-economics and so on, studied to extend dropout prediction [35]. Advanced models, like GNN, could be deployed, to treat the demographic information as features of learners (nodes) and classify the type (active/neutral/passive) of learners, or cluster them into the same group with a similar background for further analysis. Additionally, by implementing GNN models (property of invariance to node order), the analysis of the knowledge evolution process could be extended to other learning analytics tasks, e.g., adaptive online learning and early intervention, without requiring the predefined learning curriculum.

- **Comprehensive Social Network Analysis** The social interactions of students could reflect their engagement and persistence in MOOCs. However, there is a lack of serious research efforts in analysing the influence of social network structures and other features of academic assessment (e.g., time of video watching, quiz attempts) comprehensively on students' engagement [10]. In addition to student-related factors, MOOC related factors like course design and lacking of isolation are crucial dropout predictors [1, 21]. Researchers could thereby consider how to integrate structural-based social network analysis with other students' learning activities and MOOC related factors like course content using deep learning models in future.
- **Composite Behavioural Analysis** In addition to learning activity-based prediction and comments analysis, multi-modal analysis is a possible future direction. As deep learning techniques push the dropout prediction, one research goal is to understand learners more comprehensively and in-depth, regarding their satisfaction, attitudes, confusion, boredom as well as other possible sentiments, to enhance their learning in MOOCs. To do so, researchers could also incorporate more behavioural observations and analysis, such as face emotion detection and physiological reactions based on CNN and other advanced models, which also allows instructors to consider the information to adapt their course content.

5 Conclusion

This paper presents a succinct survey of deep learning techniques for analysing the student dropout problem. The survey draws several conclusions. First, unlike conventional feature engineering techniques, the current trend is to use end-to-end deep learning models, including the recent RNNs and CNNs to automatically extract features from raw data. Second, despite the nature of gradual attrition in MOOC, CNNs are increasingly deployed to avoid the long-term dependency problem and complex feature processing. Third, many studies focus on providing early prediction based on rough discrete emotions, rather than understanding more in-depth sentiments and problem inducing student dropout, and thus new methods should be developed. Fourth, we identify the recent improved work over existing deep learning techniques applied in the area. Lastly, we summarise the commonly used public datasets and suggest three future directions for the study of deep learning in MOOCs: knowledge graphs with learning analytics, comprehensive social network analysis and composite behavioural analysis.

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10 Zhongtian Sun, Anoushka Harit, Jialin Yu, Alexandra I. Cristea and Lei Shi

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