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Research Article

Survey and Comparison of Deep Learning Applications to Improve MOOC Acceptability (The HOOK Project)

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Abstract

Massively Open Online Courses (MOOCs) have been demonstrating their potential to transform traditional online education since their disruption in 2012 with two major features : instructor tutoring and social networking of learners. However some drawback lies in their completion and student success rate remaining very low. In this article, we are focusing on deep learning applications to analyze MOOC data and generate real-time indicators for learners and online professors to improve MOOC acceptability. For this survey we searched for relevant articles using Google Scholar (during the period 2017-2021) and the ERIC database (period 2019-2021) and selected twenty-one articles that demonstrated deep learning methods for MOOC approach improvement. We categorized them into three areas: "MOOC student final outcome prediction" (twelve articles), "MOOC forum post classification" (six articles), and "MOOC student current/next outcome prediction and recommendation" (three articles). We conclude that section by identifying that most deep learning architectures built for these applications focus on student final outcome prediction and use variants of recurrent neural networks (RNN). We also remark that the most occurring datasets were the Stanford MOOC Posts dataset and OULAD. Then in the second part of this article, we functionally compare these major deep learning platforms for MOOC improvement with the one we are building with France Université Numérique(FUN) named HOOK (Human Open Online Knowledge) platform.

Keywords: MOOC (Massive Open Online Courses); E-learning, Online Learning, Big Data; AI, Machine Learning; Deep Learning

Introduction: Towards Customized Online Learning

"Our civilization produces a hundred times more knowledge every century, which represents a million times more today compared to the 18th century!" (François Taddei, December 2019) and we cannot imagine spending a million times more time learning at school and university!

New ways of acquiring knowledge have to be invented even for a "well-made" head by building customized learning paths to success.

The MOOCs revolution launched in 2012 in the United States, reshaped the world of remote education with online successful learning platforms such as Coursera (https://www.coursera.org/), Udacity (https://www.udacity.com/), EdX (https://www.edx.org/) and FUN (France Université Numérique) in France (https://www.fun-mooc.fr/).

In addition to the video recording of courses and its off-line broadcasting, MOOCs bring three main features to the online learner: a social network of learners (with a community manager in supervision mode) allowing to create virtual classrooms with an interactive student community, video-tutoring (increasingly personalized) with professors and systematic and regular chat interactions between learners and teachers making their course inter-creative (e.g. exercises corrected by students in peer-to-peer mode).

Due to the pandemic which boosted e-learning and digital data-centrics transformation, 2020 was declared for instance in China the "second year of the MOOCs" with the "first year of the MOOC" being in 2012 [24]. By the end of 2020, around 16,300 MOOCs were announced or available and around 180 million students had registered to them [23].

Teaching based upon the top-down distribution of educational CONTENT in brick and mortar fashion, i.e. concentrated in a fixed centripetal space, will undergo the same revolution as all the traditional players in the e-commerce world for multimedia content and services such as TV, music, video, banking, transport or trading - with new players exclusively online or hybrid (click and mortar). MOOC-based certified degrees will be part of the future of higher education with some major demand from emerging countries.

This strong and continuous growth of MOOCs shows their potential to transform traditional education, but their major drawback is that their completion and success rates remain too low (typically between 5-10% [7]). Researchers have been investigating this issue and proposed several solutions and implementations to improve MOOCs and their success rate.

In this paper, we focus on recent deep learning applications and summarize their rationale and output. We categorized the deep learning approaches into three main topics based on how they try to improve MOOCs: "MOOC student final outcome prediction", "MOOC forum post classification" and "MOOC student current/next outcome prediction and recommendation engines". Deep learning is used to solve a supervised learning problem with a set of observations (for example video traces of students, forum posts, exercices, demographic data, profiles) and a variable indicating an outcome (for example whether the student has dropped out, whether the student has a blocking difficulty or what was the next student action).

Once trained with hundreds of examples, the model is then able to predict the response variable : drop-out, need for help or extra pedagogical resources, next visited page.

Definition of deep learning variants used in this article

In this subsection, we will review the main deep learning methods used for MOOC analysis.

Deep neural network - DNN consists of a series of stacked layers. Each layer contains functional units (neurons) connected to the units of the previous layer via a set of weights. There are many different types of neural layers. One of the most common is the fully connected layer that connects all the units directly to each unit in the previous layer. The units in each subsequent layer can represent increasingly sophisticated aspects of the original input by stacking layers [10]. Thus, deep neural networks can automatically extract relevant features without any human intervention to solve the problem [22].

The deep networks of the simplest digital neurons are called Multiple Layered Perceptrons, and they are made up of many fully connected (dense) layers of neurons [37].

Convolutional Neural Networks - CNNs are a type of digital neural network used to process data with a grid-like topology [15]. In convolutional neural networks, each convolution layer finds only relationships between adjacent elements. Lower layers may find local patterns, and upper layers may find patterns across the input scale. Convolutional neural networks are often used as a tool to extract features from raw data structures [31].

Graph Convolution Neural Networks - GCNs follow a similar architecture to standard CNNs but are generalized for graph-structured data to learn a better set of latent features present in a graph [8].

In a Recurrent Neural Network - RNN, information always passes through a loop. When the network makes a decision, it considers the current input and evaluates what it has learned from previous inputs. RNNs always add the immediate past information to the present information [2].

Gated recurrent units - GRUs are recurrent neural networks with gated mechanisms. Compared with simple RNN models, GRUs can solve gradient disappearance to a certain extent and effectively learn sequence characteristics [6].

Long short-term memory - LSTMs are recurrent neural networks in which the layers are designed to prevent gradient vanishing (gradient vanishing problem). Bidirectional LSTMs (BiLSTM) move back and forth through the sequence before moving on to the next layer. For more details, see [11,21].

A Generative Adversarial Network (GAN), in simple terms, is a battle between two adversaries, the generator and the discriminator. The generator tries to convert random noise into observations that appear to have been sampled from the original dataset, and the discriminator tries to predict whether an observation comes from the original dataset or is one of the forgeries of the generator. The key to GANs lies in the way we alternate the formation of the two networks. When the generator becomes more capable of deceiving the discriminator, the discriminator must adapt to maintain its ability to correctly identify observations that are false. This leads the generator to find new ways to deceive the discriminator, and so the cycle continues [10].

An embedding layer is a digital neural network layer that transforms the input data to a vector representation composed of the actual values. It reduces memory usage, accelerates neural networks, and, by associating similar values close together in the vector space, reveals the intrinsic properties of categorical variables. Integration of this layer helps the neural network to generalize better when data are scattered, and statistics are unknown [12].

A pooling function replaces the network's output at a certain point with a summary statistic of nearby outputs. For example, the max-pooling [39] operation reports the maximum output in a rectangular neighborhood. Pooling makes the representation approximately invariant to small changes in the input. Small change invariance means that if we change the inputs slightly, most grouped outputs do not change [15]. Global max-pooling applies the max-pooling operation on the entire sample (https://machinelearningmastery.com/pooling-layers-for-convolutional-neural-networks/).

Survey of deep learning methods on MOOC-based e-learning

For this survey, we first conducted a Google Scholar Search (https://scholar.google.com/) for the period between 2017-2021 using the search query: "MOOC" AND "success" AND "improve" AND ("deep learning" OR "neural network" OR "neural networks") and selected relevant articles from the first 100 results based on their title and abstract. We also searched the ERIC database (https://eric.ed.gov/) for the period between 2019 and 2021 using the keywords "deep learning", "MOOC" and "AI".

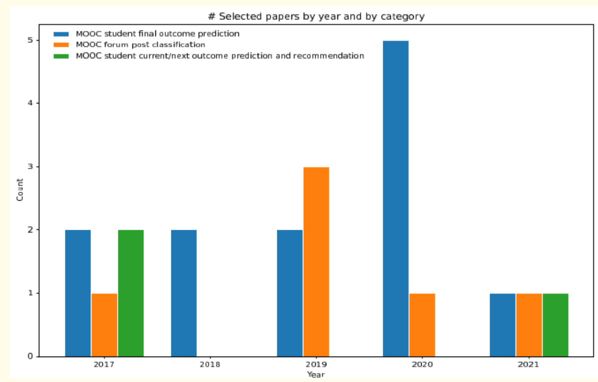

Figure 1: Distribution of the selected articles by year and by category.

Five articles from the ERIC database search and sixteen articles from the Google Scholar Search were finally selected. See figure 1 for the distribution by year and by category.

In the next sections we will examine our three classified groups of Deep Learning applications in MOOC trace analysis and summarize our findings.

MOOC student final outcome predictions

Numerous works explored different computational approaches for predicting the success or failure of students from their traces. Low completion rates, high dropout and a significant number of students in MOOCs make it impractical for instructors to assess students individually. Thus, being able to predict student final performance at an early stage would help instructors to prioritize their interactions. Also, these predictions could be used to improve MOOC personalization.

Twelve papers from our selection focused on the MOOC student final outcome predictions topic [1,9,14,16-18,26,28,31,34,35,38].

The presented datasets used in the papers in this topic are quite diverse: FutureLearn [9], Zoomi Inc [26], KDD Cup 2015 [31], Canvas [34,38], Udacity [17], Stanford Lagunita's dataset [18], OULAD

[1,14,16,28] and Chinese University MOOC [35].

Six papers of the collected works rely mainly on clickstream and student activity data [1,17,18,31,35,38].

2 works combine clickstream data with demographics [14,26]. The work of [16] uses course label data in addition to clickstream and demographics to capture the relationship between students and courses. In the work of [9], student activity data is combined with discussion forum posts and student friendships. The work of [34] used clickstream, forum data, and quiz scores.

And [26] combined clickstream data with course content features.

The researchers used various tools to implement their neural networks, including Theano, Keras, TensorFlow, Scikit Learn, and PyTorch.

Regarding the neural network training part, four papers generated features from the raw data prior to feeding it to their neural network [26,28,34,35] Others delegated the feature generation entirely to their neural network.

The presented architectures of deep neural networks are diverse but mostly rely on different kinds of Recurrent neural networks (RNN).

[31] used a combination of Convolutional neural network (CNN) layers followed by a fully connected layer and an RNN layer [16] used a graph convolution neural network (GCN) followed by a Long short-term memory neural network (LSTM) [1] uses 3 layers of LSTM neural networks in his architecture [17] architecture is based on a bidirectional LSTM network [9,14,18] used RNN-Gated Recurrent Unit (GRU) cells as hidden units [28] utilized a Multiple Layered Perceptron Neural Network with 3 hidden layers and [38] utilized a Radial Basis Functions (RBF) Neural Network.

Almost all architectures used Dropout to regularize the deep neural networks.

MOOC forum post classification

High learner to instructor ratio [32], diverse student backgrounds [36], and information overload [13] in MOOC forums make it a challenging task for instructors to track forum posts and to provide real-time support for students that need it the most.

Six papers from our selection focused on the MOOC forum post classification topic [4,5,13,32,33,36].

Identifying posts that need urgent teacher attention increases the effectiveness of monitoring MOOC forums [32]. Teachers can answer learner questions on time and help reduce dropout rates and improve completion rates [13].

In contrast to the previous case, in this topic, all papers used the same Stanford MOOC Posts dataset [25] Most of the papers define a unique set of classification goals: [4] aims to detect the intent, the subject area, the domain topics, the sentiment polarity, and the level of confusion and urgency of forum posts [13,33,36] aim to identify posts that need urgent teacher attention [32] aims to classify confusion, urgency for intervention, and polarity of the sentiment of forum posts [5] aims to identify the sentiment of forum posts.

The researchers used various tools to implement their deep neural networks, including Keras, TensorFlow, and AllenNLP.

Along with the previous topic, the presented architectures of deep neural networks are diverse and mostly rely on different kinds of Recurrent neural networks (RNN).

In the first layer of the architecture, it is common to use a pre-trained word embedding layer (Word2Vec; google-news Vectors; spaCy; GloVe). The work of [13] also explored a combination of word and character embeddings. Next, CNN network layers are used, followed by some recurrent neural networks (RNN) like LSTM [32], Bi-LSTM [33] or GRU [13], followed by a fully connected layer [13,32] or a max-pooling layer [33]. In the work of [4], an attention-based hierarchical recurrent neural was used, and [36] explored Bayesian Deep Learning using Monte Carlo Dropout and Variational Inference methods.

All architectures used Dropout to regularize the deep neural networks, except in [33], where the max-pooling layer and early stopping during training were used to prevent overfitting.

MOOC student current/next outcome prediction and recommendation engines

Learners are all different. Everyone has their learning speed, their own final goal, and their initial level of knowledge. Thus, a

MOOC aiming to achieve an optimal result for each learner should not be presented in the same way for all learners. Moreover, with the raise of MOOC popularity, MOOC platforms have accumulated a vast number of courses causing information overload [29].

Deep learning models driving personalized Next-Step/Next-Course recommendation engines [20,29] and student performance predictions for the current or next exercise [30] are key milestones to achieve customization in MOOCs, to reduce information overload, to improve the content for learners and lead them to success.

The model presented in the paper of Wang L., *et al*. [30] trains on a student's history of past code submissions of an open-ended exercise with unbounded solution spaces and predicts the student's future performance on the current or the next exercise. It makes it possible to identify students who have true knowledge gaps, anticipate student struggles, send teachers early warnings to assist or create automated hint systems providing personalized feedback in an unsupervised fashion.

In the work of Pardos., *et al.* [20], real-time data collected on the learners' navigation path and a behavioral model, based on a Recurrent Neural Network (RNN) (predicting the next page that a learner was likely to visit) are used to display navigational suggestions to learners. These suggestions aim to provide each student with a personalized pathway to the best-suited content or exercise adapted to his prior knowledge, leading to success.

These two papers make use of deep network architectures based on recurrent neural network layers using LSTM network layers [20,30].

On a higher level, at the MOOC platform, the work of Wang J., *et al.* [29] presented a graph convolution network that uses student behavior data combined with course related data to provide personalized course recommendations.

Survey summary

We have selected twenty-one articles focusing on deep learning applications to improve MOOC acceptability. Most deep learning architectures built for these applications focus on "student final outcome prediction" (12 Articles), followed by "forum post classification" (6 Articles) and "current/next outcome prediction and recommendation engines" (3 Articles).

From a bird's-eye view we could summarize our survey findings in two pie charts (see Figure 2). In the selected papers we identified twelve datasets and the most occurring ones were the Stanford MOOC posts and OULAD. We also note that the datasets are quite diverse. However, a part of the Canvas dataset, all other datasets occurred in only one selected paper.

Regarding the deep learning architectures, almost a third of articles we found were using forms of recurrent neural networks

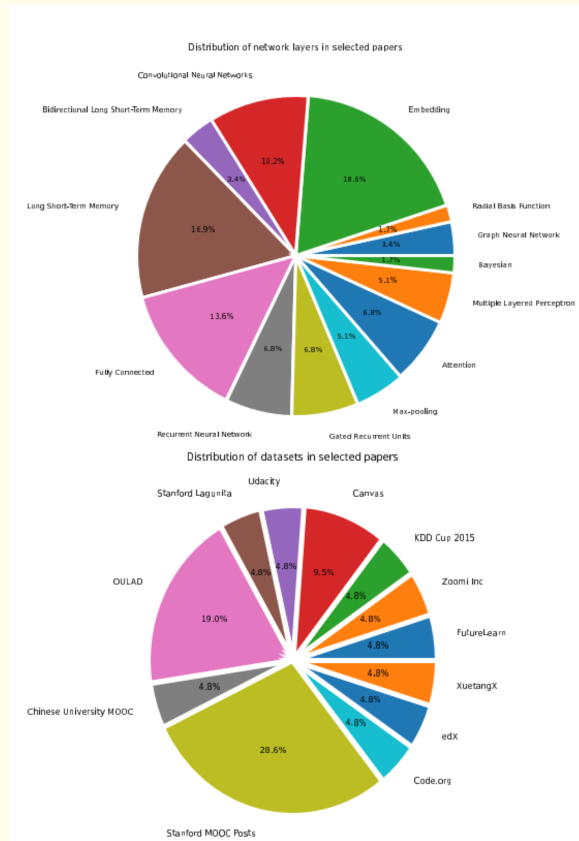

Figure 2: Distribution of the network layers and datasets in selected papers.

including: RNN, LSTM, Bi-LSTM and GRU. We also see that the embedding layers are frequent because many works focused on textual data. Moreover, fully connected layers are also commonly used as the final prediction layer.

Comparison of deep learning platforms for MOOCs and HOOK project

This section presents a short comparative table of main Deep Learning platforms for MOOCs analysis and compares them with our ongoing research project named HOOK (Human Open Online Knowledge) conducted on FUN (France Université Numérique) platform (Figure 3).

HOOK project

The first objective of the HOOK (Human Open Online Knowledge) platform is to extract knowledge from MOOC video tracking data using Machine learning and Deep learning techniques to generate real-time indicators for their expected success and share these insights anonymously with the learners, teachers, and researchers. The second objective is to use this inferred knowledge to improve MOOC learners' experience by introducing adaptive learning capabilities like customized learning paths, extra learning content, video tutoring, and feedback allowing the learners to hook and prevent them from dropping out.

Here we present the HOOK pipeline architecture we are implementing to reach that predictive role in collaboration with FUN (France Université Numérique) MOOC platform (based upon Open edX), which consists of two main pipelines: a data pipeline and an analytics pipeline. HOOK project is under development on the FUN platform.

FUN platform

Learning data are heterogeneous, multi-source, and contain personal Identifiable Information; there is a need to adopt a standard internal format, clean and anonymize data.

Within FUN platform, there exist four major services to capture learning data (tracking logs):

- Open EdX: An open-source LMS (Learning Management System)
- Marsha: An open-source video and document provider
- Ashley: A discussion forum for learning designed to be integrated into LMS
- Richie: An open-source CMS (Content management system).

These services send the captured learning data into an LDP (Logs Data Platform) for archive storage.

The previously used storage solution was Swift (OpenStack Object Storage). Then the tracking logs are processed by Ralph (a tracking logs processor). Ralph is an ongoing joint FUN project which anonymizes and converts edX tracking logs into xAPI (Experience API) statements.

Finally, anonymized xAPI statements are pushed to a database managed by ElasticSearch (selected by FUN) for long-term storage;

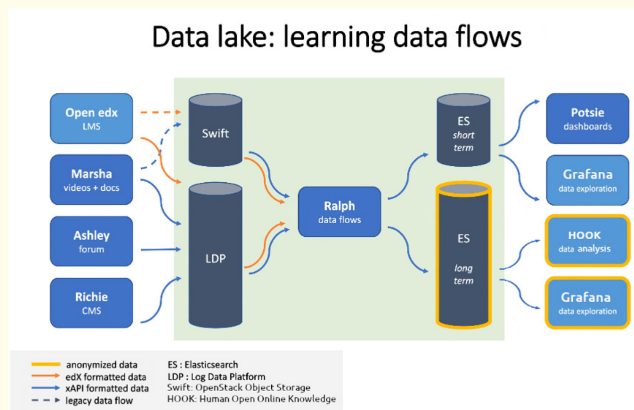

Figure 3: FUN platform embedding the HOOK data pipeline [19].

non-anonymized xAPI statements are pushed to another ElasticSearch database for short term storage.

Here is below a detailed data flow diagram of the FUN data pipeline (Figure 3).

In this diagram, we can notice that the HOOK platform is connected with the long-term Elastic Search database which plays the role of the data lake for HOOK analysis.

FUN analytics pipeline

When the data reaches the Elastic Search databases, they will be extracted by several analytics services.

At the first stage, exploratory analysis is made with Grafana (selected by FUN) which is an open-source analytics and interactive visualization web application. The insights are then integrated into Grafana dashboards and shared with the teachers. For Grafana dashboard management, Potsie (an open-source application developed by FUN) is used.

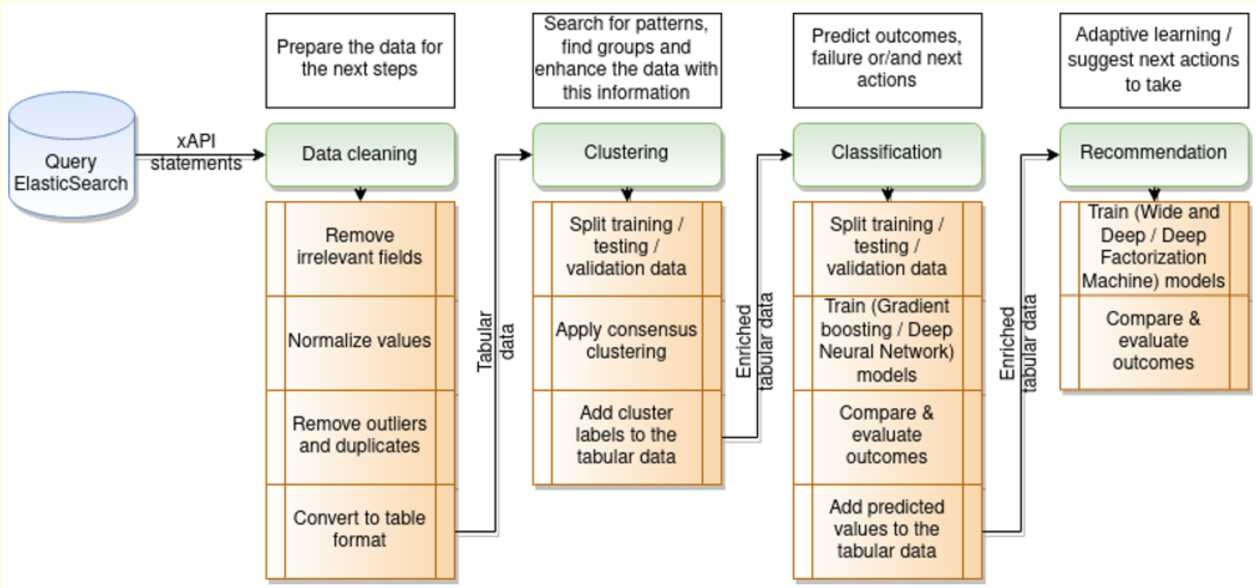

Figure 4: The HOOK Pipeline architecture.

At the second stage, the HOOK platform is used for analytics beyond the exploratory phase.

Each HOOK processing step is managed by a user-defined workflow that allows us to run various intermediate steps between the data extraction and the final model generation. The corresponding workflow is depicted below (Figure 4).

The first objective of the HOOK platform is to extract knowledge from MOOC tracking data using Machine learning and Deep learning techniques to generate indicators for their success and share these insights anonymously with the learners, teachers, and researchers. The second objective is to use the extracted knowledge to improve MOOC learners' experience by introducing adaptive learning capabilities like customized learning paths, extra learning content, video tutoring and feedback, allowing them to hook and prevent them from dropping out.

The HOOK data are analyzed in a pipeline architecture integrating a Deep Learning approach (notably GAN - Generative Adversarial Network) and a general method of generating indicators in real-time for both the teacher and the student. This allows us to

Research	Duru., *et al.* [9]	Kim., *et al.* [17]	Karimi, Hamid., *et al.* [16]	He, Yanbai., *et al.* [14]	HOOK (UCA)
Deep learning methods used and platform	Not mentioned	GritNet Tensorflow	Deep Online Performance Evaluation (DOPE) PyTorch	Not mentioned	Generative adversarial network (GAN), Tensorflow and Python

Neural network architecture	Experimented with five different architectures: Convolution, LSTM, Bidirectional LSTM, GRU, 'CNN + LSTM'	Embedding layer, bi-directional LSTM, Global max-pooling, fully-connected layer	Graph convolution neural network (GCN), Long short-term memory (LSTM)	Fully Connected Network, RNN-Gated Recurrent Unit (GRU)	Ongoing
MOOC Platform/Data Source	FutureLearn (3 MOOCs with up to 8 runs)	Udacity; (2 nano degree classes)	OULAD; (6 Online Courses)	OULAD; (7 Online Courses)	FUN (France Université Numérique); 6 MOOCS of the eMBDS (2019) and eBIHAR (2020) online masters
Type of DATA used	interaction traces, forum, student friendships	Raw interaction traces	Demographics, interaction traces, Course data	Demographics, interaction traces,	Demographics, interaction traces, Forum
Results	Predicted students' future performances with 84.62% accuracy (when trained on the same MOOC but its previous iterations) and between 77%-79% accuracy (when trained on one MOOC and tested on other MOOCs - transfer learning)	The "GritNet" algorithm is able to be transferred to new courses and to provide a substantial "AUC" recovery rate when predicting dropouts	Best F1 score: 0.88	Over 80% prediction accuracy of at-risk students	Ongoing

Table 1: Comparison of major Deep Learning platforms for MOOCs.

run various intermediate steps between the data extraction and the final model generation. One such workflow could look like depicted below:

Functional comparison of deep learning platforms for MOOC improvement

In table 1 we present a functional comparison of four Deep Learning platforms for MOOCS including HOOK.

Conclusion: Towards Customized E-learning in Virtual Multiversity's

In this survey, we summarized the appealing deep-learning methods applied to MOOC analysis and improvement; we presented an overview of deep learning applications in MOOCs which indicate that dropout prediction and forum post classification seem to be the leading applications of deep learning in MOOCs to improve their success. However, MOOC student current/next outcome prediction and recommendation engines are as well promising Deep Learning applications enabling personalization and adaptation in MOOCs. Most deep learning architectures built for these applications use variants of recurrent neural networks (RNN). We also presented and compared our ongoing project named HOOK which aims to use both Machine Learning and Deep Learning techniques to generate indicators for MOOC learners' success and provide adaptive learning capabilities like customized learning paths.

We entered this era of hybridization in e-learning (amplified by the COVID pandemic issue): the e-learning dimension based upon MOOCs will coexist in the future with traditional face-to-face teaching both for the student in initial or continuing education and for the professors by extending the shared common space of educational resources. Higher education of the future will implement this e-learning dimension to face educational challenges raised in emerging countries (namely in Africa and BRIC countries) and developed countries to face digital transformation and the professional skill challenge leading the way to "multiversity" of the future (see companion article on multiversity of the future in ASCS 3.10 (2021) p 46-49).

"The very high drop-out rates and the recourse to teaching techniques that are often very classical and too knowledge-centrics have raised questions about the learning potential of these large-scale systems" says Dominique Boullier [3].

What if, more than a threat to universities, MOOCs represented an opportunity for them to move towards a customized path to success by having a multi-channel pedagogical offer where degrees move to students opening a new era of academic internationalization.

AI brings the personalization of the courses towards this success in tailor-made teaching. The student who leaves traces of learning in the MOOCs becomes a communactor [6]. i.e. a DATA contributor to the commons useful for everyone's learning! The communactor student will go from a well-made head (Montaigne) and a well-connected head (Michel Serres) to a well-augmented head with artificial intelligence tools used before, during, and after the training process.

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