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Personalisation Online Learning using Response Machine Learning Algorithms

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ABSTRACT
Due to the epidemic, online course learning has become a major learning method for students worldwide. Analyzing its massive data from the massive online education platforms becomes a challenge because most learners watch online instructional videos. Thus, analyzing learners' learning behaviors is beneficial to implement personalized online learning strategies with sentiment classification models. To this end, we propose a context-aware network model based on transfer learning that aims to predict learner performance by solving learners' problems and improving the educational process, contributing to a comprehensive analysis of such student behavior and exploring various learning models in MOOC video interactions. In addition, we visualize and analyze MOOC video interactions, enabling course instructors and education professionals to analyze clickstream data generated by learners interacting with course videos. The experimental results show that, in the process of "massive data mining," personalized learning strategies of this model can efficiently enhance students' interest in learning and enable different types of students to develop personalized online education learning strategies.
Keywords — Blockchain, Artificial Intelligence, Autonomy, Cryptography, Privacy Protection

I. INTRODUCTION

In the last decades, technological advances have played an important and prominent role in the development of educational processes. Massive open online course (MOOC) is an outstanding innovation in the field of education, where more and more people are involved in online learning [1]. In particular, the impact of the epidemic has made learning through online course platforms (e.g., Coursera, edX, and Udacity [2]) the main way of learning for students worldwide, which offer mainly video-based course, quizzes, and forums [3]. The personalized design of the online video course plays an important role in the interest of the learners and is the main fulcrum to attract students to continue learning the course. Online learning platforms can store learner data in weblogs, which include their personal information and interactions with course content (e.g., videos, clickstreams events, forum discussions, and assessments). Video clickstreams (e.g., play, pause, search, and stop) are captured as they occur and then stored. Most learners spend most of their learning time watching video course, and as a result, many problems with learner-video interactions have gradually emerged [4].

Learner sentiment analysis can be performed by collecting, analyzing, and representing data related to learners' interactions with the course that provides researchers and teachers with an opportunity to understand learners' behavior and assess their performance through their interactions with the video content [5]. Several studies on learner engagement and explorations of patterns of learner behavior with video interactions have focused on analyzing data collected from learners' interactions with different forms of course [6–8]. Related to this, many studies have provided many mechanisms to improve the quality of learning in MOOCs by exploring engagement behaviors and course content to predict learner performance and to reduce dropout rates [9, 10].

Educational environments face increasing complexity and diversity [11]; for example, students from different locations can take the same course. With regard to diversity, instructional designers are constantly challenged to adapt to the individual needs of students. Therefore, they must adopt teaching methods that are appropriate for different students [12]. This is the reason for the popularity of personalized learning. Personalized learning defined in the National Educational Technology Initiative supported by the U.S. Department of Education means that learning platforms can optimize learning paths and instructional methods based on the needs of each learner [13]. Such a learning platform allows students to pursue their personal learning goals at their own pace [14]. Thus, the main benefit of personalized learning is its ability to adapt to the needs of different students. This benefit is supported by empirical evidence, which suggests that personalized learning allows instructional designers to meet students' needs and helps students clarify and improve their understanding of learning objectives [15, 16].

E-learning helps the traditional learning process take a step forward by providing students with materials that can help them learn anytime and anywhere [23, 24]. However, many studies have shown that web-based online learning still lacks intelligence that may not be appropriate for each learner's characteristics [25]. Wong et al. [7] proposed an autonomous approach to self-organization by creating learning objects (LO) that can provide learners with a good LO structure. Three common types of learning resource filtering are described in [10]: content-based (CB), collaborative filtering (CF), and hybrid filtering (HF). The use of CF in [26] will be analyzed based on the similarity between learners' scores and then predict which substance is more suitable for them. In contrast, the lack of rating defects in CF methods is discussed in [11], which occurs when users do not have sufficient rating documentation. The CF approach will face difficulties with high data sparsity. CB works by providing recommendations for each learning subject that fit the student's learning goals and preferences. Therefore, CB will consider some learners' factors such as their skills or talents, goals, attitudes, and psychological styles in the CB recommendation system [7, 16].

II. CONTEXT-AWARE NETWORK MODEL BASED ON TRANSFER LEARNING

A. MOOC Data Acquisition Objectives

This section presents the idea of implementing deep learning in an existing IoT system architecture. The architecture is divided into two parts, one of which is the camera part that collects the video movements of students for action recognition [4, 14]. The collection of videos was broken down into 11 small video clips with four different actions for the students: entering the classroom, standing, sitting, and walking out of the classroom. The video clips are then classified into images with specific frames and the dataset for video-to-image classification is discussed. After the IoT system identifies student activity, it combines the results with the sensor dataset and determines whether the MOOC video content is the focus based on the context of the data as well as decides whether to inform students that they should focus on students. Every 10 minutes, the process takes data reading from context-aware sensors. Figure 1 depicts the data collection and the identification process of the sensor to control the student informed information use. Two different experiments were done to predict the output of the video and sensor datasets. Convolutional 3-dimensional (C3D) models are applied to action recognition and long- and short-term memory (LSTM) to predict the output of sensors [30].

To collect data, a context-aware sensor classroom is created. The sensor data are collected through a Raspberry Pi board and the students' motions are recorded by a video camera. Collect data from temperature, humidity, and luminance sensors using low-power context-aware sensors. Use MySQL [7] to manage the database. Video-to-image data require large datasets to obtain proper efficiency, so working with the C3D dataset makes the dataset large enough to be used for training and testing of action recognition experiments. Using passive infrared sensors (PIR) covering 360°, the largest area of motion can be detected. The same can also be used separately from different sensors to collect different data when students enter the classroom.

Placement of sensors for data collection for sensors cover all possible space in the room, so errors are reduced. PIR sensors are placed to collect all the actions that are collected in the MySQL database provided by the server.

B. Transfer Learning Based on MOOC Video Data

Transfer learning is a common approach that trains small domain datasets into large domain datasets. In practical applications, most of the datasets are usually the largest in the domain where feature extraction can be effectively utilized. The C3D and transfer learning models proposed in this paper as shown in Figure 2 show how MOOC data can be combined with the classroom in human action data domain and transfer learning. Since the MOOC data are taught by a single person, while the classroom action dataset is composed of multiperson actions, the dataset faces a great challenge in transfer learning [31].

Transfer learning helps to build networks of knowledge-sharing concepts, which actually help to train datasets with learned concepts [32]. In this paper, we implement transfer learning to train our experimental action dataset using a large regional dataset of the MOOC video dataset and apply this transfer learning to C3D. The model in this paper successfully captures the feature vector for the first task and then redefines the convolution function with an additional fully connected layer and retrains the feature vector. Using 128 layers of convolution to improve programming efficiency, the image dataset added for transfer learning does not require large filtering layers. Finally using fully connected layers, classification can be performed. This makes it easy to transfer the knowledge to the network to perform another task. Finally, strategies for personalized learning inform the students.

C. Context-Aware Network

To further incorporate all the scenarios in the MOOC, we categorized these into effective categories to further enhance students' strategy development for online personalized learning. The complete architecture is shown in Figure 3, which shows how the proposed context-aware network with a transfer learning architecture works. Two different architectures can be seen working in parallel to collect and predict sensor and action recognition outputs. Transfer learning is performed on the human action image dataset. The first part is action recognition, showing how the data are collected and used for feature extraction. C3D is used as a feature extraction tool to identify four different behaviors of students in the classroom, that is, entering, sitting, standing, and exiting the classroom. CNN is arguably the most widely used method in human behavior recognition. It consists of multiple hidden and pooling layers and fully connected layers.

In order to avoid merging too many irrelevant details and noise in the sensor data fusion process and to minimize the effect of artifacts, we use the following steps to perform the fusion of the detail layer.

Step 1. The weight matrix is computed by the absolute value of the large rule.

Step 2. The weight matrix, using Gaussian filtering, is processed in equation (6).where.

Step 3. The initial fusion of detail layers and, by the weighted average rule, is obtained by; that is, we have

Step 4. The optimization strategy WLS is used to optimize to obtain the fused detail layer. The procedure is as follows: Let the weigh and p denote the space position. The parameter ε is usually set to 0.0001 to prevent from dropping to 0. It is a window centered on position p. A window that is too large causes poor fusion and consumes too much time, while a window that is too small does not eliminate the effect of noise. Minimization term aims to minimize the geometric distance between the detail layer and the fused detail layer; minimization term aims to make the fused detail layer closer to the model detail layer, so that the output data are more characteristic is a global parameter to control the weights of these two components. Equation (9) is converted into matrix form where, and are represented as vectors, and is a diagonal matrix with.

Minimizing equation (10) yields the linear system of equations: Since, equation (11) can be simplified asThe fused detail layer is obtained by using equation (12). By analyzing the areas of sensor data containing noise or not related to the visual detail information or related to the visual detail information, it can be seen that the optimized strategy WLS can obtain a better-fused detail layer.

D. Experimental Setup

To demonstrate the effectiveness and practicality of the proposed model, a case study of two MOOC course was conducted. Firstly, data preprocessing was performed, including feature extraction from video clickstream data. As shown in Tables 1 and 2, we observe that the implementation of representing clickstream data in the (MMDS SELF-PACED) course takes longer than representing clickstream data in the (Automata SELF-PACED) course [18], which means that the time depends on the size of the clickstream data in order to consider more efficient and clearer execution of the visualization algorithm considering the running time [5, 13]. Data are generated separately each week for each participant in each course. This makes the model more flexible and efficient and requires little time to visualize the entire data. In the prediction phase, we considered unbalanced datasets, converted the datasets obtained during feature extraction into appropriate model input data, constructed shape-consistent padding vectors, and then marked them before feeding them into the model layer. The dataset was divided into 70/30 training/testing to determine the prediction of the learner's performance [12].

E. Visualization Results and Model Performance

In this section, we investigate the effectiveness of the proposed model for assessing learner behavior through video clickstreams and explain the possible relationship between learner behavior and their performance on the study dataset. The behavior of learners watching videos to complete the first task in a given week is classified as a community gathering within the network based on structural clustering generated based on structural identity, which is closely related to kindness. Each cluster was given a different color. As shown in Figure 4, the size of the video nodes is proportional to the number of associated learner nodes, which indicates the status of the learner's utilization of the video, and this stage allows the teacher to monitor the learner's behavior (e.g., the learner's behavior and the most viewed videos) [15]. In addition, teachers can determine which learners are more likely to drop out, such as the red and orange notes.

In general, we focus on how the learner interacts with the viewed video. If learners take a long time to interact with the video (reflecting a high level of interest), which implies that they make an effort while watching the current video (e.g., most pause/backward search events), this can be explored in real-time video utilization in order to more precisely analyze specific video utilization. Thus, instructors can directly select videos of interest, such as videos of most events. For example, we selected video (2) from the "Theory of Automata" course and video (14) from the "MMDS Self-Paced" course, which are the most popular videos.

III. CONCLUSIONS

This paper proposes a context-aware network model based on transfer learning, which aims to predict learners' performance by solving their problems and improving the educational process, contributing to a comprehensive analysis of such student behavior and exploring various learning models in MOOC video interactions. The experimental results show that, in the process of "massive data mining," the accuracy of this model is 90.30% better than the baseline, and it can realize different types of students to develop personalized online education learning strategies.

The scheme in this paper achieves a certain effect of personalized learning strategy, but the model is too large, and the model structure can be optimized in the future. On the other hand, scenario analysis can be done directly from the MOOC video content without focusing too much on the students, who change too much, resulting in inaccurate predictions.

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