

# LearnerExp: Exploring and Explaining the Time Management of Online Learning Activity

Huan He

Key Laboratory of Intelligent  
Networks and Network Security,  
Ministry of Education  
Xi'an Jiaotong University  
Xi'an, Shaanxi, China  
hehuan@mail.xjtu.edu.cn

Qinghua Zheng

School of Electronic and Information  
Engineering  
Xi'an Jiaotong University  
Xi'an, Shaanxi, China  
qhzheng@mail.xjtu.edu.cn

Bo Dong

School of Continuing Education  
National Engineering Lab for Big  
Data Analytics  
Xi'an Jiaotong University  
Xi'an, Shaanxi, China  
dong.bo@mail.xjtu.edu.cn

## ABSTRACT

How do learners schedule their online learning? This issue is concerned by both course instructors and researchers, especially in the context of self-paced online learning environment. Many indicators and methods have been proposed to understand and improve the time management of learning activities, however, there are few tools of visualizing, comparing and exploring the time management to gain intuitive interpretation. In this demo, we introduce the **LearnerExp**, an interactive visual analytic system designed to explore the temporal patterns of learning activities and explain the relationships between academic performance and these patterns. This system will help instructors to comparatively explore the distribution of learner activities from multiple aspects, to explain the time management of different learners groups with predictions of learning performance.

## CCS CONCEPTS

• **Information systems** → **Data analytics**; • **Human-centered computing** → *Visualization systems and tools*; • **Applied computing** → E-learning;

## KEYWORDS

Online learning, time management, visualization

### ACM Reference Format:

Huan He, Qinghua Zheng, and Bo Dong. 2019. LearnerExp: Exploring and Explaining the Time Management of Online Learning Activity. In *Proceedings of The Web Conference (WWW'19)*. ACM, New York, NY, USA, 4 pages. <https://doi.org/10.1145/1234567.1234567>

## 1 INTRODUCTION

Accessing world class educational resources without geographical and social boundaries has become the daily behavior of online learners. With the advantages of learning anywhere and anytime, learners can schedule their learning at their own pace. However, this self-scheduled learning process also challenges their time management [1, 7]. In the less supervised online learning environment,

the inappropriate scheduling of study time (e.g., absence, procrastination, etc.) may lead to reduced learning performance and even exam failures [8], which in turn would result in reduced completion rate and course rating [1]. Therefore, understanding the time management pattern of online learning activities has been an important issue for both learners and instructors.

With the support of learning management system (LMS), the detailed learning activities can be tracked via logs (e.g., viewing videos, reading materials, posting threads, etc.). Existing studies have proposed many indicators and models based on these logs to measure the time management features, such as the interval time between two tasks [1], the time that students spent on a certain task [3], the remaining time between the deadlines [2], the aggregated daily activity count [7], etc. By using these indicators, recent studies examined the learners' behavioral patterns [6], self-regulated learning strategic [4, 5], the influences on learning performance [8], visualization tools for supporting self-regulated learning [2], etc. These indicators and methods provide basis for measuring and improving the time management. However, there is a limitation that the temporal differences in the measurements of learning activities are not explorable, since the time information embedded in learning activities is aggregated for computational efficiency and interpretability.

To address this issue, we introduce the LearnerExp system for both instructors and learners to explore and explain the time management intuitively. First, we propose the activity vector to represent daily learning activities based on well-studied indicators and existing models. Moreover, we embed the activity vector in the calendar-like activity matrix to facilitate users understand the learning process intuitively. Second, we use grade point prediction model based on convolutional neural network to explain the relationships between learning performance and time management. Third and last, we develop a visual analytic system for course instructors to explore the temporal activity patterns of different learner groups. In addition, we also develop a calendar widget for learners to schedule their own progress. Main contributions of this work are summarized as follows.

- A learner activity model for describing and analyzing the time management in learning activities, which not only captures the temporal aspect of learning activities, but also supports visual interpretation.
- A web-based interactive visual analytic system for exploring and explaining the time management of online learning activity based on the proposed learner activity model.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

WWW'19, May 13-17, 2019, San Francisco, CA USA

© 2019 Copyright held by the owner/author(s).

ACM ISBN 978-1-4503-5103-4/18/02.

<https://doi.org/10.1145/1234567.1234567>

## 2 LEARNER ACTIVITY MODEL

In this section, we introduce the learner activity representation and the prediction model for analyzing the time management.

### 2.1 The Learner Activity Representation

In online courses, the time-stamped student-generated events are recorded by the LMS and saved in logs, we count these events on a daily basis to describe the learning activity of each day. As shown in Figure 1(a), the day activity is measured by a set of indicators, such as daily student-course interaction count, video viewing time, etc. Based on the day activity, the whole activities in a semester can be represented as the activity vector (Figure 1(b)). In terms of notation, we let  $\mathbf{x}_i$  be the activity vector for student  $i$ , where  $i = 1, \dots, N$ . The dimensionality of activity vector  $\mathbf{x}_i$  is  $D \times K$ , where  $K$  is the number of indicators and  $D$  is the number of days in the semester.

In order to visualize the activity vector, we compress the  $D \times K$ -dimensional activity vector into  $1 \times D$ -dimensional vector, and then embed this compressed vector in the calendar-based  $W \times 7$ -dimensional activity matrix by date, where  $W$  represents the number of weeks in a semester (usually  $W < 28$ ). As shown in Figure 1(c), the compressed day activity is represented as a color-encoded cell (the darker the higher, indicates that the activity on the corresponding date is more frequent). In this demo, we use a weighted sum of all indicators to compress day activity according to the suggestions from instructors.

Since time information is embedded in both  $D \times K$ -dimensional activity vector and  $W \times 7$ -dimensional activity matrix, these two representations are able to capture the temporal aspect of learning activities. As shown in Figure 1(d), the learning activities of five learners are fully recorded by the activity matrix, and different patterns of time management can be intuitively presented.

### 2.2 The Grade Point Prediction Model

With the learner activity representation, we use a grade point prediction model based on convolutional neural network to analyze the relationship between time management patterns and grade point (we convert exam scores into grade points from 0 to 4).

As shown in Figure 1(e), the model consists of three convolutional layers using the rectified linear unit (ReLU) as activation function to capture the temporal features of the activity vector. Specifically, the first two column-wise convolutional layers take convolutions that capture the short-term (e.g., 1 cell = 7 days) and long-term (e.g., 1 cell = 4 weeks) patterns of learning activity, respectively. The third row-wise convolutional layer takes convolutions that capture the pattern of activity indicators at each timepoint. Then, the fully-connected layer extracts latent representation from the convolutional layer via a sigmoid function. Finally, the last layer outputs the probabilities of each grade point by using a softmax function.

We trained this model on the dataset from the online undergraduate program of our university, which consists of 10,529 students and their learning logs of an English course. The prediction results will be used to support the exploration of the relationship between different time management patterns and grade points in our LearnerExp system.

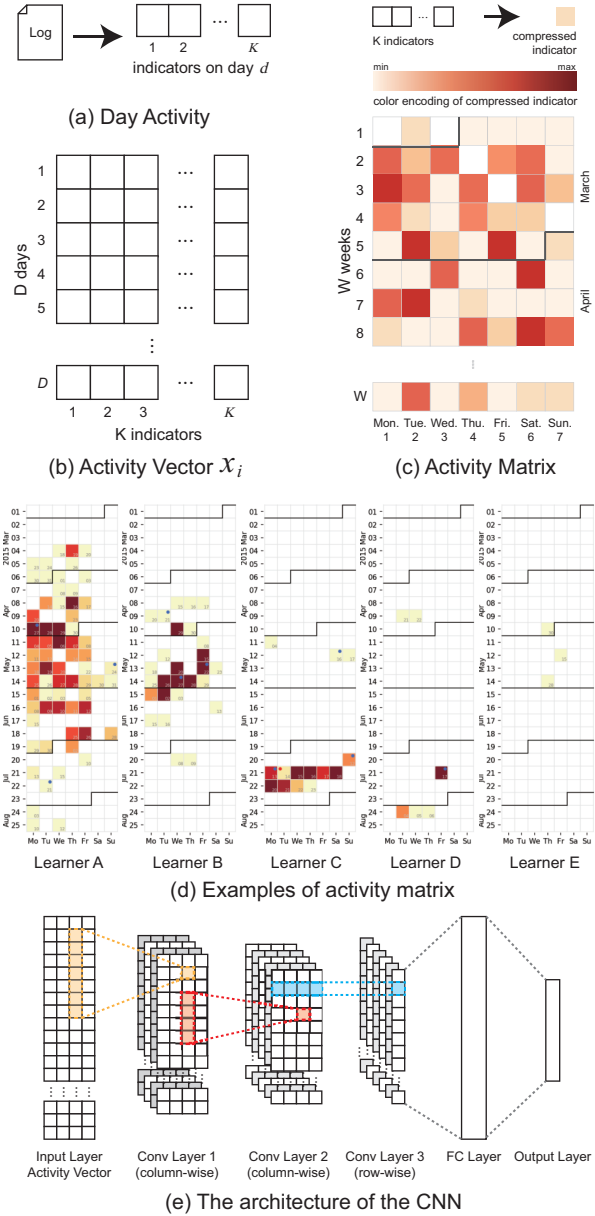


Figure 1: The learner activity representation and the prediction model based on convolutional neural network

## 3 THE LEARNEREXP SYSTEM

### 3.1 The Architecture

The architecture of LearnerExp system is shown in Figure 2. It consists of four major components: *data collection module*, *data storage module*, *activity analysis module* and *visualization module*.

**Data collection and data storage module.** In data collection module, we use Python scripts to collect course data and raw logs from the LMS. After filtering irrelevant information and filling missing fields, the preprocessed learner log data is saved in the data

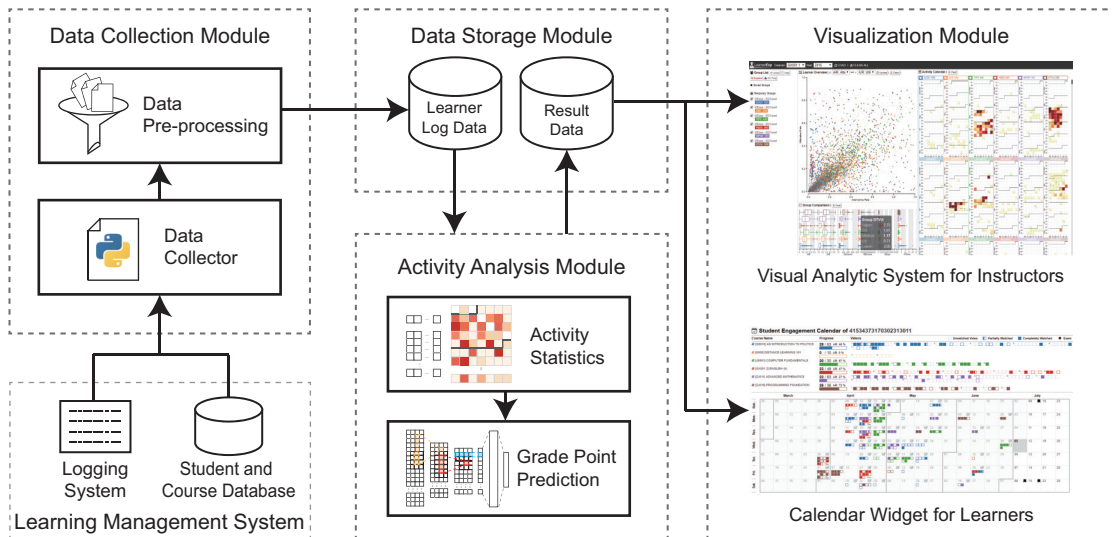


Figure 2: The architecture of the LearnerExp system

storage module. In addition, to facilitate access from the visualization module, the intermediate results of statistics and predictions are also saved.

**Activity analysis module.** This module includes two submodules: the activity statistics module measures the activity vector of each learner and generates the activity matrix defined in Section 2.1. Then, the grade point prediction module predicts the probability of each learner’s grade points based on the pre-trained model mentioned in Section 2.2. The learners with a higher probability of grade 0 (i.e., failing the exam) will be grouped by the probability value for further analysis in the visualization module.

**Visualization module.** We developed two applications to make full use of the analysis results. First, we integrate a web-based calendar widget in the dashboard of the LMS to help learners understand their own activity history (Figure 3(a)). Learners can see their activity history immediately after login. Second, we provide a web-based visual analytic system that enables course instructors to explore the temporal patterns of learners’ activities from various aspects.

### 3.2 Visual Design

In this section, we illustrate the visual design of the LearnerExp system and the interactions among the views. As shown in Figure 3, there are four coordinated views to show the analysis results from different perspectives: the Group List (Figure 3(b)), the Learner Overview (Figure 3(c)), the Group Comparison view (Figure 3(d)) and the Activity Calendar view (Figure 3(e)).

**The Learner Overview and The Group List.** To provide course instructors with intuitive impression on the overall activity distribution of all learners, we use scatter chart to present the statistics on the entire semester (Figure 3(c)). In this chart, each gray dot represents a learner, while other colored dot represents a learner who belongs to a specific learner group. Both the x-axis and the y-axis can be set to a specified indicator to see the distribution of same population under different indicators.

There are two types of learner groups in our system: the prediction groups generated by the model described in Section 2.2,

and the temporary groups customized by selecting learners on the Learner Overview. We developed an interactive selector to make it easier for users to intuitively select specific learners of interest (Figure 3(c-1)). By drawing a closed shape on the scatter chart with mouse, users can create a group of the selected dots within the shape. The newly created group will be automatically named and displayed in the “Temporary Groups” of the Group List (Figure 3(b)). To facilitate identification of learner groups in different views, the color-encoding used in the Group List is also used in other views.

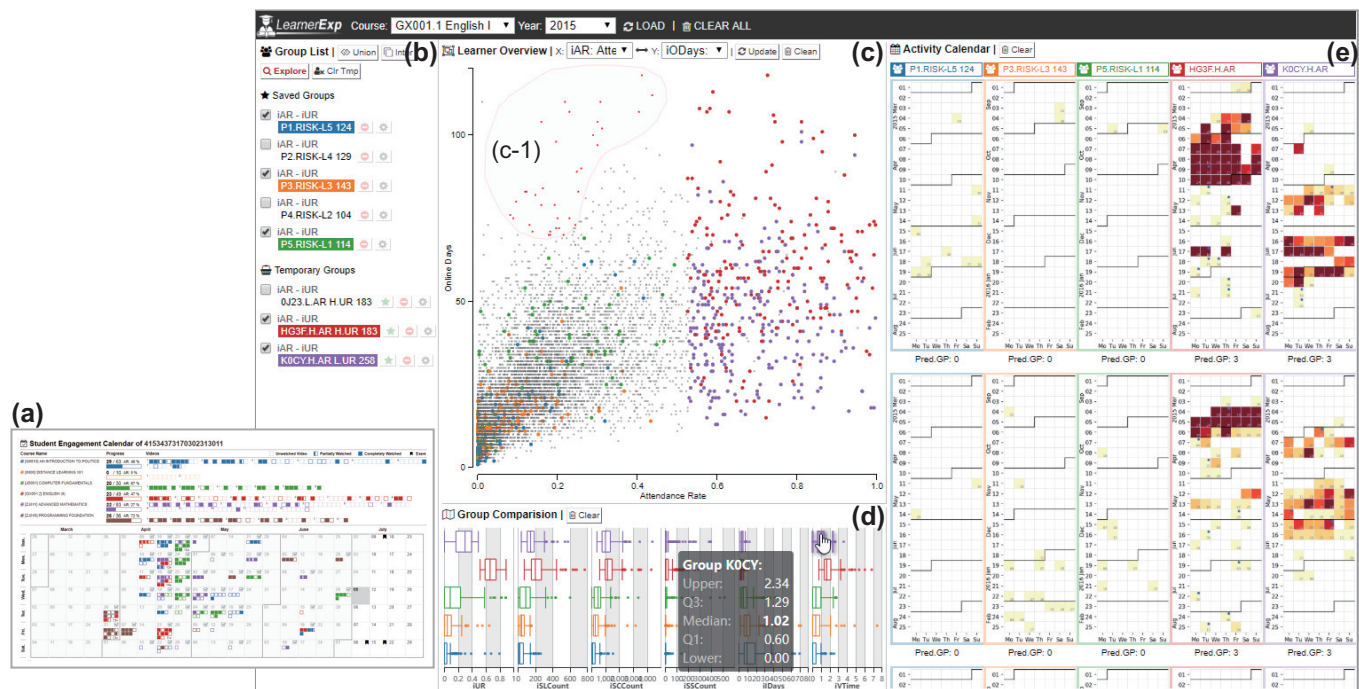
**The Group Comparison View.** This view presents a set of box charts to simultaneously compare the distribution differences in learner groups across multiple indicators. As shown in Figure 3(d), from left to right, each box chart displays an indicator, in which each series represents a learner group from top to bottom. The color of each series is consistent with the color displayed in the Group List (Figure 3(b)). When the mouse is over the series, the detailed statistics of the group on this indicator will be displayed.

**The Activity Calendar View.** In this view, the activity matrix defined in Section 2.1 is displayed to explain the details of learner’s learning activities. This view displays the learner groups in columns from left to right, in which the activity matrix of each learner is shown from top to bottom. When the mouse is over each activity matrix, the corresponding dot in the Learner Overview will be enlarged, and the corresponding location in each box chart will be marked to explain the learner’s relative performance in the whole population and in the group.

## 4 DEMONSTRATION

During the demonstration the attendee will evaluate LearnerExp<sup>1</sup> with a real dataset from our university, which is the same dataset as we mentioned in Section 2.2 but without personal privacy information. Additionally, we provide an exemplified scenario in which the course instructor wants to find the learners who may fail the posttest exam. The demonstration scenario is the following.

<sup>1</sup>Screencast for LearnerExp: [https://youtu.be/j\\_mtLp-8v0U](https://youtu.be/j_mtLp-8v0U)



**Figure 3: Screenshot of the LearnerExp system. (a) The calendar widget integrated in learner's dashboard. (b) The Group List. (c) The Learner Overview. (d) The Group Comparison view. (e) The Activity Calendar view.**

(1) The user starts by loading data. After selecting the course in the "Course" drop-down list and clicking the "Load" button, the corresponding dataset will be loaded into the web page. All the learners of this course will be shown in the Learner Overview, and the prediction groups with different probability of failing the exam will be listed in the Group List.

(2) Next, the user can select groups and click the "Explore" button. Then, the selected groups will be colored, and the details will be displayed in each view. In the Learner Overview, the dots belong to each group will be colored and enlarged to show their relative position in the whole. For example, as show in the Figure 3(c), when the the x-axis and y-axis are set to *Attendance Rate* and *Online Days*, the distribution of the green group is higher than that in the orange group. In the Activity Calendar view, the user can check the activity matrix and grade point prediction of each learner in each group to examine the relationship between them.

(3) In addition to the prediction groups, the user can customize groups of interested learners for comparative exploration with the interactive selector (Figure 3(c-1)). After creating new groups, the user can select these newly created groups from the "Temporary Groups" and click the "Explore" button to continue exploring.

(4) Finally, after repeatedly exploring different groups, the user may be interested in a few customized groups and plan to analyze them in the future. The LearnerExp provides the function to save the customized groups of interest. By clicking the star-icon button next to the group label in the Group List, the corresponding temporary group will be saved and moved to the "Saved Groups".

## ACKNOWLEDGMENTS

This research was partially supported by "The Fundamental Theory and Applications of Big Data with Knowledge Engineering" under the National Key Research and Development Program of China with Grant No. 2018YFB1004500, the MOE Innovation Research Team No. IRT17R86, the National Science Foundation of China under Grant Nos. 61721002, 61532015, and Project of China Knowledge Center for Engineering Science and Technology.

## REFERENCES

- [1] J. Broadbent and W. L. Poon. 2015. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education* 27 (2015), 1–13.
- [2] Kalle Ilves, Juho Leinonen, and Arto Hellas. 2018. Supporting Self-Regulated Learning with Visualizations in Online Learning Environments. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education (SIGCSE '18)*. ACM, New York, NY, USA, 257–262.
- [3] Ayaan M. Kazerouni, Stephen H. Edwards, and Clifford A. Shaffer. 2017. Quantifying Incremental Development Practices and Their Relationship to Procrastination. ACM, 191–199.
- [4] René F. Kizilcec, Mar Pérez-Sanagustín, and Jorge J. Maldonado. 2016. Recommending Self-Regulated Learning Strategies Does Not Improve Performance in a MOOC. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale (L@S '16)*. ACM, New York, NY, USA, 101–104.
- [5] René F. Kizilcec, Mar Pérez-Sanagustín, and Jorge J. Maldonado. 2017. Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education* 104 (Jan. 2017), 18–33.
- [6] Mohammad Javad Mahzoon, Mary Lou Maher, Omar Eltayeb, Wenwen Dou, and Kazjon Grace. 2018. A Sequence Data Model for Analyzing Temporal Patterns of Student Data. *Journal of Learning Analytics* 5, 1 (April 2018), 55–74.
- [7] Jihyun Park, Renzhe Yu, and Fernando Rodriguez. 2018. Understanding Student Procrastination via Mixture Models. In *Proceedings of the 11th International Conference on Educational Data Mining*. 11.
- [8] Tzu-Chi Yang, Meng Chang Chen, and Sherry Y. Chen. 2018. The influences of self-regulated learning support and prior knowledge on improving learning performance. *Computers & Education* 126 (Nov. 2018), 37–52.