Learners' Performance Evaluation Measurement Using Learning Analytics in Moodle

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Abstract In recent years, the development of online environments has been rising exponentially and educators and learners are moving toward online learning systems. These online learning systems are open-source applications that have their advantages and disadvantages. Moodle is one of the widely used open-source learning platforms used by most institutions all over the world. Even though moodle provides a good framework for learning, it is static with minimal functionalities. The need for student preferences and their contexts is required for understanding and optimizing learning environments in a better way. The paper presents an approach to collect and retrieve student behaviors from the log files and table of moodle and classify learning preferences using the standard Naïve Bayes classifier based on the standard Felder Silverman learning style model. The retrieved learning preference based on students' behaviors and actions supports educators to view the preferences of students and to improve and enhance their teaching.

Keywords Learner analytics · Learning management system · Learning style · Moodle · Naïve Bayes classifier

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A. Joshi et al. (eds.), *Information and Communication Technology for Competitive Strategies (ICTCS 2020)*, Lecture Notes in Networks and Systems 191,
https://doi.org/10.1007/978-981-16-0739-4_87

1 Introduction

Learning analytics collects and analyzes the data which is generated by learners during the interactions in both online and offline learning environments. It acts as a decision support tool in teaching, learning, and educational management.

In this paper, we describe how learning analytics can be provided as pointers of students' performance in the course. Students' activities related to assessments are considered as the key measurements. An overview of the emerging field of learning analytics is described initially, followed by a description of the case study which is done in moodle with the help of the learning analytics tool in moodle. The summary of the analysis helps us to conclude students' performance in that particular course as well as semester performance.

It covers three levels of analytics such as personal level, course level, and department level. The personal level does analytics on the performance of individual students, learning resources, and other students' study habits. Intelligent curriculum, conceptual development, and social networks are referred to in course-level analytics. The department level of learning analytics can identify the pattern of result (success/failure) and do predictive modeling which can be taken as the corrective measurement in quality teaching and students' performance [1].

2 Literature Review

Online educational technologies are adopted in all educational institutions during this pandemic. How students are interacting with these environments and technologies are still under research and learning analytics is the emerging approach to address this. It includes a variety of data gathering tools and analytical techniques that are used to examine students, interaction, activities, and performance on tasks [1]. These tools can support researchers to identify and analyze the diversity of learning behaviors that can be taken place in these environments [2].

Learning analytics can be utilized for improving the quality of teaching, curriculum, and assessment. Usage of logs from e-learning applications was not utilized properly in e-learning research. The term learning analytics refers to these data which is used to analyze the study behavior of the students [3].

The terminology around 'analytics' in education is evolving. Despite calls for its use in the early 1990s, usage logs from e-learning applications have been under-utilized in e-learning research [4]. The use of this automatically captured data, which records who accessed what and when to study student behavior, is now termed learning analytics [5]. This can be contrasted with academic analytics, which considers similar data at an institutional level [6].

Moodle is the world's largest online learning management system (LMS). It has a very user-friendly interface that is regularly reviewed improved and can be customized as per the user's requirements [7]. To increase usability, moodle has introduced features of learning analytics [8].

Moodle is categorized as four services such as descriptive, predictive, diagnostic, and prescriptive. Descriptive tools give an idea about what happened and predictive tools provide the clue that what will happen next. The reason for the result is evaluated by diagnostic tools and suggestions for improvement are provided by prescriptive tools. There are several reports, blocks, and other plugins for moodle that provide learning analytics.

Learning analytics tools are one that can support the user to improve learning outcomes. The application of big data and analytics in education is the representation in learning analytics. There are many plugins like reports, blocks, and other plugins that are available in moodle to provide learning analytics. Some of the plugins are described below [9].

Logs are important plugins which are activity reports and available at the site and course level. A teacher as an administrator can generate a log of activity from the report option. A combination of fields of students such as date, activity, actions and level are selected for generating the log. Logs can be filtered as per levels like teaching level and participating level [10]. There are other plugins like activities, live logs, feedback, quiz statistics, course participation, survey, etc., in the moodle to support to analyze student performance [11]. Various systems like moodle activity viewer, Intelliboard, etc., are integrated with moodle to do learning analytics externally.

3 Methodology

3.1 Moodle-Based E-learning Portal

The online courses created in Moodle LMS have rich course topics represented in different component forms such as texts, power points, pdf, word, exams, hyperlinks, and assignments. The interaction of students is represented by using forums discussions and chats where the students can post topics and reply to others and view others' opinions. Any interaction of the students performed in moodle is stored in the log files and also in the database. As the portal is available on the Web site of the institution, the students with Internet access can access the course materials at any time.

3.2 Felder Silverman Learning Style Model (FSLSM)

Each student has their own learning style. This paper focuses on student learning style behavior patterns extraction based on the standard model of the FSLSM. FSLSM is a standard learning style model tested in various education systems. According to

Table 1 Felder Silverman's learning dimensions and learner characteristics

Learning dimensions	Learner characteristics	
Processing	**Active**: Do something physical by involving in the discussion, applying, or explaining to others	**Reflective**: Prefer observation and tend to think about information rather than doing active experimentation
Perception	**Sensitive**: Tend to do more practical and careful with details. Like to solve problems using standard methods and doing hands-on work	**Intuitive**: More innovative and tend to discover possibilities and relationships. Prefer abstractions and mathematical formulations and good at grasping new concepts
Input	**Visual**: Prefer visual representations such as diagrams, charts, graphics, charts, etc., to best remember the information	**Verbal**: Prefer verbal information such as lectures or written documents
Understanding	**Sequential**: Prefer to learn each topic in well-structured information sequentially in step by step	**Global**: Prefer to learn topics randomly in large chunks without seeing the relationship between them. Easily grasp the big picture and able to solve complex problems quickly

FSLSM [9, 11], learning style preferences are determined based on four different dimensions: processing, perception, input, and understanding which are grouped into various learner characteristics as sensitive/intuitive, visual/verbal, active/reflective, and sequential/global as shown in Table 1.

3.3 System Architecture Overview

The proposed architecture (Fig. 1) shows the entire process performed on the e-learning platform moodle for creating student reports.

When students enroll and take the online course on moodle, the students' interaction is being captured in log files and stored into the moodle database on the WAMP server. Further, the captured data on these files and tables have been analyzed to extract the behaviors of the students. Finally, the classification of student behaviors is done using a standard Naïve Bayes classifier to detect the learning style based on the standard FSLSM. The output can be used by educators to improve the learning of the students by making the course content based on their preferences.

Data Collection. In the context of students' performance, the information can be acquired explicitly (by collecting students' profile data) or implicitly (by monitoring students' behavior, such as visits to teaching courses, documents downloaded). The explicit method includes the personal data of the students such as identification

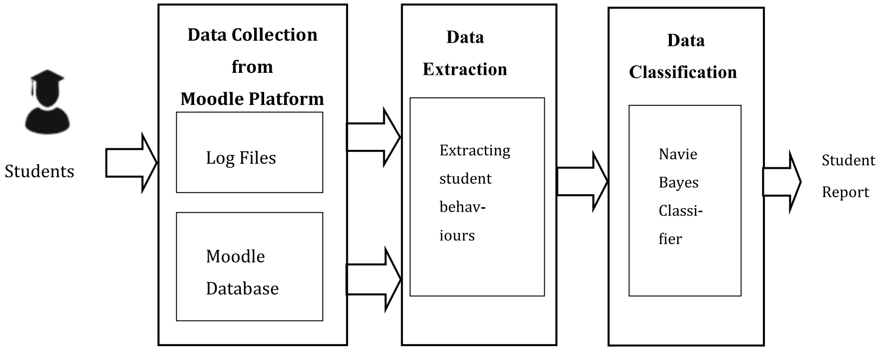

Fig. 1 Overall system architecture

number, name, mode of attendance, university number, date of birth, date of registration, e-mail, phone number, education, profession, address, place of birth, and nationality. The implicit method acquires the student behavior (the type of files, the time spent with reading files, the number of times a particular file is accessed, the number of visits/postings in forum/chat, number of visits and time spent on assignments, amount of time spent on a test, number of performed tests, number of visits and time spent on assignments, etc.) automatically from the log events and tables stored in the database of Moodle LMS. The proposed system focuses on both the explicit and implicit methods to collect students' data.

Capturing student profile data. In the proposed system, the explicit data of students registered for the online courses in Moodle LMS are obtained using the software that manages student data in the institution. The static data such as identification number, name, mode of attendance, university number, date of birth, date of registration, e-mail, phone number, education, profession, address, place of birth, and nationality, etc., are obtained and stored in the comma-separated values (CSV) file for further processing.

Capturing Log Event. When the student logs in for the first time and enrolls for the course, all the course contents are made available and provide access rights to various facilities such as formative assessment, self-assessment quizzes, news forums, discussion groups, chat rooms, and easy authoring tools for creating course contents such as videos, PowerPoint presentation, pdf, word, and other files including hyperlink insertion created by the instructor. The students access the material as per their preferences.

While accessing the courses and access other facilities of moodle, their daily interaction is obtained by observing the behaviors that are recorded in the log files automatically. The instructors can access the reports that record which course contents and activities of a course have been accessed, when, and by whom. One of the reports 'Logs' shown in Table 2 generates a filtered report showing information about the student activities. The information stored is 'Time', 'User full name', 'Event context',

Table 2 Sample log file data

Time	User full name	Event context	Component	Event name	Description	Origin	IP address
5/08/20, 16:21	alaa alfahdi	File: Chapter 1-Networking	File	Course viewed	The user with id ‘523′ viewed the ‘resource’ activity with course module id ‘2358’	Web	5.21.253.78
5/08/20, 16:19	Alaa	Quiz: Chapter 1	Quiz	Quiz attempt viewed	The user with id ‘509′ has viewed the attempt with id ‘313’ for the quiz with course module id ‘3243’	Web	5.21.253.78
4/07/20, 15:38	Sofia	Quiz: Chapter 2	Quiz	Quiz attempt reviewed	The user with id ‘539’ has had their attempt with id ‘434’ for the quiz with course module id ‘3243’	Web	5.162.128.223
4/07/20, 15:15	Hasna	Forum: Networking	Forum	Discussion viewed	The user with id ‘540’ has viewed the forum discussion for the forum with course module id ‘3243’	Web	5.162.128.223
4/07/20, 15:14	Hasna	Assignment: Chapter 1	Assignment	Submission form viewed	The user with id ‘349′ viewed their submission for the assignment with course module id ‘3846’	Web	5.162.128.223

'Component', 'Event name', 'Description', 'Origin', and 'IP address'. The log events that are captured are stored in the database in the WAMP Server.

The details of the log files header are given below:

- **Time**: The date and time on which the student accesses the page while using the LMS.
- **User full name**: This identifies the name of the student who visited the LMS.
- **Event Context**: Involves the name of the Event accessed by the student.
- **Component**: This includes the component such as quiz, assignment, forum, chat, and resources accessed by the student.
- **Event name**: This involves the behavior and actions of the student who access the LMS.
- **Description**: This gives a detailed description of the events performed with user id and course id.
- **Origin**: Represents the origin of all messages.
- **IP address**: This is the temporary address assigned to the computer to identify the student by the Internet service provider (ISP). This address is also used to identify revisited students.

Capturing Moodle Tables. The moodle database has more than 200 tables that are created for each course. The data in these tables keep track of students' significant activities regarding that particular course. From these tables, the important data required for student interaction and other related actions can be obtained using Structured Query Language (SQL) queries.

Data Extraction. Both log events and moodle tables are used to extract student behavior and actions required for detecting learning styles. Table 3 shows the relationship between the learning styles of FSLSM dimensions, learning styles, behavior patterns, and learning contents. Based on this mapping, the corresponding behaviors from the log files and moodle database can be extracted for each student to determine their learning style as the final output. This output supports educators to recommend learning content to the students based on their learning style and also helps students to understand the concepts in a better way.

Extracting student behaviors and actions from log events. Log events are used to monitor the activity of each student. From the log events, the most important actions for each activity shown in Table 4 such as the type of files (PowerPoint presentation, video, graphics, pdf, word, hyperlinks) the student accesses, the time spent with reading files, the number of times the student access a particular file, the number of visits/postings in forum/chat, number of visits and time spent on assignments, amount of time spent on a test, number of performed tests, number of visits and time spent on assignments are accessed for each student and these data are concatenated and saved in a single CSV file which is used to determine the students' learning style.

Extracting student behaviors and actions from moodle tables. The moodle tables are used to extract the behavior patterns of students such as number of visits/postings in forum/chat, number of visits and time spent on assignments, amount of time spent on a test, number of performed tests, number of visits, and time spent on assignments

Table 3 Relationship between FSLSM dimensions, learning styles, behavior patterns, and learning content category

FSLSM dimensions	Learning styles	behavior patterns	Learning content category
Perception	Sensitive	Amount of time spent on a test, no. of revisions before handing in a test, no. of performed tests, no. of visits and time spent on examples, performance on questions regarding facts	Facts, case studies
	Intuitive	Performance on questions regarding theories, no. of visits and time spent on exercises	Theoretical text
Input	Visual	Amount of time spent on contents with graphics, performance in questions related to graphics	Image, diagram, charts, video, and others
	Verbal	No. of visits/postings in forum/chat	Audio, text, and others
Processing	Active	No. of visits/postings in forum/chat, no. of visits and time spent on exercises	Example, practical exercise, activity, discussion, experimental, problem solving, and others
	Reflective	Amount of time dealt with reading material	Question, examples, links, readings, and others

Table 4 Activities versus actions of WebLog files

Activities	Actions
Quiz	Quiz attempt viewed, quiz attempt reviewed, quiz attempt submitted, quiz attempt started
Assignments	Submission form viewed, course module viewed, submission created, a file has been uploaded, status of submission has been viewed
Chats	Message sent, chat viewed
Forums	Discussion viewed, post created
Word	Course viewed
PDF	Course viewed
Powerpoints	Course viewed
Videos, graphics	Course viewed
Hyperlinks	Course viewed

Table 5 Set of attributes selected per student in moodle courses

Name	Description
id_student	Identification number of the student
id_course	Identification number of the course
num_sessions	Number of sessions
num_assigment	Number of assignments done
num_quiz	Number of quizzes taken
a_scr_quiz	Average score on quizzes
num_posts	Number of messages sent to the forum
num_read	Number of messages read on the forum
t_time	Total time used on moodle
t_assignment	Total time used on assignments
t_quiz	Total time used oil quizzes
t_forum	Total time used on forum

are obtained using SQL queries. Tables 5 and 6 show the summary table which integrates the most important information about the online activities in the courses.

Data Classification using Naïve Bayes Classifier. The demographic characteristics of the students and their behaviors and actions extracted from log events and moodle tables in some of the tasks such as chats, forums, tests, assignments, and files accessed are collected in three separate CSV files for each dimension and are analyzed and classified using the Naïve Bayes classifier to identify the learning style of students.

The Naïve Bayes classifier algorithm is the most straightforward and fast classification algorithm successfully applied for various applications such as text classification, sentiment analysis, and recommender systems. Initially, the train_test_split() method is applied to split the data set as 70 and 30% for the training and testing, respectively. Then the training is done by calling the method GaussianNB() and then fit() method used to fit the training data.

Table 6 Online activities of students in the moodle courses

Name	Description
course	Identification number of the course
n_assigment	Number of assignments done
n_quiz	Number of quizzes taken
n_quiz_a	Number of quizzes passed
n_quiz_s	Number of quizzes failed
n_posts	Number of messages sent to the forum
n_read	Number or messages read on the forum
total_time_assignment	Total time spent on assignments
total_time_quiz	Total time spent on quizzes
total_time_forum	Total time spent on forum

4 Experimentation and Results

The proposed approach is experimented on Moodle LMS by collecting the log events and moodle tables used by approximately 100 students studying one semester in computing science course in the institution.

The performance is evaluated based on various parameters such as accuracy, precision, and recall. Table 7 contains the results of the performance of the Naïve Bayes classifier, showing a classification report that shows the values of precision, recall, $F1$-score, and accuracy, classified to the three dimensions of FSLSM. The overall classification accuracy obtained is 85%.

The final results are used to cluster the students that have the same learning style based on FSLSM three dimensions. Clustering is a technique of grouping data into a smaller number of clusters so that the records in the group are very similar to each other based on the attributes of the data compared. Figure 2 shows the cluster of sample students populations based on learning style according to FSLSM dimensions.

5 Conclusion

The paper proposes an analysis of student data on the e-learning portal moodle to determine the learning style of each student based on FSLSM. The final result shows that the student learning style is classified precisely and accurately using the Naïve Bayes classifier based on three FSLSM dimensions thereby obtaining an overall classification accuracy of 85%. The research is restricted to a limited number of students and focused on the computer science domain. Future research could include more number of students under various domains. Moreover, further research could extend by extracting more student activities from the moodle tables for more accurate learning style classification and also attempt with other standard classifiers and use it for predictions. The final result supports educators to analyze the student preferences and design their learning contents based on their knowledge and requirements. The educators can either improve or change their approaches to working with students or to engage more with students. The educators can either change their approach for the specific student or opt for learning materials that better fit the student's needs.

Table 7 Classification report

Classifier	Performance measures	FSLSM dimensions				
		Processing				
		Extremely_reflective	Medium_reflective	Neutral	Medium_active	Extremely_active
Navie Bayes	Precision	1.00	0.78	1.00	0.64	1.00
	Recall	1.00	1.00	0.77	1.00	1.00
	$F1$-score	1.00	0.88	0.87	0.78	1.00
	Accuracy	87%				

FSLSM dimensions								Overall accuracy
Perception					Input			
Extremely_intuitive	Medium_intuitive	Neutral	Medium_sensitive	Extremely_sensitive	Extremely verbal	Extremely visual	Neutral	
1.00	1.00	1.00	0.19	0.00	1.00	1.00	1.00	
1.00	1.00	0.28	1.00	0.00	1.00	1.00	1.00	
1.00	1.00	0.43	0.33	0.00	1.00	1.00	1.00	
67%				100%				85%

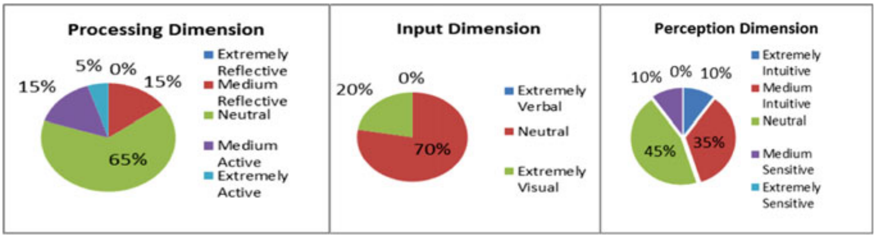

Fig. 2 Cluster of students populations based on learning style

Acknowledgements This paper is part of funded Project 'Construction and Retrieval of Ontology Based Semantic Learner Profile' from Research Council, Sultanate of Oman in call 2018.

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