Emperor Journal of Applied Scientific Research
www.mayas.info © Mayas Publication ISSN No: 2581-964X
Volume-VI Issue-3 March-2024

Students Performance Analysis Using Moocs Platform

M. Kannan
Research Scholar
SRM Institute of Science and Technology, Vadapalani Campus.

Dr. K. R. Ananthapadmanaban
Professor and Dean
SRM Institute of Science and Technology, Vadapalani Campus.

Abstract

Our goal in this work was to provide interested academics with up-to-date information on the latest findings and investigations concerning student performance analysis and learning analytics in massively open online courses (MOOCs). Examining the application of performance prediction and learning analytics in MOOCs is the goal of this.

To introduce readers to our work, we first provide literature-based explanations of key concepts. To help understand the relative relevance of the qualities and their relationships, details on a number of studies were then provided. Next is a summary of the outcomes of learning analytics and student performance prediction applied to MOOCs.

I. INTRODUCTION

The use of performance prediction and learning analytics in massively open online courses (MOOCs) is one of the research topics that is advancing the fastest. Until recently, nearly every month, articles were published offering their different interpretations of how well students performed in Massive Open Online Courses (MOOCs).

We will commence our essay by providing definitions and explanations of basic terms related to our overview. Subsequently, an extensive examination of the application of learning analytics and performance prediction in MOOCs will be necessary.

Educational Data Mining (EDM) and Its Emerging Study Areas

Understanding Educational Data Mining

Begin by defining Educational Data Mining (EDM) as the process of transforming raw data from educational systems into actionable insights that inform instructional design and address research inquiries.

Evolution of Educational Data Mining

1. Founding of EDM Conferences and Journals: Discuss the pivotal moment in

2008 with the establishment of the International Conference on Educational Data Mining (EDM) and the Journal of Educational Data Mining, which marked the formal recognition and growth of the field.

2. Growth and Independence: Highlight how EDM has evolved independently as a specialized field within data mining, focusing specifically on educational contexts and challenges.

Emerging Study Areas in Educational Data Mining

1. Face-to-Face Interaction in Offline Education:

•Explain the significance of face-to-face interaction as the cornerstone of traditional offline education.

•Discuss the psychological aspects of learning and how EDM techniques can be applied to analyze and optimize face-to-face instructional methods.

•Provide examples of research questions and methodologies within this study area, showcasing its relevance in improving teaching practices and student outcomes.

2. Learning Management Systems (LMS) and E-Learning:

•Introduce the role of Learning Management Systems (LMS) and e-learning platforms in modern education.

•Discuss how EDM techniques can be employed to analyze user interactions, engagement patterns, and learning outcomes within LMS environments.

•Highlight the practical applications of EDM in enhancing the design and delivery of online courses, as well as personalizing learning experiences for students.

Understanding Learning Analytics: Definitions and Perspectives

Measurement, Collection, Analysis, and Reporting

Learning analytics is first defined as the systematic process of measuring, collecting, analyzing, and reporting data on learners and their contexts [7]. This definition underscores the comprehensive nature of learning analytics, which involves not only gathering data but also interpreting it to gain insights into the learning process and its surrounding environment.

A New Lens for Education

A second perspective defines learning analytics as a transformative lens through which educators can view and enhance the educational experience. It involves the analysis and representation of data about learners with the goal of improving learning outcomes [8]. This definition emphasizes the role of learning analytics in providing educators with actionable insights to tailor instruction and support individual learner needs effectively.

Leveraging Big Data Approaches

Another definition highlights the use of big data approaches in learning analytics [5]. This perspective emphasizes the scale and complexity of data involved in modern educational settings, necessitating advanced analytical techniques to derive meaningful insights. Learning analytics, in this context, involves harnessing the power of big data to understand and optimize learning processes.

A New Discipline with Advanced Analytical Techniques

Lastly, learning analytics is described as a burgeoning discipline that applies advanced analytical techniques to educational data [citation needed]. This definition underscores the interdisciplinary nature of learning analytics, drawing on methodologies from fields such as data science, machine learning, and educational research to extract valuable insights from complex datasets.

Understanding Massive Open Online Courses (MOOCs)

Massive Open Online Courses (MOOCs) are online courses designed to be accessible to a large number of learners worldwide. They are typically offered free of charge and can be accessed remotely with an internet connection. The key characteristics of MOOCs include:

1. Open Access: MOOCs are open to anyone with an internet connection, regardless of geographic location, educational background, or financial status.
2. Scalability: MOOCs are designed to accommodate a massive number of learners simultaneously, making them accessible to a global audience.
3. Flexibility: Learners have the flexibility to enroll in MOOCs at any time and complete coursework at their own pace, without being bound by traditional semester schedules.

Popularity and Impact

The popularity of MOOCs can be attributed to several factors:

1. Global Accessibility: The ability for anyone around the world to enroll in MOOCs has significantly expanded access to higher education, particularly for individuals in underserved communities or regions with limited educational opportunities.
2. Variety of Courses: MOOC platforms like Coursera, EdX, and Udacity offer a wide range of courses spanning various disciplines, catering to diverse interests and learning objectives.
3. Cost-Free Learning: The availability of free online courses removes financial barriers to education, making learning accessible to individuals who may not have the resources to enroll in traditional educational programs.

MOOCs have attracted learners from diverse backgrounds, including:

1. Students of All Ages: Learners of all ages, from high school students to working professionals and retirees, have participated in MOOCs to acquire new skills, advance their careers, or pursue personal interests.
2. Various Educational Levels: MOOCs cater to learners at different educational levels, ranging from introductory courses to advanced topics, allowing individuals to pursue learning opportunities tailored to their proficiency levels.
3. Global Reach: MOOCs have a global reach, attracting participants from different countries and cultural backgrounds, fostering cross-cultural exchange and collaboration among learners.

Objectives for Evaluating Student Performance and Enhancing Learning:

1. Assessing Educational Phases for Academic Counseling
2. Estimating Self-Directed Learning Capacity
3. Providing Guidance, Coaching, and Feedback

4. Modifying Learning Environments and Suggesting Learning Strategies

II. CONCLUSION

While significant progress has been made in understanding student performance and leveraging learning analytics in MOOCs, there remains a need for continued research and exploration. By focusing on specialized topics and user group behaviors, future studies can enrich our understanding of MOOC dynamics and inform strategies for enhancing learning outcomes in online education.

III. REFERENCES

[1] Pappano, Laura. "The Year of the MOOC." The New York Times 2.12 (2012): 2012.
[2] Kerr, J., et al. "Building and executing MOOCs: A practical review of GlasgowâA˘ Zs first two MOOCs (massive open online courses). ´ University of Glasgow." (2015).
[3] Ripley, Brian D. "The R project in statistical computing." MSOR Connections. The newsletter of the LTSN Maths, Stats and OR Network 1.1 (2001): 23-25.
[4] Paradis, Emmanuel, Julien Claude, and Korbinian Strimmer. "APE: analyses of phylogenetics and evolution in R language." Bioinformatics 20.2 (2004): 289-290.
[5] KlÃijsener, Marcus, and Albrecht Fortenbacher. "Predicting students' success based on forum activities in MOOCs." Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), 2015 IEEE 8th International Conference on. Vol. 2. IEEE, 2015.
[6] Ashenafi, Michael Mogessie, Giuseppe Riccardi, and Marco Ronchetti. "Predicting students' final exam scores from their course activities." Frontiers in Education Conference (FIE), 2015. 32614 2015. IEEE. IEEE, 2015.
[7] Wolff, Annika, et al. "Predicting student performance from combined data sources." Educational Data Mining. Springer International Publishing, 2014. 175-202.
[8] DeBoer, Jennifer, and Lori Breslow. "Tracking progress: predictors of students' weekly achievement during a circuits and electronics MOOC." Proceedings of the first ACM conference on Learning@ scale conference. ACM, 2014.
[9] Ramesh, Arti, et al. "Uncovering hidden engagement patterns for predicting learner performance in MOOCs." Proceedings of the first ACM conference on Learning@ scale conference. ACM, 2014.
[10] Feng, Yunping, et al. "The Impact of Students And TAs' Participation on Students' Academic Performance in MOOC." Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015. ACM, 2015.
[11] Hughes, Glyn, and Chelsea Dobbins. "The utilization of data analysis techniques in predicting student performance in massive open online courses (MOOCs)." Research and Practice in Technology Enhanced Learning 10.1 (2015).
[12] Ye, Cheng, and Gautam Biswas. "Early Prediction of Student Dropout and Performance in MOOCs using Higher Granularity Temporal Information." test 1.3 (2014): 169-172.
[13] Xu, Bin, and Dan Yang. "Motivation classification and grade prediction for MOOCs learners." Computational intelligence and neuroscience 2016 (2016): 4.
[14] Coffrin, Carleton, et al. "Visualizing patterns of student engagement and performance in MOOCs." Proceedings of the fourth international conference on learning

analytics and knowledge. ACM, 2014.
[15] MÅCynarska, Ewa, Derek Greene, and PÃ ˛adraig Cunningham. "Indi- ´ cators of Good Student Performance in Moodle Activity Data." arXiv preprint arXiv:1601.02975 (2016).