

## Chapter 5

# Web Data Mining in Education: Decision Support by Learning Analytics with Bloom's Taxonomy

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### ABSTRACT

*Web data mining for extracting meaningful information from large amount of web data has been explored over a decade. The concepts and techniques have been borrowed into the education sector and the new research discipline of learning analytics has emerged. With the development of web technologies, it has been a common practice to design online collaborative learning activities to enhance learning. To apply learning analytics techniques to monitor the online collaborative process enables a lecturer to make instant and informed pedagogical decisions. However, it is still a challenge to build strong connection between learning analytics and learning science for understanding cognitive progression in learning. In this connection, this chapter reports a study to apply learning analytics techniques in the aspect of web usage mining and clustering analysis with underpinning Bloom's taxonomy to analyze students' performance in the online collaborative learning process. The impacts of intermediate interventions are also elaborated.*

### INTRODUCTION

Techniques for web data mining has been developed over a decade. It aims to extract large amount of data collected over the web for further analysis to obtain useful information. Based on the purposes and natures, an analysis is usually categorized into one of the three aspects of web data mining, namely web content mining, web structure mining and web usage mining (Sakthipriya et al., 2015). Applications of web data mining can be found in different areas such as e-commerce (Verma et al., 2015), social networking (Russell, 2013) and health care (Lai & Shi, 2015). Enlightened by the impacts of web data mining, related concepts and techniques have been borrowed to the education sector since 2011 and the new research area of learning analytics has emerged. Baker and Inventado (2014) suggested that educational data mining is concerned with the analysis of large scale educational data using data mining methods.

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In the first International Conference on Learning Analytics and Knowledge held in 2011, learning analytics was defined as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs”. It is a newly emerging research discipline rooted from business intelligence and web analytics which focuses on handling large amount of data collected from websites using computer technologies (Siemens, 2012; Ferguson, 2012). As emphasized by Larusson and White (2014), learning analytics is an ideal strategy to look into the learning process. Results obtained can be fed back into the learning and teaching process for making decisions to adapt subsequent pedagogy for further enhancing teaching effectiveness. The U.S. Department of Education (2012) also stated that it is important to ensure that key decisions about learning are informed by data. The learning analytics, therefore, helps understand the learning system and supports decision making in an educational setting.

With the development of web technologies, it has been a common practice to integrate online collaborative learning activities in designing courses in higher education (e.g. Lai & Ng, 2011, Brindley et al., 2009). The educational benefits of online collaborative learning have been confirmed in numerous studies (Chiong & Jovanovic, 2012). However, in the development of assessing online collaborative learning, most previous studies incorporated measurement on learning only after the collaborative activities by filling out a self-report questionnaire, reviewing the products, interviewing participants for collecting feedback and carrying out after collaboration observation (Gress et al., 2010). The lecturer was hard to provide instant feedback to learners and almost impossible to make decisions to adapt teaching strategies. Few research can be found to monitor and assess the online collaborative process. Actually, researchers has raised the importance to look into the online learning process for making decisions to adapt teaching strategies for enhancing students’ learning (Lera-Lopez et al., 2010). This rationale aligns with the purpose of assessment for learning. Under the rationale of assessment for learning, the first priority of assessment design and practice is to serve the purpose of pupils’ learning (Black & Wiliam, 2003). The collected evidence is used to adapt the learning and teaching strategies so as to meet the learning needs (Black & Wiliam, 1998). However, to analyze online learning process can be regarded as highly complicated (Gress et al., 2010). It is also very labor intensive to process large amount of data when the class size is large and participation is high (Persico et al., 2010; Brookhart et al. 2010; MacPhail & Halbert, 2010). Since the main purpose of learning analytics is to analyze large amount of data, related concepts and techniques can be considered as a possible solution to analyze the online learning process so as to make further decisions on pedagogy.

However, the development of research on learning analytics is still in an early stage. One of the challenges of learning analytics is to build strong connection with the area of learning sciences (Ferguson, 2012). Although some researchers attempted to suggest methods to analyze the online learning process (Mazzoni & Gaffuri, 2010; Lera-Lopez et al., 2010; Pantaleon & Saiz, 2010; Trentin, 2009), learning theory was seldom incorporated in the framework of analysis. The measurement of learning progression was mainly based on students’ performance in different points of evaluation. The inadequacy is that the methods suggested in previous studies cannot evaluate at which cognitive level of learning the student achieved. It is therefore not easy to make decisions on the way forward for improvement. Therefore, although related measurement and assessment strategies helps to track students’ participations in online learning environment and different reports or charts may provide some reference information, the design of an analysis that based on sound learning theory for understanding cognitive progression to make informed decisions is still a challenge.

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