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# Using Learning Analytics to Improve Digital Game-Based Learning

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## Abstract

*Learning analytics provides the education researcher with the opportunity to collect and analyse a wide range of data related to learners and their contexts for the purpose of improving learner engagement and outcomes. While much of the focus of learning analytics has been on learning management systems, game-based learning offers the possibility of gathering rich data using the programmatic features of a game engine. Any interaction by a learner with the game-based environment can be tracked, with contextual data recorded. This paper presents a model for collecting game-based learning data that shows from a practical perspective what kind of data (such as events and timings) to collect and how it can be analysed with the express purpose of improving learning experiences and outcomes. A proof of concept is presented based on the game-based learning of graph theory. Graph theory is a branch of mathematics used in many scientific disciplines, for example to model molecules, atomic structures and the evolution of species. A virtual reality-based game introduces students to the fundamentals of graph theory, for example vertices and edges, and engages them in active learning as they connect vertices according to rules presented to them. Each action is recorded in a database for analysis, including a detailed log of student progress through an exercise, recording when vertices are correctly or incorrectly connected and the varying pace of progression through an exercise. The paper discusses how the educator can quickly analyse data to identify and correct common mistakes made by students, for example those based around a misinterpretation of the rules or a difficulty with the game's mechanics. The paper also discusses how building learning analytics into a game early in its development can be useful as a means of formative evaluation as prototypes are iteratively improved through early and frequent stakeholder engagement.*

**Keywords:** *learning analytics, game based learning, virtual reality, active learning, graph theory*

## 1. Introduction

Learning analytics (LA) is an emerging and growing field of study of increasing interest not just to individual educators and researchers but also to educational institutions, governments, industry and the public [1]. LA can be used to improve student retention, learning outcomes, engagement, relevance of learning content, and to identify where learning supports can be targeted [2]. A widely-used definition of LA was provided at the 1st International Conference on Learning Analytics:

> *Learning analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs.*

While LA often focuses on learning management systems, this paper focuses on the generation and storage of data during digital game-based learning (DGBL) for decision-making purposes. It explains what types of data can be stored and how and when the data can be analyzed to support decisions with varying degrees of immediacy, such as the algorithmic decisions executed by a game at runtime to provide an adaptive learning experience, or the analysis of data to support formative evaluation during the development process.

The paper ends with a brief discussion of a prototype game that teaches introductory graph theory and how it has been designed to take advantage of LA.

## 2. Digital Game-Based Learning and Learning Analytics

There are several studies which show that games have potential as a learning tool that enhances a learner's experience when compared with more traditional teaching approaches [3,4]. DGBL can be particularly effective in teaching science concepts if the game is carefully designed to be conceptually-integrated [5]. This section discusses how data can be stored and analyzed to enhance the learner's experience and outcomes, and aid DGBL design.

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## 2.1 Behavioural and Outcome Data

Many theories or models of learning can be categorized as being either outcome or process focused. According to the behaviourist perspective of education, when learning occurs it is because of observable events in the environment [6]. With outcome-focused taxonomies of learning such as the revised Bloom's taxonomy [7] or Biggs's SOLO taxonomy [8] (both shown in Fig.1), it could be argued that the *process* of learning is important when seen as a progression. In the case of SOLO, for example, the understanding of a concept can be observed to progress through several stages of comprehension (beginning with the most primitive unistructural understanding) to the point where a learned abstract concept can be applied in any context (the extended abstract understanding). This offers the DGBL designer opportunities to store data as a player's understanding demonstrably progresses. An example of this approach is the *learning path model* [9] which uses progression through the Bloom's revised taxonomy cognitive domain (from basic *remembering* through to *creating*) as the basis of a visualization of student learning.

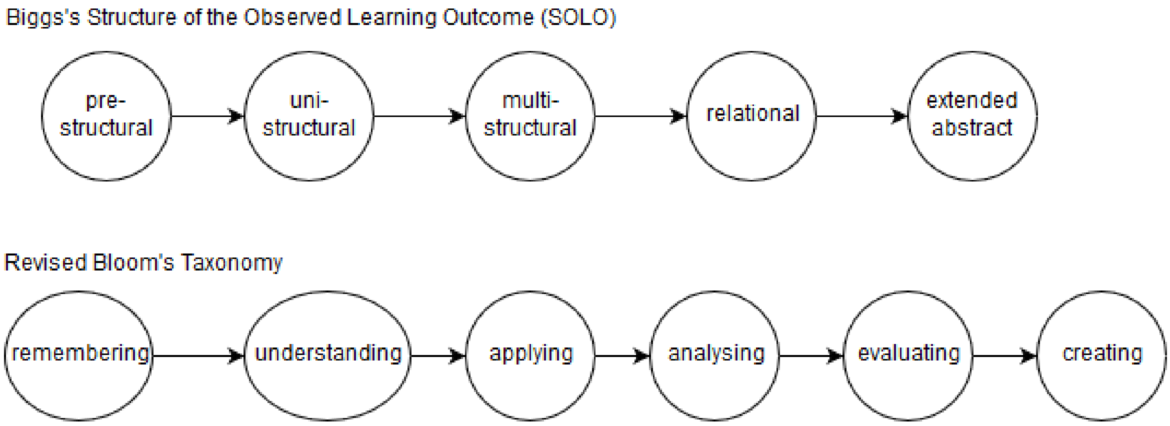


Fig.1. Taxonomies of learning as a progression of understanding

Each data point will often represent an *event* with a *context*. With a progression through a taxonomy of learning, the data points will represent changes of state: for example, the state changes from *unistructural understanding* to *multistructural understanding* (using Biggs's SOLO taxonomy). The context could include additional properties, such as a timestamp or a score, and there may be other performance indicators, such as a number of attempts before successful accomplishment of a task.

## 2.1 Four Uses of Gameplay Data

As well as what type of data will be stored, of equal importance is how and when that data will be used. This subsection discusses four examples of how data can be used to improve learning outcomes and learner experiences, but also at what stage in the instructional design and delivery process it can bring that benefit.

1. ***Formative Evaluation:*** Gameplay data can be analyzed prior to the final delivery of an educational game to improve its quality. Several models of instructional design, such as ADDIE (described by [10]), emphasize continuous evaluation as part of an iterative cycle. Formative evaluation can be used as a means of revising instruction [11]. By analyzing gameplay data during trials of prototypes, issues can be identified and resolved to improve the learning experience and outcomes, and ensure a greater degree of universal design.
2. ***Summative Evaluation:*** Gameplay data can be used post-delivery as part of the overall summative evaluation process. It can be useful as part of a continuous improvement cycle that feeds back into the design of the next iteration of a DGBL solution so that a new cohort of learners benefit from the experiences of prior learners.
3. ***Adaptive Learning:*** The algorithms that underpin adaptive learning in DGBL can be as simple as providing contextual learning content when a player has demonstrated a lack of mastery of a particular topic, or they could be more complex with varying degrees of artificial intelligence (AI) or use of semantic networks (research in this area is surveyed in [12] and [13]). A game designer should also ensure that a player stays in what is known as the flow channel (based on the research of Csikszentmihalyi [14]) where a game avoids becoming too frustrating (too difficult) or boring (too easy or repetitive). Games can be designed to be adaptive, presenting

the right level of challenging content, based on a player's historical gameplay data to remain in the flow channel.

4. ***Formative feedback*** can be provided at regular intervals, such as at the end of a level or the game. Players can receive feedback about overall performance as an individual or on a comparative group basis. This is greatly more prompt than activities graded by a teacher or lecturer. Prompt feedback is one of the principles of good practice in education [15].

## 3. Case Study: The Graph Game

The Graph Game is the working title of a DGBL solution under development by the author. The game introduces players to the fundamentals of graph theory and is being built on a virtual reality platform (Unreal Engine 4 with Oculus Rift VR headset).

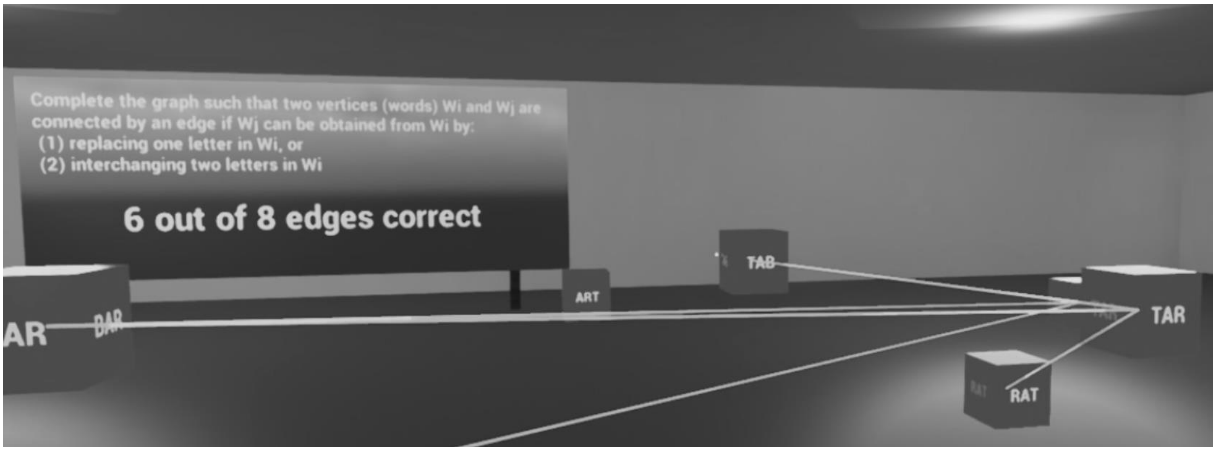


Fig.2. Example challenge in The Graph Game featuring formative feedback

Players begin with a tutorial level that introduces the mechanics of the game and some initial fundamental graph constructs: vertices, edges and graphs. As each mechanic is introduced (such as how to connect two vertices), a data point is stored with a timestamp. It is easy to identify from gameplay data where a player has had difficulty mastering a mechanic by subtracting a timestamp from the previous timestamp and noting the time differential.

In another level, players complete a graph according to specified rules (Fig.2). The sequence of connecting vertices, number of incorrect connections, and total time of completion are all stored. The player receives visual feedback (incorrect connections are represented by red edges) along with formative feedback (time taken to complete and number of correct versus incorrect connections). The game progresses from level to level, with the player demonstrating a unistructural up to an extended abstract level of understanding (as per the SOLO taxonomy). Gameplay data also allows pace of learning to be monitored.

Finally, though more uses of gameplay data are envisaged, player task completion times are displayed on a leaderboard for comparison of individual performance against group performance.

## 4. Conclusions

Learning analytics is seen as increasingly important and should be a consideration when a DGBL designer begins the process of mapping learning processes and outcomes to a game. Learning can be seen as a progression of understanding with changes of state that can be recorded as a DGBL player accomplishes tasks. Gameplay data allows for rich data analysis that can allow games to be adaptive in real time, motivate players to continue playing, and help the designer design more effective games during the initial DGBL implementation phase and post-delivery as part of a continuous improvement cycle.

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