Implications of learning analytics for serious game design

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***Abstract*— This paper addresses the implications of combining learning analytics and serious games for improving game quality, monitoring and assessment of player behavior, gaming performance, game progression, learning goals achievement, and user's appreciation. We introduce two modes of serious games analytics: in-game (real time) analytics, and post-game (off-line) analytics. We also explain the GLEANER framework for in-game analytics and describe a practical example for off-line analytics. We conclude with a brief outlook on future work, highlighting opportunities and challenges towards a solid uptake of SGs in authentic educational and training settings.**

Keywords- Learning analytics; Serious games; Game design; Assessment; Performance

I. INTRODUCTION

In this paper we address the implications of combining two major trends in technology-enhanced learning research: 1) serious gaming, and 2) learning analytics (LA).

Serious games (SGs) can be defined as games with non-entertainment goals, used to educate, train and inform [1]. The use of SGs to support the learning process has a long tradition as a teaching, training and learning method [2]. The main features of SGs have been addressed by several authors [3, 4] highlighting learner involvement through exploration, experimentation, competition and co-operation.

The difficulties on measuring learning outcomes achieved through SGs' use have been a main barrier for successful deployment and adoption of SGs within formal education [5] and corporate training [6]. But recent interests in LA may help to compensate for this. Fournier, Kop, and Hanan [8] define LA as the "measurement, collection, analysis and reporting of data about learners and their context, for purposes of understanding and optimizing learning and the environments in which it occurs". It provides new opportunities for tracking and analysing learners' behavioural data and interpreting them in an educational meaningful way. Integrating LA into SG design is expected to improve the assessment of progress, performance, learning outcomes, game quality and user appreciation [4].

Next we will describe topical issues in the field of in-game assessment and explain how it can be combined with LA as SGs analytics. We will distinguish between two modes of SG analytics: 1) in-game (real time) analytics, and 2) post-game (off-line) analytics. In addition, we will explain the GLEANER framework for game-based LA and touch upon a practical example of posterior analytics. We conclude with a short outlook on issues and future work.

II. THE ASSESSMENT OF LEARNING IN SERIOUS GAMES

In principle, all SG make use of in-game mechanisms for the assessment of player performance and progress, for an appropriate response to the player's actions. Since games are interactive and complex software systems that commonly apply logical (game) rules for evaluating appropriate system responses, they in principle generate a large set of user data that could be used for monitoring and assessment purposes [9]: Game challenges or contents are adapted to the players' actions; inappropriate actions may induce guidance like corrective feedback. Indeed, many games monitor the player's progress in the game and assess the level of performance achieved (e.g. performance scores, levels).

High performance in a game play, however, does not necessarily imply effective learning. In general, game play is inherently linked with performance, which goes with an attitude of achieving milestones and high scores. In contrast, learning often requires opportunities for reflection, informed repetition, pauses, and even the preparedness to make mistakes and learn from these. Hence, in many aspects the process of gaming may conflict with the process of learning. This conflict between learning and performance will be larger as games offer more open choices and freedom of movement to the learners: As nowadays many SGs tend to reflect approaches to realistic, contextualized problem solving, self-directed learning, and a wide range of 21st century skills relevant for today's knowledge workers [7]. One might say that many games analyse player data, but fail to analyse the learning.

Although quite some research has been directed to in-game and unobtrusive assessment methodologies like [11] that heavily relies on logging data to interrelate observable in-game behaviours to a competency-based score model which quantifies learning outcomes rather than performance. Or approaches like stealth assessment [10], which allows the provisioning of feedback to players during the game play complying with implicit learning. Still the assessment of learning in SGs is far from being straightforward and asks for additional methods and models that produce valid evaluations and evidences of learning in games, which requires additional player data. The current wealth of data, gathered through web-based logging, tracking engines, sensors such as eye trackers, location tracking and motion detectors, in combination with emerging learning analytics methods is exactly what we need to improve the monitoring and assessment of game-based learning.

III. Linking Learning Analytics and Serious Game Design

Learning analytics offer powerful tools for the assessment of game-based learning. The related processes of data gathering and analysis for the evaluation of serious games can be implemented at least in two possible ways [7], cf. Figure 1.

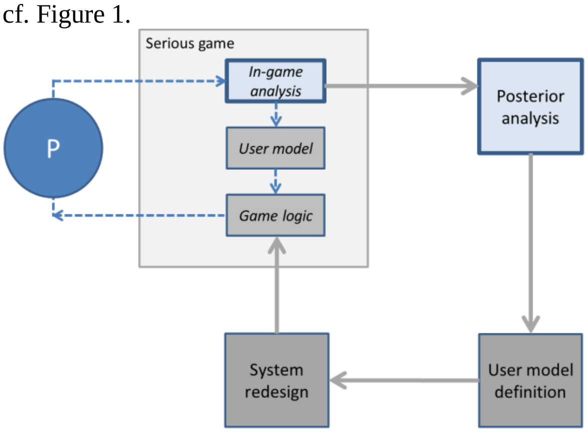

Figure 1. In-game analysis and off-line (posterior) analysis

First, in-game analysis refers to collecting information from the individual player during game play in order to check the adequacy of the experience [7] and to provide individual support and personalisation of the game/learning experience [12]. Second, an off-line (posterior) analysis gathers data from a population of players/learners for the purpose of quality assurance, evaluation and improvement of the SG design.

Although these approaches have different objectives, the type of data needed may be very similar. Thus, to take full advantage of the LA benefits, it is wise to consider its integration in the initial SG conception and design. In all cases, it is beneficial to define and include a semantic layer, which translates sub-symbolic actions such as keystrokes and mouse clicks during game play into meaningful clues, related to the educational game design, game narrative, game context and the tasks carried out. Overall, in order to check the learning achievements, an assessment approach is required, that mutually links behavioural indicators, with learning goals, competence frameworks, activities, and assessment criteria. This can be covered by the model presented in [10].

Even there are not widely accepted or standard methods to clearly link the SG educational design with the LA game data, several initiatives are working on that direction. In the next sections two of those initiatives are presented.

IV. The GLEANER Framework

As part of joint research activities in the Games and Learning Alliance (GALA), we have developed a LA general framework and a data service for linking learning analytics and serious gaming.

The Games and LEarning ANalytics for Educational Research (GLEANER, cf. Figure 2) has been devised and is being implemented to support tracking and analysing learners behavior in-game activities [13].

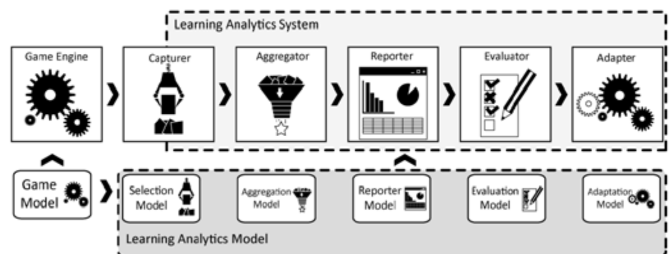

Figure 2. Main components of GLEANER

The Learning Analytics Model (LAM) defines a sequence of steps as well as the information required for every step, whereas the Learning Analytics System (LAS) implements all the processing functions required by the model (see Figure 2). Both, LAS and MAS comprise five interlinked components that describe the workflow namely: Data selection/capturing (Step 1), Data aggregation (Step 2), Data reporting (Step 3), Data evaluation (Step 4), and Game adaptation (Step 5). The LAS component is created as a service that collects all traces generated by the game. The service may be remotely located, according to the Service Oriented Architecture paradigm. The game pushes information to the server through a specific API. And the instructors can access the server in order to monitor the players' performance evolution [13]. Moreover, it is necessary to edit and manage a machine-readable model mapping the tracked game events and the expected pedagogical goals and outcomes.

However, in order to obtain maximal benefits of the LA, the implementation of this has to be considered already during the design of a game. The idea is to link the educational goals of the game with the in-game observable data and to support their collection.

V. A SERIOUS GAMING ANALYTICS EXAMPLE

Although the work in GLEANER is still in progress next we demonstrate how SG analytics can be achieved in practice and are not restricted to a unique SG environment or LA approach. Particularly, we refer to the off-line analysis that we have carried out for the VIBOA-games used by the Utrecht University [7]. These games were developed with the EMERGO SG engine (www.emergo.cc). With respect to the GLEANER's components of data capturing, the EMERGO engine was capable of tracking and logging every single player action and the involved game objects and attributes. Because of the component-based architecture of the EMERGO engine, an aggregator (the next step of GLEANER model) was built to generate a joint status history file: typically a time-ordered relational database of events and associated objects, attributes, parameters and values. Because of the nature of the off-line analysis carried out, we did not use a built-in analyser but common software tools (e.g. SPSS) for data processing and reporting (GLEANER step 3). The evaluation (GLEANER step 4) comprised a comparison of a set of primary variables (e.g. total time spent, number of trials for tasks completion and task execution time) in order to analyse players' preferences, bottlenecks and variability of behaviours. Here, the adaptation (GLEANER step 5) focused on the definition of a set of technical changes at system level for better meeting the actual SG requirements. Overall, posterior analysis provided a rich data set with various informative clues about user behaviours. For example, we could simply conclude that the inclusion of (expensive and laborious) video recordings in the games was worthwhile since players intensively consulted them [7].

VI. CONCLUSIONS AND NEXT STEPS

This paper has discussed how the fields of SGs and LA can be combined to improve the assessment of player behaviour, gaming performance, progress, learning outcomes and game quality. It also analysed the SG assessment main issues in relation to learning and performance evaluations and the need of detailed assessment models and user data for producing valid assessments of learning and how to take advantage of the LA tools. Research challenges still lie in the full exploration and validation of gaming analytics methods and tools, in particular in the development of real time procedures for adaptive gaming and personalised support; and the appropriate definition and implementation of valid assessment models and criteria. Full implementations and instrumentation of GLEANER-like approaches are becoming of ever more relevance and urgency. Particularly, the development and testing of simple, user-friendly tools for teachers or non-technical persons (e.g. for supporting the steps of reporting and evaluation mentioned in the GLEANER model) is the necessary precondition for the successful adoption of these new approaches by practitioners. Finally, the issue of LA interoperability across different games, genres and platforms/engines is also an essential factor for a solid uptake of SGs in authentic educational and training settings.

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