Learning Analytics for Educational Game Design: Mapping Methods to Development

V. Elizabeth Owen, Games+Learning+Society Center at University of Wisconsin-Madison

Introduction

Big data in education (c.f. U.S. Department of Education, 2012) has fostered emergent fields like educational data mining (Baker & Yacef, 2009; Romero & Ventura, 2010) and learning analytics (Siemens & Long, 2011). Simulations and educational videogames are obvious candidates for the application of these analytic methods (Gee, 2003; Steinkuehler, Barab, & Squire, 2012), affording big data situated in meaningful learning contexts (Mislevy, 2011; Shute, 2011; Clark et al., 2012). In the design of these game environments, experts assert that players rarely interact with the game in exactly the way the designers envision, and thus heavily emphasize early, repeated usertesting (Schell, 2008; Salen & Zimmerman, 2004). With the added element of content-specific learning goals, or concrete growth over time in a domain-specific skill, attending and adjusting to organic play patterns becomes even more vital (c.f. Shute, 2011; Norton, 2008; Institute of Play, 2013). Thus, just as design-based research in the learning sciences involves data-driven, iterative refinement of measurement tools and experimental design (Barab & Squire, 2004), educational game design needs to incorporate learning-specific assessment mechanisms and leverage sophisticated techniques to understand nuanced learner patterns in play – informing development from the earliest stages of design.

This paper presents a framework of educational data mining methods for optimizing design of games for learning from the earliest development stages. Specifically, it aligns telemetry-based assessment structures and applied learning analytics to inform three stages of development: initial core design, alpha and early beta usertesting, and final design overlay of learner-adaptive gameplay. To establish a baseline of analytics for reference throughout the design process, we begin with a literature review of data mining in digital learning environments. Then, applications of these analytics (visualization, association mining, and prediction) to specific design processes will be discussed in the context of each development stage, supported with examples from GLS game research and current work in the field.

Theoretical Framework: Data Mining in Digital Learning Worlds

Many commercial videogame developers are implementing analytics in games for usability testing (e.g. Drachen et al., 2013) and marketing (e.g.Ross, 2013). However, many of these methods are not learning-specific, nor tailored to measuring growth in educational knowledge or skill over time (c.f. U.S. Department of Education, 2012). Representing a host of education-specific machine learning tools, Educational Data Mining (EDM) can provide excellent groundwork for defining data mining methods readily applicable to these large data sets (Baker & Yacef, 2009; Romero & Ventura, 2010). This section will review current literature in EDM, and articulate visualization, relationship mining, and predictive modeling as base methods categories for our discussion of game-based learning analytics.

Educational Data Mining

EDM “is concerned with developing methods for exploring” large educational data streams (Baker & Yacef, 2009, p. 324). EDM is an emergent, multi-disciplinary field in constant evolution (c.f. Romero & Ventura, 2010). As a result, EDM experts survey the field from a variety of different perspectives (Baker & Yacef, 2009; Romero & Ventura, 2010; U.S. Department of Education, 2012). Baker & Yacef (2009) as and the U.S. Department of Education (2012) focus on data modeling goals and methods, while Romero & Ventura (2010) organize around the human subjects of study and educational context (classrooms, e-learning spaces, etc.). However, a common EDM schema can be derived by extracting two mutual methodological components: 1) broad analysis goals, and 2) specific analysis methods.

The main common components of EDM are broad analytic goals and specific methods. Broad analysis goals (or “metagoals”) common to the expert EDM synopses are visualization, relationship mining, and prediction (c.f. Baker & Yacef, 2009; Romero & Ventura, 2010; DoE, 2012). Visualization involves graphic representations of data to elucidate patterns; relationship mining looks specifically at associative patterns in the data; and prediction can project outcomes via algorithms of sequence, probability, and regression. The last core EDM component, specific method types, are subunits of these metagoals. These method types include: descriptive visualization, social networks, clustering, association, classification/regression, and pattern mining (Figure 1). A loose mapping of these specific methods to the broad metagoals of EDM is visualized in Figure1.

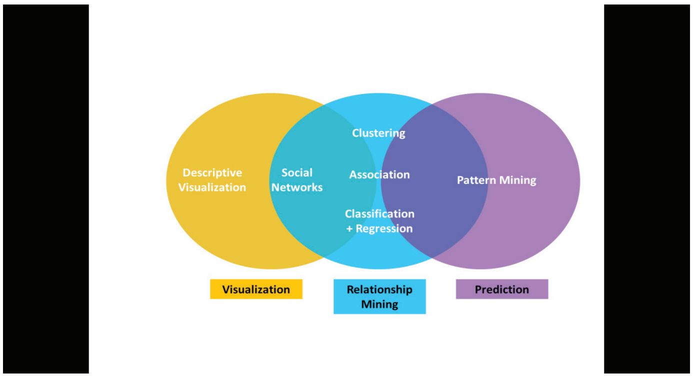

Figure 1: EDM analytics – specific methods loosely mapped to three base metagoals

These specific methods, applied in various EDM contexts, have powered recent work in the field. Descriptive visualization has been used in virtual learning environments to chart the most popular student resources, time on site, and item-specific performance measures (e.g. Feng & Heffernan, 2006). Social network analysis and related techniques have been used to track blog-based citations (e.g. Simmons et al., 2011), make teacher tools to visualize learner trajectories for optimized student grouping (Berland et al., 2013) and convey hierarchical changes in social structures over time (Carley, 2003). In related relationship visualization examples, clustering has been used to identify learner groups and explore user patters of navigation (e.g. Kerr & Chung, 2013).

Relationship mining through association has been used in EDM to provide indicators for curricular improvement of e-learning and online educational environments (e.g. Retalis et al., 2006). Classification and regression, building on association, belong to the predictive modeling metagoal. They have been leveraged to provide insight on e-learning profiles and learning style (e.g. Yu et al., 2008), projected student performance (e.g. Ibrahim & Rusli, 2007), and create teacher-friendly collaborative learning tools (Anaya & Boticario, 2011). The last category, pattern mining, are methods that capture and analyze sequential events. These can include Natural Language Processing for student text interpretation (e.g. Song et al., 2007), Markov chain modeling for showing learner trajectories (e.g. Fok et al., 2005), and Bayesian networks for probability-based student modeling (e.g. Millán et al., 2010).

Phase I (Early Core Design): Articulating a Learning Data Framework

As evidenced by EDM, one challenge for data mining in educational systems is identifying, capturing, and outputting salient learning data for analysis. Clickstream events are, in their natural state, massive and inchoate; data for collection must be specifically identified, tagged, and collected (c.f. Baker & Yacef). These captured data then directly affect the kind of analyses possible. In educational games, identifying salient learning features (these data for collection) can be a challenge. Indeed, identifying valid information “about what the student knows, believes, and can do without disrupting the flow of the game” is a “main challenge” of educators in using games to support learning (Shute, 2011, p. 508). Yet, identifying this data in early development stages is vital, because it affects our ability to understand player experience during and after the design process.

Games & Learning Data: A Brief Review

Squire asserts that games as designed experiences (2006) provide endogenous engagement (Costikyan, 2002) for the player through “roles, goals, and agency” (Squire, 2011, p. 29; Norton, 2008). Thus by definition, in *learning* games, there can exist two kinds of designed mechanics: one related to progression through the gameworld as an engaging context (Schell, 2008; Gee, 2005; Salen & Zimmerman, 2004); another a more direct measure of the content the game is trying to teach (e.g. Clarke-Midura et al., 2012). Ideally, these two overlap; good educational games meld learning mechanisms with the core mechanics of the game, where gameplay itself is the only necessary assessment (Gee, 2012; Shute, 2011). With a multitude of mechanics, some related to content measurement and others to play progression, how can critical features be identified?

Some theoretical models help answer this question, striving to identify learning-salient data in virtual learning worlds. Among the most prominent of these is ECD, an assessment data framework that revolves around aligning educational content with learning evidence from tasks in the educational space (e.g. a task model). ECD, however, has been tailored specifically to use in simulations, and does not deal with specific click-stream implementation details (Mislevy, 2011). One game-tailored framework used at GLS incorporates the idea of a task model while identifying information on basic play progression, capturing gameplay as more than a series of academic tasks (Halverson & Owen, in press). This framework, also an implementable API, is called ADAGE (Assessment Data Aggregator For Game Environments). In short, ADAGE records information on task model moments in the game – called Critical Achievements (CAs), designed to directly measure learning gains – but it also captures context-rich play progression through the narrative space.

Data Frameworks: Informing Early Design

In the early design process, using a learning game data framework can not only help pinpoint existing data features for usertesting insight and later analysis – it can inspire the creation of helpful learning measures in-game (like critical achievements). ADAGE is just one example, and is used below to show how a strong learning data framework can empower early design efforts.

At GLS, ADAGE and CAs have become a core part of a larger design process. Unlike simulations, educational games are not driven completely by a task model, and the immersive designed experience of the game has been held at a premium (Squire, 2006). Thus, CAs are a harmonious element (rather than a driving force) in core game design. Moments considered important for measuring learning can be built into the design process, crafted with the goal of informative yet seamless feature of gameplay. In game design literature, these critical achievements can be seen as part of game mechanics, which is only one element of core design – balanced with the vital elements of narrative, dynamics, and aesthetics (c.f. Schell, 2008; Salen & Zimmerman, 2004).

These kinds of key assessment mechanics have been built into existing GLS games as part of collaboration with scientists in the UW community. GLS design partners match subject matter content to video game genres, translating procedural academic knowledge into narrative-based verbs of play. In the context of these games, the ADAGE framework has been critical for the design team to determine the relation between the game flow and the content model.

One strong example of the Critical Achievement data structure supporting early design is in *Fair Play.* The player in put in the shoes of the main character, Jamal, who experiences implicit bias as a first year graduate student. In this context, Jamal has conversations with several students and faculty, during the course of which he must identify a recently experienced implicit bias in order to progress. Seamlessly built into the game design in early development stages, this CA mechanic helps measure player understanding without breaking narrative (Owen & Ramirez, in submission).

Crystals of Kaydor, a game in the *Tenacity* collaboration with the Center for Investigating Healthy Minds, provides several examples of CA mechanics built into early game design for the purpose of measuring student skill growth. *Crystals of Kaydor* is an RPG designed to cultivate the development of pro-social behavior through collaborative social interactions. The player controls a robot who has crash-landed on an alien planet. For the first kind of CA, in order to win the aliens' trust, the player must play close attention to non-verbal cues, tracking aliens' facial expressions and intensity through a slider interface. Secondly, the player must then correctly select the emotion of the alien, and for the last CA, choose an emotional response to the aliens' affect. Alongside CAs, ADAGE play progression data has also provided a context-rich backdrop to evaluate play progression in relationship to learning (Beall et al., 2013).

During early design phases, anticipating evidence of learning and play progress is vital, because it directly impacts the kind of analyses – and insights about player behavior – that become possible. ADAGE serves as just one example of a framework that can help do this. For instance, building in CAs in initial phases of game design (rather than clunky late-game additions or identified post-hoc by desperate researchers) has several advantages. First, it helps beautifully integrate play progression and learning measurement mechanics for a seamless player experience. Second, these designer-specified mechanics directly inform data structures and early-phase analytics, making usertesting results even more relevant to developers. Thirdly, these key learning mechanics provide anchoring measurement points for educational researchers, who can then provide insight into growth patterns that inform final in-game scaffolding design (see late-beta section below).

Phase II (Alpha and Early Beta Development): Analytics for Usability Testing

Strong data structures enable telemetry analysis for data-driven design in the alpha and early beta phases. Visualizations and descriptive analytics (Figure 1) can be particularly helpful in refining UI design, as well as identifying bugs and player attrition points. All of these analytics, based in click-stream data, can greatly complement qualitative usertesting methods like interviews, surveys, and think-alouds.

In refining UI design, visualization and descriptive statistics of player usage can be key tools in the alpha and early beta design process. For example, during work on the *Tenacity* project, GLS conducted focus-testing groups for UI functionality and design. Player navigation through levels was analyzed and visualized through a network diagram, showing most frequented levels of the game – and it was discovered only one available level of the game was getting little to no use at all. Upon revisiting the UI map selection menu, designers realized most players catch that is it was a scrolling menu (with the last level out of sight). Immediately, the UI was redesigned with all levels showing (in a matrix format), and the problem disappeared. Additionally, in one slider mechanism for *Tenacity*, the player-entered value could range between 0-1 (with the default being 0.5). A simple distribution graph of these slider scores showed most responses at *exactly* 0.5. Upon further review of the UI, it was realized that most people were simply skipping the self-report, thus reporting the default value. This, also, was remedied immediately, and movement on the slider was then required to unlock progress (Beall et al., 2013).

Visualization of telemetry data can also be a powerful tool in identifying bugs and player attrition points. Using statistical visualizations of event frequencies, including game-restart flags and duplicate events, can highlight points of systemic dysfunction. Spatial visualizations of common attrition points can also indicate dysfunctional level design. For example, early phase *Tenacity* analytics included histograms of the “restart game event” and duplicate quest-starting events in order to catch large-scale game crashing. Integrated with corroborating interview data, these data isolated areas of game malfunction (Beall et al., 2013). Similarly, visualizations using state changes and ADAGE virtual context were used to heat map player progression in the GLS *Anatomy Browser*, showing exactly where learners were getting stuck and consequently quitting (1). A similar example exists for early design and testing of *Fair Play,* where positional data was recorded to create a heatmap of player activity. One map level (aerial view) in the game was programmed to show color-coded areas of frequent player travel (Owen & Ramirez, in press). This helped inform placement of in-game assets critical to content exposure and game advancement.

Phase III (Final Stages of Design): Scaffolding for Learner-Adaptive Play

In final stages of game development, after extensive data collection with late-beta builds, learning analytics can be used to predict in-game actions and performance most characteristic of learning. This knowledge of ideal player behavior can then inform the final design phase: user-adaptive, fully scaffolded play for optimized in-game learning. To this end, optimal player actions, sequential pathways, and assessment growth trajectories can each be explored through learning analytics (including visualization, prediction, and pattern mining methods).

Player actions and events most characteristic of learning, whether related to play progression or Critical Achievements, can be effectively modeled with various prediction and association mining methods (Figure 1). These studies include use of correlation, classification trees, and probability nets to better understand which player moves predict learning. For example, ADAGE game study has explored learning in *Progenitor X* through correlation of in-game success and failure with pre-post learning outcomes (e.g. Halverson & Owen, in press). Predictive modeling with classification and regression trees (CART) has explored in-game performance and learning (e.g. DiCerbo & Kidwai, 2013; Owen et al., 2014). Bayesian networks have also been used with this data theme, probabilistically connecting chunked performance data to creative problem solving in games (e.g. Shute, 2011). If gameplay models show certain actions at certain points to be more predictive of learning, then player-triggered scaffolding (e.g. help resources) can be implemented in-game to help keep players on track at these crucial points.

Sequential learner pathways can also be modeled using machine learning methods. Specifically, visualization and predictive modeling (including clustering and pattern mining) have been used with success in learning games research to capture learner trajectories. For example, SimCityEDU researchers are building player profiles by identifying groups of using hierarchical cluster analysis, then contrasting these groups according to level of in-game success (Institute of Play, 2013). In another visualization example, ADAGE-based heatmaps can visualize learners’ critical pathways though the game (e.g. Owen & Ramirez, in press). A heatmap of top learner actions can highlighting a high-performer, learner-centric path through the game. Markov modeling, a pattern mining method, has been used to illustrate the probability of play sequences among different learner groups (e.g. Clark et al., 2012). With text data, natural language processing is another pattern mining method that can be used to discern algorithmic differences in game-based discourse patterns over time (e.g. Mechtley & Berland, in submission). With any of these sequential learner trends identified, adaptive scaffolding could then be placed in-game to support students’ progress along paths connected with learning gains.

Lastly, growth in player performance between specific points of assessment (e.g. Critical Achievements or isomorphic game tasks) can be tracked especially well using data mining methods of prediction. These prediction methods can include pattern-mining methods and Bayesian reasoning, used to forecast which growth patterns indicate learning. For example, Bayesian Knowledge Tracing (BKT) is an algorithm that can predict learning moment-by-moment based on multiple performances on a chosen task (e.g. Baker, Corbett, & Aleven, 2008). BKT has also been used in tandem with detectors, which are automated models that can predict student behavior from log file data (e.g. Baker et al., 2004). Recently, the application of detectors has extended to goal-driven learner behavior in games (e.g. DiCerbo & Kidwai, 2013). In application to games, these powerful algorithms can help designers anticipate and support in-game performance indicative of learning.

Conclusion

In core design, alpha usertesting, and final-stage adaptive play design, telemetry-based analytics in educational game development play a key role in optimizing learner experience. This paper maps a clear framework of learning analytics methods to learning game development phases – from core data structures, to bug killing, to customized, automatic scaffolding design. Leveraging these powerful analytic tools of visualization, association mining, and predictive modeling throughout the design process is key to supporting players in a user-adaptive, engaging play experience optimized for learning.

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Endnotes

(1) https://itunes.apple.com/us/app/anatomy-browser/id523208752?mt=8

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