Let's Talk About Intelligent Tutoring Systems and Games for Learning

Andre Denham, Arizona State University, adenham@asu.edu

Abstract: There is a growing community of games for learning researchers conducting foundational work on game adaptivity. Their interest lies in the difficulties in ascertaining direct learning gains from instructional digital game play. The common belief is these difficulties arise from a "one-size fits all" approach to instructional game design (Beal et. al., 2002). A potential means to address this issue could lie in the incorporation of artificial intelligence and/or design elements of intelligent tutoring systems within an instructional game's decision-making architecture. Assessing and adapting to the learner's instructional needs during gameplay would theoretically result in increased learning gains. This fireside chat will begin with a discussion on the affordances of adaptivity within games for learning. The conversation will then transition to a discussion on the limitations and challenges of implementing adaptive game play, and will conclude with a discussion on future directions in research on adaptivity within games for learning.

Introduction

There is a growing community of games for learning researchers conducting foundational work on game adaptivity. Their interest lies in the difficulties in ascertaining direct learning gains from instructional digital game play. The common belief is these difficulties arise from a "one-size fits all" approach to instructional game design (Beal et. al., 2002). A potential means to address this issue could lie in the incorporation of artificial intelligence and/or design elements of intelligent tutoring systems within an instructional game's decision-making architecture. Assessing and adapting to the learner's instructional needs during gameplay would theoretically result in increased learning gains.

This belief is born out of the long-standing challenge within educational technology to provide instruction that adapts to address learner's individual differences (Thorndike, 1911; Dewey, 1964; Cronbach & Snow, 1977; Como & Snow, 1986; Tobias, 1989). Adaptive instruction, "an educational approach that incorporates alternative procedures and strategies for instruction and resource utilization and has the built-in flexibility to permit students to take various routes to, and amounts of time for, learning" (Wang & Lindvall, 1984, p. 161), is beneficial for several reasons. The first benefit is that adaptive instruction allows for multiple paths to learning and learning goals. The second benefit is adaptive instruction leverages the current aptitudes and skills of the learner in order to strengthen areas of weakness. The third and final benefit is that adaptive instruction better prepares learners to succeed in future learning opportunities (Glaser, 1977).

Adaptation Within Education

Human tutoring is commonly believed to be the most effective form of direct instruction (Bloom, 1984). One reason is the ability of the human tutor to focus their attention on one particular student and tailor the instructional support that they provide. Adapting instruction to meet the current needs of a learner is pointed to as a valuable skill in the arsenal of an effective tutor. Unfortunately, it is logistically impossible to provide one-on-one tutoring within contemporary, compulsory school settings. Students greatly outnumber teachers, the finances do not exist to support hiring more teachers, and a host of other issues make it difficult to implement this instructional model. The advent of the personal computer heralded a technological solution to issues surrounding one-to-one instruction. Computers don't get tired, are always available, are able to make human-like decisions, and can store vast amounts of data, which can be used to provide the dynamic instructional support to learners. One of the more successful attempts at emulating human tutors through the use of a personal computer is an intelligent tutoring system (ITS).

Intelligent Tutoring Systems

The general goal of the field of intelligent tutoring is to increase learning efficiency. These can be conducted through the use of instructional models, which can be one-to-one, many-to-one, or one-to-many models. For example, traditional grouped instruction has one teacher for many learners. One to one instruction is found in tutoring settings. Within a many-to-one model a learner is provided with instruction from a variety teachers that address personal pedagogical needs. Intelligent tutors seek to take advantage of opportunities provided by computers, the Internet, and the fields of artificial intelligence (AI) and cognitive science to provide one-on-one, many-to-one, and one-to-many learning environments.

Well-designed intelligent tutoring systems have consistently been shown to improve learning outcomes in a variety of different domains. For example, *AnimalWatch*, an intelligent tutor designed to help pre-algebra students solve word problems, produced equivalent learning gains with human tutors, but in half the time (Beal, et. al. 2005). Eliot, Williams, and Woolf (1996) developed an intelligent learning environment to teach medical personnel how to manage the effects of cardiac arrest. An evaluation of the intelligent tutor revealed that it produced results comparable to those produced by a human instructor. Based on these successes within the field of intelligent tutoring (and many more), it is theorized that the integration of an intelligent tutoring systems or cognitive tutor within the architecture of instructional games would help in the acquisition of learning gains.

VanLehn (2006) characterizes an intelligent tutoring system as having two loops: the inner loop and the outer loop. These two loops contain elements that make them an appealing inclusion within the architecture of an instructional game. The outer loop is responsible for selecting tasks for the learner to complete. The inner loop, on the other hand, is responsible for administering the steps that a learner has to complete in order to show competency on a task. In addition, VanLehn states, "the inner loop can give feedback and hints on each step. The inner loop can also assess the student's evolving competence and update a student model, which is used by the outer loop to select a next task that is appropriate for the student" (VanLehn, 2006, p. 227). By applying these characteristics of within instructional game architecture, one can avoid the one-size-fits-all approach to the sequencing of tasks within instruction and provide an adaptive, personalized learning environment.

Adaptive Games for Learning

Embedding adaptivity within an instructional digital game has several pedagogical advantages. The first is that it allows for personalized feedback. In order to assess the current state of a learner, without interrupting game play, Pierce, Conlan, and Wade (2008) designed the ALIGN (Adaptive Learning In Games through Non-invasion) system architecture. ALIGN is made up of four processes, which work together to provide an individualized learning experience: inference, context accumulation, intervention constraint, and adaptation realization. This system was used to provide feedback and affective support to the user based on their game play. While their study was exploratory, the researchers found those players that received adaptive hints after an unsuccessful experience within the game showed marked improvement on future attempts on the same task than those who played a one-size-fits all version of the same game.

Another affordance of adaptive digital games for learning is the adjusting of the game style to the learner. Magerko, (2011) describes S.C.R.U.B. (Super Covert Removal of Unwanted Bacteria), which is a game being developed to teach about microbes that are resistant to antibacterials and their transmission within a hospital setting. S.C.R.U.B. is actually a collection of small (mini) games that are being designed to teach students about these super strong strains of microbes and how they can be transmitted from person to person from either contact with contaminated surfaces or human-to-human contact. Adaptation of the game takes place through the matching of the users play style preference to their learning style preference. While this adaptation is not dynamic (play and learning style preferences are determined by a pre-test), the researchers have developed a prototype, with the ultimate goal being dynamic game adaptation.

Goetschalckx et al. (2010) condensed adaptations within instructional digital games to two categories: Dynamic Difficulty Adjustment and Dynamical Estimation of Player Abilities. One important characteristic of games is their ability to provide challenge. AI can be used within instructional digital games to provide the appropriate amount of challenge to a user. This is accomplished through the creation of a player model. Challenge is an important element of successful game design as it serves to maintain motivation and engagement, which are important contributors to learning. AI is a beneficial addition to the architecture of any digital game because when tuned precisely, it can provide the optimal level of challenge, while providing the learner with the exact instructional content that is needed.

Intelligent Tutoring Systems and Games

Attempts at combining features of intelligent tutor systems with features of games can be classified in one of three approaches: 1) Adding game features to an existing ITS, 2) adding ITS features to an existing game, and 3) building a combined ITS and game. An example of the first technique would be the incorporation of game features within Grockit (Bader-Natal, 2009), an online intelligent tutor designed to prepare students for the Graduate Management Admission Test (GMAT) and the Scholastic Aptitude Test (SAT). Grockit (Bader-Natal, 2009) sought to leverage pedagogical affordances of specific game features in an attempt to encourage synchronous collaboration between tutees. This interaction between tutees was deemed beneficial because it provided a solution to the problem of correcting misconceptions of learners by allowing other tutees to remediate. In order to facilitate this correction of misconceptions through peer remediation, Grockit allowed tutees with similar interests to form learning communities where they worked with peers with similar interests on study problems. Within learning communities, tutees could play games designed around answering exam questions. Within the game, all tutees were presented with the same question, which they were all required to answer. Once all participants had answered the question, they were provided with the correct answer and allowed an opportunity to discuss the question and the answer. Within the main lobby of the learning community, tutees received feedback through the game features of points, performance statistics, leaderboards, and badges.

An example of the second technique of adding ITS features to an existing game would be *River City* (Nelson, 2007). *River City* is multi-user virtual environment in which learners are placed in a 19th century town and tasked with determining why residents are getting sick. In order to gather evidence players can talk to other three-dimensional agents within the world, read books, and collect and analyze samples. All of the information that players feel is important can be kept in a logbook. *River City's* instructional purpose is to provide an environment in which players can increase their scientific inquiry skills while also learning about bacteria. The investigator sought to explore the effect of adding an individualized guidance system within *River City* in order to increase learning gains. The individualized guidance system was designed based on adding features of ITS. An expert modeling and coaching system was integrated, which demonstrated to players the proper way to conduct an inquiry and answer questions within River City. This ITS feature is akin to the feature set one would find in a step-based ITS. In addition to the expert modeling and coaching system, a part-to-whole ITS trainer called the Legitimate Peripheral Participation System was designed to guide the players through inquiry tasks by assigning specific tasks and systematically increasing the responsibility of players in gathering evidence. While no significant differences were found between those who played the ITS enhanced version of *River City* and those who didn't, there were significant differences found between participants based on gender in terms of learning outcomes.

Finally, the third technique of building a combined ITS and game was explored by Rowe et al. (2009) within a game called *Crystal Island*. *Crystal Island* has a similar instructional objective as *River City*, with the main differences being the inclusion of intelligent agents, which have tutorial and narrative orientations, and a focus on pathogens versus bacteria. The intelligent agents in the game were constructed to provide affective instructional support by attempting to display empathy to the learner. An additional difference between *River City* and *Crystal Island* is that *Crystal Island* has more structured learning activities, while *River City* was built based on a theoretical framework of socio-constructive and situated cognition. In an investigation of the impact of *Crystal Island* in terms of providing affective support to learners, *Crystal Island* outperformed the control condition in providing affective instructional support, but no significant differences were found between the control condition and affective condition in increasing learning gains.

There seems to exist potential for the adaptation of instructional game play based on an estimation of the abilities of the player and their affective state (based on observable and unobservable variables, expert model, learner model, etc.). This would buck the trend of one-size-fits-all instructional games by providing a personalized learning environment that is optimally tuned to address the current learning needs of a student. This approach to games for learning design is definitely in its infancy, but is definitely an area worthy of investigation. This discussion will serve as another contributor to the growth of the field by providing a forum to discussion past successes, current projects, and future directions.

This fireside chat will begin with a discussion on the affordances of adaptivity within games for learning. At this point the conversation will shift to a discussion of the three approaches to marrying intelligent tutoring systems and games. Specifically we will discuss approaches to integrate ITS goals and game goals. Furthermore, we will discuss the instructional domains and game genres which lend themselves to a marriage between ITS and games. The conversation will then transition to a discussion on the limitations and challenges of implementing adaptive game play, and will conclude with a discussion on future directions in research on adaptivity within games for learning.

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