

Dynamic Guidance in Digital Games

Using an Extensible Plan-Based Representation of Exploratory Games to Model Student Knowledge and Guide Discovery Learning

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Abstract. This paper describes a novel application of a task-based knowledge representation that seeks to facilitate automated guidance of task-based learning through the core mechanics of digital games.

Keywords. Digital games, exploratory ITS, narrative, planning, knowledge representation.

1. Introduction

Over the past few decades, Intelligent Tutoring Systems (ITS) have advanced to the point that many research-based systems exceed the teaching effectiveness of traditional classroom-based instruction [1]. Contemporaneous with this success, commercial digital game technologies have shown remarkable advancement in graphics, human-computer interaction, and financial significance. Although both fields have evolved to include a broad diversity of applications and genres, intriguing confluences of goals and challenges are apparent. Yet in the collaborative efforts to date to exploit this confluence, cynics say that the educational elements “suck the fun out” of games [2]. This paper proposes a knowledge representation structure and a general computational framework that leverage automated planning to integrate arbitrary sets of learning goals within the core mechanics of games. Our intention is to provide a general system that builds games where the learning and the fun are deeply intertwined.

2. Background

The core conceptual models posited by games and ITS to guide exploration are remarkably similar. Game researchers describe the goal of guidance is to lead the player down the “optimal game play corridor” [3], reproduced in Figure 1(a). Even a sporadic observer of the game industry will encounter multiple replicas of the chart shown in Figure 1(a) when the subject of learning or guidance is introduced [3,4].

Readers familiar with learning theory will recognize the similarity between the “optimal game play corridor” and Vygotsky’s “Zone of Proximal Development” or ZPD

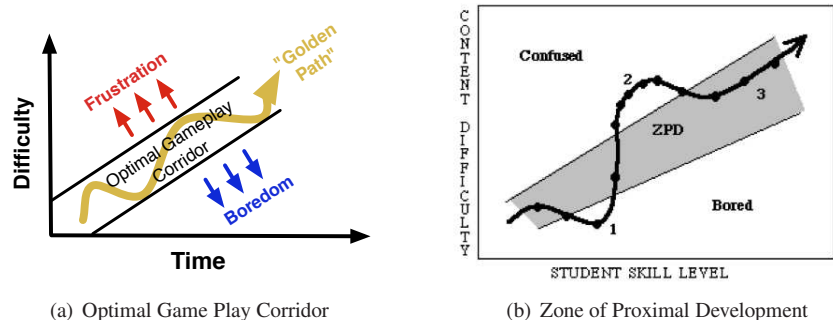


Figure 1. Isomorphic Concepts of Guidance

[5,6]. This encouraging confluence has inspired an extensive research record to leverage the game paradigm within intelligent tutoring, from Smithtown [7] through many subsequent systems [8,9,10] with varied successes. However, de Jong recently noted that for exploratory or scientific discovery ITS, there is still no general approach to balance guidance and student initiative “in such a way that learning is supported effectively, but the inquiry process is not reduced to following cookbook instructions.” [11]

Independent of the evolution in ITS, commercial games now implement a wide array of learning principles. Because games that are more difficult to learn make less money, game designers have become quite adept at embedding all necessary instruction into game play. “In essence a game manual has been spread throughout the early episodes of the game, giving information when it can be best understood and practices through situated experience.” [12] What games lack, however, are deep models of an individual user’s knowledge of the domain that can be applied to dynamically adjust to player behavior. Instead, producers of games rely on increasingly extensive and expensive play testing to statically calibrate the potential challenges in the game so as to reach the widest possible audience of players. Extensive testing is required at design time because unlike an ITS, a commercial game lacks the intelligence to guide a player past an arbitrary obstacle at run-time.

3. A Plan-Based Representation of the Core Mechanics of Digital Game Play

To capture the deep structure of core game mechanics, our representation is grounded in STRIPS-style [13] descriptions of the indivisible actions which affect the domain. Our system can begin by automatically deriving a set of meta-conditions from the known features of the preconditions, effects, constraints and parameters of all the tasks available in the domain. We then model the student’s knowledge of the domain with a rough-grained five-valued scale to represent the system’s estimate of the likelihood that the student knows about a particular facet of each domain task. For example, in a game that teaches the processes involved in aerobic cellular respiration, the student may know that one effect of the Krebs cycle is the production of CO_2 waste but not yet know another effect of the process is the production of H_2O . This could be represented in the student model by noting that the CO_2 production of a particular action in the Krebs cycle is known, while the effect that produces H_2O is still not known.

4. Integrating Game Mechanics With Learning

This representation is being implemented within a new system called Annie. Annie constructs an initial tutorial plan consisting of a plausible partially-ordered sequence of student and system-initiated actions that is designed to bring about a specific goal state for the world, including a particular state of task knowledge acquisition in the student model. The plan marks out the optimal game play path for the user prior to the start of the session, but it is continually revised based on student actions.

Annie's execution loop iterates each time an action is taken in the world, either by the student or the system. Following the action Annie consults an extensive library of general **diagnostic** templates to update its student model. These templates encode domain-independent plan reasoning diagnostics such as cases where a student seems to be ignorant of a precondition of a particular operator. Annie uses the updated student model in consulting a second extensive and domain-independent library containing **remediation** templates that can be used to generate narrative scaffolding. These templates are described more fully in [14].

Although these templates target a fairly primitive level of specific elements describing tasks, their hierarchical compositions mirror methods in which learning principles are currently embedded in games. An auxiliary goal for Annie is to take the learning principles currently embedded in games, like those featured in Gee's thoughtful and wide-ranging survey [12], and make them available at run-time as tools for dynamic adaptation to learners' needs. Gee describes 36 different learning principles, for which nearly a dozen map well to plan-based implementation structures.

An example of just one of these is the "Explicit Information On-Demand and Just-in-Time Principle" Gee describes this as the system giving explicit information "both on-demand and just-in-time, when the learner needs it or just at the point where the information can best be understood and used in practice". Commercial games achieve this by carefully scripting the progress of each segment of the game and extensively testing players to ensure that the right amount and type of help is given at the right times.

In games that are less tightly scripted and more exploratory, it is difficult for the system to deduce what the player is trying to do now or plans to do next. Without that knowledge it is difficult to choose the right help at the right time. Annie leverages its plan-based student model to solve this problem. As the student demonstrates correct or incomplete knowledge of the tasks in the domain, Annie applies its diagnostic templates to update its model of what the student knows. In addition, Annie can leverage the rich space it computes of all possible successful plans to rank the student's "knowledge gaps" by criticality and urgency. It does this by grouping the set of actions that could execute next, and the set that could be executed after one intermediate action, the set that could execute after two intermediate actions, and so on. This provides an urgency metric. Across these different urgency levels, the system can prioritize the most likely gaps in the student model based on its past observations of student behavior.

When Annie detects a knowledge gap diagnosed through its template library whose urgency is sufficiently high, a library of remediation templates is consulted to select the most useful plan revision template. Plan revisions may include things like changes to parts of the world that have not yet been explored, introduction of new characters in the game, or direct instructive interactions with the player through non-player controlled characters.

Space limitations prevent a broader exploration of the relationship between game play mechanics for learning and our knowledge representation. For a more complete discussion, see reference [15].

5. Conclusion

This paper has identified some of the difficulties inherent in building intelligent educational games, specifically the challenge of integrating pedagogy with core game play. We have briefly described a plan-based knowledge representation we believe can address this challenge for a subset of task-rich exploratory environments. We are building a system that leverages this representation to provide intelligent tutoring and plan to evaluate its teaching effectiveness in a game built using a commercial 3D game engine. An issue that may be explored in future work is whether the knowledge representation we have developed may be applied to manage student motivation and provide new mechanisms for evaluating student knowledge and performance.

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