Realtime Knowledge Space Skill Assessment for Personalized Digital Educational Games

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Abstract

Digital Educational Games offer immersive environments through which learners can enjoy motivational and compelling educational experiences. Applying personalization techniques within these games can further enhance the educational potential, but the often realtime and narrative-driven focus of games presents many challenges to traditional adaptation approaches. This paper describes an approach to the realtime assessment of learner skills for personalization that was implemented and evaluated as part of the ELEKTRA European Commission funded project.

1. Introduction

Digital Educational Games (DEG) are an emerging area in which personalization techniques, traditionally developed within the Adaptive Hypermedia (AH) research domain, are being applied. A major issue that has plagued online learning solutions for quite some time has been the high levels of drop out [1] often precipitated by poor intrinsic motivation and relevance in the material presented. Non-adaptive DEGs seek to address the motivation issue by presenting the learner with a compelling and engaging environment and backdrop in which to learn. Through rich narratives [2], engaging gameplay [3] and a fidelity to real world situations [4] these games strive to engage and motivate the learner. Combining personalization techniques with such educational games has the potential to further improve the relevance of what is offered to the learner. A broad range of adaptation axes, such as Cognitive feedback, Meta-cognitive feedback, Affective/motivational feedback, Knowledge based hinting and Progression hinting [5] may be considered.

In order to offer appropriate adaptive interventions three challenges must be overcome: 1) modeling of the learner’s knowledge acquisition (also referred to as cognitive gain) must be achieved in realtime; 2) adaptive hypermedia techniques, which are typically applied to web-based systems, also need to operate in realtime; 3) the personalizations offered must not adversely impact the flow [6] of the game. The challenges of realtime adaptation and the maintenance of flow [6] stem from the need to maintain a learner’s immersion within the gaming experience.

This paper focuses on the first of these challenges, while referencing the others, by presenting how the Knowledge Space Theory (KST) [7] [8] was adopted as a realtime, probabilistic approach to progressively modeling a learner’s skills and knowledge whilst engaged with an immersive DEG. It provides a brief overview of the current state of the art in DEGs and Adaptive Hypermedia, along with the basics of KST. The paper will also introduce the ELEKTRA research project, its architecture and the Skill Assessment Engine, a realtime KST-based modeling engine for personalized DEGs.

2. Background

DEGs have reported successful outcomes by integrating adaptation and strong storylines with inherent motivational qualities. The DARPA funded Tactical Language and Cultural Training System (TLCTS) [2] has shown effective learning outcomes achieved through the application of adaptation. Façade [4] and the Virtual Team Collaborator (VTC) [9] have shown that a strong narrative, an adaptive narrative in the second instance, can provide immersive experiences. Whilst both of these showed benefits, their technical approach was highly complex and involved the authoring of several narrative strands. The Adaptive Learning In Games through Non-invasion (ALIGN) system [5] eases this authoring burden and is an expansion on the proven APeLS multi-model, metadata driven approach [10], but it does not specifically focus on narrative issues.

Adaptive Hypermedia Systems have typically dealt with narrative from a different perspective. Most prevalent examples come from the adaptive eLearning domain where narrative usually refers to the flow of a
Knowledge Space Theory (KST), introduced by Doignon and Falmagne [13], provides a theoretical framework within which the knowledge or skill state of a learner can be determined. It is based on a prerequisite competence structure that describes the relationships between different skills. For example, a learner should typically be able to perform fraction addition before they can multiply them. If the learner exhibits evidence of fraction multiplication it may be assumed that they can also add fractions. Such probabilistic reasonings enable a system to infer a learner’s skill state based on partial evidence [7]. The fundamental approach taken in KST is to reduce the number of possible pieces of evidence needed about a learner to an optimal set. In this way the Knowledge State of a learner may be assessed through the minimum number of inferences, thus achieving maximum efficiency. This is only possible by examining the domain in which the learning is occurring and identifying the underlying prerequisite relationships that exist between concepts. This is a time consuming and expert task that involves describing a learning domain, such as mathematics, in terms of formal prerequisite relationships. Specific educational tasks, such as the learner interacting with a virtual experiment, are broken down into specific sub-tasks. Success or failure in these sub-tasks forms evidence that facilitates the probabilistic update of the learner’s model. The certainty is dependent on the level of inference required. However, as only partial evidence is needed to assess a skill state it can be done very efficiently. When applied to DEGs KST has the potential to provide the basis of a time sensitive approach to modeling a learner’s acquisition of knowledge and skills [8].

3. The ELEKTRA Project
One of the core design strategies of the ELEKTRA project [14] was to separate the gaming environment from the learning adaptation [15]. This was realized through the two core components the Game Engine (GE), responsible for graphics, audio, and gameplay, and the Learning Engine (LE), which is responsible for the adaptation of the educational experience. The communication from the GE to the LE provides the evidence on which adaptation is performed, and conversely the LE to GE communication contains the game adaptations to be executed. In this service-driven approach to adaptation [16] the LE reasons over educational concerns that have been abstracted and inferred from the basic game evidence.

The nature of the game evidence sent from the GE is game specific and consists of player actions, movements, and task successes or failures. This information however is not immediately useful for educational adaptation, requiring a degree of inference by the LE. Inference within the LE is the first step in the four stage process employed to provide effective non-invasive adaptation. The four stages employed are inference, context accumulation, adaptation constraint, and adaptation selection. Further details of the four stage adaptation process are detailed in [5].

The design of the LE and the four stage adaptation process allows for the educational adaptation to be performed without regard for the game specifics. The LE effectively infers and abstracts game actions into educational evidence that can be reasoned over in a generic manner, thus enabling it to be employed for different games with minimal alteration. A key example of this is the abstraction of skills provided through the Skill Assessment Engine (SAE). The SAE effectively maps user actions within the game to skill evidence, and further generates a probabilistic skill model for the learner.

The second stage of the adaptation process involves accumulating game and learner evidence. In consideration of the large quantity of evidence accumulated, potentially dozens of items per second, the use of XML based models, a traditional approach in many Adaptive Hypermedia Systems such as APeLS [10], becomes impractical due to manipulation and reasoning speed. Consequently all data is accumulated in a working memory provided by the Drools rule engine. The use of the Drools rule engine provides an efficient means to reason over large data sets using declarative logic.

In order to perform adaptation within the GE the LE must have an a priori abstracted understanding of the adaptations possible. Within the LE these adaptations are represented as Adaptive Elements. An Adaptive Element consists of an adaptation identifier used by the game and associated metadata indicating the probable outcome of the adaptation and when it can be suitably used. An example Adaptive Element in the ELEKTRA game would be the Non Player Character (NPC) Galileo giving an encouraging hint such as, “Yes. It isn’t easy, and I’m not sure that I would do any better in your position, but you must persevere.” Such an Adaptive Element would have an abstracted outcome description of “encouragement”, and a suitability requirement of the Galileo NPC being present.

The following are the benefits of using Adaptive Elements:

Elements:
Educational adaptation does not need to be concerned with realizing adaptations. It facilitates the independent authoring of the game engine and the adaptation logic.

The third LE stage of adaptation constraint is concerned with ensuring that only appropriate Adaptive Elements are used. By using constraint rules, only feasible and appropriate Adaptive Elements are made available for selection in the final LE stage. The selection of adaptation is achieved through adaptation rules that examine the accumulated learner data and the available Adaptive Elements.

Through an authentic evaluation using secondary school physics students, the ELEKTRA game proved to be effective and successful. The ELEKTRA game is a narrative-driven adventure game where the learner/gamer must overcome several physics-oriented puzzles. They are guided by an NPC representing the ghost of Galileo who advises and encourages them as they interact with experimental apparatus. The skills they acquire are directly relevant to tasks they will face whilst playing the game. Through the evaluation of ELEKTRA, the real-time and appropriate nature of the adaptation was favorably received.

4. Skill Assessment Engine
Interpreting evidence sent by the Game Engine (GE) is central to the first inference step of the four stage ELEKTRA process. The Skill Assessment Engine (SAE), a component of the Learning Engine (LE), is responsible for translating each learner’s actions within the game into a list of probabilities that show the likelihood of each relevant skill having been acquired by the learner. This assessment of a learner’s skills must be done in an implicit fashion so as not to negatively impact their flow through the game.

The domain specific skills to be acquired in the ELEKTRA game were organized according to KST into a prerequisite knowledge structure, which was encoded as an OWL ontology and parsed by the SAE at design time. The parsing process had a dual purpose: firstly it extracted each valid skillstate (a unique combination of skills a user could have at any one time) from the ontology; secondly it converted these skillstates into a binary matrix, which could be more efficiently processed by the SAE at runtime, than the more verbose OWL representation. The runtime performance of ontologies, even quite small ones, is poor and insufficient for use in time sensitive DEGs.

During the game, the user faces various learning challenges, with specific educational rules triggered depending on their interactions with learning objects, such as virtual experimental apparatus (Fig. 1). Learning objects are traditionally seen as static pieces of content, usually HTML, with associated metadata. In ELEKTRA a learning object was an interactive experience that was woven into the game narrative. Each learning object has skills associated with it, thus if a rule relating to a learning object is fired through a learner’s interaction the SAE must run its algorithm to determine which skillstates (and subsequently which individual skills) have increased or decreased in probability. Once the thresholds for skill probabilities have exceeded a pre-determined value, the user is said to have acquired this skill. These calculations must be done in less than 200ms so that the delay in the LE selecting an appropriate intervention for the GE is not noticeable to the user. For the purposes of the work presented here below 200ms is the definition of real-time. The adjustment in skill probabilities is taken into account in stage two of the ELEKTRA process where all evidence from the game and user is accumulated. Thus any change in skill probabilities has influence over which adaptive interventions are eventually presented to the user within the game environment.

![Figure 1. The ‘Slope Device’](image)

The initial ontology created for the ELEKTRA game contained 83 skills and had over 10 million corresponding skillstates. Because of the large number of skillstates it meant that there would be latency issues when applying the SAEs algorithm at runtime. Any such delay would be detrimental to selecting appropriate adaptive interventions in a timely fashion. Thus a reduced version of the skill list and its corresponding prerequisite relation was developed, which contained 25 skills of a lesser granularity. These skills contained 12,414 skillstates, which was a number that could be processed at runtime with minimal delay by the SAE.

Because of the issue regarding the maximum amount of skillstates that can be efficiently processed by the SAE, the scalability of the solution is in question. For ELEKTRA this was not an issue due to
the limited scope of the game, however for larger games with many more learning situations (and associated number of skillstates), it would not be a viable technique to process the entire skill structure as a single entity at runtime. The next iteration of the SAE, currently being researched and developed as part of the European Commission 80Days project [18], will tackle this precise problem. By working with partitions (with a correspondingly reduced number of skillstates) and not the complete ontology, the next version of the SAE will provide a scalable and practical solution for the runtime calculation of a user’s current skills.

5. Evaluating Skill Assessment
The evaluation of the SAE relied on the comprehensive log files generated by the Learning Engine. These log files detailed every action performed by the learner, the corresponding skill probability changes, and any adaptations sent to the Game Engine. The following graphs illustrate how a learner’s skill probabilities change after successive task attempt. The large circles indicate skills that were targeted with adaptations following a task attempt, i.e. each circle indicates a personalized adaptation that was presented to assist the learner.

![Figure 2. Skill probability change with task attempts, student A.](image1)

The graphs shown in figures 2 and 3 plots of ten skill probabilities against the number of learning task attempts in a learning object. It shows ten of the twenty-five possible skills. The remaining skills have been omitted as they were not relevant to the specific task and so showed negligible change. Through comparing the final skill probabilities of the student A (Fig. 2) and student B (Fig. 3) it is evident that the SAE has effectively identified skills deficiencies and provided adaptations accordingly. This is particularly noticeable in task attempts 14 and 15 in figure 2, and in task attempts 13-15 in figure 3.

By way of example, consider the plotline with square markers (with a starting probability of approximately 0.8) in Figure 2. This line indicates the learner’s knowledge about gravity. The line with small circles starting at a probability of about 0.7 represents their knowledge of magnetism. The experiment they are interacting with was referred to as the ‘slope device’ and enabled a learner to experiment with the effect gravity has on a falling object. They could attempt to impact the objects trajectory by manipulating a magnet and fan. In the case of the learner shown in figure 1, they initially exhibited slightly poor control over these mechanisms, by altering the magnet when the falling object was made of wood. This is exhibited in drops in the skill probability of both the gravity and particularly the magnetism skills. From task attempt six onwards the learner receives adaptive hints and exhibits an improvement in both skills. The learner shown in figure 2, however, did not improve after the adaptive hinting and a drop in their skills (corresponding to weaker performance in the task) is seen.

![Figure 3. Skill probability change with task attempts, student B.](image2)

Although it appears that the relatively high probability skills receive more frequent adaptations, this is a result of the learning task in question dealing predominantly with these skills. Additionally it should be noted that not all hints are explanatory, such an example would be the adaptation given for task attempt four for both students. This adaptation was the following congratulatory dialogue for the recent skill increases, “I knew you were up to this challenge”.

Due to the finite number of Adaptive Elements available, skills with dropping probabilities are not always targeted for adaptations. This is by design as it
is not always feasible or appropriate in a game context to select a particular adaptation.

The starting probability of each skill is determined from the distribution of a particular skill across all skillstates. Initially all skillstates are assigned a uniform probability, thus making no assumptions of a learner’s prior knowledge. This was again a design decision as it was felt that an explicit pre-test would adversely impact the game experience. However, paper-based pre-tests were used as part of the evaluation to investigate cognitive gain.

6. Future Work and Conclusion
This paper has presented the Skill Assessment Engine, a component of the ELEKTRA DEGs Learning Engine. This component is responsible for the realtime evaluation of a learner’s skills through interpreting evidence from a Game Engine. By using the probabilistic-based Knowledge Space Theory the SAE can determine a learner’s probable skillstate with a minimum of evidence. However, this approach, whilst effective within the limited scope of the ELEKTRA game, does not seem to scale well. This is due to the large number of possible skillstates that can exist with even just a limited number of skills. As part of the 80Days project [18], a continuation of ELEKTRA, a solution is being proposed that involves partitioning the Knowledge Space. This approach will enable the SAE to function much as it did in ELEKTRA, but a solution for mapping the boundaries of partitions needs to be derived. That said, the approach proposed in this paper shows much potential for effectively and efficiently assessing learners’ skills when there is a realtime consideration.

7. References