RAPID COMPETENCE DEVELOPMENT IN SERIOUS GAMES
Using Case-based Reasoning and Threshold Concepts

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Abstract: A major challenge in todays fast pace world is the acquisition of competence in a timely and efficient manner, whilst keeping the individual highly motivated. This paper presents a novel based on the use of serious games driven by Case Based Reasoning (CBR) tailored by Threshold Concepts (TC) to present the learner with the most efficient choice of game scenarios to address their present competence gap. This allows the learner to maximise their time in competence development. This is current work-in-progress.

1 INTRODUCTION

Serious games for educational purposes have a number of potential advantages over more traditional learning methods and on-the-job training. These include tolerance and encouragement of risk within a safe environment, thus promoting and encouraging experimentation instead of passive learning (Kebritchi and Hirumi, 2008). In addition, serious games increase motivation, provide ego gratification, encourage creativity, socialization and above all are fun. Evidence for their efficacy as educational tools is growing with a growing number research studies finding improved rates of learning and retention for serious games compared with more traditional learning methods (Druckman and Bjork, 1991; Charles and McAlister, 2004). Therefore, serious games should must be fun to play but also effective in supporting learning within the targeted learning domain. Some argue that many past serious games have been successful in addressing one of these objectives but not both: they are either fun to play but hit-or-miss when it comes to educational goals and outcomes, or else they effective as learning tools but stunted as games (Van Eck, 2006).

Sometimes, according to Van Eck (2006), games fail to achieve either objective and are like offspring who inherit only the bad features of each parent. An important aspect of pedagogy is individualization. Given the variation in learning styles, personal preferences, well designed games should not create a "one-size-fits-all" learning environment. In this context, one question that arises is: "How can we create game-based learning environments capable of providing effective learning plans tailored to each individual learner?".

To address this question, we start from the premises that the game-based learning environment must present the user personalized learning plans and game scenarios. Moreover, these plans and scenarios must adapt to the user's needs as he performs. We propose a case-based approach to the generation of learning plans and game scenarios, which has already been used with serious games with success. In addition, Case-Based Reasoning (CBR) has proven to yield good results for the adaption of on-line tutoring systems. However, the planning potential of CBR has yet to be exploited in relation to the creation of learning plans. This being our main research direction, we take a step further,

and address the possibility of integrating the emerging paradigm of Threshold Concepts.

The paper is structured as follows. In section 2, we discuss some current approaches that apply CBR to human learning. This is followed by an overview of the Threshold Concept paradigm, the benefits it brings to the design of the learning material. In section 4, we present our hypothesis on how CBR, CBP, serious games and threshold concepts can be used for a learning environment following modern learning theories. In section 5, we present our conclusions.

2 HUMAN LEARNING AND CBR

Case-Based Reasoning (CBR) is an artificial intelligence paradigm that involves reasoning from prior experiences: it retains a memory of previous problems and their solutions and solves new problems by reference to that knowledge. This is the main difference from rule-based reasoning systems, that normally rely on general knowledge of a problem domain, and tend to solve problems from scratch or from first principles. Usually, the case-based reasoner is presented with a problem (the current case). In order to solve it, the reasoner searches its memory of past cases (the case base) to find and retrieve cases that most closely match the current case, by using similarity metrics. When a retrieved case is not identical to the current case, an adaptation phase occurs. During this phase, the retrieved case is modified, taking the differences into account (Pal and Shiu, 2004). Finally, the cases are retained in the case base for future use. These four steps are defined by Aamodt and Plaza(1994) as Retrieve, Reuse, Revise, and Retain.

Developed from CBR, case-based planning (CBP) systems address problems that are represented by goals and have solutions that are plans. Like traditional case-based reasoners, CBP systems build new cases out of old ones. Unlike CBR systems, CBP systems put emphasis on the prediction of problems: when encountering a new plan, CBP systems anticipate the problems that can arise and find alternative plans to avoid the problems. Plans are indexed by the goals satisfied and problems avoided (Hammond, 1990).

The idea of using CBR for human learning has appealed to a number of researchers, partly due to the roots of CBR in cognitive science which explains the similarity of CBR to human problem solving behaviour (Richter and Aamodt, 2005). There are many examples in the literature of day-to-day human reasoning and planning that highlight the

important role of previously experienced situations and of analogy in human problem solving (Schank, 1996; Kolodner et al., 1996).

CBR for human learning purposes has been a topic of study for a number of years, with significant developments in the fields of intelligent tutoring systems and adaptive hypermedia. One of the latest developments is the ILMDA (Intelligent Learning Material Delivery Agent), designed by Soh and Blank (2008). It combines CBR with system meta-learning for enriching the system with self-improving capabilities. The learning domain is computer science for undergraduates. In another approach, Gomez-Martin et al. (2005) present a metaphorical simulation of the Java Virtual Machine to help students learn Java language compilation and reinforce their understanding of object-oriented programming concepts. Unlike these two systems, where the problems have direct mapping to the correct solution and the targeted domains are well defined, we are creating a system for use in two very complex domains: Project Management and Innovation. In these domains, the problems are open-ended and the required competences are complex and difficult to model. Therefore, our approach is to create an environment capable of reasoning with very complex, poorly structured domain knowledge. In addition, we bring improvements by planning learning based around longer term goals, rather than one step ahead. It is worth pointing out that our system is a highly interactive serious game, instead of text based.

3 THRESHOLD CONCEPTS

The Threshold Concept (TC) Framework focuses on identifying those aspects of a discipline that are essential to a grasp of the discipline, that are likely to be difficult and once overcome will transform the learner's view of that discipline. This means the learner will now begin to think as does a practitioner of their discipline, e.g., thinks as a manager, thinks as an innovator. It arose from a study of the teaching of economics but has now been taken up by educational researchers and teachers across a wide range of disciplines (Flanagan, 2009). "Difficulty in understanding TC may leave the learner in a state of liminality (Latin limen "threshold"), a suspended state in which understanding approximates to a kind of mimicry or lack of authenticity" (Meyer and Land, 2003). The originators of the framework, Meyer and Land, characterize the TC as: (i)Transformative: once a TC is understood, a significant shift appears in the student's perception

of the subject; (ii) Integrative: once learned, TCs are likely to bring together and relate different aspects of the subject that previously did not appear to the learner; (iii)Irreversible: given their transformative potential, a TC is also likely to be irreversible, difficult to unlearn; (iv)Bounded: a TC will probably delineate a particular conceptual space, serving a specific and limited purpose; (v)Discursive: Meyer and Land suggest that the crossing of a threshold will incorporate an enhanced and extended use of language; (vi) Troublesome: TCs are likely to be troublesome for the learner. The framework draws on Perkins' discussions of how knowledge may be troublesome e.g. alien, incoherent or counter-intuitive (Perkins, 2006). In grasping a TC a student moves from an apparent 'common sense' understanding to an understanding which may conflict with perceptions that have previously seemed self-evidently true.

Cousin (2006) suggests some influences that TCs can have in the design of a university course curriculum: first, they enable teachers to focus on what is fundamental to grasp of the taught subject, a 'less is more' approach to curriculum design; once identified, the tutor becomes aware of the areas where students might encounter problems; then, they might need recursiveness in order to be mastered; they also require listening from tutor's side in order to hear what the students' misunderstandings and uncertainties are in order to engage with them (Cousin, 2006). Cousin characterized in 2009 the TC framework as a transactional curriculum enquiry (Cousin, 2009). This would require a partnership between the discipline's experts, educational re-searchers and learners in which curriculum inquiry and curriculum design are seen as feeding into each other rather than as sequential activities.

Recently it has been suggested that two contemporary and powerful conceptual frameworks, TCs and variation theory share a key pedagogic principal and share a central common focus (Meyer et al, 2008) warranting further examination. Although first used in (Dienes, 1967), variation theory of learning is now associated with a much more formalized approach rooted in phenomenography (Marton and Booth, 1997). It states that a key feature of learning involves experiencing that phenomenon in a new light (Marton and Trigwell, 2000). Marton argues that "there is no learning without discernment and there is no discernment without variation". Therefore, in order for students to discern the object of learning, they must experience how they vary. The key elements that are relevant here may be summarized as its four patterns of variation: (i)contrast - experience something else to compare it with,

(ii)generalization - experience varying appearance of an object, (iii)separation - experience a certain aspect of something by means of varying it while other aspects remain invariant and (iv)fusion - experience several critical aspects simultaneously.

The work of Bernhard's group (Cartensen and Bernhard, 2008) on applying variation theory to a circuit analysis problem in which a TC is embedded and the study by Flanagan, Taylor and Meyer (2009) on how a TC in engineering comes into view when approached from two very different engineering contexts, strengthen Meyer and colleagues' suggestion for further examination. Problem-based learning has also been suggested in (Biz/ed, 2009) for facilitating a learner's traverse across the liminal space. Other recent studies of Meyer and colleagues (Meyer et al., 2009) show how meta-learning can help at overcoming TCs and its importance in identifying transformation. To sum up, all these studies show positive results over the improvement of the learning process by integrating TCs. In this context, we consider that TCs are indispensable for an efficient, beyond the current state-of-the-art, learning environment.

4 A NEW APPROACH

To the best of our knowledge, there has been no previous work addressing how the TCs can be incorporated into serious game design. The consideration of the suggested roles that TCs might play in the design of university curriculum augurs well for a neat transfer to game-based curriculum design. Nevertheless, the "transactional curriculum enquiry" aspect does not lend itself quite so readily to the serious game environment. Still, it might well be accommodated by a serious game envisaged as a component of blended learning where mentors facilitate a learner's traverse across the liminal space encountered on meeting a TC.

The idea of using a blended learning mixing the above mentioned learning theories resonates with a serious game using case-based reasoning. First of all because the design of a serious game must be based on established instructional strategies and learning theories (Kebritchi and Hirumi, 2008; Charles and McAlister, 2004; Van Eck, 2006) and problem-based approaches already proved a high potential in game-based learning. The synthesis of CBR and problem-based learning has been the object of several studies suggesting a fruitful fusion. The adaptive nature of CBR lends itself for including ideas of variation theory of learning into serious games and CBR has also been studied in relation

with Meta-Learning (Soh and Blank, 2008) showing that a detailed analysis and adaption of the learning process can be used to improve students' results.

A "by-product" of CBR is the case-base which brings together all the experiences created by learners using the system. This enables the environment to integrate case-based learning (CBL). CBL allows the students to view how others act, analyze and compare with their own actions and has already been successfully used in serious games. Moreover, the case-base can be analyzed in order to identify learner models enabling the adaption of plans for each such model. Another analysis direction would be to determine if action patterns exist, which might lead to the identification of TCs. By analyzing the dynamics of the cases, we expect it is also possible to identify learners' passages through the liminal space. Considering Davies' and Mangan's claim (2006) that TCs cannot be isolated from the social background of the learning process, we can analyze how TCs are cultural dependent and if their grasping difficulty differs from one learning community to another.

To the best of our knowledge, there exists no previous work that combines so many learning strategies, and that utilizes the established case-base from such a wide variety of angles.

In Figure 1, we illustrate how CBR can be incorporated into the learning process within a game-based learning environment. At the start of the process, the learner decides to achieve more competences. A case for the case-based planner is derived from the plan goal (targeted competences), by the set of possible intermediate goals (competence gap), and the plan preconditions (the learner model and his current competences). Drawing on this data, the system uses case-based planning to generate personalized plans for the learner. From a list of recommended games, the learner chooses the first game to play. As he or she plays, an experience is generated and added to his or her trail.
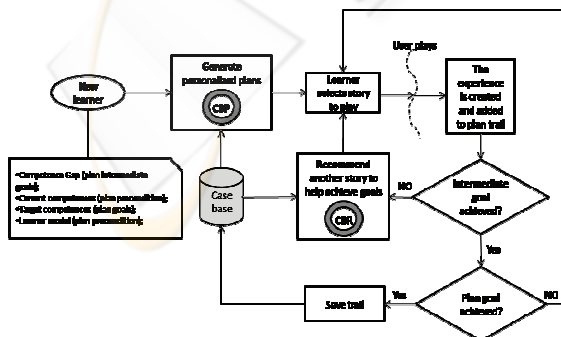

Figure 1: Proposed case-based learning process.

Depending on the learner's performance, the sys-tem decides if the intermediate competences have been achieved. If the learner has failed to achieve them, the case-based planner identifies the situation as a failure and tries to recover in two ways: i) the planner anticipated the problem and will have already assigned a recovery plan for a particular story. If this is the case, the planner will choose the recovery plan with highest eligibility value; ii) otherwise the planner will undergo a CBR process to recommend other stories to the learner in order to bring him or her to the required standard in relation to the intermediate competences. This is similar to the process suggested by variation theory in which stories associated with TCs are adapted to help the learner master the concept. When all the goals of the plan have been achieved, the trail is saved and becomes part of the case base.

4.1 The Case Base

In a CBR system, a case is a pair problem-solution. In our system, the problem is represented by the goal, preconditions and learner model, as shown in Figure 1. Still depending on the solution, we have two kinds of cases: story cases, where the solution is a story, and plan cases where the solution is a plan. A plan is an ordered sequence of stories. Experiences are instances of stories generated each time a learner plays a story, whereas trails are instances of plans, therefore sequences of experiences. Experiences and trails are used to evaluate the stories and plans respectively.

On the basis of these definitions, we can formalize the case knowledge of the system as containing a set of knowledge assets with a story at the core. Each story holds references to the experiences it has seeded. The stories are interconnected into plans, which are associated with a set of trails that link together experiences. These knowledge assets have associated social data created by the community, such as feedback, ranking, peer assessment, tags, etc. This leads to a very big search space and consequently to the challenge of indexing knowledge chunks.

4.2 Generating the Plans

The plan generation described above uses a case-based planning approach based on 4 phases.

Plan Retrieve. Starting with the goals and preconditions, the planner searches the case base to find plans with similar descriptions, which yielded good results for the learner. In order to do this, the system must consider different types of knowledge

and reasoning methods such as similarity metrics, utility metrics, statistical reasoning and collective filtering. The exact combination of reasoning methods is still an open issue. Another challenge is to decide how to weight and then combine all the obtained values. We will consider shifting this responsibility to the system itself by making it capable of analyzing the outcome using its own reasoning and adapting the measures accordingly. However we proceed, one principle that we will follow in our work is for the system to recommend and orient the learner, while allowing the learner to choose from the list of recommended options. If the goal competences are related to TCs, the planner will retrieve the plans and stories which were most successful in facilitating the learners in surpassing the threshold. Another focus of research related to this phase concerns the situation where student are new to the system. In this situation, the system will not yet hold enough information to be able to assign a learner model to the student. In this context, a conversational CBR (CCBR) approach might be used. A CCBR system is used when the problem is not completely known and, therefore, the traditional retriever has no data to match the cases to. The system starts a conversation with the user, asking him questions which discriminate between learner models by traversing a decision tree. As the learner model is drawn out from this conversation, and the other problem data are know, the system selects the suitable cases. An even more attractive direction would be to adapt CCBR so that, instead of using conversations to figure out the learner model, learners are given stories to play, where the stories are chosen in such a way that the user's actions lead the reasoner along the same discriminative decision tree.

Plan Reuse and Revise. The differences between the goals of retrieved plans and the goals of the current learner are identified and used to adapt the plan. If the goal competences are not similar, the competences to be removed are identified and the associated stories are removed from the plan. If the current targeted competences usually entail the mastery of some TCs, the plan is adapted so that it targets these TCs. The obtained plan and stories are then analyzed using domain knowledge to make sure that they are coherent, and revised if needed.

Plan Retain. The plan and its trail are saved in a temporary storage after it has been played by the learner. Then, periodically these plans and trials are analyzed and filtered. For the stories which failed (eg.: the learner did not achieve the related competences), the planner updates its fail expectation, and saves the recovery plan which

worked. The recovery plan is represented by the stories the learner played until they achieved those competences. At this stage, if the plan is a new one, it is assigned a utility and eligibility value. If the plan is a reused one, these values are updated. When a contingency story has a better eligibility value than the story in the original plan, it replaces the story in the plan. An important challenge here is to filter out the plans and stories which are not considered relevant for future use.

4.3 When the Learner Gets Stuck

Besides plan generation, we use a case-based reasoner to recommend stories which might help the learner get over the stages where he or she gets stuck in the learning process. When the learner fails to achieve the supposed intermediate goals, the planner detects a fail. This failure might be interpreted by the planner as either an expectation failure or plan failure. A learner might get stuck in a game by not making any relevant progress, which leads to frustration. In this case, the case-based reasoner suggests targeted stories or story episodes, starting from one which poses problems to the learner, but adapted based on the variation patterns from variation theory. This adaptation must be made in relation to a TC, if one has been identified to be involved in the difficulty. The system would also recommend to the learner that they watch similar experiences to see how other learners handled the situation, and actually provide the option of allowing the learner to replay the games. In addition, the system might show the learner graphs and statistics on their performance, their learning patterns, and if possible, suggest enhancements of his learning style. In this way, learners would have the chance to analyze their overall progress and how it was achieved, and thereby have facilitated the process of meta-learning. Associated with this, the system can improve its reasoning as it is being used by analyzing which of its suggestions were most beneficial, giving these a bigger weight in the future.

5 CONCLUSIONS

The paper outlines the work-in-progress concerning the research of rapid competence development in shorter time-to-competence. The approach is based on the use of serious games, where the learner's plans are composed of games determined by a reasoning process that combines CBR with CBP, shaped by TC. Initial concepts have been experimented resulting in the proposed framework

with the next phase involving the integration with the serious game supporting competence development in both project management and innovation. Further research is being carried out to validate the approach and evaluate the effectiveness of learning, including the role and impact of TCs. This presents the challenge of determining which plans and stories have previously been most effective in helping learners to grasp the TCs.

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