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Technical Report UU-CS-2016-003

April 2016

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www.cs.uu.nl

ISSN: 0924-3275

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Abstract. In this paper, we explore theoretical and practical aspects of the automatic generation of knowledge spaces from problem solving strategies. We show how the generated spaces can be used for adapting strategy-based problem solving learning environments (PSLEs).

Keywords: intelligent tutoring systems, knowledge space theory, strategies, student modelling

Intelligent Tutoring Systems (ITSs) can be almost as effective as human tutors in supporting learning problem solving [4]. Most problems are solved incrementally, step by step, by applying a certain problem solving strategy. During the last decade a domain specific language (DSL) for explicitly modelling such strategies has been developed [2]. Rules in this strategy language describe how exercise objects can be transformed. The language defines a number of operators to explicitly model a sequence and a choice of rules or strategies, recursive application etc. Strategies form a hierarchical tree structure and rules are the leaves of those trees. The strategy language has been applied to building a number of intelligent tutoring systems and serious games, and for providing feedback in existing educational environments. We are currently exploring how the structure of different graph-based student models can be automatically generated from a strategy for solving a particular class of problems. In this paper we present theoretical and practical aspects of the automatic generation of one such model, namely a fine-grained learning space, for enabling adaptive learning and assessment in strategy-based problem solving environments.

Knowledge space theory (KST) is a mathematical framework for describing feasible knowledge states of a student [1]. A knowledge domain can be divided into knowledge components, such as skills, competences, exercise items, etc. A knowledge state is a feasible subset of those components. A knowledge space is the set, closed under union, of all the feasible knowledge states. Knowledge space \mathbb{S} is a learning space if, for each non-empty state $S \in \mathbb{S}$, there exists at least one $c \in S$ for which $S \setminus \{c\} \in \mathbb{S}$. Each state in a learning space is fully specified by its two fringes, the inner fringe, containing the most advanced concepts of the state, and the outer fringe, containing the concepts that can be learned next. KST has

been shown to be an excellent framework for both assessment of knowledge and adaptation in a number of PSLEs and serious games [1,3].

Rules and strategies written in the strategy language by Heeren and Jeuring describe valid sequences of steps for solving a given problem. We show how strategies also divide procedural knowledge of a domain into a set of hierarchical knowledge components which form a knowledge space. We define knowledge of a strategy as the ability of a student to apply it to any exercise object from its domain. In other words, knowing a strategy means knowing at least one of the derivations generated by the strategy, for any exercise object. In the core strategy language, a strategy can be expressed as either the sequence or choice of its sub-strategies, recursive application of a single sub-strategy or as an application of a single sub-strategy to a subexpression. Let s be a *sequence* of sub-strategies $s_1, s_2 \dots s_n$. Then s is a knowledge component with $s_1, s_2 \dots s_n$ as its prerequisites and also the inner fringe of the state $\{s\} \cup \{s_1, s_2 \dots s_n\}$. Let c be a *choice* between the sub-strategies $c_1, c_2 \dots c_n$ and let \mathbb{C} be a set of all the minimal subsets of $\{c_1, c_2 \dots c_n\}$ that are sufficient for solving all the objects solvable by c . Then any of the subsets of \mathbb{C} is a valid knowledge state and an alternative prerequisite of any strategy for which c is a prerequisite. Let r be a *recursive* application of s_r . Then r is a knowledge component with s_r as its prerequisite. Finally, let sub be an application of s_{sub} to a subexpression. Then sub is a knowledge component with s_{sub} as its prerequisite. The entire knowledge space can be generated by recursively applying the previous definitions to a top level strategy. The generated space is also a learning space. In addition to being used for adaptive assessment, as described in [1], the generated space can be used for adaptive learning. At each state, feedback can be generated at the granularity level of its inner fringe. The outer fringe of each state defines rules and strategies a student is ready to learn. To select the appropriate next exercises, we need to efficiently query available exercise objects. We propose, but have not implemented yet, a data structure equivalent to an inverted index, with a dictionary consisting of derivations and posting lists consisting of suitable starting objects for a given derivation.

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