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ABSTRACT

To attain highly efficient instructional conditions, it is important to adapt instruction to the individual trainee. This so-called personalization of training by dynamic/automatic task selection is the focus of this paper. Recently, cognitive load measures have been proposed as a useful addition to conventional performance measures like speed and accuracy. The combination of conventional performance measures and cognitive load measures can be used to obtain information about the mental efficiency of instructional conditions. The paper argues that the dynamic/automatic selection of learning tasks on the basis of mental efficiency will have a significant influence on the optimization of the learning process. First, a review of various task selection approaches is given. A distinction is made between static and dynamic task selection approaches. In both procedures the training is based on the trainee's prior knowledge. However, the selection of a set of learning tasks can either be chosen by the teacher/trainer prior to the start of the training (static procedures) or can be adjusted during the training (dynamic procedures). It has been proposed that when teaching student complex cognitive skills, part-task training can have a higher learning efficiency and reduced training costs than whole-task training (Wightman & Lintern, 1985). The whole-task and part-task approaches are used as subcategories for static and dynamic selection, yielding four approaches. Then, a new approach using mental efficiency in a dynamic whole-task procedure is presented. (Contains 31 references.) (Author/AEF)

Selection of learning tasks based on performance and cognitive load scores as a way to optimize the learning process

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Abstract

To attain highly efficient instructional conditions, it is important to adapt instruction to the individual trainee. This, so-called, personalisation of training by dynamic/automatic task selection is the focus of the present paper. Recently, cognitive load measures have been proposed as a useful addition to conventional performance measures like speed and accuracy. The combination of conventional performance measures and cognitive load measures can be used to obtain information about the mental efficiency of instructional conditions. We argue that the dynamic/automatic selection of learning tasks on basis of mental efficiency will have a significant influence on the optimization of the learning process.

1. Introduction

People are faced with increasingly demanding working environments in modern society. The time constraints are increasing and task environments are getting more complex. People have to master complex working skills quickly and efficiently, because training time is often limited and mistakes can lead to dangerous situations and high costs, especially in technical domains such as aviation and industry. One way to meet these requirements is to create more efficient training by personalizing instruction

The primary goal of this article is to argue that task selection based on mental efficiency optimizes the learning process. Mental efficiency is a combined measure that uses information on performance measures and cognitive load measures (Paas & Van Merriënboer, 1993). Existing Intelligent Tutoring Systems (ITS) only use performance measures as a determinant for task selection. Although cognitive load sometimes is measured, it is not used as a determinant for task selection

In this article, we will first give a review of various task selection approaches. We make a distinction between static and dynamic task selection approaches. In both procedures the training is based on the trainee's prior knowledge. However, the selection of a set of learning tasks can either be chosen by the teacher/trainer prior to the start of the training (static procedures) or can be adjusted during the training (dynamic procedures).

It has been proposed that when teaching student complex cognitive skills, part-task training can have a higher learning efficiency and reduced training costs than whole-task training (Wightman & Lintern, 1985). We will use the whole-task and part-task approaches as subcategories for static and dynamic selection, yielding four approaches. These are static whole-task approaches, static part-task approaches, dynamic whole-task approaches, and dynamic part-task approaches. Then a new approach using mental efficiency in a dynamic whole task procedure will be presented. Finally, we will discuss this approach.

2.1 Static whole-task selection approaches

The elaboration theory (Reigeluth & Stein, 1983) states that one should start with the simplest kind of typical task that an expert would perform and to gradually progress to more complex tasks. All the tasks in the training are whole-tasks. Furthermore, the sequence of the tasks in the training is preset before the training.

The elaboration theory makes a distinction between task expertise and domain expertise. Recently, a new approach, the Simplifying Conditions Method (SCM), for building task expertise has been developed. It offers guidance for analyzing, selecting, and sequencing the learning tasks. Given that any complex task has some conditions under which it is easier to perform than under others, a SCM sequence begins with the simplest version of the task that is still fairly representative of the task as a whole. Then it gradually progresses to more complex versions of the task until the desired level of complexity is reached, making sure that the learner is aware of the

relationship of each version to the other versions. Each version of the task is a class or group of complete, real-world performances of the task (Reigeluth, in press).

Another new approach, called the familiarity approach, uses the prior knowledge (familiarity) of the trainees and the difficulty of the tasks to base the training sequence on (Scheiter, Gerjets, & Tack, 2001). The first lessons or parts of a training contain high familiarity and are of low difficulty. As a learner progresses through the lessons or training, familiarity decreases and difficulty increases.

The SCM and the familiarity approach share many aspects. Both approaches, rightfully, claim that the training should be adjusted to the prior knowledge of the trainee. After having correctly performed a task of a low complexity, the complexity is gradually increased during the training. Note however, that the training has been preset and the sequence of the tasks in the training is not subject to any change. These approaches do not adapt to the needs of the individual trainee. They only adapt to the prior knowledge of a target group and not specifically to each individual learner before the training starts.

2.2 Static part-task selection approaches

Wightman and Lintern (1985) have proposed that when teaching students complex cognitive skills, part-task training can have a higher learning efficiency and reduced training costs than whole-task training. Segmentation is one of the three of methods of task decomposition that were discussed and evaluated by Wightman and Lintern (1985). Segmentation involves partitioning a whole task into components along spatial or temporal dimensions. Prior to the training the size of these components is adapted to the prior knowledge of the trainee.

A well-known method of segmentation-based training is backward chaining, in which the last component of a task is practiced first and earlier components are introduced later in the training (Proctor & Dutta, 1995). Benefits of backward chaining in comparison to whole-task training may originate from the role of knowledge of results (KR) in learning (Wightman & Lintern, 1985). Wightman and Lintern (1985) have suggested that, as a result of training, the perceived competency in performing the final task component can act as KR for the preceding components, thus facilitating learning of earlier components of the task.

Ash and Holding (1990) found that forward chaining, in which the order for adding task components is first to last, was more effective for learning selective keyboarding skills. Forward chaining may sometimes be superior to backward chaining because in this method task component-completion feedback is always proximal to the component task being introduced (Proctor & Dutta, 1995).

An approach that is linked to segmentation is the blocked versus random scheduling approach. These part-task sequencing methods have been contrasted with each other in numerous studies (e.g., Carlson & Yaure, 1990). The random schedule contained four rules intermixed from trial to trial within practice blocks, compared to the blocked schedule that contained only a single rule appearing repeatedly with each practice block. It was found that acquisition performance for a set of individually presented component skills was better when the components were practiced in a blocked schedule than in a random schedule. However, retention and transfer performance was better following a random practice schedule. These results have been replicated by Lundy, Carlson, and Paquiot (1995).Their explanation for this finding was that random practice provides a richer set of cues for distinguishing among the items in a set. This results in more accurate retrieval of a particular item from long-term memory. The richer set of cues is another way of saying that the variation was higher. They furthermore reasoned that rule-specific processing occurred in the blocked schedule and that relational processing occurred in the random schedule. Rule-specific reasoning emphasizes the need to reconstruct rule-like procedures in working memory. Relational reasoning emphasizes the opportunity to compare multiple representations, thus making relations, in working memory. These two processes resemble the rule automation and schema acquisition processes that were identified by van Merriënboer and Paas (1990).

The hierarchical approach that was developed by Gagné (1968) also is a static part-task approach. It is based on the observation that a skill is made up of simpler "component skills" that you must learn before you can learn the larger, more complex skills of which they are a part. Gagné distinguished five intellectual skills that are increasingly detailed and difficult. At the bottom level there are discriminations, followed by concrete concepts and defined concepts, at the next level there are rules and at the top level there are high-order rules. The hierarchical arrangement of these five skills helps one to figure out what the prerequisites a given skill might have. To make sure the learner is not confronted with learning tasks of skills that (s)he already has mastered, the training needs to be started at the level of "entering knowledge" of the learner. A hierarchical sequence is one which never teaches a skill before its prerequisites (Gagné, 1968).

All three approaches, rightfully, claim that one should adapt the training to the trainee's prior knowledge. And like the hierarchical approach states, some skills should be learned before a trainee can start to learn a more

complex skill. However, none of the approaches allows adaptations to the individual trainee to be made during the training.

2.3 Dynamic whole-task selection approaches

The last decade, dynamic approaches have been widely used to adapt more efficiently to the needs of the individual trainee. It is possible to respond to the learner's problems during the training, with decisions being made that are typically based on the performance of the trainee.

In order to keep track with the trainee's history of the tasks and the correlating performance, many ITS (Intelligent Tutoring Systems) use a student model. A student model builds a knowledge base of the trainee, and updates that knowledge as the trainee progresses through the tasks of the training. Certain learning objectives have been specified prior to the training, which are used to check the progress of the trainees. Performance measures are collected and are compared to the learning objectives. After this comparison, the selection rules indicate the next learning task to present to the learner.

However, many approaches focus on elaborating the operationalization of student modelling while not being clear on the selection rules that are being used. These approaches include psychometric approaches (for a discussion, see Everson, 1995), agents (e.g., Capuano, Mersella, & Salerno, 2000; Giroux, Leman, & Marcenac, 1995), and fuzzy logic (e.g., Virvou, Maras, & Tsiriga, 2000). Mostly, the primary function of student models is to give specific feedback to the learners about their performance. An ITS that explicitly describes the selection rules that are being used is CASCO (Completion Assignment Constructor). CASCO is an ITS for the dynamic construction of assignments to practice introductory programming (Van Merriënboer, Luursema, Kingma, Houweling, & De Vries, 1996). Based on different actions of the trainee, CASCO can decide whether the trainee has learned the programming skill or not, can adjust the amount of presented information by increasing or decreasing information in the completions tasks, and decide to either delete or add the program code, explanations, questions, and instructional tasks (Van Merriënboer, & Luursema, 1995).

CASCO uses several straightforward selection rules. The most important rule states that a good problem is suitable to present new learning elements and to practice known learning elements. CASCO could therefore be classified as a Progressive Mental Model (PMM). The other rules state that a good problem is not too difficult, has not been presented to the learner before, and is suitable to remediate learning elements the learner makes mistakes with.While the learner is working on an assignment, student diagnosis takes place in order to update the student model. The learner's results on questions and instructional tasks form the input of student diagnosis. For all learning elements that have already been presented to the learner, the so-called Expertise and Incompetence are computed (Van Merriënboer, Krammer, & Maaswinkel, 1994). Expertise indicates the learner's proficiency in correctly using a particular learning element, while Incompetence indicates the learner's tendency to make errors with a particular learning element. For each learning element, the Expertise and Incompetence are further modeled as fuzzy sets. The truth value of the membership of those sets may range between 0 and 1. To keep track of the students' progress two sets have been developed. The Learning Set, which contains the learning elements that the learner is already practicing but has not mastered yet. And the Incompetence Set, which contains the learning element that the learner is already advancing in but still makes mistakes with (Schuurman, 1999).

It is common for ITS to base their student model and task selection on performance measures like speed and accuracy. We argue that it is important to use mental effort as an additional determining factor because different students can attain the same performance level with different amounts of invested mental effort.

2.4 Dynamic part-task selection approaches

The first dynamic task selection approach, in a very raw version, was branching. This part-task approach attempts to diagnose the learner's response, usually on the basis of a multiple-choice question. The training starts with offering pieces of information and during the training more information is added with each next step until the trainee reaches the state where the whole task can be performed. This process is also known as snowballing (van Merriënboer, 1997). After the learners have been presented a certain amount of information, they are given a multiple-choice question. If they answer correctly, they branch to the next body of information. However, if they are incorrect, they are directed to additional information, depending on the mistake they made (Clark, 1997). The amount of branching may vary considerably, from occasional branch points to branching after every student's response. Branching can be based on individual performances, cumulative performance, or student choice. The direction of branching can either be forward, sideways, or backward. Forward means that the learner skips

information that most students see. Backwards means that the learner is returned to repeat instructions. And sideways means that the learner is exposed to extra information that most learners skip (Allesi & Trollip, 1991).

Most of the research on branching has been done in the 1960s and 1970s. Although the theoretical foundation is good and makes sense, the practical part of proving the superiority of branching over normal fixed sequencing appeared to be difficult. There are several studies that showed evidence in favor of the branching sequence over a fixed sequence (Coulson, Estavan, Melaragno, & Silberman, 1961; Hurlock, 1972; Slough, Ellis, & Lahey, 1972), but most studies fail to show a superior effect of branching (Campbell, 1962; Glaser, Reynolds, & Harakas, 1962; Holland & Porter, 1961; Lahey, 1973). It was stated that the Computer Assisted Instruction programs usually consisted of a simple algorithm for branching among a few fixed alternative questions. Such rigid plans do not provide a model of how a tutor can adapt the generation of tasks to suit the particular needs of each student (McArthur, Stasz, Hotta, Peter, & Burdorf, 1988). Furthermore, the costs and time needed to complete a part-task training are mostly very high.

3. The use of mental efficiency in a dynamic whole-task selection approach

Our approach incorporates various elements of the discussed task-selection approaches. Like in the whole task approaches we start with the simplest version of a whole task. The complexity of the training should be adjusted to the trainee's prior knowledge. In other words, the familiarity should be at an appropriate level. All the versions of a whole task are categorized in learning tasks which gradually increase in complexity in respect to each other. The trainee starts with the lowest complexity and proceeds to the highest complexity, while the pace of the progression depends on performance and cognitive load measures. Like in CASCO (e.g., Van Merriënboer, Luursema, Kingma, Houweling, & De Vries, 1996) we can adjust the amount of information that is presented to a learner. Dependent on the learner's performance and load, the information can be decreased, kept constant, or increased. Furthermore, as in the dynamic approaches we can select learning tasks during the training and adjust to the individual learner's needs during training.

Another characteristic of the approach is that instead of presenting more whole tasks, it can be more efficient to present part-task training for the part of the task that the trainee has not mastered yet. Consider for example learning how to drive a car. If a trainee has mastered steering skills, gas-and brake skills but still has not mastered the shifting gear skill, then this skill should be practiced in isolation until the required performance level has been reached. With part-task training of this component the costs in terms of cognitive capacity will decrease and the learner will be able to acquire the whole task more efficiently.

Cognitive load has been acknowledged as an important factor in the training of complex cognitive skills. When learners acquire simple skills, cognitive load only plays a minor role. A badly designed training does not necessarily have negative effects because learners can invest mental effort to compensate for the bad design. However, when learners are presented with a training of complex skills, they are not able to so anymore. They do not have mental effort for this purpose because the training generates a high cognitive load upon the learner's capacities. Students can attain a high performance but with varying amounts of load. By taking cognitive load into account the decision in task selection can lead to optimal individual learning. Learners attain the highest performance when they have to invest an optimal amo unt of load. Therefore, we propose to use performance measures in combination with mental effort measures for dynamic task selection. A procedure for combining mental effort and performance measures in a measure of mental efficiency was described by Paas and van Merriënboer (1993). The efficiency measures take differences in cognitive capacity, expertise, and motivation into account. The use of mental efficiency is expected to make the individual training more efficient, and to lead to better transfer results.

A first confirmation for this claim was found in a study conducted by Camp, Paas, Rikers and van Merriënboer (2001). They compared four methods of task selection in the domain of air-traffic control. Learning tasks could be presented in a fixed order from simple to complex, or the selection could be based on performance, mental effort, or the combined measure of both, mental efficiency. Although, they did not find differences in transfer performance as a function of learning task selection method, the results showed that participants in the mental efficiency condition were confronted with high variability of learning tasks, and that participants in the performance condition were confronted with low variable learning tasks.

We believe that our approach is a promising one. It takes more information about the learner's learning progress into account than the conventional approaches. Mental efficiency combines performance measures and cognitive load measures on which the task selection decisions are based. Furthermore, tasks can be presented in different formats to the trainee. Dependent on the mental efficiency of a previous task, the decision can be made whether the learner support can be decreased, kept constant or increased. The variability is high, which means that

trainees will be exposed to various analogies that induce schema acquisition. Because of the higher training efficiency, trainees participating in our approach should also be able to reach better results on transfer tasks. We are currently developing more experiments to obtain more evidence for the expectation that our approach indeed leads to more efficient individualized training.

4. Discussion

The goal of this article was to argue that task selection based on mental efficiency is a promising approach for optimizing the learning process. In order to reach this goal, we first gave a review of various task selection approaches. We made a distinction between static task selection approaches and dynamic task selection approaches. Within these main approaches, a distinction was made between whole-task and part-task approaches. The resulting four approaches were static whole-task approaches, static part-task approaches, dynamic whole-task approaches, and dynamic part-task approaches. The static whole-task approaches including the familiarity approach (Scheiter, Gerjets, & Tack, 2001) and the elaboration theory (Reigeluth & Stein, 1983) claim that the training should be adjusted to the prior knowledge of the trainee. After having correctly performed a task of a low complexity, the complexity is gradually increased during the training. Our main critic on the static aspect was that the training has been preset and the sequence of the tasks in the training is not subject to any change. In this situation it is impossible to optimally adapt to the needs of the individual trainee, especially during training.

The static part-task approaches, including segmentation (Wightman & Lintern, 1985), blocked vs. random schedules (e.g., Lundy, Carlson, & Paquiot, 1995) and the hierarchical approach (Gagné, 1968), showed that part-task training can be useful at some occasions. However, because of its high costs and long duration, we propose to use part-task training only as an additional part of whole-task based training. The static aspect of the part-task approach also was criticized for its inability to adapt efficiently to the learner's needs during training.

Dynamic whole-task approaches including Intelligent Tutoring Systems (ITS) have been focussing on the operalization of selection rules. Many articles describe the functionalities of their student models in great detail but do not explicitly describe the selection rules that have been used. CASCO was identified as an exception to this rule. Our main critic on dynamic whole-task approaches was that they only use performance as the determining factor for task selection. We argued that cognitive load can provide additional information about the learning progress of a trainee.

Dynamic part-task approaches including branching (e.g., Campbell, 1962) were the first to try to diagnose the learner's response. However, the programs that used branching usually consisted of a simple algorithm for branching among a few fixed alternative questions. This does not enable one to efficiently adapt to the particular needs of each student (McArthur, Stasz, Hotta, Peter, & Burdorf, 1988).

Instead, we suggested a mental-efficiency based dynamic whole task procedure with the possibility for additional part-task training. Task selection is based on a combined measure of performance measures and cognitive load measures called mental efficiency. Furthermore, the sequence of the learning tasks is not preset but is dependent on the mental efficiency of the individual trainee. It is important to adapt instruction to the individual learner to attain efficient instructional methods. Preliminary evidence for the success for the use of mental efficiency in dynamic task selection was found in the study of Camp, Paas, Rikers and van Merriënboer (2001).

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