A Framework for Identifying Working Memory Capacity from the Log Information of Learning Systems

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Abstract: Working memory capacity (WMC) is a cognitive trait that affects students' learning behaviors to perform complex cognitive tasks such as reading comprehension, problem solving, and making decision. Considering students' WMC when providing them with course materials and activities helps in avoiding cognitive overload and therefore positively affects students' learning. However, in order to consider students' WMC in the learning process, an approach is needed to identify students' WMC. To address this problem, we introduce a general framework to automatically identify WMC from students' behavior in a learning system. Our approach is generic and designed to work with different learning systems. It connects to the learning systems' database and extracts students' behavior data to analyze them for indications about their WMC. The proposed approach has been implemented as an extension to a tool for detecting learning styles, enabling this tool to additionally identify students' WMC. By knowing students' WMC, teachers can provide meaningful recommendations to support students with low and high WMC. Furthermore, such information is the basis for designing adaptive systems that can automatically provide students with individualized support based on their WMC.

Keywords: Working Memory Capacity, Student Modeling, Learning Systems

Introduction

Working memory capacity (WMC) is an individualized ability of the human brain to keep active a limited amount of information for a very brief period of time. In recent years, researchers have found that WMC can affect attention control and performance of cognitive tasks [4][7]. Results of these studies have shown that students with low and high levels of WMC have very different performances on different attention levels during performing cognitive tasks. If the students' cognitive load is too high, it will affect them in learning effectively. Knowing the levels of students' WMC can help in many ways to enhance learning and teaching in learning systems. Getting information about students' WMC can be used as input for adaptive systems to provide students with customized learning content and activities to suit their individual WMC.

This paper introduces a student modeling approach and a detection tool to identify students' WMC from the activity log data of learning systems. The student modeling approach profiles students from the activity log information available in the learning systems and identifies students' learning behaviors, including linear navigation, constant reverse navigations, and performing simultaneous tasks. Furthermore, a learning style detection tool, DeLeS [8], has been extended in order to detect not only learning styles but also WMC. By extending DeLeS, all the functionality that is needed to get the data from any learning system is used. Then, different preprocessing and calculation procedures are applied in order to identify both WMC and learning styles. The approach and the tool are developed in a generic way and are therefore applicable for any learning system.

The next section presents related studies about WMC and approaches to identify students' WMC. In section 3, our concept for identifying WMC is introduced, including explanation on the preprocessing steps, the relevant behavior patterns of WMC detection, and the transition from the behavior data to WMC. The architecture for identifying WMC from students' behavior is discussed in section 4. Section 5 concludes the paper.

1. Literature review

1.1 Working Memory Capacity

The human memory system works similar to an information processing system and operates like an advanced computer system [2]. Atkinson and Shiffrin [2] proposed a memory model including three types of memory: sensory memory, short-term memory, and long-term memory. They also pointed out that information is received by sensory memory to arrive in another temporary store called short-term memory (STM) or working memory (WM). STM and WM clearly share a close relationship referring to transient memory. However, they also have different definitions in terms of empirical and conceptual distinctions [11]. The capacity of STM is typically accessed via the immediate serial recall of a list of information. Miller [13] proposed the "magical number seven" in 1956 to give the earliest quantification of the capacity limit associated with short-term memory. The WM is used to hold information actively in the mind and to manipulate that information to perform a cognitive task. WMC refers to the processing of a limited amount of information in transient memory storage for a short time [3]. The works of Woehrle and Magliano [14] have focused on identifying individuals' WMC from different aspects, such as reading comprehension, academic achievement, and attention control. They also suggested in their study that working memory may be a core cognitive ability that underlies and constrains our ability to process information across cognitive domains. WMC is also crucial to many learning activities in online learning because students have to hold information while engaging in an online learning activity.

1.2 Identifying and Considering WMC in learning systems

For enabling rich adaptivity, the student model is an important part of learning systems [8][9]. A student model in an adaptive learning system tracks students' information based on the system's beliefs about students. The process of building and updating a student model is called student modeling. Chen [5] focused on modeling and scaffolding students' cognitive skills related to learning from work-out examples as well as from their exploration activities. Conati and Maclaren [6] analyzed students' browsing data recorded in the log file of a web-based learning system to conclude that students' cognitive style (field dependence and independence) and learning behaviors are related. Cognitive trait model (CTM) is another student modeling technique that profiles students according to the four cognitive traits: working memory capacity, inductive reasoning ability, associative learning skills, and information processing speed [12]. In the CTM, certain learning behaviors, called Manifestation of Traits, are used to infer students' cognitive traits from the students' behaviors in an online course. While the CTM focuses on detecting cognitive abilities in a particular system with a predefined course structure and types of learning objects, our approach aims at identifying cognitive abilities in learning systems in general.

2. Concept of WMC Detection

This section describes our concept of WMC detection from students' continuous behavior in any learning system. In order to analyze students' behavior and detect relevant behavior patterns, some preprocessing of behavior data and course data has to be done. More concretely, the preprocessing includes (1) the identification of learning sessions, (2) filtering out activities that are not dedicated to learning as well as activities where students visit a learning activity only for very short time, and (3) building a Learning Sequence Table called LSEQ table that includes structure of the course in terms of the predefined sequence of learning activities/objects in a course. In learning situations, there are several behavior patterns known in literature that give indications for a person's WMC [9][12]. Three mplementation patterns (IPs) in terms of learning objects, properties, and types of navigational behavior which can then be implemented domain independently. These patterns are linear navigation pattern, constant reverse navigation pattern, and performing simultaneous tasks pattern. These types of navigational behavior are described by a relation function, R(preLO, currLO). This function relates two learning objects (LOs), the source (preLO) and the destination (currLO). The following paragraphs describe the three IPs, including a brief discussion on their effects on WMC, a definition and example of each IPs.

With respect to the IP of linear and non-linear navigation, linear navigation means that students learn the materials linearly and follow the learning sequence of the course defined by teachers. Huai [10] found that students with high WMC tend to focus on linear navigation and students with low WMC tend to use non-linear navigation. If a student can learn materials linearly, her/his working memory is able to deal with the consecutive information easily [10]. For example, when LO B is learned, and the previous LO of LO B (defined in LSEQ table), LO A, has been learned before, linear navigation is found, no matter whether other LOs are visited between LO A and B. If this linear navigation is found, it gives an indication for high WMC. Otherwise, non-linear navigation will be found, which gives an indication for low WMC.

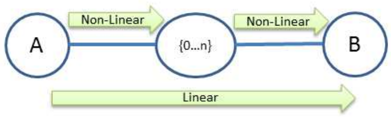

Figure 1. A sample of linear navigational behavior

With respect to the IP of constant reverse navigation, reverse navigation includes revisits of already visited LOs. Constant reverse navigation indicates that a student frequently goes back to an already visited LO. The process of constant reverse navigation is caused by an insufficient WMC to hold on the materials that have just been visited [12]. When the learning materials that a student just read on the previous page should still be fresh and in his/her working memory, the constant need to navigate backwards is a sign of working memory deficiency. The definition of constant reverse navigational behavior is that there are more than two LOs revisited in the same learning session and the navigational relations of these LOs are not defined in the LSEQ table (and therefore not in line with the sequence of LOs in the course structure). Figure 2 shows a sample of constant reverse navigational behavior including the following relations of navigation: *R(A, B)*, *R(B, C)*, *R(C, D)*, *R(D, A)*, *R(A, C)*. In these navigational relations, two relations, *R(D, A)* and *R(A, C)*, are not defined in the LSEQ table and the two destination LOs, A and C, are revisited. Thus, the constant reverse navigational behavior is found, which gives an indication for low WMC.

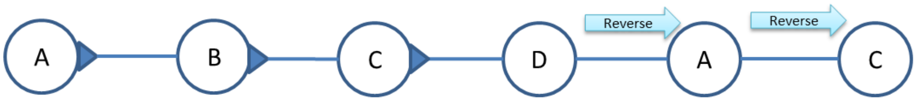

Figure 2. A sample of constant reverse navigational behavior

The IP of performing simultaneous tasks pattern is transferred from the MOT describing the ability of attentional control on performing two tasks simultaneously. The results of previous studies showed that when performing two tasks simultaneously, low WMC participants were less accurate than participants with high WMC [7][14]. For identifying this pattern, the overlaps navigational behavior is investigated which indicates that a student tries to perform two tasks simultaneously. As shown in Figure 3, if a student visits at least one other LO in between *LO A* and its evaluation, *EA*, overlaps navigational behavior is found. In such a situation, the student learns *LO A* first and then learns other LOs before taking the evaluation of *LO A*. Therefore, she/he will need to remember the concept of *LO A* in her/his working memory while learning other LOs. If the student then passes the evaluation of *LO A*, the simultaneous tasks pattern is found, which gives an indication for high WMC; if she/he fails, the non-simultaneous tasks pattern will be identified, which gives the indication for low WMC.

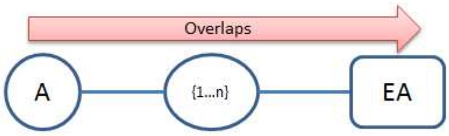

Figure 3. A sample of overlaps navigational behavior

3. An architecture for identifying WMC from learning systems

The proposed architecture for identifying WMC from any learning system is based on the architecture of DeLeS, a tool developed to automatically detect learning styles in any learning system. The proposed architecture (and DeLeS' architecture) consists of two components: the data extraction component and the calculation component. In order to identify WMC, the data extraction component of DeLeS is extended and extracts the learning sessions of each student, the learning activities of each learning session, and the LSEQ table of each course. These extracted data are then passed on to the calculation component, which is responsible for calculating the students' WMC based on the three IPs and the corresponding navigational behaviors of students. If a navigational behavior is detected in a relation between two LOs, this relation is considered as an activated relation for the particular behavior. In each learning session, a value is calculated for each pattern based on the number of activated and non-activated relations in this session. This value shows how strongly the student's behavior represents the respective pattern. Subsequently, each value is transferred to its indication for WMC (e.g., a high value for linear navigation provides an indication for high WMC) and then the indications for all patterns are summed up and divided by the number of patterns. The result of this calculation represents the indication for WMC of this session. Each learning session also contains a weight, which determines the influence of each session on the overall value of WMC and is calculated based on the number of activated relations in a session for all patterns. In order to calculate the student's WMC, the WMC indication of each session is multiplied by the weight of the respective session. Subsequently, the results for all sessions are summed up and divided by the number of sessions.

4. Conclusions

As identified in past studies [1][14], different levels of WMC have potential to affect students' learning performances. This paper introduced a framework for identifying students' WMC from their activity log data in learning systems. The proposed framework is based on a student modeling approach in order to identify different levels of WMC, and extends the DeLeS tool to analyze activity log data from a variety of learning systems [8]. Therefore, the framework is not restricted to a particular learning system. The DeLeS tool is used to preprocess the log data. Then, these data are used to find three navigational behaviors: linear navigation, constant reverse navigation, and overlaps navigation, and calculate students' WMC from these behaviors. Future research will deal with investigating the use of additional behavior patterns to be added to our student modeling approach. Furthermore, we will use the information about students' WMCs to provide teachers with recommendations for designing and improving learning contents and course presentation.

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