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Correlating Working Memory Capacity with Learners´ Study Behavior in a Web-Based Learning Platform

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Abstract: Cognitive pre-requisites should be taken into consideration when providing personalized and adaptive digital content in web-based learning platforms. In order to achieve this it should be possible to extract these cognitive characteristics based on students´ study behavior. Working memory capacity (WMC) is one of the cognitive characteristics that affect students' performance and their academic achievements. However, traditional approaches to measuring WMC are cognitively demanding and time consuming. In order to simplify these measures, Chang et al. (2015) proposed an approach that can automatically identify students' WMC based on their study behavior patterns. The intriguing question is then whether there are study behavior characteristics that correspond to the students' WMC? This work explores to what extent it is possible to map individual WMC data onto individual patterns of learning by correlating working memory capacity with learners´ study behavior in an adaptive web-based learning system. Several machine learning models together with a rich context model have been applied to identify the most relevant study behavior characteristics and to predict students' WMC. The evaluation was performed based on data collected from 122 students during a period of 2 years using a web-based learning platform. The initial results show that there is no linear correlation with learners´ study behavior and their WMC.

Keywords: working memory capacity, learner's study behavior, personalized learning, machine learning

1. Introduction

A number of learning systems have been developed aiming to support personalized and adaptive learning based on learners' cognitive characteristics (Chang et al., 2015; Graf, 2010; Van Merriënboer & Ayres, 2005). Two of those key cognitive characteristics are working memory and executive functions associated with working memory. Working memory has a limited capacity and refers to the ability to store and manipulate information simultaneously (Baddelev, 2012). Traditionally, WMC has been measured by complex working memory tasks such as the operation span, reading span, and counting span (Unsworth, et al., 2005). What these tasks have in common is that one must keep in mind the sequences of unrelated items (i.e., the storage component) while subsequently performing an intervening task (i.e., the processing component). However, in online learning platforms, the possibility of measuring WMC for all students using cognitive demanding and time-consuming tasks is limited. Mapping individual WMC onto individual patterns of learning is a difficult task and requires expert knowledge from different disciplines. Together with researchers and experts in Cognitive Science, Medical Science and Computer Science, we investigated to what extent it is possible to map individual WMC data onto individual patterns of learning by correlating working memory capacity with learners´ study behavior in an web-based learning system called Hypocampus[1].

[1] https://www.hypocampus.se/

The rest of the paper is organized as follows: Section 2 provides a description of related work in this field while section 3 describes the approach we are using to predict WMC based on students' study behavior data. Section 4 briefly described extraction of user study behavior characteristics. Section 5 presents the evaluation results of our experiments together with conclusions.

2. Related Work

A search of the literature revealed few studies which have attempted to automatically measure student's WMC based on students' study behavior (Chang et al., 2005; Qinghong et al., 2014). Chang et al. (2005) suggest an approach to calculate students' WMC based on students' navigational behavior patterns and learning style. Another researcher (Qinghong et al., 2014) integrated test questions into educational systems in order to measure student's cognitive level. Based on these test questions, the system provides recommendations of different learning resources with a level of difficulty appropriate to the student's WMC. The drawback of this approach, however, is that students are required to perform additional questionnaires to their study program, which might be time consuming and distract them from their original learning activities. Overall, these studies indicate a great potential of identifying students' WMC based on learners´ study behavior data (such as behavior patterns, browsing patterns, game tasks). However, it is still not clear how previous researchers modeled users' "study behavior" and which study behavior characteristics help to identify students' WMC. The rationale for the present study is two-folded. First, the evidence for working memory and WMC being predictive of school performance is extensive (de Smedt et al., 2009; Alloway & Alloway, 2010). Secondly, we can notice an increasing amount of efforts to introduce online learning platforms to support different educational processes. Students using these online platforms generate a massive amount of data. Big data tools and artificial intelligence techniques provide new opportunities to measure learners' cognitive characteristics. Thus, there is an opportunity to further investigate how students WMC can be predicted automatically in online learning systems.

3. Our Approach for Predicting WMC

In order to measure WMC, we asked 122 students to perform an operation span to measure students' WMC. These WMC values are used as the baseline for training and validating the proposed models. When students use the Hypocampus platform during their studies, their user data is stored (named as "logfiles" in Figure 1) in a systematic way. In order to predict individual differences in WMC (shown as *"Test results"* on Figure 1) as a function of study behavior (extracted from *"Log files"* as shown on Figure 1), we applied several machine learning models such as multiple linear regression, logistic regression, artificial intelligent tools (AI) and a rich context model (Sotsenko et al.,, 2016) . Lastly, we used these trained models for predicting students' WMC value as shown in Figure 1.

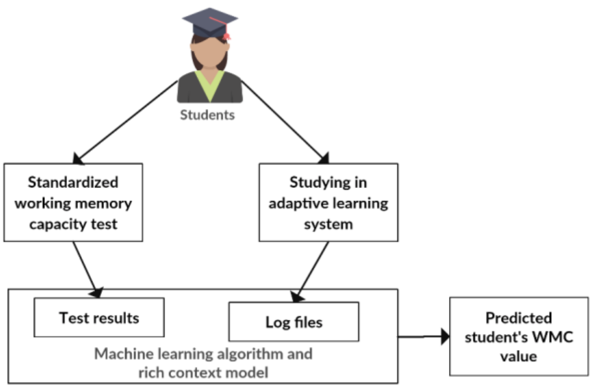

Figure 1. The general idea of our approach.

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4. Extracting User Study Characteristics

In order to describe students´ study behavior and select relevant characteristics for estimating their WMC we first decide to *(a) identify and use sequential study behavior pattern* in the analyses; afterwards, we *(b) excluded the repetitions* on a basis of having only first attempt answers; finally, we *(c) analyzed the repetitions* in order to find "remembering/forgetting" characteristic. In total 64 user study behavior characteristics were identified and used to correlate with student's individual WMC values.

5. Results and Conclusions

We applied four approaches to predict the WMC value based on the learners´ study behavior data (64 user study behavior characteristics): a *multiple linear regression* (MLR), a *logistic regression* (LOR), a *neural network* (NN) *regression*, and a *rich context model* (RCM) (Sotsenko et al., 2017). The validation was performed on dataset from 122 students using a 5-fold cross-validation approach. We used the root mean square error (RMSE) to evaluate the models (as shown in Table 1).

Table 1.

RMSE values for sequential study behavior characteristics.

Algorithm	RMSE
Multiple Linear Regression	20
Logistic Regression	21
Neural Network Regression	18
RCM	19

Overall all models performed with similar RMSE in range between 18-21. These results show that more relevant user study characteristics should be added/found in order to improve the results. Additionally, considering the size of our sample data (N=122), we suggest that it should be further tested and validated with larger datasets.

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