Knowledge Tracking Variables in Intelligent Tutoring Systems

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Abstract: In this research we propose a comprehensive set of knowledge indicators aimed to enhance learners' self-reflection and awareness in the learning and testing process. Since examined intelligent tutoring systems do not include additional messaging features, the introduction of common set of knowledge indicators differentiates our approach from the previous studies. In order to investigate the relation between proposed knowledge indicators and learner performance, the correlation and regression analysis were performed for 3 different courses and each examined intelligent tutoring system. The results of correlation and regression analysis, as well as learners' feedback, guided us in discussion about the introduction of knowledge indicators in dashboard-like visualizations of integrated intelligent tutoring system.

1 INTRODUCTION

Researchers' efforts and technology development combined in e-learning are constantly enhancing teaching and learning process. Although human tutoring is still widely believed to be the most effective form of instruction, the intelligent component of e-learning systems deals with uncertain situations that appear in education process. The possibility of learning anywhere, any-place and any-time contributes to the widespread use of e-learning. Today, as one of the e-learning platforms, Intelligent Tutoring Systems (ITSs) are in widespread use in education with positive impact on student learning (Baker, 2016). ITSs respect learner's individuality, as in traditional "one-to-one" tutoring, all in order to support and improve learning and teaching process. These e-learning platforms provide immediate and customized instruction or feedback to learners, usually for certain domain knowledge and without intervention from a human teacher.

During teaching, learning and testing process, ITSs generate vast amounts of data which may be crucial for creation of better systems and improvement of education overall. Generated data is analyzed using different techniques and methods, while research efforts to advance the understanding of student learning are mostly being pursued in the fields of learning analytics (Koedinger et al., 2013; Long and Siemens, 2011) and educational data mining (Baker and Yacef, 2009; Romero and Ventura, 2007). By examining learner's data logs, these research areas offer the possibility to support teaching, learning and testing process in ITSs.

2 CONCEPT MAP BASED ITSs

The process of developing ITSs often includes collaborative domain knowledge modelling, starting from the expert's natural language description of their knowledge in a form of concepts and their relations, at the same time forming the inventory of the domain ontology (Carnot et al., 2003). In the focus of this study are ITSs that use ontological domain knowledge representation, in which students are taught domain knowledge graphically presented as a network of nodes and relations between them – as a concept map. Concept mapping technique was developed by Novak's research team in the 1970s who based their research on Ausubel work in learning psychology (Ausubel, 1968) with fundamental idea that learning takes place by the

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assimilation of new concepts and propositions into existing concepts and propositional frameworks held by the learner (Novak and Cañas, 2008). The concept map grows around a focus question, while helping learners see how individual ideas and concepts form a larger whole.

Since 2003 we have followed two directions of research, development and application of concept map based ITSs - Controlled Language Based Tutor (CoLaB Tutor, Figure 1) and Adaptive Courseware Tutor Model (AC-ware Tutor, Figure 2) (Grubišić, 2012; Žitko, 2010).

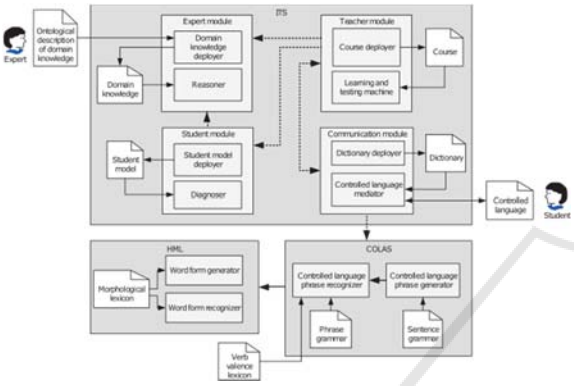

Figure 1: CoLaB Tutor.

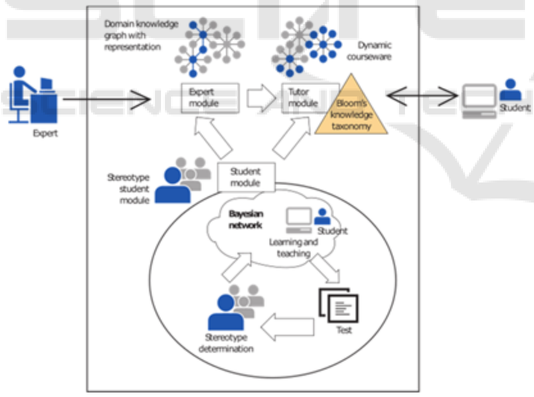

Figure 2: AC-ware Tutor.

2.1 CoLaB and AC-ware Tutor

The examined ITSs are specific in term of structural components, main idea and implementation. CoLaB Tutor's forte lies in teacher - learner communication in controlled natural language, while AC-ware Tutor focuses on automatic and dynamic generation of adaptive courseware based on learner stereotypes, Bayesian networks and Bloom's knowledge taxonomy. Both Tutors share the idea of iterative process of learning and testing, until the learner finishes courseware at a certain knowledge level. Also, both Tutors do not include additional messaging features, such as forum or chat.

The previous experience guided us in the development of a new integrated ITS - Adaptive Courseware & Natural Language Tutor (AC&NL Tutor) (Grubišić et al., 2015). Since 2015, AC&NL Tutor is in its development phase, with support of the United States Office of Naval Research Grant.
In this preliminary research we will examine LA opportunities in CoLaB and AC-ware Tutor (Tutors), with aim to introduce supporting dashboard-like visualizations in the integrated AC&NL Tutor.

3 RESEARCH OBJECTIVES

This research study aims to address the following research questions:
- Which knowledge indicators can be extracted from experimental Tutors' logs?
- What is the relationship between proposed knowledge indicators and learner performance?
- How the proposed knowledge indicators can be used in supporting dashboard-like ITS visualizations?

4 BACKGROUND

So far, researchers tracked different types of data in order to measure different aspects of learners' behavior during online learning. In order to discover connections between gathered data, as well as, to investigate the model in which a single aspect of data (predicted variable) is the consequence of combination of other aspects of the data (predictor variables), relationship mining and prediction are frequently used methods. In term of selecting variables and investigating the relation between online behavior and learner performance, the number of studies revealed positive results.

The factors that were previously investigated as predictor variables included: student's performance in previous courses, on initial test, or on assignments during the experiment; student's behavior in term of single online activities (i.e. the number of log-in times) and collaborative online activities (i.e. the number of forum posts read); student's affective states while learning online; student's perception about the online education, cognitive-motivational factors or study habits; demographic and other factors; or combination of previous factors.

In the research study by Lin and Chiu (Lin and Chiu, 2013), selected course tracking variables demonstrated a positive and statistically significant correlation with student final grade, where the number of online sessions demonstrated a medium-large effect size with explaining 15% of the variance in the student final grade. The remaining 4 variables (the number of original posts created, the number of follow-up posts created, the number of content pages viewed and the number of posts read) had a small-medium effect size with each explaining from 2% to 8% of variance in student final grade. In the prediction analysis of the same research, approximately 16% of the variability in academic performance was explained including 3 predictor variables: the number of online sessions, the number of follow-up posts created, and the number of posts read. Macfadyen and Dawson (Macfadyen and Dawson, 2010) reported regression model which incorporated key variables such as total number of discussion messages posted, total number of mail messages sent, and total number of completed assessments and which explained more than 30% of the variation in student final grade. Previous model was further applied to predict student retention, which correctly identified 81% of students who achieved a failing grade. Also, Morris et al (Morris et al., 2005) discovered similar results as previous research studies in which approximately 31% of the variability in achievement was accounted for by student participation measures, with 3 statistically significant variables: number of discussion posts viewed, number of content pages viewed, and total seconds in viewing discussions. Besides research studies that revealed positive results, Abdous et al (Abdous et al., 2012) analyzed online communication in live video streaming courses and did not find positive correlations between students' number of questions, chat messages, login times and students' success.

The mentioned data extracted from the learners' logs is usually presented on dashboard-like systems' visualizations and includes: login trends, performance results, content usage, message analysis and social network (Park and Jo, 2015). ITSs' dashboards differentiate in term of targeted users (teachers and/or learners), as well as intended goals. There are dashboards focused on the representation of raw data and dashboards that involve prediction algorithms. Descriptive approach enables learners' self-reflection and awareness of what and how they are doing, while prescriptive approach provides feedback on learners' activities to the teacher, learner or Tutor itself.

5 PROPOSED KNOWLEDGE TRACKING VARIABLES

During teaching, learning and testing process in Tutors, learners adaptively pass through courseware, gain score on tests, while doing all of that in the certain amount of time. Tutors represent ITSs without additional features such as forum or chat and they are mainly oriented on adaption or communication in natural language. Because of the previous, our approach focuses on tracking knowledge using comprehensive set of Knowledge Tracking Variables (KTVs): total number of objects (#O), total number of concepts (#C), total score gained on Tutor (#S) and total time spent online (#T). The proposed approach is relevant for various tutoring examples, because courseware can generally be presented as a group of lessons, videos, presentations etc., while total score and time can be calculated accordingly.

In CoLaB Tutor, objects are presented as groups of concepts seen in the learning process and concepts are presented as nodes of the concept map seen in the learning process. In AC-ware Tutor objects are presented as total number of content pages seen in the learning process while concepts are presented as concept map nodes seen in the learning process. The main difference between Tutors' scoring systems lies in fact that CoLaB Tutor calculates negative points for incorrectly answered questions, while AC-ware Tutor's score includes only the maximum points earned for each answered question. Total time is calculated out of data logs, in a way if there was no learner activity for more than 30 minutes, it is assumed that learner took a break from the learning process. The complete learner record consists of KTVs in the following form: #Objects, #Concepts, #Score, #Time in minutes and #Final exam score.

6 THE RELATIONSHIP BETWEEN ONLINE BEHAVIOR AND LEARNER'S PERFORMANCE

The relationship between online behavior (KTVs) and learner's performance (total score on final exam, FE) was examined by conducting the experiment in the winter semester 2015/2016.

6.1 Research Methodology

During the winter semester 2015/2016, 156 undergraduate and graduate students from 3 faculties participated in the research study. The study included 3 online courses that had aim to teach different domain knowledge: Introduction to computer science, Theory of e-learning and Introduction to programming. Data collection was generated in specific Tutors' environments, with over 100.000 database records. Several pre-processing methods were used in data transformation process: standardization of data formats and syntax correction, grouping of data, and Python implementation of algorithms for calculation of total values of KTVs. After learners finished online courses on Tutors, data logs were analyzed using SPSS statistical package.

Descriptive indicators, including number of students (row #Students), mean values (row Mean), minimum (row Min), maximum (row Max) and standard deviations (row SD) for each KTV and specific Tutor are presented in Table 1. Since we observe 3 courses, raw data (#O, #C, #S) for particular Tutor (columns CoLaB and AC-ware) is normalized to the scale 0-100, according to the maximum value of the group that used particular Tutor and selected course. Total time spent on each Tutor for specific course is calculated in minutes.

The average user on CoLaB Tutor in 65 minutes went through 90% of all objects, 91% of all concepts, gained 70/100 score, and on the final exam got score of 42/100. The average user on AC-ware Tutor in 48 minutes went through 20% of the maximum number of pages seen in learning process, 78% of all concepts, gained 50/100 score, and on final exam got score of 45/100.

6.2 Correlation Analysis

To further investigate the relationship between KTVs and final exam performance, correlations are calculated and presented in Table 2. In case of CoLaB Tutor, the results revealed positive and statistically significant correlations ($p<0.01$, $p<0.05$) between the number of objects, concepts and online score as KTVs and final exam score.

In term of objects and online score, revealed correlations correspond to small-medium effect size ($r<0.30$), with 5% of variance explained in the final exam performance each. In term of concepts, correlation corresponds to medium effect size ($r=0.30$-0.50), with 10% of variance explained in the final exam performance. In case of AC-ware Tutor, there are positive and statistically significant correlations ($p<0.01$, $p<0.05$) between all KTVs and final exam score. In term of the number of objects and concepts, revealed correlations correspond to small- medium effect size ($r<0.30$), with 6% and 8% of variance explained in the final exam performance.

Table 1: Descriptive statistics for courses under study.

		CoLaB Tutor				AC-ware Tutor			
KTV	**Indicator**	**S1**	**S2**	**S3**	**Total**	**S1**	**S2**	**S3**	**Total**
	#Students	41	29	26	96	27	24	32	83
#Objects	**Mean**	4.53	5	3.11	*90.05*	12.55	2.45	3.56	*20.82*
	Min	1	5	1	20	1	0	0	0
	Max	5	5	4	100	44	9	40	100
	SD	1	0	1.14	21.33	10.66	2.3	7.71	24.73
#Concepts	**Mean**	41.12	28	32.42	*91*	68.33	30.37	53.18	*78.62*
	Min	29	28	1	2.27	39	11	40	28.20
	Max	43	28	44	100	71	39	83	100
	SD	4.24	0	15.48	21.97	7.94	12.06	13.84	24.02
#Score	**Mean**	37.66	14.07	29.66	*70.85*	295.22	93.79	58.40	*50.05*
	Min	16.54	6.45	0	0	43	0	0	0
	Max	50.79	18.02	51.53	100	348	168	336	100
	SD	9.76	3.03	20.98	27.28	93.53	69.84	81.28	41.83
#Time	**Mean**	70.78	73.89	48.69	*65.73*	98.91	28.71	20.74	*48.88*
	Min	0	34	0	0	4.78	0	0	0
	Max	226	113	174	226	269.55	82.58	173.36	269.55
	SD	57.42	24.35	47.38	47.59	55.42	25.25	35.58	54.09
#Final exam	**Mean**	65.60	34.27	16.53	*42.85*	48.81	85.43	14.96	*45.24*
	Min	33	6	0	0	12	66	0	0
	Max	94	80.5	36	94	91	93	42.5	93
	SD	13.50	18.79	11.05	25.46	19.71	7.06	11.46	32

Table 2: Correlations between final exam score and KTVs.

KTV	CoLaB	AC-ware
#O	0.224*	0.252*
#C	0.323**	0.288**
#S	0.229*	0.410**
#T	-0.023	0.315**
* 0.05 significance level ** 0.01 significance level		

In term of online score and total time spent online, revealed correlations correspond to medium effect size (r=0.30-0.50), with 16% and 9% of variance explained in the final exam performance.

6.3 Regression Analysis

The Pearson correlation coefficient cannot determine a cause-and-effect relationship; it can only establish the strength of the association between two variables. From the set of KTVs, seven potentially significant indicator variables revealed in correlation analysis were further included in the regression analysis. Regression models are generally developed using hierarchical or block wise approaches for cases in which predictors have been identified in previous or published works. In the absence of such information, a backwards stepwise approach for entering potentially significant variables into a model is a robust and valid approach (Field, 2005; Macfadyen and Dawson, 2010).

In case of CoLaB Tutor, the regression analysis generated a 'best predictive model' of the final exam score (F(10.949), p=0.00), as a linear measure of the total number of concepts (showed in Table 3). The total number of concepts, as KTV and knowledge indicator, is statistically significant contributor (p<0.05) and multiple squared correlation coefficient for this model is 0.104, indicating that around 10% of the variability in learner performance in these courses can be explained by this KTV for online behavior.

Table 3: Regression analysis for CoLaB Tutor.

	USC		SC
Var	β	SE	β
C	8.788	10.588	
#C	0.374	0.113	0.323

Table 4: Regression analysis for AC-ware Tutor.

	USC		SC
Var	β	SE	β
C	30.609	5.051	
#S	0.312	0.077	0.410

In case of AC-ware Tutor, the regression analysis generated a 'best predictive model' of learner final exam score (F(16.350), p=0.00), as a linear measure of the gained online score (showed in Table 4). The total score gained online, as KTV and knowledge indicator, is statistically significant contributor (p<0.05) and multiple squared correlation coefficient for this model is 0.168, indicating that around 16% of the variability in learner performance in these courses can be explained by this KTV for online behavior.

The previous findings may be discussed using learners' feedback about difficulties they encountered during the use of Tutors. CoLaB Tutor's limited communication skills during dialogue were an obstacle for some students, who occasionally struggled to find 'the right words'. The previous could contribute to the non-significant small correlation between the total time spent on CoLaB Tutor and learners' performance.

Although all other KTVs were positively correlated with the learners' performance for both Tutors, only finished courseware in CoLaB Tutor and total score in AC-ware Tutor resulted as predictors of learners' performance. The learning process in AC-ware Tutor seemed to be more tedious than the learning process in CoLaB Tutor. AC-ware Tutor presents more text which learners have to memorize, so some of the learners had practice to photograph lesson screens during the experiment, making easier testing process and completing the courses without mastering the concepts. The more appropriate learning behavior in CoLaB Tutor could contribute to the significance of finished courseware as learner performance predictor.

In term of scoring systems, the main difference between Tutors is in calculating negative points during testing process. CoLaB Tutor calculates negative points for incorrectly put concepts during the dialogue, while AC-ware Tutor lets learners to make mistakes during this learning-by-testing process. AC-ware Tutor's total score which includes points only for correct answers resulted as the strongest predictor of learners' performance. Based on the obtained results we may conclude that Tutors probably lead to different measured aspects of knowledge (and learning). The higher predictive value of gained score in AC-ware Tutor compared to the finished courseware in CoLaB Tutor imply that online score is probably more similar to the level of knowledge examined through paper-pencil final exam.

7 FURTHER RESEARCH AND FUTURE DASHBOARD

The analysis results follow the idea of supporting learners in online learning by using KTVs. Since integrated AC&NL Tutor will encompass main structural components of both Tutors, the information about passed courseware and gained score should be presented in the learning and testing process. After the learner finishes online course, total time spent online should also be presented. From the teacher point of view, all available knowledge information should be visible on dashboard, enabling teachers to additionally intervene and support learners. The descriptive role of dashboard will help on learners' self-reflection and awareness. The prediction power of revealed KTVs in this research study will be verified in the winter experiment 2016/2017. The experiment protocol will be enhanced in term of strengthening learner motivation, better learner preparation at the beginning of the experiment and monitoring learner progress during the experiment.

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