

The International
JOURNAL
of
TECHNOLOGY
KNOWLEDGE
& SOCIETY

Learning Technologies

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VOLUME 1, NUMBER 2

INTERNATIONAL JOURNAL OF TECHNOLOGY, KNOWLEDGE AND SOCIETY
<http://www.Technology-Journal.com>

First published in 2005/2006 in Melbourne, Australia by Common Ground Publishing Pty Ltd
www.CommonGroundPublishing.com.

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ISSN: 1832-3669
Publisher Site: <http://www.Technology-Journal.com>

The INTERNATIONAL JOURNAL OF TECHNOLOGY, KNOWLEDGE AND SOCIETY is a peer refereed journal. Full papers submitted for publication are refereed by Associate Editors through anonymous referee processes.

Typeset in Common Ground Markup Language using CGCreator multichannel typesetting system
<http://www.CommonGroundSoftware.com>.

Learning Technologies

Past, Present and Future

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Abstract: This paper describes, first, the learning technologies, as they exist in the US. Then it presents the current work called CML+, a methodology for teaching valuable algorithms to graduate students as well as company employees or government employees. This method has been implemented in Windows 2000, using a GUI based language called IDL (Interactive Data Language) 6.1. The future of this technology will also be discussed.

Keywords: CML+, Learning Technologies, Implementation, Present and Future Technology

Introduction

STUDIES HAVE SHOWN that though e-learning has become widespread, the results of using it are not always satisfactory. People often find it difficult to use existing online learning technologies and they often have problems with retaining what they have learned. The problem addressed in this paper is the increasing demand for more effective e-learning tools, especially those emphasizing the learning-by-doing approach.

The purpose of this paper is to show how CML, an e-learning system that autonomously teaches algorithms, can help transform online learning. CML stands for "Complexity Measure of Learning". It utilizes an innovative method for measuring the progress of the student's work at each step of learning, thereby enhancing the value of the e-learning process. This is particularly useful in teaching algorithms to computer engineering, electrical engineering, and aeronautical engineering students, and to employees of companies in these fields. The CML system achieves this greater effectiveness through its enhancements to learning-by-doing technology.

Significance of the Themes

Since the themes and the area investigated by the paper are those of an intelligent tutoring system, it is important to report on the state of this technology and its significance. The primary significance of the themes of autonomous tutoring and AI-based tutoring systems is that the application of AI techniques to teaching tasks has shown a great improvement in learning, in the last 30 years, as evidenced by the formal assessment performed on these applications. Therefore, it is worthwhile to pursue a similar task currently, in the case of engineering algorithm tutoring.

The author has performed a thorough survey of current literature on intelligent tutoring systems. The survey found that there are numerous e-learning systems that are available, but unfortunately, none of them address the specific need of engineers learning the algorithms that are important for them. However, the engineers want and need such a system, as shown in technical conversations and experiments with the engineering community. Therefore, it is important to develop a system that helps the engineers in this crucial aspect.

The survey shows that, as a background to the modern research, several researchers have explored the application of artificial intelligence concepts to the task of teaching a variety of subjects. Section 4 expounds some of the more important and successful ones for this purpose, and shows their effects on the student mastery of a skill. To further establish the significance of this work, we have to also demonstrate to what degree such an intelligent tutoring system can address the engineer's education and training needs. The significance will be clearer as more and more companies, government agencies that employ engineers, and educational institutions use the intelligent system called CML, and interviews are conducted regarding the use of the system. The interviews conducted regarding the current tutoring systems are based on the experience of the interviewees and the solid evidence published in peer-reviewed sources; these show convincingly that such tutoring systems offer the best opportunity possible using technology, particularly in situations where one-to-one human tutoring is not feasible.

The role of motivation in determining the outcome of training environments is critical in the present and future applications of intelligent tutoring systems. Though accurately measuring motivation can be a problem, it is found in the case of engineers who



need to learn algorithms, there is enthusiasm to gain the most from the training experience, without a tutor.

This paper will expound upon the themes of autonomous tutoring (where the students learn without a human tutor) and intelligent tutoring (where the human intelligence in teaching is duplicated, as much as possible).

Specific e-Learning Needs in Training Engineers

Changes Driving Online Learning for Engineers

Professors of Engineering Schools in the U.S. clearly see the lack of the students' numerical skills as a greater problem than their lack of work ethics. Between 37 and 44% of all professors in the nation believe that difficulty in numerical fields is a reason why we do not create as good engineers for companies as we should. Many also feel that technology in engineering education is insufficiently utilized. More than 41% of modern professors in the U.S. see computers and the Internet as the key avenue for exercises and applications. More than 41% of these professors also acknowledge that computers, enhanced software and even the Internet will be vital in training future engineers (Educationnews.org, 2005).

Fall 2002 and Fall 2003 enrollment data for foreign national undergraduate and graduate students in the U.S. indicate that a new trend may be developing. Rather than following the past increasing trends for foreign students and the current increasing trend for engineering as a whole, foreign national enrollments are now entering a period of decline (EngineeringTrends.org, 2005).

In the US, graduate degrees in these disciplines are down about 25 percent for the past decade, even as the U.S. National Commission on Mathematics and Science Teaching for the 21st Century projects that by 2008 the technology-driven economy will add 5.6 million U.S. jobs in the health sciences and computer industries that require these advanced skills.

As a result, many schools in the U.S. are already considering a cutback on the number of courses that are currently offered. This means that valuable courses may be offered less, and thus the need for an online system like CML (Complexity Measure of Engineering) at a company like Lockheed Martin, U.S.A., is even more imminent. There is also the backdrop of tuition hikes, enrollment caps, cuts in public funding and increased governmental pressures for accountability measures, at universities.

In addition, the IEEE (Institute for Electrical and Electronic Engineers), one of the world's leading engineering organizations, has indicated the need to increase the availability of technical course offerings, particularly through online systems such as CML. Their goal, of course, is to provide professional development opportunities. They want to encourage and support the use of technology, e.g., multimedia and information superhighway, in engineering education. They also wish to develop outreach activities for company employees.

Finally, a continuing education group for engineering with participation from both university and industry, including on-site personnel from both sides, is recommended by universities in the U.S. (Sengupta, 2005). Such continuing education includes innovative courses and curriculum, especially in design, that can be tested and made available to other institutions.

Ensuring Effective Online Learning for Engineers

It is found that most engineers tend to forget even the crucial aspects of their learning within a few months of taking a course. To offset this, there must be methods for helping them learn by doing, and allowing them to make mistakes in a safe learning environment. However, most inexpensive e-learning solutions available today are no more effective than books. They simply present information, rather than provide the engineers with meaningful learning activities.

An effective way to teach new skills is to put learners in the kinds of situations in which they need to use those skills. Engineers should come to understand when, why, and how they should use target skills on the job. They should receive key lessons just in time, as they work through their problems; that means, when they want to know the information, when it will make the most sense to them, and in such a way that learners will be most likely to remember the information later when they need it in their work (Schank, 2004). However, they cannot always rely upon a human tutor to be present when they need to receive their lessons.

Following this ideal, the current learning technologies should try to help engineers obtain the knowledge necessary for their immediate application.

Review of Literature

Literature of the last 30 years that show the successful applicability of intelligent tutoring systems, are worth mentioning. This particular literature will be briefly discussed in this section, and the successful applications will be exposed.

There has been previous research on problems and solutions involving e-learning effectiveness. For example, there is an early cognitive architecture for developing systems involving mental behavior in learning, called Soar (Rosenbloom, Laird & Newell (Eds.), 1993). This set the stage for integrating machine (computer) process with human learning-by-doing. This technology designs human reasoning capability into intelligent, specialized software, providing psychologically relevant, sophisticated solutions for complex problems. Soar Technology's state of the art, "highly human" intelligent agents automate complex tasks, simplify human-system interaction, and simulate human-like behavior for military or civilian applications. Researchers all over the world, both from the fields of artificial intelligence and cognitive science, are using Soar for a variety of tasks. It has been in use since 1983, evolving through many different versions to where it is now.

Basically, the Soar system provides the systems based on it the ability to use all available knowledge for every task that the system encounters. But it cannot provide the complete rationality that it originally aimed for. Unfortunately, the complexity of retrieving relevant knowledge puts this goal out of reach as the body of knowledge increases, the tasks are made more diverse, and the requirements in system response time become more stringent. The best that can be obtained currently is an approximation of complete rationality.

The design of Soar can be seen as an investigation of one such approximation. All decisions are made through the combination of relevant knowledge at run-time. In Soar, every decision is based on the current interpretation of sensory data, the contents of working memory created by prior problem solving, and any relevant knowledge retrieved from long-term memory. Decisions are never precompiled into uninterruptible sequences. By implementing Soar into robotic environments, computer scientists developed an integrated human-machine learning interaction or multi-agent system (Information Sciences Institute, 2005). However, this development is not an e-learning system.

It is also found that the measure of learning used by Soar and its applications do not have any *a priori* justification (in conversation with Dr. Paul Rosenbloom, 2002).

From 1983-93, several computer scientists and cognitive scientists have developed a rule-based theory, which introduced cognitive skills into production rules. This is a framework for different tasks, and also a theory about how human cognition works. One of its important features is that it allows researchers to collect quantitative measures that can be dir-

ectly compared with the quantitative measures obtained from human participants.

It has been used successfully to create models in domains such as learning and memory, problem solving and decision-making.

In the immediate past, it enabled domain-independent procedures that are only acquired by human actions. This process resulted in machine-based "tutors" to enable feedback and enhance the learning experience. Follow-on programs utilizing this method included a LISP language tutor (Corbett & Anderson, 1991), and a Geometry tutor (Anderson & Reiser, 1985; Anderson, Boyle & Yost, 1986; Anderson, Boyle, Corbett & Lewis, 1990).

Subsequent tutors in the teaching environment have appeared, including an algebra tutor (Matz, 1982; Milson, Lewis, & Anderson, 1990), and tutors that teach the PASCAL language and PROLOG language (Anderson, Conrad, Corbett, Fincham, Hoffman, & Wu, 1993). This algebra tutor is highly successful in application; it is used in thousands of schools across the country. Such "Cognitive Tutors" are currently being used as a platform for research on learning and cognitive modeling as part of the Pittsburgh Science of Learning Center, U.S.A.

However, none of these programs addressed online learning of high-level algorithms. Thus, as companies and universities began demanding a more effective online learning technology for higher-level instruction, a gap opened up between the need and the solution.

A company called Socratic Arts also produced several different online courses, on Internet, for example; but these did not include algorithms in electrical engineering, computer engineering or aeronautical engineering. (socraticarts.com, 2005).

Though many learning systems are often decentralized and distributed, none of them addresses the needs of learners of high-level algorithms, such as the company employees who might want to learn Digital Signal Processing algorithms on the job. The current learning systems mostly focus on students learning high school algebra, geometry, HTML, etc. So, there should be products that teach high-level algorithms online, and use a proper educational model that can measure learning as the students are working on the problems.

The tutoring technology developed by the author is designed to fill precisely this gap between the need to teach complex algorithms online and the shortcomings of existing tools.

Before describing the features and advantages of the tutoring system based on the Complexity Measure of Learning (CML), let us review the research design and data, and the analysis of the data, that demonstrate the enhancement to online learning-by-doing represented by this system.

Research Design and Data

CML System Data Use, System Design and Experiments

The author’s own work is a cognitive system that reasons intelligently, using appropriately represented knowledge, in order to perform the task of providing a measure of what a person learned about a crucial algorithm. The proposed system provides a well-founded representation of the measure—that is, a much clearer, more precise indication of how the student is doing.

The project models an innovative system called CML (Complexity Measure of Learning), using rule-based and case-based reasoning as well as mathematical techniques and proofs, and also describes CML’s development as a computer program. The measure of learning is called the complexity measure, since it is a formula that measures how much work is being done in the process of learning, just as the complexity of an algorithm measures how much work the algorithm itself is doing. However, CML is a different concept than the complexity of the algorithm, and is calculated differently. There are also proofs to justify this measure.

Because the formulation of this measure is rigorous, and can be justified, it can be further proven

that a CML-based system can teach every algorithm that can be implemented effectively on a computer. Thus, this project advances the state-of-the-art represented by other contemporary tools, in the sense that not only does it provide an effective method of teaching, but it also provides *proofs* for what it does. In this way, it avoids common problems that can arise with data management, for example, a reviewer not understanding what or how much a student has learned.

As far as the mechanics of the material presentation goes, this system uses an image compression technique, for providing commands to the student and providing explanations of each step. The trainee or the student learns by emulating on the screen what an algorithm would have output at each stage of its execution, given a certain input. The system computes the measure of the student’s learning at each stage by assigning him a number and comparing the number to the ideal solution contained within the CML. The system is autonomous, and thus no human teacher is available or needed. It is planned that this system will be augmented to include several important algorithms, in 2005.

The following flow-chart describes basically how the system works:

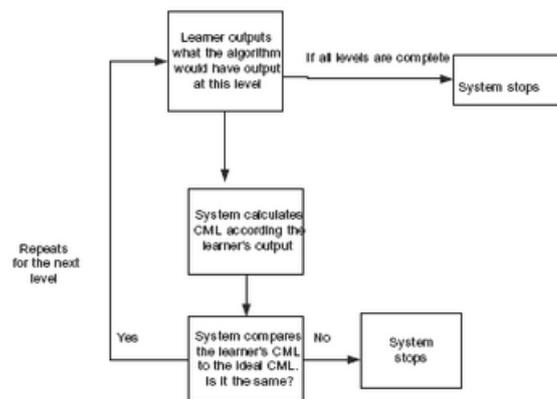


Figure 1: Flow-Chart of the System

The research design is outlined in the above diagram. Taking note of the great need for teaching high-level algorithms to graduate students and company employees, the author invented and developed a method for measuring the learning of algorithms that applies to such teaching. She justified the method, including the measure, by proofs, and implemented the system on computer.

The system teaches each algorithm separately, with explanations and elaborations of the related material, on the computer. But people only learn al-

gorithms by working them out. So, besides the detailed explanations and elaborations of the material, the system asks the student to work out the step-by-step answer to the numerical problem stated. At each step (or level), the student provides the required answer, and the system autonomously judges the answer by comparing it with the correct answer that is built in.

The program also assigns certain points to the student if he or she gives the correct answer, and accumulates the total number of points in a database.

If the student provides the wrong answer, the system asks him or her to re-work the steps, and displays further explanation of that particular step. At the end, the student determines whether his or her total accumulated points add up to the ideal number of points, which is a representation of the measure of learning in this particular case. In the case of many algorithms, there are associated graphs, for which the system obtains the correct numbers from the student, and autonomously produces the graph, based on those numbers.

A simple example will be helpful in explaining the system. Suppose that a student is learning Mergesort, a sorting algorithm that takes an unsorted list of numbers, for example, the list of (4 7 3 9 6 2 1 8), and sorts them in ascending order, resulting in (1 2 3 4 6 7 8 9).

The algorithm does this by first breaking up the given unsorted list in smaller sublists, such as (4 7) (3 9) (6 2) (1 8), then into lists with only 1 member each, such as (4) (7), etc. This is called Stage 1. Then the algorithm puts the list back together, in a sorted manner, thus resulting in the list (1 2 3 4 6 7 8 9). This is called stage 2.

This has been implemented on the author's system, and tested on five different representative groups of students of Santa Clara University, USA. Five different sets of interviews were carried out, to establish the need for the instrument as well as the experience of the students. The number of students in each of these sets is as follows: there are 5, 5, 7, 8 and 10 students who were interviewed and requested to work out the demonstration program. One of these tests is described here in the form of a graph; it depicts the

testing of a student with a list of 8 numbers. This student represents the average of the group of 10 students, and so the output of his work is representative of the experiment. The student learned Mergesort in 6 trials. The ideal CML for Mergesort is found by a formula, which is instantiated in the case of 8 input numbers, as the number 55. This is the "ideal CML", the ideal Complexity Measure of Learning, where the total number of original program inputs is 8.

The graph below illustrates the case of the student who has broken up the list successfully, but had trouble putting it back together in a sorted manner. In the first trial (the 0th trial), he only completed 10 portions of the ideal CML of 55 correctly. The program takes note of this fact and assigns him the number 10; since $10 < 55$, the program asks him to start the merging process again, from the point at which he made the mistake. The system keeps track of how many correct points he has accumulated so far. At the next trial, the student scores 28, which is the result of accumulating 18 more points, added to the previous 10 correct ones. The program notes that this is less than 55. So, the program lets him start again, from the point at which he made the last mistake. The third trial (numbered as trial 2) brings out the performance as 36. Since this is still less than 55, the program lets the student do the work a fourth time. This process repeats until his CML is 55. At that time the process stops, since the CML indicates that the student has succeeded in learning Mergesort properly. This student's score represents the average of his group.

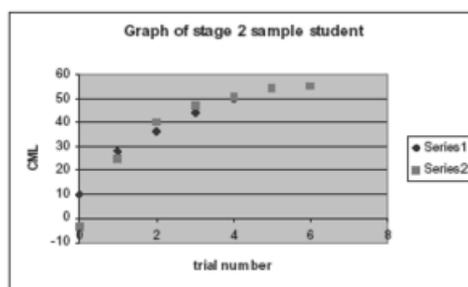


Figure 2: Graph of a Student whose Score Represents the Average

No other existing tool does this job, as extensive search shows. In the given graph, the point at the top, where the two series meet, is the element that illustrated the complexity of this student's learning.

This tool was tested (using more complex algorithms than sorting) on five different groups of students at Santa Clara University, California, USA, as stated before. These were graduate students of various engineering disciplines and Applied Math-

ematics, consisting of both male and female students. Some of them were foreign students from various countries, and some were American students, by birth. The study was conducted over five quarters (3-month periods). They were all in their 20's.

The metrics were as follows: the students were asked to try out some electrical engineering and aeronautical engineering systems. They had some knowledge of these algorithms, through the past

courses that they had taken, but in the trials, they showed a marked improvement as they tried out the same algorithm a second and a third time. The smaller number of mistakes they made, in the subsequent trials, measured their improvement. This was the baseline. Besides this, the students were also asked to write down their reaction and like/dislike of the system.

The table presented in section 6 shows how learning has improved overall, for each student involved in a group of 5 students tested.

Advantages and Possible Shortcomings

The difference in learning, and the improvement of learning, with this tool is the meta-tool of the Complexity Measure integrated in the software. The implementation of this measure constantly tracks the student's performance across his/her learning of very complex algorithmic processes. As the five experiments conducted with the students in 5 different quarters show, they demonstrated remarkable improvement in their learning. The results of one of the experiments, with 5 students, are presented in section 6, in the form of a table. In the written portion of the tests, they unanimously stated that they liked the system, and think that this system should be implemented in classrooms and industries.

However, there are possible shortcomings of the system that should be addressed. These shortcomings are currently contemplated, since the system has not been in actual use by either companies or the U.S. government yet. Once adapted for actual use by companies and government, some of these issues can be resolved. The role of motivation in determining the outcome of training environments in industries and government, has not yet been formed. So, one does not know yet who will gain the most from the training experience.

It is also contemplated that machine learning can be utilized to augment the knowledge base of this system, during its use. That has not been tried yet. Which architectures will be most suitable for the implementation of this system at a practical level, that is, for industry usage or government usage, has not been determined yet.

To present further material on critical self-awareness, it was found that the student user's experiences were positive. This was gathered from the written reports that they provided, after trying out the system. However, there are practical limitations at present; the system is not yet in actual use by any industry or any branch of the U.S. Government. So, we do not yet know about the users' experiences when they come from industries or the government, in the U.S.

Data Analysis and Further Use of Data

In this section, we further explain the result of the experiments.

The author obtained the original data that motivated the formation of this measure from long and acute observation of the employees of Lockheed Martin Company, USA. She found that they do need such knowledge of algorithms, either because they have not had all the algorithms in the course of their regular studies, or that they have simply forgotten many of the crucial algorithms. Several managers and senior scientists of Lockheed Martin have also admitted that not only the young employees, but also the senior people can gain knowledge by using the CML system, including, for example, senior people with a Ph.D. in one specific field, who need to communicate and collaborate with Ph.D.'s from another specific field. They can quickly learn algorithms that are necessary for the job.

Lengthy talks with these employees and managers provided the necessary data to start this work. Similar data were obtained from NASA Kennedy Research Center, Florida, USA.

When the work (prototype system) was in progress, it was demonstrated, at various stages of its development, to some Lockheed Martin employees in the USA, and also to several graduate students of Engineering and Applied Mathematics, Santa Clara University, Santa Clara, California, USA; the latter tried out the system, in 5 different teams of students. The decrease in the number of mistakes as the students try out the system more and more shows positive results.

The written and oral evaluations from these trials were also highly encouraging; the students reported, on the average, about 60% increase in learning, when such a system is used, together with their classroom learning. They also wanted to see some more graphical features added. Taking note of this data, the author and the team of software engineers will incorporate some more graphical elements in the system.

The following clustered column chart shows one student's improvement in learning, as he tried out several cases of algorithms using the CML system. This student, again, represents the average of the group, in improvement. This average is 60%. This is calculated by asking the students about the percentage of improvement that they felt best describes their improvement in learning, and also by noting the decrease in the number of mistakes. Series 1 shows the number of times the student learned by trying out the same algorithm, and the series 2 shows the percentage of the improvement of his learning.

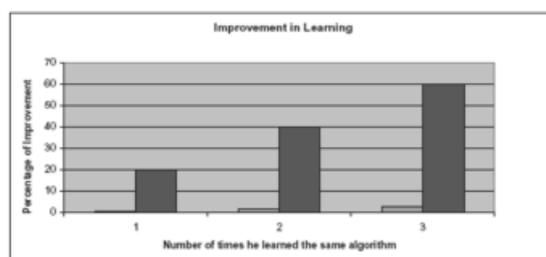


Figure 3: Clustered Column Chart Showing the Average Percentage in Improvement for One Group

The students have also reported increased retention of the algorithm that they learned, since they can reinforce their learning by subsequent times that they try out the algorithm. Of course, this type of learning has some inescapable qualitative or subjective aspects. Not everyone will make the same amount of improvement in learning an algorithm 3 times.

But this improvement is encouraging for students, thanks to a system like CML. The improvement was

tracked by the decrease in the number of mistakes that the student made. It was also tracked by the student comments in the written report that they produced, after each time each student tried out the system.

The following table shows how learning has improved overall for each student in a group of 5, involved in the study. This is provided in terms of percentages.

Table 6-1 : Table Showing the Percentage of Improvement in Learning an Algorithm, for a Group of 5 Students, after Trying out the CML System

A Report on the Graduate Students' Improvement in Learning			
Students ¹	Percentage of Improvement	Students	Percentage of Improvement
Student 1	50	Student 4	70
Student 2	50	Student 5	70
Student 3	60		

¹The Author, Santa Clara University, USA

Conclusions

As the research and data from the application of the CML study show, the tool improves learning by approximately 60%, on the average. Therefore, the study indicates the CML system to be a promising and useful enhancement in online learning methods for complex algorithms.

Based on the initial results from this implementation, the next step will be to add more algorithms that are more challenging to learn, and present this to companies that can utilize such implementation. In addition, the CML tool will be used in the universities, where the learning providers need to integrate technology in their education package, to better prepare their students for real professional life. Teachers,

in turn, will have the need and the opportunity to make use of this technology, to stimulate the aptitudes of their students.

An augmentation will involve the testing of more algorithms, general expansion of the system with voice recognition possibilities, and also the possibility of a goal-oriented system. Extensions that utilize the power of multimedia projects will be applied. Application of neural network techniques is also contemplated. Modern PDA-integrated technology will be applied. In other words, the goal is to evolve CML so that it can be used on laptops, mobile phones and PDA's (Personal Digital Assistants). All of these are possible with the current state of computer technology, and these are the refinements that will be completed.

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About the Author

Dr. Suchitra Abel

I was born in India, but currently I am a US citizen. I have worked for several industries, including SRI International and Lockheed Martin. I have also taught at several major universities. Currently, I teach at the Department of Computer Engineering, Santa Clara University, Santa Clara, California, USA. I am the author of this paper and the implementation of the CML+ system, which has been found to be highly effective for learning crucial algorithms like Fast Fourier Transform. It is being used as supplementary material in several graduate courses. Company employees or government employees, e.g. NASA employees, will also benefit by using this system.

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