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Artificial intelligence and voice-powered electronic textbooks

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Abstract
Textbooks have long been an integral part of classroom education. As much of the information world has moved online, so, too, have textbooks followed. Unfortunately, commercially-available electronic textbooks (e-textbooks) are typically little more than .pdf versions of their paper counterparts, thus not exploiting other technologies that could be used to increase student learning. The present paper describes e-textbook technology that uses artificial intelligence (AI) and voice/natural language technologies to increase student learning. As students are learning a lesson, they can verbally ask the e-textbook questions about the topic and receive answers much the way they can when using personal assistants on smart phones. When students have completed the lesson, the e-textbook assesses whether they have learned the material by verbally asking questions and allowing students to answer verbally. Any deficiencies are immediately remediated. When students finish the assessment, they do practice problems as they would in a standard e-textbook. The difference is that with the present technology, all work is done step-by-step on an electronic worksheet where the underlying AI technology monitors each step and provides hints when requested and feedback when mistakes are made. The present technology was tested experimentally by having students either use it or leading publisher Pearson's Algebra 2 Common Core e-textbook to learn division of complex numbers. Students were then given a post-test to measure their learning. Students using the AI and voice/natural language-powered e-textbook scored four times high on the post-test than those using Pearson's e-textbook. The results suggest that AI and voice/natural language technologies can improve educational performance when incorporated into e-textbooks.

Keywords: integral, textbooks, education, intelligence, incorporated

Introduction

Textbooks have long been a staple of the educational system. Teachers have used textbooks as a basis for their lesson plans and homework assignments. Students read their textbooks to learn basic concepts, which in turn would be reinforced by the teacher in the classroom. Students then dutifully copy their homework assignments from their textbooks onto their notebooks, do their work and turn that work into their teachers for grading. This has been the mainstay of education for much of the past couple of hundred years.

The past generation has seen major changes in the educational system and, indeed, in the world. Much of our information has shifted from paper to electronic/digital format. We go to websites instead of libraries and we read digital newspapers and books instead of paper-based ones. Our sources of digital information have become more ubiquitous and smarter. Cellular phones now double as microcomputers and tap into global networks of information. Technologies such as artificial intelligence (AI) and voice/natural language processing make obtaining information even easier as we can now simply talk to our electronic devices, ask them questions and receive answers about virtually any topic.

Education has slowly made its way into the digital world also as electronic learning (e-learning) platforms have proliferated. Recently, textbooks themselves have found their way online and many classrooms either supplement or have replaced traditional paper-based textbooks with their electronic counterparts. Unfortunately, as online and other electronic services have been quick to exploit new advances in technology, electronic textbooks (e-textbooks) have lagged behind, often being little more than .pdf versions of their paper-based counterparts. While such e-textbooks may provide convenience and resilience compared to their paper-based counterparts, they do little to enhance the effectiveness of the textbook as a teaching tool. In fact, a recent study found no difference between paper-based textbooks and e-textbooks in terms of teaching effectiveness (Laketa and Drakulic, 2015) [7]. The study cited e-textbooks' lack of interactivity and their inability to personalize education to the needs of each student.

There have been attempts made in recent years to improve the quality of e-textbooks. However, often these involve improving the readability of the text rather than improving the teaching value (Gunawan, 2018) [5]. Others have focused on factors such as interoperability of content across platforms and lifespan of software tools used to create e-textbooks (Lokar et al., 2011) [10]. A third group has focused on the types of information that e-textbooks should contain (Ivanova and Osmolovskaya, 2016) [6].

While each of these categories of recommendations may very well enhance the user experience of students who use e-textbooks, it is unclear how they may improve overall student learning. The present paper is concerned with creating a paradigm shift in how e-textbooks are constructed, using state-of-the-art technologies such as artificial intelligence (AI), machine learning and voice/natural language processing to produce large enhancements in student learning. The remainder of the paper describes an e-textbook to teach division of complex numbers that was constructed using these technologies.

This technology was then compared to a commercially-available e-textbook, Pearson Algebra 2 Common Core--a .pdf-based e-textbook, created by industry leader Pearson to see which version resulted in greater student learning. Our hypothesis is that our AI and voice-powered e-textbook would lead to greater student learning of the material.

Methods

Participants

Participants were 20 students who were recruited from middle school and high schools in Fairfax and Loudoun counties in Virginia and Montgomery County in Maryland. Each one was enrolled in a geometry math class, which means that they had previously taken Algebra I, but had not taken Algebra II. It was necessary that each student had previously taken Algebra I since knowledge of how to multiply two binomials is necessary to learn the subject matter taught in the present study. However, it was also necessary that each student had not yet taken Algebra II since the subject matter of the present study, division of complex numbers, is a topic that is covered in the Algebra II curriculum. We wanted to make sure that participants in the present study had no prior knowledge of this topic. All participants met this criterion.

Topic Taught and E-textbook Technology Used

The topic used in the present study was division of complex numbers of the form a + bi, where i is the square root of -1. This topic is typically part of the Algebra II curriculum.

There were two core technologies used. First, for the control condition, there was the Pearson Algebra II Common Core electronic textbook used by students in Fairfax County schools. For division of complex numbers, there is a unit explaining how to divide complex numbers, followed by six practice problems. Additionally, both conditions had a 20-question paper and pencil post-test that was common to both conditions.

The experimental condition technology consisted of the AI and voice technology software described below. The instructional part consisted of both text and video versions of how to divide complex numbers.

Querying the E-textbook

While a student goes through the division of complex numbers lesson, he or she has the ability to verbally query the system and receive an answer to his or her question. This is done by clicking on a microphone icon located on the top right part of the screen and then speaking the question. The student's question is translated into text and shown to the student, who can edit it if there is a mistake in the speech to text process. Alternatively, the student can type in the question directly instead of speaking it.

Since there are multiple ways to ask a question, the first step of the process is to match the student's question with a question the e-textbook can answer. Semantic similarity calculation is the key process used here. The basics of the semantic similarity calculation is word embeddings. Word2vec is a group of related models that are used to produce word embeddings. These models are shallow, two-layer neural networks that are trained to reconstruct the linguistic contexts of words. With Word2vec technology, we use multiple methods to calculate the semantic similarity between two sentences. The easiest method is the baselines method. This method takes the average of the word embeddings of all words in each sentence and calculates the cosine between the resulting embeddings. The result of the calculation is between 0 to 1. If two sentences are highly similar, the score is closer to 1. For example, the sentence "a man is cutting up a cucumber" has the same meaning as the sentence "a man is slicing a cucumber." The score of these two sentences is 0.97. A similar process is used when a student asks a question. Semantic similarity technology outputs the highest score between the student's question and all the questions in our database. If the score of a question is extremely low (for example, less than 0.15), the student's question may not be a normal sentence. It may be no logical sentence or just repeating words. In this case, our system requests that the student input a more well-structured sentence. If the score of this question is high enough (for example, higher than 0.8), we claim that this question has the same meaning with student's question. If the score of this question is intermediate (for example, more than 0.5 and less than 0.8), the system is not quite sure of the meaning of the student's question. In this case, we match the student's question to the question with the highest similarity score that the system can answer. The student is then asked if the matched question is what the student is asking. If the student says yes, the system answers the matched question. If the student says no, the system looks for the next highest match above .5 and asks again. A maximum of three cycles are possible. If the system goes through three matching cycles and finds no match or it cannot find a match with a similarity rating above .5, it assumes it cannot answer the student's question and informs the student of that fact.

Assessing the Student

Following the instruction, the e-textbook assesses the student to see if he or she understood the material. The assessment uses the same voice interface as the querying feature. Students are verbally presented with questions and respond in kind. The system then processes the students' responses and matches them to the underlying knowledge model. If there is a match as described in the previous section, the correct answer is deemed to have been given. If the match is between .5 and .8, the system clarifies what the student stated as described above. If the match is low or the student states that the system's interpretation of the student's response is wrong, the system assumes the student gave the wrong answer and corrective feedback is provided.

The assessment queries themselves are derived from an underlying knowledge model of the subject matter to be mastered. The knowledge model is based on the Integrated Knowledge Structure (INKS) framework developed by John Leddo (Leddo, 1994) [8], which combines several knowledge types described in the cognitive psychology literature. These include factual or semantic knowledge (Quillian, 1966) [12], general problem solving plans or scripts (Schank and Abelson, 1977) [13], problem solving procedures or production rules (Anderson, 1982) [1, 2, 3], and causal principles or mental models (de Kleer and Brown, 1981) [4] that explain why procedures are down. Queries are presented to students that are derived from each of these types of knowledge (e.g., "What is i?", "How do you divide two complex numbers?") to assess whether they have a thorough understanding of the subject matter being taught. Our previous research (Leddo and Sak, 1994) [9] found that assessments of student knowledge produced using the INKS framework as their bases correlated .88 with how well students could solve practical problems that use this knowledge.

The Electronic Worksheet

When students finish learning the subject matter and are assessed and remediated if necessary, they proceed to an electronic worksheet where they can do practice problems. This is analogous to the practice problem section of a traditional textbook, with two notable exceptions. First, instead of copying the problems onto a separate sheet of paper and doing the work on that paper, students see the problems on the screen and do the step-by-step problem solving directly on an electronic worksheet supplied by the e-textbook. When this happens, the e-textbook can process the students' step-by-step work and offer hints when requested or corrective feedback to mistakes when made (this is described in more detail below). Second, unlike with a traditional textbook or e-textbook, students can type their own problems onto the electronic worksheet and receive hints and feedback just as what happens when they solve problems taken from the database (the mechanism for this is also described below).

In the present experiment, each question provided to the student involved division of complex numbers of the form (a+bi)/(c+di), where a, b, c, and d are integers. Once the student sees the problem, he or she types in his or her work step-by-step on the electronic worksheet. The worksheet is organized by lines, with one line given for each step. When a student is through typing in a step, he or she clicks on an enter button and the step is evaluated by the AI technology. If the step is correct, the student proceeds to the next step. If the step is incorrect, the worksheet line the step is on is highlighted in yellow and the feedback box explains why the step is wrong and how the step should be corrected. When the student completes the problem by entering the correct answer, the students is notified in the feedback box. There is a hint button that students can use. In this case, the hints are tied to the step that the student has recently completed and gives the student information on how to complete the next step. There are three hints available, each at successive levels of detail. For example, in the problems involving division of complex numbers, the general hint tells the students to multiply by 1. The second hint tells the students to try to eliminate the imaginary part of the denominator. The third hint tells the student to multiply by the complex conjugate of the denominator. The actual numbers from the problem are populated into the hint's text.

The hints and feedback capabilities are made possible through AI. The AI component of the system is based on John Anderson's ACT-R framework (Anderson, 1990) that has formed the basis of numerous AI-based instructional systems. The core of ACT-R is a production rule system where sequential procedures are stored based on the antecedent conditions that trigger them. The system then matches the student's input to the step that is listed in the production rule sequence. A match is considered to be a correct step and a mismatch is considered to be an incorrect step. ACT-R allows for more than one pathway to a solution, which is beneficial since there is generally more than one way to solve a problem.

Typically, people who build AI-based systems for education that are modeled after ACT-R enumerate each problem-solving path that is possible for solving the problem. This is done for each specific problem that the system will deliver (cf., Aleven et al., 2006) [3]. This becomes particularly cumbersome if the software will ultimately deliver many problems (as would any large scale educational system) or if the system is intended to be flexible enough to allow students to enter their own homework or test-study guide problems as our system allows.

Therefore, in order to create a more flexible system that can support any problem within a problem class, we wrote our system to operate on generalized problem types where the numbers used in the underlying production rule model the AI engine uses are parameterized rather than instantiated. For example, a typical ACT-R system might model a simple solution path for adding (2 + 3i) + (3 + 4i) as

Step 1: (2 + 3i) + (3 + 4i)
Step 2: (2 + 3) + (3i + 4i)
Step 3: 5 + 7i.

This would require a separate model for every possible problem that the system would deliver to a student. By parameterizing each variable, we create a system that requires only one knowledge model per problem type plus the particular variable values for each problem. Therefore, our solution path for the same problem looks like

Step 1: (a + bi) + (c + di)
Step 2: (a + c) + (bi + di)
Step 3: evl(a+c) + evl(b+d)i. (evl means to evaluate the sum of a+c)
Problem 1: a=2, b=3, c=3, d=4, and so on for each problem to be used.

This method means that the system can generate unlimited problems to present to the students and the AI technology can respond to them since its representation of the problem is generic rather than hardcoded. For each possible step, there are multiple pathways that are permissible and we supplemented the algorithm with mathematical expression evaluators that recognize equivalent inputs (e.g., a+bi and bi+a are mathematically equivalent).

For each step in the process, the possible errors a student could make are enumerated. For each error, there is associated text that describes the error and the way to correct it. Similarly, three hints, each progressively more specific, are also created for each step in the process. The benefit of our parameterized approach to representing the problems is that these hints and feedback can also be written generically and then populated with specifics from the problem. For example, in a standard algebra problem type of ax+b=c, if a person subtracts the value of b from one side of the equation and not the other, we can write the corrective feedback as "You subtracted b from one side of the equation and not the other. You need to subtract b from both sides of the equation." However, rather than saying "b", the system would replace that b with the actual number used in the problem. This format allows for one general piece of feedback to be used in any problem of this type where the user makes this particular mistake. It is this feature that allows the student to enter his or her own problem since the system in not tied to any particular set of numbers.

Procedure

The participants were first screened to make sure that they did not already know how to divide complex numbers. Upon completion of the initial screening, participants were assigned to one of the two technology conditions. A total of 10 participants were assigned to each condition.

The first part of the instructional process was having participants in each group learn the concept. In the control condition, participants read the appropriate section of the Pearson e-textbook on dividing complex number problems. They then did the six practice problems listed in the e-textbook and given feedback as to whether or not they got the correct answer. In the experimental condition, participants used the present AI and voice-powered e-textbook technology. Their session consisted of learning the material, going through the assessment, and doing the six practice problems on the electronic worksheet. Afterwards, all participants were given the 20-question post-test.

Results

The answers to the 20 questions on the post-test were scored based on whether the correct answer was given. The mean number of correct answers by participants, broken out by condition, is shown in Table 1. As can be seen in Table 1, participants in the Pearson electronic textbook condition averaged 4.4 correct answers or 22% on the post-test. In US schools, this is generally considered to be a failing grade (F). Participants using the AI and voice-powered technology averaged 17.5 correct answers or 87.5% on the post-test. In US schools, this is generally considered to be in the B+ grade range.

A t-test was performed on the data and revealed a statistically significant difference between the means $t = 6.40$, $p < .00001$. This suggests that adding AI and voice technologies to e-textbooks can greatly improve performance. There is a secondary finding that is worth noting. In any educational setting, there will always be some students who learn no matter how they are taught and some who will struggle. Therefore, in addition to looking at overall means, it is useful to explore how robust an educational technology is in teaching all of the students who use it. To do this, we examined the variability in scores between the two groups to see the degree to which the technology appears to help all students who use it.

In the Pearson group, the post-test scores ranged from 0 to 16 (0% to 80% correct), suggesting that the technology is more effective for some students than others and that it is not particularly robust across students. Only two students scored above 50%, which means eight of 10 students would receive failing grades. In the AI and voice-powered e-textbook group, the post-test scores ranged from 14 to 20 (70% to 100%). This suggested that, while some students did outperform others, in general, all students performed reasonably well. In order to test statistically whether the AI and voice-powered e-textbook is more robust across students than the Pearson e-textbook, we looked at the variability in performance. To do this, we conducted a Levene's Test for Homogeneity of Scores Variance across the two groups. The results was statistically significant, $F(1, 18) = 11.43$, $p = .003$, indicating that the AI and voice-powered e-textbook showed more consistent performance across students than did the Pearson.

Discussion

The primary purpose of the research was to investigate whether adding AI and voice technologies to e-textbooks would enhance learning compared to the current, primarily text-based format used in commercially-available e-textbooks. Since Pearson is one of the largest textbook publishers and a leader in e-textbooks, its e-textbook served as an ideal comparison to the present technology, which uses both AI and voice/natural language technologies to bolster learning. The results showed both a main effect for technology with regard to learning and a difference in variability in student performance.

The main effect is important because it shows that AI and voice/natural language technologies have enormous potential to improve learning when embedded in e-textbooks. Overall, students using the AI and voice-powered e-textbook performed four times better than those using the standard text-based e-textbook. This is equivalent to getting a B+ versus an F in school. This difference is not only statistically significant, but also clinically significant as it creates a low-cost, scalable means to improve education.

Equally relevant, the AI and voice-powered e-textbook technology showed itself to be robust across students, with no student scoring below 70% on the post-test and five of ten students scoring in the A range without any teacher intervention. This suggests that the technology may be highly useful in outside-the-classroom settings such as self-directed learning or home schooling. In contrast, the Pearson e-textbook did not show itself to be robust across students as scores ranged from 0% to 80% with eight of ten students scoring in the F range and only one scoring above a D. Results showed that the AI and voice-powered e-textbook technology produced consistently high scores, whereas the Pearson e-textbook produced inconsistent results that were predominantly on the low side. These results suggest that the Pearson text-based e-textbook is neither particularly effective at producing high performance nor robust across students while the present one with AI and voice/natural language technology is effective at producing high performance and is highly robust across students.

Conclusion

As noted in the Introduction, there is a significant push to move traditional paper-based textbooks to electronic formats. While this creates ease of delivery, there has been little attempt to use current, state-of-the-art technologies such as AI and voice/natural language processing to enhance the teaching effectiveness of e-textbooks. The present paper demonstrates how the addition of these technologies can greatly improve how well students learn. Furthermore, the features outlined in this paper seem intuitively compelling. It makes sense that if a person can ask a smart phone a question and receive an answer, that a student should be able to do the same with an e-textbook. It makes sense that e-textbooks should verify that students are actually learning the material presented and, if not, provide corrective instruction. It makes sense that e-textbooks should allow students to enter their work step-by-step and receive hints when they are stuck or corrective feedback when they make mistakes. It makes sense that students should be allowed to enter their own problems into the e-textbook and get the same types of hints and feedback when solving problems, thus giving the e-textbook the opportunity not only to support the publishers' problem sets but also to support homework problem sets and test study guides supplied by teachers.

In addition to these education-enhancing feature, the present project team is working on other features that should further enhance the e-textbook effectiveness and provide further support to the education community. We note that unlike a tradition paper-based textbook or current commercially-available e-textbook, the present AI and voice-powered textbook technology is highly interactive and collects voluminous data regarding students' learning. These data can be used to enhance the educational process in several ways.

First, it has been long established that different students learn differently, i.e., have different learning styles. The present technology is well-suited to provide students with different content format based on diagnosed learning styles. This can be accomplished by creating different versions of the content to support different learning styles (e.g., visual, hands-on) and then using machine learning to optimize the selection of content for each user based on the user's queries, responses to the e-textbook's assessment queries, and performance on problem solving (including seeking hints).

Second, just as there are multiple ways to ask a question, there are multiple ways to answer them. A good teacher or tutor often tries to understand how a student thinks, so he or she can find the best way to explain concepts or answer questions. For example, one way to answer a question is to provide a straightforward answer. Another is to relate the question the student has asked to another concept the teacher knows the student knows about. A third might be to answer the question in terms of a real-world example or a familiar analogy. Again, machine learning could be used to optimize how the e-textbook answers student queries and presents its own assessment questions and corrective feedback to insure that students understand what is being communicated.

To accomplish this goal, there are two requirements. It is necessary to have multiple ways of answering questions and providing feedback that are tied to different response methods. The key is to collect the right data that can be used to inform the machine learning algorithm as to what the right method is for each student. An obvious source of data is to look at the student's overall performance, which includes responses to future assessment queries and problems that are given. However, the interaction process with the student may provide additional data that are useful. For example, if a student does not understand the response given, he or she may reply "I don't understand what you said" or something similar such as "huh?". The student may respond "I understand", but that may not be as diagnostic as one would hope because the student may either think he or she understands but does not or may be reluctant to admit to not understanding the answer. Another source of data could be follow-on questions or comments that indicate understanding our lack thereof. For example, if a student asked how to rationalize the denominator of a complex fraction and then, after receiving an answer asked, "What do I do with the imaginary part after I FOIL the denominator and combine the like terms?", the implication would be that he or she did not understand the explanation of how to rationalize the denominator. Perhaps the most useful indication that the student was given an optimal response to a query is when the student makes an insightful comment showing that he or she was able to extrapolate an answer to other contexts. For example, if a student is told to multiply numerator and denominator of a complex fraction by the conjugate of the denominator so as to rationalize the denominator (thus explaining the principle behind the process) and then he or she asks "So is this why we also multiply the denominator of a fraction by its conjugate when that denominator contains a square root?", the implication is that the explanation of the principle helped the student make a connection to another concept and is a useful way to explain concepts to him or her.

The third enhancement is data analytics. Currently, the AI and voice-powered e-textbook technology is collecting a lot of data regarding each student. These include questions they ask about the content they are learning (which may be an indication of what they understand or do not understand), responses to assessment queries, and the steps they enter on the electronic worksheet as well as the hints they request and mistakes they make during problem solving. These data provide a snapshot of how well students have learned the material and what gaps in knowledge they still have. Such data are valuable to relevant stakeholders. Parents are always interested in how well their kids are doing in school and where they need help. These data could be used to create customized reports for parents for each of their children.

Teachers would benefit as well. Most teachers do not have the time to assess each student individually and often may not know where a class is struggling until after viewing the results of tests and quizzes. By that time, it may be hard to go back and remediate these deficiencies as they have to go on to the next lesson. This may explain why, in the United States, roughly 75% of 12th graders perform below grade level in math (National Assessment of Educational Progress, 2016). Using the current e-textbook technology, the software could prepare reports for teachers each night as students do their homework, thus providing feedback on student needs that could be used to plan the next day's lesson. Moreover, since the present technology is capable of guiding students through the learning process, this would free up teachers to spend more time with students who need extra help.

Schools and educational agencies could benefit from these reports as well. Concepts that students across the board need help with could inform educators as to what parts of the curriculum need to be strengthened. Reporting could also indicate whether some teachers need additional training, as in cases where their students perform lower than those in other classes within the same school or school district. Educational agencies are also often concerned with educational differences across students of different gender and ethnicity. The reporting provided by the present technology could provide real time insight into such differences and whether interventions (such as content customized to learning styles) are being effective.

Finally, such reporting would be valuable to publishing companies. Paper-based textbooks and e-textbooks that present content but do not collect data on student performance have no way of informing the publishing companies as to how well their textbooks are teaching students. The data from the present study suggest that current textbooks are not very effective by themselves at teaching concepts to students. As such, this places the burden on the teachers to make up the difference and get students to a proficient level. As shown above, this is an uphill battle as the majority of US students perform below grade level in each core subject. There is enormous room for improvement. The present technology could inform publishers as to what parts of their textbooks are effective in teaching students and what parts need to be improved. This would not only improve the educational system but also provide publishers who adopted such technology a decisive advantage over their competitors.

Overall, the present technology shows tremendous promise in improving educational outcomes. This is true in terms of both the features currently implemented and potential enhancement features such as the three just described. We believe the potential is virtually unlimited in being able to provide each child with a high-quality education that is responsive to the requirements of his or her educational system and customized to his or her unique learning style and needs. As technology progresses through the 21st century, there is no reason for textbooks to be stuck in the 19th.

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