Application of Learning Science to Improve Student Learning in the MBA Decision Science Course

Edward R. Sim
Hardin-Simmons University

This paper will address the practical application of learning science principles to improve student learning in the MBA decision science course. The paper will provide a review of the major concepts of learning science and a discussion of the empirical findings from that field that can be applied to improve student learning in the decision science course. The paper will also address my efforts at integrating these concepts into my course curriculum.

LEARNING SCIENCE

Recent studies in learning science have provided a number of useful findings that can help instructors in the structuring of their courses, the presentation of material, and the learning effectiveness of their assignments. For example, studies have shown that frequent practice tests, distributed practice, interleaved practice, and elaborative interrogation can improve student learning. In this paper, I will review the basic ideas of each of these learning techniques and then discuss how I applied those ideas in my decision science class.

Practice Testing

The learning science research clearly supports the learning benefits of using low stake quizzes or practice tests to improve student learning. Dunlosky (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013), in his review of ten common learning techniques, rates practice tests as having high utility.

Most researchers believe that practice tests are effective because they force retrieval of information from the student's long term memory and thus help to consolidate the memory making it easier to recall later (Anderson, 2014; Roediger III, 2014) . In addition to learning that occurs during the actual practice test, researchers also believe that practice tests also benefit student learning by helping them identify weaknesses in their understanding of the material and therefore helps them to focus their studying (Roediger III, 2014). According to the findings in the learning science literature, tests that require more generative recall, like short answer tests, are more effective than fill in the blank and multiple choice tests (Bjork, Dunlosky, & Kornell, 2013; Dunlosky et al., 2013; Richland, Kornell, & Kao, 2009). In addition, they also state that more tests are better than fewer, and the longer the spacing between tests the better. In general, the researchers have found that the effectiveness of practice tests are generalizable across different age groups, students with different ability levels, and different types of learning material and tasks (Dunlosky et al., 2013). In addition, researchers have also found that feedback improves the learning effectiveness of practice tests (Ambrose et al., 2010).

TABLE 1
UTILITY RATING FOR LEARNING TECHNIQUES

Learning Technique	Utility
Elaborative interrogation	Moderate
Self-explanation	Moderate
Summarization	Low
Highlighting	Low
Keyword mnemonic	Low
Imagery use for text learning	Low
Rereading	Low
Practice testing	High
Distributed practice	High
Interleaved practice	Moderate

The difficulty in implementing a lot of practice tests or quizzes, in the decision science course I teach, is with time constraints. Since we only meet once a week and we cover a model in about two weeks, lecture and problem solving take most of the allotted class time. I do, however, give on-line quizzes and assign problems that the students take between classes. The difficulty of this approach, however, is that I am never sure how “unaided” their actual work is. Since the real benefit of practice tests are the forced retrieval of information, using study aids like notes or the texts limits most of the benefits of the practice. Typically, I use our learning management system (Blackboard) to implement my on-line quizzes. Recently I changed the grading setting so that only the highest grade on the quiz is recorded. I have also increased number of attempts allowed to four, and have encouraged them to take their first attempt at the quiz as completely “unaided”. I emphasize the learning benefit of this approach. I also mix problems and terms from previous work into the current weekly quiz. For example, if I am teaching linear programming and the previous model was forecasting I will include both problems on the quiz (or as assignments). Overall, the quiz scores have risen and most students take the quiz at least twice.

Distributed Practice

Distributed (spaced) practice means spreading the to-be-learned material over time or encounters as opposed to mass practice, which means studying the material all at once. Dunlosky (see table) rates this learning technique as having high utility (Dunlosky et al., 2013). In general, researchers have found that spacing the study of to-be-learned material is more effective than mass study of the same material for long-term retention even if the same amount of time overall is spent on studying the material (Cepeda, Pashler, Vul, Wixted, & Rohrer, 2006; Rohrer, 2009). Research has also shown that longer time delays are more effective for long term retention than shorter time delays. However, the time delay (spacing between studying sessions) mostly depends on how long you want to retain the information. Some research has suggested that the spacing interval should be 10-20% of the desired interval of retention (Cepeda, Vul, Rohrer, Wixted, & Pashler, 2008). To retain something for a week, space the intervals 12-24 hours apart. To retain something for a year, space the intervals 30 to 70 days apart. Researchers believe that spacing works because the time delay between study sessions forces the learner to work harder to retrieve the information and thus helps to consolidate the information in long term memory. Shorter delays between studying sometimes fool the learner into thinking they know the information (for long term retention) because the information is more easily retrievably but the information is quickly forgotten (Bjork et al., 2013). Some evidence has suggested that the effectiveness of distributed practice are generalizable across different age groups, students with different ability levels, and different types of learning material and tasks. Although, as Dunlosky (Dunlosky et al., 2013) has noted in his review of the literature, the research in distributed practice learning technique is not as extensive as that of practice tests.

Distributed practice, to some extent, comes naturally in the presentation of the course material in the decision science class. First the students see the material in the lecture, then the problem solving sessions afterward, and then again in the text reading and home assignments. I've lengthened the time interval between practicing specific problem types by putting some problems from the prior weeks into my current assignments. However, this approach is limited because the new material usually requires significant time for the students to master and additional problems can create quite lengthy assignments.

This semester I tried shifting my topics to get the effect of spaced practice. Normally, in the decision science course, optimization techniques are taught in sequence: linear programming, integer programming, and non-linear optimization (most texts follow this organization). This semester, however, I taught LP and IP (weeks 1-4) and then later in the course taught non-linear optimization (week 13). Since non-linear optimization builds on the concepts of linear optimization I thought it would be a good review of the LP material. It took longer to get though the material, but I did see an improvement on the LP problems on the final exam.

Interleaved Practice

Interleaved practice involves alternating different kinds of problems into a practice set. For example, instead of having all problems of a similar type (e.g. forecasting) problems are mixed together so that students shift between different problems as they practice. Dunlosky, in his review of ten common learning techniques, rates interleaved practice as having moderate utility. The theory behind interleaved practice is that interleaving problems help students discriminate between different types of problems so that they will more likely to use the correct solution method for each one. This is accomplished, researchers believe, because when working with similar problems, solution algorithms are stored in working memory (Taylor & Rohrer, 2010). However, with different types of problems, solution information must be retrieved from long term memory, and thus memory traces are consolidated. The effect is similar to the distributed or spaced practice since interleaving problems spaces the practices (Rohrer, 2009). However, some researchers believe that the learning benefit comes from the enhanced ability of students to discriminate between problem features (referred to as the discriminative-contrast hypothesis in the learning science literature). Some evidence has suggested that the effectiveness of interleaved practice are generalizable across different age groups, students with different ability levels, and different types of learning material and tasks. Although, as Dunlosky has noted in his review of the literature, the research in distributed practice learning technique is not as extensive as that of practice tests (Pressley, McDaniel, Turnure, Wood, & Ahmad, 1987).

Typically in the decision science course, one model (e.g. forecasting) is covered and then the next model and so on. The only time students see the models in a "mixed" problem set is on the exam. This semester I tried more mixed (interleaving) problem types within assignments and quizzes. To cut down on the amount of class time I spend on reviewing previous problems, I usually post homework videos that show (step by step) the solutions to a selected set of homework problems. The students also have previous model-specific videos they can refer to. I also mix problems types within each model. For example, LP can be applied to a wide variety of problems (marketing, inventory, finance, etc.), so the problems can be mixed - which should aid long term memory retention (Oppenheimer, 2008).

Elaborative Interrogation

Elaborative interrogation (generation) is essentially the idea that students are asked to generate an explanation before being shown the solution. For example, students could be asked to analyze a problem and devise a decision strategy before being taught decision analysis strategies. Dunlosky, in his review of ten common learning techniques, rates elaborative interrogation practice as having moderate utility. Researchers believe generation works because it requires students to link the current problem with prior knowledge (Miller, 2009; Pressley et al., 1987). This connection with previously stored information helps to consolidate memory of the information. Research has showed that effectiveness of elaborative interrogation is relatively robust and is generalizable across different age groups, students with different ability levels, and different types of learning material and tasks. However, some evidence suggests that effectiveness of elaborative interrogation is moderated by the prior knowledge of the student in that content area (Dunlosky et al., 2013).

I used elaborative interrogation in the decision science course to try to simulate student thinking about the topics and models we cover. For example, I often ask to students to make forecasts (using whatever intuition they may have) about the future value of some time series data. I then ask them to explain the reasoning for their prediction. Later on we examine the same problem using forecasting techniques. I think the problems in the decision science course are particularly good for using elaborative interrogation. Linear programming problems are good examples. Students could be told the profit levels of certain products and the resources needed to make the products and then asked the production level for each product they choose. Another example I used in class was a decision analysis problem that involved a fairly complicated narrative of chance events, probabilities, and outcomes. Specifically, they had to decide, based on the case narrative, which of three decisions they should make regarding a legal case (take a settlement offer, counteroffer, or go to court). The class was clearly divided on which of the three decisions was best. After, some discussion about their reasoning, but with no evaluation on my part, I tabled the discussion and moved onto the analysis of other problems using decision analysis. I put the same problem (the legal case) that we had talked about in class (before starting decision analysis) on the final exam and nearly every student got the problem right.

SUMMARY

Recent studies in learning science (Anderson, 2014) have provided a number of useful findings that can help instructors with the structure of their courses, the presentation of material, and the learning effectiveness of their assignments. In this paper, I have reviewed some of those findings in regard to specific learning techniques; practice test, distributed practice, interleaved practice, and elaborative interrogation. I have also discussed how I have applied these ideas in my decision science class. At this point, I don't really have any performance data to offer about efficacy of these techniques to the particular content of the MBA decision science course. But there is significant experimental evidence in the learning science literature that these learning strategies will improve student learning. I am hopeful that using these learning strategies will allow my students to retain enough information that they can apply the problem solving and critical thinking learned in class to real world problems.

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