Facilitating Conceptual Learning Through Analogy And Explanation

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Abstract. Research in cognitive science has shown that students typically have a difficult time acquiring deep conceptual understanding in domains like mathematics and physics and often rely on textbook examples to solve new problems. The use of prior examples facilitates learning, but the advantage is often limited to very similar problems. One reason students rely so heavily on using prior examples is that they lack a deep understanding for how the principles are instantiated in the examples. We review and present research aimed at helping students learn the relations between principles and examples through generating explanations and making analogies.

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INTRODUCTION

How can we facilitate students' deep learning of new concepts? One approach to this problem is to examine what knowledge components comprise 'expert understanding' and then design learning environments to help novices construct that knowledge. Research on expertise has shown that experts 'perceive' the deep structure and principles of domain relevant problems, use that knowledge to identify and execute a set of strategies and procedures appropriate for the task, and flexibly transfer their knowledge to new contexts [1-4]. This research suggests that a key component of expert knowledge is their understanding of the relations between the principles and the problem features.

Unlike experts, novices do not work forwards from the domain principles but instead use backwards-working strategies [5] and rely on prior examples to solve new problems [6-8]. Although using examples enables novices to make progress when solving new problems, they are often only able to apply such knowledge to near transfer problems with similar surface features [9]. Furthermore, students prefer to use examples even when they have access to written instructions or principles [10, 11].

One reason that students may rely so heavily on prior examples is that they lack a deep understanding for how the principles are instantiated in the examples. That is, they lack the knowledge and skills required for relating the principle components to the problem features. Learning activities to help students acquire these relations should improve their conceptual understanding and future problem solving.

Research in cognitive science has shown that two powerful learning activities are generating explanations and making analogical comparisons. In the current work we explore how these two activities can facilitate students learning of the conceptual relations between principles and examples.

EXPLANATION

Much work in cognitive science has shown that explanation can facilitate learning and transfer [12-14]. Self-explanation, or the process of explaining to oneself with the goal of making sense of new information, is positively correlated with learning gains in a variety of domains including biology [15], computer programming [16], mathematics [14, 17], and physics [18] among others. Self-explanation is not merely correlated with greater learning, but laboratory experiments have also documented a causal connection. For example, Chi et al. [15] have shown that students who were prompted to self-explain while reading a biology text generated more inferences and acquired a deeper conceptual understanding than an

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unprompted group as measured by pre- and post-test questions.

The two cognitive mechanisms hypothesized to underlie the self-explanation effect are generating inferences and repairing mental models [12]. Generating inferences helps the learner construct causal connections between concepts and develop a more accurate mental model of the principle or problem. Self-explanation also provides an opportunity to notice gaps, misunderstandings, or faulty assumptions in a learners reasoning, giving them an opportunity to revise and correct it.

In the next section we report a study that examined how particular types of explanations can help students learn the relations between principles and examples.

Explanation Experiment: Explaining to Generalize versus Specialize

Math and science instruction often consists of both principles and examples. Since a learner could explain either type of information, we investigated how the *content of the explanation* affects what is learned and to what situations the resulting knowledge transfers. We examined two types of explanation: 1) using principles to explain examples and 2) using examples to explain principles.

We hypothesized that using a principle to explain an example (*specialization explanation*) would result in a specific understanding of the principle embedded in the context of the example being explained. This type of explanation should promote the construction of a mental model of the example and facilitate subsequent performance on problems that use the same principle with similar content. In contrast, using examples to explain a principle (*generalization explanation*) was hypothesized to result in an abstract understanding of the principle. This type of explanation should promote schema construction and facilitate subsequent performance on problems that use the same principle but with different content.

We tested these hypotheses in a laboratory experiment in which students gave either specialization or generalization explanations when learning about two elementary probability principles (permutations and combinations).

Methodology

Forty UIUC students were paid $8 for their participation.

The experiment had a between-subjects design and consisted of a learning and test phase. In the learning phase, participants were randomly assigned to either a specialization or generalization condition. Specialization participants first read a probability principle and a worked example, explained the solution to a second example, and then read the solution to that example. This procedure was then repeated for the second principle. Generalization participants first read the two worked examples, explained the principle, and then read the principle. This procedure was then repeated for the second principle.

In the test phase all participants solved ten probability word problems (5 for each principle). Four of the problems had the same surface content (i.e., same story line and objects but different numbers) and six had different content (i.e., different story line and objects). The participant's task was to first decide which formula applied and then solve the problem.

We predicted that the specialization group would perform better on the same content problems whereas the generalization group would perform better on the different content problems.

Results and Discussion

Table 1 shows the data for learners who successfully completed the learning task (2/3 of the learners). Both groups showed high accuracy for the same content problems. This suggests that both types of explanations facilitated an understanding of the principle that could be applied to problems with the same contents as the learning examples. However, the specialization group had faster decision times than the generalization group (Cohen's d effect size of .55) suggesting that their understanding of the principle was more closely tied to the contents of the example and facilitated fast access to the principle for problems with the same content.

TABLE 1. Mean (and se) accuracy and decision times (seconds) for the Specialization and Generalization groups on the same and different content problems.

	Accuracy	Decision-Time
Same Content		
Specialization	.79 (.07)	23.7 (2.2)
Generalization	.79 (.05)	31.5 (2.7)
Different Content		
Specialization	.39 (.05)	40.0 (4.7)
Generalization	.51 (.04)	41.7 (4.9)

For the different content problems the generalization group showed better accuracy than the specialization group (d = .93). This result suggests that using the examples to explain the principle resulted in a more abstract understanding of the concept that facilitated performance on problems with contents different from those of the learning problems.

In sum, the *type of explanation* is critical to what is learned and to where that knowledge transfers. Using principles to explain examples resulted in a specific understanding of the principle in the context of the example whereas using examples to explain the principle resulted in a more abstract understanding of the principle. Next we examine a second path to conceptual knowledge by analogical comparisons.

ANALOGY

Analogical comparisons have been hypothesized to facilitate the acquisition of a *problem schema* [19], a knowledge representation of a particular problem category. It includes declarative knowledge of the principle, concepts, and formulae, as well as the procedural knowledge for how to apply that knowledge to solve a problem. Schemas have been hypothesized as the underlying knowledge structures supporting expert performance [1-4].

Analogical comparison operates through aligning and mapping two example problem representations to one another and then extracting their commonalities [19-21]. This process discards the elements of the knowledge representation that do not overlap between two examples but preserves the common elements. The resulting knowledge structure typically consists of fewer superficial aspects than the examples, but retains the deep causal structure of the problems.

Several factors are known to improve schema acquisition including: more examples [19], greater variability of the examples [22, 23], instructions that focus the learner on structural commonalities [24, 25], or subgoals of the problems [26, 27], and examples that minimize students cognitive load [28].

In the current work we were interested in how different types of problem comparisons affect learning and transfer [29].

Analogy Experiment: Near-miss versus Surface-different Comparisons

The purpose of the experiment was to examine the effect of near-miss versus surface-different problem comparisons on learning and later problem solving. Near-miss comparisons involve two problems that have the same content and structure but with one critical surface change that highlights some aspect of the principle structure (e.g., switching the variable-object assignments across the problems). Surface-different comparisons consist of problems in which the same principle applies but each uses different contents.

We hypothesized that near-miss comparisons would focus the learner on how the variables were instantiated in the problem and would benefit performance on tests of principle use (which emphasize assigning objects to variables). In contrast, surface-different comparisons were hypothesized to focus the learner on the fact that multiple contents can be associated with a principle and would benefit performance on tests of principle access (that emphasize choosing the relevant principle). We were also interested in whether poor learners, who generally rely more on content, might show stronger effects.

Methodology

Thirty UIUC students were paid $8 for their participation.

The experiment had a within-subjects design and consisted of a learning and a test phase. In the learning phase participants learned about four probability principles by reading a worked example and then solving either a near-miss or surface-different practice problem. For near-miss comparisons participants solved problems that had the same content as the worked example but with reversed object correspondences (the same objects assigned to different variables). For surface-different comparisons participants solved problems that had different (but analogous) content as the worked example but with reversed object correspondences. Participants learned two principles with near-miss comparisons and two principles with surface-different comparisons.

In the test phase participants solved four use and four access test problems (one for each principle). All of the test problems had new contents and non-obvious object correspondences to that of the learning problems. For use problems participants were asked to assign the values from the problem statement to the correct variables in the given formula. For the access problems the participants were given all four formulae and their task was to choose the correct equation.

Results

Participants were split into two learning groups (good and poor learners) based on a median split of their performance on the practice problems (M = .84, SD = .09 and M = .55; SD = .15 respectively). Table 2 shows the mean performance for each learning group on the use and access tests.

TABLE 2. Mean use and access scores (and se) as a function of learning condition for good and poor learners. Adapted from Nokes & Ross [29].

	Use	Access
Good Learners		
Near-miss	.96 (.02)	.91 (.05)
Surface-different	.93 (.04)	.79 (.06)
Poor Learners		
Near-miss	.90 (.03)	.46 (.09)
Surface-different	.79 (.08)	.58 (.10)

The good learners showed high performance across all of the tests with unexpected lower performance in the surface-different condition on the access test. In contrast, the poor learners showed the predicted effect: the near-miss comparisons improved principle use (d = .51) whereas the surface-different comparisons improved principle access (d = .32).

These results suggest that near-miss comparisons help poor learners understand how the structure of the problem relates to the variables in the formula whereas surface-different comparisons help them learn how to tell which principles are relevant. This interaction suggests that different types of comparisons may be useful for teaching (poor) students different aspects of the principle knowledge.

CONCLUSIONS

Research in cognitive science shows that there are multiple paths to facilitate conceptual learning. One is through generating explanations and a second is through making analogical comparisons. The research presented in this paper shows that the type of explanation (explaining the principle or example) and the kind of problem comparison (near-miss or surface-different) is critical to what is learned and to where that knowledge transfers. In ongoing work we examine how these activities can improve students' learning of physics in the college classroom (see the Pittsburgh Science of Learning Center for current projects - http://www.learnlab.org).

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