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Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 40(0)

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Publication Date

2018

From Dissimilar to Similar: Reverse Fading Assistance Improves Learning

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Abstract

When students solve problems with access to examples showing worked out solutions, they often resort to shallow methods like copying that do not result in learning. An open question is therefore how to encourage deeper processing in this type of instructional context. To address this question, in the present study, we investigate the impact of manipulating problem-example similarity over the course of a problem-solving session in several ways, including *faded assistance* (high to low similarity), *reverse faded assistance* (low to high similarity), and a control group with *high, constant assistance*. We found that the reverse faded assistance condition resulted in the greatest learning gains. We analyzed the gaze behaviours to shed light on this finding and found that participants in this condition focused significantly more on the problem solution, suggesting more cognitive processing during problem solving than in the other conditions.

Keywords: worked examples, faded assistance, learning, eye-tracking

Introduction

When students are solving problems in a domain like math or physics and encounter an impasse because they are missing the domain knowledge to generate the problem solution, they often turn to examples for assistance (i.e., problems that show not just the final answer but its step by step derivation). What students learn from this activity, however, depends on whether they engage in deep processing that fosters learning (Muldner & Conati, 2010; VanLehn, 1998). Unfortunately many students miss learning opportunities because they engage in shallow strategies (VanLehn, 1999), as we now describe.

Impact of problem-example similarity on cognitive strategies

When students refer to an example as they are solving a problem, they are faced with a choice: they can copy from the example, or they can try to learn from it. Copying involves transferring the example solution over to the problem. Since there are often superficial differences between the problem and example corresponding to, for instance, variable names, copying may require replacing example constants with ones needed for the problem solution (Reed, 2012; VanLehn, 1998). In contrast, learning involves inferring the underlying domain principles required for the generation of the solution.

An established cognitive strategy that fosters learning from examples is self explanation, namely the process of explaining instructional materials to oneself (Chi, Bassok, Lewis, Reimann, & Glaser, 1989). In our target instructional context, i.e., one involving a problem to be solved and an example, there are two opportunities for self explanation. One comes in the context of the example: a student can self explain the example solution by making inferences over and beyond the example solution steps. A type of inference that is highly correlated with learning relates to induction of the domain rule that generated the solution step(s) of interest (Chi & VanLehn, 1991). In particular, because worked examples show the solution steps but not the rules that generated them, students who self explain in this manner can subsequently apply the rule not only to the present problem but also subsequent problems (without the help of the example). Self explanation is a beneficial strategy because it requires active processing of the materials (Chi, 2009). To date, to the best of our knowledge only one study has directly measured self-explanation from examples in a context that makes them and the problem available at the same time (Muldner & Conati, 2010). A second opportunity for self explanation comes in the context of the problem: a student may encounter an impasse, and overcome it by inferring the rule from the problem (without referring to the example), for instance by relying on commonsense or overly-general reasoning (VanLehn, 1999). As is the case with self explanation from the example, self explanation from the problem fosters learning (Aleven & Koedinger, 2002; Loibl, Roll, & Rummel, 2017).

While learning can in theory happen as a by-product of copying, students who copy do not tend to also learn the underlying domain rules (Chi et al., 1989; Reed, Dempster, & Ettinger, 1985; VanLehn, 1999). Copying is more likely to happen when the problem-example differences are easy for students to resolve, such as differences in variable names between the problem and example solution (Muldner & Conati, 2010; Reed, 2012). This type of difference is illustrated in the *Problem-Example*$_1$ pair in Table 1. This problem-example difference can be resolved by generating a mapping between the variables appearing in the problem and example specifications (Reed, 2012), and using the mapping to replace the example constants by ones needed for the problem solution. This process results in a correct problem solution without requiring learning of the domain principle that generated the copied step.

It is established that highly similar examples facilitate shallow copying without encouraging learning (Lee, Betts, & Anderson, 2015; Muldner & Conati, 2010; VanLehn, 1998). However, examples that are too different are also not helpful (Reed, Ackinclose, & Voss, 1990; Ross, 1987). In particular, not surprisingly, if the example solution does not involve overlapping knowledge (rules) with the problem, the exam-

Table 1: *A problem and two examples (similarity of problem-example$_1$ pair is high; similarity of problem-example$_2$ pair is low)*

Problem **Solve for *a*:**		**Example$_1$** **Solve for *x*:**		**Example$_2$** **Solve for *x*:**	
$b = (ad)/c$	[MULTIPLY]	$y = (xw)/z$	[MULTIPLY]	$y = w\,(x/z)$	[DIVIDE]
$bc = ad$	[DIVIDE]	$yz = xw$	[DIVIDE]	$y/w = x/z$	[MULTIPLY]
$(bc)/d = a$		$(yz)/w = x$		$z\,(y/w) = x$	

ple will not help the student to either correctly copy or to learn the underlying principles. Thus, traditionally, problem-example differences have been avoided in situations that involve problem solving in the presence of examples (Weber, 1996). However, more recently, there has been renewed interest in investigating the potential benefits of problem-example differences.

Muldner and Conati (2010) showed that certain differences between the problem and example encouraged self-explanation and learning during problem solving where students had access to an example for each problem they had to solve. The differences, corresponding to problem-example constants, were systematically introduced using a computer tutor to block superficial copying (and thus encourage self-explanation). Similarly, Lee et al. (2015) found that superficial differences between problem-example pairs that blocked shallow transfer of the example solution improved subsequent performance on tests where the example was no longer present.

Both Muldner and Conati (2010) and Lee et al. (2015) found that differences between problems and examples made students work a little harder (e.g., Muldner and Conati (2010) showed that differences increased time on task and self explanation), and subsequently fostered learning. However, forcing students to deal with differences may impose a high cognitive load. To address this issue, here we investigate the impact of transitioning the level of similarity between problem-example pairs over the course of a problem solving session. One way we operationalize this transition is by having the initial problem-example pairs be highly similar, but gradually introducing some problem-example pairs that include differences between them. This type of 'faded assistance' has been shown to be beneficial in other instructional contexts (Atkinson, Renkl, & Merrill, 2003; Tullis, Goldstone, & Hanson, 2015). An alternative way of manipulating the problem-example similarity that we also investigate involves first presenting problem-example pairs that include certain differences, and gradually introducing some highly similar problem-example pairs. While this may initially impose a high cognitive load, the productive failure paradigm provides some precedent for this order of presentation (from harder to easier, given that problem-example pairs that include differences are harder for students to process than ones that are highly similar). The productive failure paradigm involves students first working on a novel problem without instructional support, and subsequently providing them with the canonical solution to the problem - it turns out that struggling initially can be highly beneficial, more so than just receiving the canonical solution (Kapur, 2014; Schalk, Schumacher, Barth, & Stern, 2017).

Method

Materials: Problem-Example Pairs. Our study involved problems and examples in the domain of algebra[1]. Each problem was presented alongside one example showing a step by step solution. We manipulated the similarity between a given problem-example pair to be either *high* if the only difference between the problem and example corresponded to different variable names in their specifications and solutions, and as *low* if the example solution was generated by applying a sequence of algebraic operations (i.e., rules) in an order different from that required for the problem solution. To illustrate these concepts, we will use the problem and the two examples in Table 1. The solutions for all three require the application of two rules embodying two algebraic operations (*eliminate variable by multiplying both sides by it, and eliminate variable by dividing both sides by it*, labelled *MULTIPLY* and *DIVIDE* in Table 1, respectively). The similarity between the problem and example$_1$ pair is *high* because the only difference between them corresponds to variable names. In contrast, the similarity between the problem and example$_2$ pair is *low*, because example$_2$ pair's solution involves a different order of rule applications than required for the problem. Critically, however, the problem requires the same knowledge (rules) for its solution as example$_2$ pair, and so it affords the opportunity to infer the two rules from its solution (e.g., via self explanation of the example), and subsequently apply them to the problem solution.

We generated three sets of 12 problem-examples pairs (each set requiring the application of three to four rules for their solutions, held constant across the sets, see Table 2). In each set, within a given problem-example pair, the respective solutions involved the same rules and number of rules, meaning that the examples provided the opportunity to learn the necessary rules and apply them to the problem's solution.

[1] Algebra was chosen as it allowed rigorous control of both superficial and structural similarity between the problem-example pairs.

We manipulated the similarity through the type of assistance the examples provided, as follows: (1) *high, constant assistance*, where the similarity between all 12 of the problem-example pairs was high (variable name differences only - this was essentially our control condition); (2) *faded assistance* (high to low), where the similarity between the initial problem-example pairs was high, but faded to low by the last few problems; (3) *reverse-faded assistance* (low to high), where the similarity between the initial problem-example pairs was low, but faded to high by the last few problems. Note that as shown in Table 2, both the faded and reverse-faded sets contained some low similarity and some high similarity problem-example pairs (in contrast to the high assistance set, which only contained high similarity pairs). As mentioned above, because in a given problem-example pair the respective solutions involved the same set of rules, the examples provided the opportunity to learn the necessary rules and apply them to the problem's solution. Thus, the key differences between the three sets of problem-example pairs are whether they facilitated copying (the case for the high constant assistance set), and the nature of the fading mechanism (faded vs. reverse faded assistance).

Materials: Pretest and Posttest. We used a pre and posttest to assess learning gains (each had the same eleven algebra problems, but the pretest had different variable names as compared to the posttest; examples were not included in either test, because we wanted to measure students' ability to solve problems in the absence of assistance). Each question was graded based on the number of rule applications needed (this is a more sensitive measure than just assigning a grade of 0 based on one mistake early on in the solution).

Apparatus and Problem Solving Interface. An SR Research Eye Link 1000 eye tracker was used to capture gaze and fixation data during the problem solving phase of the study. To solve problems and refer to examples, participants used a Java-based application we created, shown in Figure 1. Because eye tracking data was collected that was sensitive to movement, to minimize head movement, the interface included a virtual keyboard. Participants used this virtual keyboard (bottom of Figure 1) to enter solutions and perform related actions (e.g., move on to the next problem, erase an entry).

Table 2: Sequencing of problem-example pairs based on similarity and the number of rules required for the solutions. Legend: *Sim* = similarity; *H* = high similarity, L = low similarity

High	Sim	H	H	H	H	H	H	H	H	H	H	H	H
	#rules	3	3	4	3	4	4	3	3	4	3	4	4
Faded	Sim	H	H	H	L	H	L	H	L	H	L	L	L
	rules	3	3	4	3	4	4	3	3	4	3	4	4
Reverse	Sim	L	L	L	H	L	H	L	H	L	H	H	H
	rules	3	3	4	3	4	4	3	3	4	3	4	4

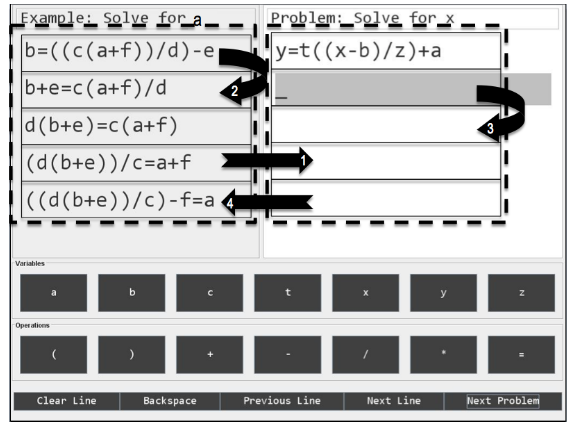

Figure 1: The interface used to solve problems and refer to examples. *The boxes illustrate the areas of interest (AOI) used for the analysis and were not visible to participants.*

Participants. The participants were undergraduate students ($N = 60$, 34 female) who had not taken mathematics in university. Participants were given the option to participate either for bonus course credit or for monetary compensation ($20).

Design and Procedure. We used a between subjects design with three conditions:

- *high assistance* (n = 20), involving only high similarity problem-example pairs that provided constant assistance (see Table 2, first row)
- *faded assistance* ($n = 21$), involving initially high similarity problem-example pairs, faded to low similarity pairs by the last three problems (see Table 2, second row)
- *reverse-faded assistance* (n = 19), involving initially low similarity problem-example pairs, transitioning to high similarity pairs by the last three problems (see Table 2, third row).

The participants were randomly assigned to a given condition. After 20 participants were run, we began a stratified random sampling procedure based on pretest performance to equalize a priori knowledge between the conditions[2].

The procedure for the three conditions was the same. Each session was conducted individually in a quiet room. Participants completed a paper and pencil pretest (up to 20 minutes), were introduced to the problem solving interface and given a training problem (5 minutes), and then were calibrated on the eye tracker. The experimental phase then began. Prior to starting, participants were told that *"...the goal isn't to be fast but rather to treat this as if you were practising solving problems to prepare for a test, so do what you would normally do when studying"*. Participants used the problem-solving interface (Figure 1) to work on the 12 problems in their respective condition (as noted above, each problem included a

[2]pretest performance was measured by grading the pretest before proceeding with the eye-tracking portion of the experiment.

corresponding example). No feedback for correctness was provided and participants worked at their own pace. After finishing the problem solving phase, participants completed a paper and pencil posttest (up to 20 minutes).

Results

Our analysis was guided by the following research questions:

1. Does the type of assistance (high, faded, reverse faded) influence learning?
2. Does the type of assistance impact where participants devote attention (e.g., to the example vs. the problem)?
3. Does the type of assistance impact attentional patterns that could be indicative of copying and self explanation?

To answer these questions, we used between subjects ANOVAs with type of assistance (high, faded, reverse faded) as the independent variable, and the analysis-specific dependent variable (e.g., learning gains, see below). Post hoc tests were done using Tukey's HSD test. Prior to the analysis, we created boxplots for all dependent variables on a per condition basis and SPSS-flagged outliers were removed.

Which type of assistance fosters learning the most?

We first verified that the pretest scores were equalized across conditions prior to the experimental phase and this was indeed the case, $F(2, 57) = .24$, $p = .790$, $\eta_p^2 = .01$. We used the standard method to operationalize learning, by calculating the difference between posttest and pretest to obtain the learning gain for each participant, i.e., Post % - Pre %. The mean gains for each condition are shown in Figure 2. The reverse faded assistance group obtained the greatest gains, and, in contrast to our expectations, the faded assistance group obtained the lowest learning gains, with the high assistance participants falling in the middle.

An ANOVA with learning gain as the dependent variable found a significant effect of type of assistance, $F(2, 56) = 3.46$, $p = .038$, $\eta_p^2 = .11$, with post hoc tests indicating that participants in the reverse-faded assistance condition had significantly higher learning gains than the faded assistance group, $p = .029$. No other differences were significant.

Does assistance impact attention to example vs. problem?

To determine if the type of assistance influenced where participants were devoting their attention (e.g., to the example vs. the problem), we extracted the total time each participant spent looking at the example area and at the problem area, respectively (see dashed line in Figure 1 indicating these two areas of interest, AOIs).

As far as the example, as shown in Figure 3, left, there was little difference between the three conditions in terms of the total time participants spent looking at the example (and indeed the effect of assistance was not significant, $F(2, 56) = .38$, $p = .686$, $\eta_p^2 = .01$). In contrast, the type of assistance did have a significant effect on the total time participants spent

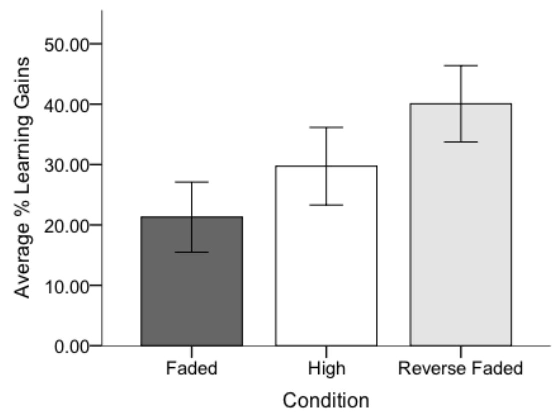

Figure 2: Learning gains (Post % - Pre %) for each condition (faded assistance, high assistance, reverse-faded assistance). Error Bars: +/- 1 Standard Error.

looking at the problem area, $F(2, 54) = 9.58$, $p < .001$, $\eta_p^2 = .26$. As shown in Figure 3, participants spent significantly less time looking at the problem in the high assistance condition than in (1) the faded assistance condition, $p = .012$, and (2) the reverse faded assistance condition, $p < .001$.

For the sake of completeness, we also present the results related to total time spent, which mirror the pattern we found above (note that the total time will be slightly longer than time spent on the problem or example, because the latter does not include time spent looking at other areas, like the virtual key board or away from the screen). In general, the high assistance group devoted the least amount of total time during the experimental phase (on average, 10.2 minutes), as compared to the faded and reverse faded groups (on average, 13.1 and 14.2 minutes, respectively). The overall effect of assistance on time was significant, $F(2, 54) = 5.84$, $p = .005$, $\eta_p^2 = .18$, with the high assistance group spending significantly less time than the reverse faded assistance group, $p = .004$, and marginally less than the faded assistance group, $p < .055$. The examples were highly similar to their corresponding problems in the high assistance condition, and this reduced the total amount of time participants devoted.

Does assistance impact sequences of fixations?

In the context of problem solving with access to an example, sequences of fixations between the areas of interest (e.g., between the problem and example solution steps) can provide an indication regarding the type of cognitive processing participants are engaging in (e.g., copying, self explanation). Here, we focus on four types of fixation sequences:

1. *example-problem (Ex-Pro)* sequences involve a fixation on an example solution step (any of the AOIs in the example area in Figure 1) and a subsequent fixation on a problem solution step (any of the AOIs in the problem area in Figure 1, see arrow 1 in Figure 1 for an example), indicating a shift in attention from the example over to the problem. Such sequences could be indicative of copying (since copying

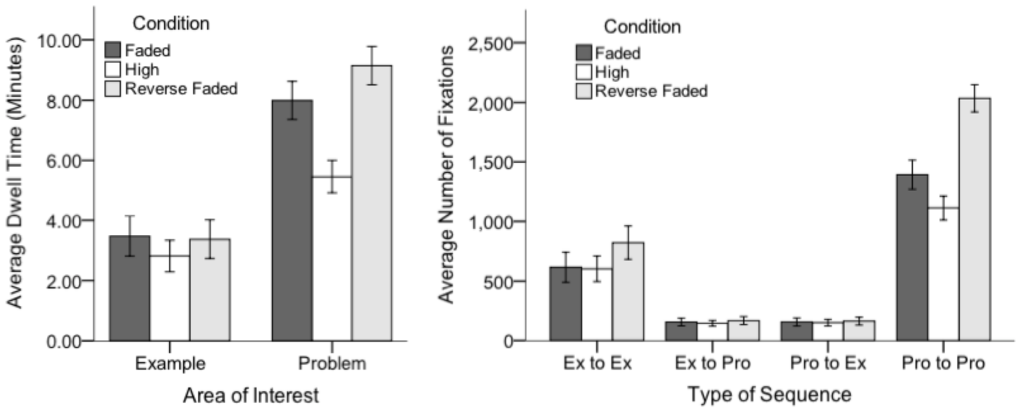

Figure 3: Total time spent looking at the example and the problem (left) and total number of each type of sequence (right), for each condition (high assistance, faded assistance, reverse-faded assistance), prior to the removal of outliers. Error Bars: +/- 1 Standard Error.

requires looking at the example and then back over to the problem).

2. *example-example (Ex-Ex)* sequences involve a fixation on an example solution step and a subsequent fixation on any other example solution step (a shift between any of the AOIs in the example area in Figure 1, see arrow 2 in Figure 1 for an example), indicating a shift in attention from one example solution step to another. Such sequences could be indicative of self explanation of the example (since self explanation can involve studying the example solution steps).
3. *problem-problem (Pro-Pro)* sequences involve a gaze shift from one problem step to another, here taken to be indicative of self explanation of the problem (see arrow 3 in Figure 1 for an example).
4. *problem-example (Pro-Ex)* sequences involve a fixation on a problem solution step and a subsequent fixation on an example solution step (see arrow 4 in Figure 1 for an example), indicating a shift in attention from the problem over to the example. Such sequences could be indicative of checking one's solution against the example.

The type of assistance had a significant effect on one of the sequences, namely *problem-problem* (see Figure 3, right, $F(2, 50) = 15.09$, $p < .001$, $\eta_p^2 = .38$). Post hoc analysis confirmed that the reverse faded assistance group had more attentional shifts between the problem's solution lines as compared to the constant assistance condition, $p < .001$, and the faded assistance condition, $p < .003$. The constant assistance group also had significantly fewer *problem-problem* sequences than the faded assistance group, $p = .041$.

Discussion and future work

When students encounter examples highly similar to the problem they are solving, they tend to copy without learning. Thus, several recent studies have investigated the potential benefits of problem-example differences in terms of discouraging superficial copying and fostering learning (Lee et al., 2015; Muldner & Conati, 2010; Weitnauer, Carvalho, Goldstone, & Ritter, 2014). In the present study, we investigated the impact of problem-example differences in a novel context, by manipulating differences over the course of a problem solving session. Our key finding was that a reverse faded assistance method, one that initially presented low similarity problem-example pairs but transitioned to high similarity pairs, resulted in the highest pre to post test gains. The learning results were corroborated with our eye tracking analysis, which also shed light on where participants were devoting attention in the three conditions.

Why did participants benefit the most from a 'reverse faded' assistance paradigm? In contrast to the other two conditions, the reverse faded assistance group was immediately faced with problem-example pairs that superficially looked different. However, the knowledge (i.e., rules) needed to generate both the problem and the example was isomorphic - the only thing that we varied in the present study was the order of the rule applications in the respective solutions. This difference in the initial problem-example pairs may have encouraged participants to engage in deeper processing in general - we have some evidence of this occurring, since participants in the reverse faded assistance condition devoted more time overall and more time to the problem in particular.

What were participants doing that increased their time on task in the reverse faded condition? While we do not have verbal protocols, it may be that the problem-example differences in the reverse faded assistance condition encouraged self-explanation of the problem solution, once participants realized that superficial copying was infeasible. The reverse faded assistance condition also eventually provided the canonical solution by providing highly similar examples later on in the problem session, after participants may have initially struggled to resolve differences, and thus critical feedback, which in general aids learning (Schalk et al., 2017).

An unexpected result was that the high assistance condition resulted in larger learning gains than the faded assistance condition - while this difference was not significant, this trend was surprising given the prior work showing the benefits of faded assistance (Tullis et al., 2015), albeit in contexts that do not involve mathematical domains of the type targeted here. A potential explanation as to why the faded assistance condition obtained the lowest learning gains is that this condition started with examples that were easily applied to the problem with minimal alteration, facilitating copying and discouraging self explanation. After the initial highly similar problem-example pairs provided high assistance by the virtue of the high problem-example similarity, participants were presented with a lower-similarity problem-example pair, meant to transition them over to a situation where they would have to invest more effort in transferring the example solution. However, participants in this condition may have failed to recognize that the example at this stage blocked copying and proceeded to copy incorrectly. A complementary explanation is that participants in this condition may have superficially copied the first few example solutions, and then arrived at the examples that blocked copying - at this stage they had fewer opportunities to view the canonical solutions, in essence receiving less feedback from the examples.

The present study and analysis opens up avenues for future work. A key one relates to more fine grained eye tracking analysis than presently done. In particular, to date we have not looked at how attention, as measured by eye tracking, differs between individual problem-example pairs in a given session, nor how attention patterns change over time. As for the latter, it would be interesting to investigate if patterns of attention change at different rates over time during a problem solving session (e.g., whether participants in the reverse faded condition paid less attention to the example initially but reversed that attention pattern when confronted with similar examples). Another avenue of future work relates to scan path analysis to investigate how participants shifted their gaze over time (e.g., Anderson, Anderson, Kingstone, and Bischof (2015)), such as looking between lines of the example and then looking at one line of the problem, indicating study of the example as well as potential application to the problem.

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