Providing implicit formative feedback by combining self-generated and instructional explanations

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Abstract. Formative feedback for a learner typically uses human or artificial intelligence to draw an inference about a learner's knowledge state from the learner's actions, and select a learner-directed response. To tackle cases when such intelligence is not easily available, we are exploring ways of providing implicit formative feedback: A learner's action is to respond to an explanation prompt, and the learner-directed response is to provide an instructional explanation. We consider explanations for correct examples to mathematics exercises, but the exciting implications will be for less well-defined domains that are challenging for cognitive tutors to model. To motivate learners to explain and to increase implicit feedback, we also explore prompts to compare the self-generated and instructional explanations.

Keywords: explanation, self-explanation, learning, comparison, formative feedback

1 Introduction

Traditionally, feedback to students has often been *summative*, such as midterm scores and state exams, where even the application of advanced psychometric techniques leads to measures that provide a summary assessment of some attribute. The pen- and paper- tests typically administered and the time needed for another human to grade and assess places a natural delay between a student's behavior(s) and the provision of feedback about that behavior.

Now that learners' behavior is increasingly in a computerized or online environment, there are three key implications. The first is that many tests and measures typically considered as (summative) assessments can be analyzed instantaneously and automatically. The second is that online digital environments allow for the *delivery* of sophisticated instruction and formative feedback. The third is that the constant logging of data on a computer means that a much wider range of student behaviors is available as fodder for 'assessments', which can then be analyzed and used to provide *formative feedback* to students.

As evidenced by the current workshop and extensive research in the learning sciences [1] [2] [3], great progress has been made in developing formative assessments and feedback. However, the issue of providing formative feedback raises two core challenges.

The first is that providing formative feedback that helps learning seems to be constrained by how accurately an automatic system can diagnose a learner's knowledge state, infer what instructional tactic is likely to deliver formative feedback that moves the learner to a more effective knowledge state, and ensure the learner successfully uses this instruction or formative feedback. While there have been great strides in developing the data mining and artificial intelligence capacities to achieve all three of these goals, is there a way to mitigate these constraints through a complementary approach to the problem of providing formative feedback?

The second challenge is that – even if the above issues could be solved – learners may not learn general metacognitive skills of self-regulation – to identify gaps in their knowledge, consider how to fill them or seek out new information, and engage in effective learning strategies that move their understanding forward.

One potential way to address both of these issues is to provide information from which *learners* can generate *implicit* formative feedback, and structure the instructional environment to support learners in generating and using this feedback.

This paper outlines a paradigm for doing this and reports the design of an ongoing study. Learners are asked or prompted to self-generate explanations, then are provided with normative answers or instructional explanations that respond to the same prompt, and finally are guided to compare their self-generated explanations with the instructional explanations provided. This draws together work in education and psychology on the benefits of *self-explanation* [4] [5], on how to provide appropriate instructional explanations for students [6] [7], and on the benefits of comparison for learning [8].

Context for introducing implicit feedback: Worked example solutions in Khan Academy mathematics exercises

While the general framework can be applied to many contexts, the current study examines the generation, consideration, and comparison of explanations in the KhanAcademy.org exercise framework (www.khanacademy.org/exercisedashboard). This provides a large collection of mathematics exercises with a similar format, used by tens of thousands of students. It is therefore a widely applicable context in which to develop a paradigm for providing implicit feedback from self-generated and instructional explanations.

Figure 1 shows an example of an exercise we have augmented. The typical (non-augmented) exercise starts with a statement of a problem for the student to solve, which is outlined in the box surrounded by a dark black line. When ready, students can type in a proposed answer and then receive feedback on its correctness. At any point, students can also request a hint, which reveals the next step of a worked example solution to the problem. Students have to enter the correct problem to advance, but because every problem provides on-demand "hints" which step-by-step reveal the solution, they can eventually do so (the last step is simply the answer).

This design already builds in some form of implicit feedback, if it is assumed that students first try to consider steps in the problem's solution before requesting hints. A hint or solution step can therefore give them implicit feedback about the appropriateness of what they were considering before.

Incorporating self-generated and instructional explanations

The template for Khan Academy's mathematics exercises ensures that students must generate or simply be told the correct answer by the end of each exercise. Our augmentation of the exercises all occurs after the student receives feedback that they have entered the correct answer – whether they generate it themselves, are helped by hints, or need to go to the very end of the solution to see the answer.

As shown in Figure 1, the typical Khan Academy math exercise (labeled *practice-as-usual*) is augmented using three instructional tactics: (1) Including prompts for students to *self-generate* explanations; (2) Including *instructional* explanations directed at these prompts, ostensibly from another student or teacher; (3) Asking students to *compare* their self-generated explanations to the instructional explanations.

The *self-generate* explanation prompt appears beside a solution step, in a distinctive purple font and accompanied by a text box for students to type their response. The example in Figure 1 has the prompt "Explain what this step means to you:". The *instructional* explanation can be shown in a similar position, such as "Another student explained this as:…". The *compare* judgment solicits a comparison of the student's own explanation with the *instructional* explanation which was supposedly provided by someone else: "How similar is your explanation to the other student's explanation?".

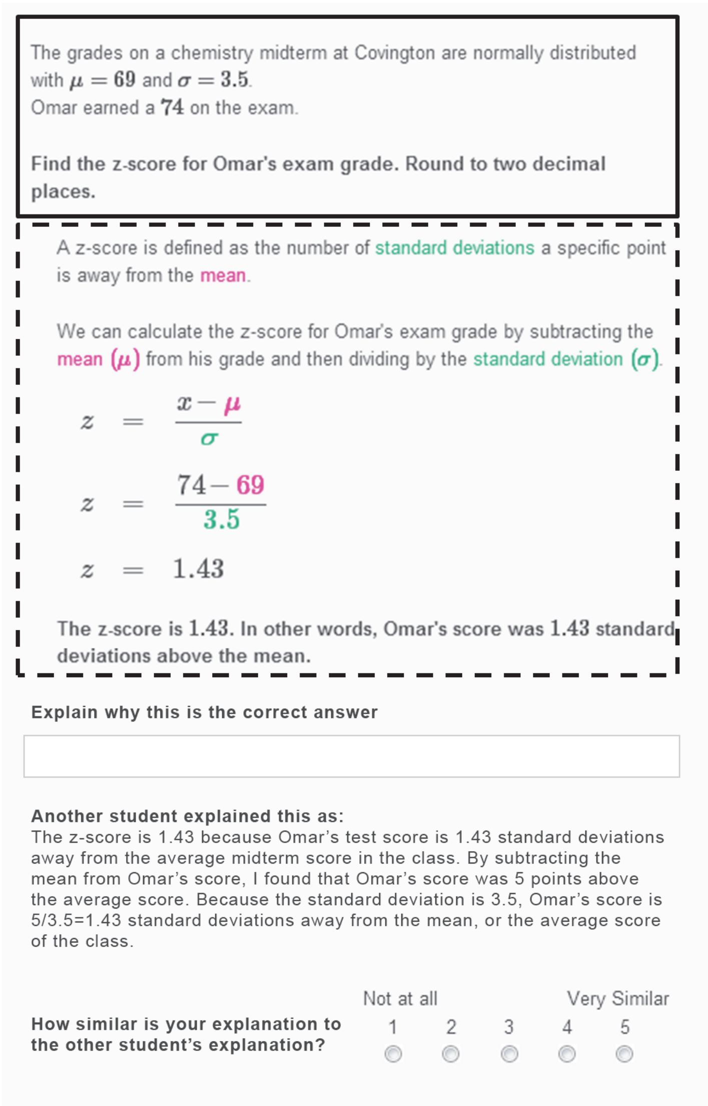

Figure 1: Illustration of worked example solution in typical Khan Academy exercise, and how the problem can be augmented with: (1) a prompt to self-generate an explanation for the correct answer, (2) An instructional explanation, ostensibly from another student, (3) A request for a learner to compare his/her explanation with the instructional explanation. The *practice-as-usual* exercise can be found at https://www.khanacademy.org/math/probability/statistics-inferential/normal_distribution/e/z_scores_1

Experiment

The ongoing study will be conducted using a convenience sample of adults recruited from Amazon Mechanical Turk, as well as undergraduate students. The goal is to investigate this paradigm in a controlled laboratory setting, and then extend it to a realistic educational environment with students in a high school, or introduce it on the actual Khan Academy platform, in an extension of an ongoing collaboration with Khan Academy.

The study independently manipulates whether or not learners are prompted to *self-generate* explanations for the correct answer (once it is obtained), and whether or not they are provided an *instructional* explanation for the correct answer. This results in four conditions:

Practice-as-usual with the typical Khan Academy exercise and no self-generated or instructional explanation.

Self-generated explanation (but no instructional explanation) which includes the prompt to explain why the answer is correct.

Instructional explanation (but no prompt to self-generate an explanation) which provides an explanation that is supposed to come from another student.

Self-generated and *instructional* explanations. This condition is key to evaluating whether learning can be improved through using explanations to provide implicit formative feedback for learners. As described in the next section, several variables are manipulated in this condition to investigate the most effective means of combining self-generated and instructional explanations.

Self-generated and instructional explanations: Order & Comparison

To further investigate the learning benefits of self-generated and instructional explanations, the condition in which participants receive both a self-generated and instructional explanation is made of four nested conditions. These are generated by experimentally manipulating the *order* of self-generated and instructional explanation (self-generated prompt first, then instructional explanation, vs. instructional then self-generated) and whether or not a *comparison* is requested (no comparison prompt, vs. a comparison prompt). The comparison prompt asks learners to rate similarity of self-generated and instructional explanations, such as can be seen in Figure 1: "How similar is your explanation to the other student's explanation?", rated on a scale from 1 (not at all) to 5 (very similar).

It should be noted that the self-generated and instructional explanation are never onscreen at the same time, to avoid simple copying or rote responses. Whichever is presented first simply disappears on the appearance of whichever is presented second.

The design therefore produces four conditions: *Self-Instructional*, *Instructional-Self*, *Self-Instructional-Compare*, *Instructional-Self-Compare*. The manipulations that produce these conditions allow us to investigate whether and when learners receive implicit formative feedback from generating explanations, receiving instructional explanations, and engaging with prompts to compare these explanations.

Summary

The study outlined here aims to investigate whether the proposed combinations of self-generated and instructional explanations have a beneficial impact on learning. The study can shed light on how to design a learning environment to provide implicit formative feedback, by examining how accuracy and speed in exercises is influenced by the relative effects of self-generating explanations, receiving instructional explanations, doing both, and comparing one's self-generated effort with an instructional explanation. More generally, the software adaptation of the Khan Academy exercise framework provides a setting to ask an even broader range of issues: such as changing the type of explanation prompts, features of the instructional explanations, the kinds of comparison prompts used (listing vs. rating, analyzing differences vs. similarities, contrasting explanation quality by identifying pros & cons of each, or by grading or rating different explanations).

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