Learning Online via Prompts to Explain

Abstract
Prompting learners to explain their beliefs can help them correct misconceptions upon encountering anomalies -- facts and observations that conflict with learners’ current understanding. We have developed a way to augment online interfaces for learning by adding prompts for users to explain a fact or observation. We conducted two experiments testing the effects of these explanation prompts, finding that they increase learners’ self-correction of misconceptions, though these benefits of explaining depend on: (1) How many anomalies the prompts require people to explain, and (2) Whether anomalies are distributed so that individual observations guide learners to correct ideas by conflicting with multiple misconceptions at once.

Author Keywords
Explanation; self-explanation; learning; generalization; statistics; misconceptions; anomalies;

ACM Classification Keywords
H.4 Information Systems Applications; H.5 Information interfaces and presentation; K.3.1 Computer Uses in Education; J.4 Social and Behavioral Sciences

Introduction
People are constantly learning from interactions with software, which can often involve revising their existing beliefs based on anomalies or facts that contradict what they currently believe. For example, in online contexts, users learn right/wrong answers while solving
exercises, informally learn surprising facts while browsing like Wikipedia articles, and also learn how to work with interfaces when their observations conflict with their current understanding.

In this work, we design and evaluate interfaces to help learners effectively resolve conflicts between what they understand or predict, and what they observe.

One strategy for helping learners realize misconceptions is to prompt them to reflect and provide explanations for unusual facts. Prompts asking learners for explanations are also a valuable tool for augmenting interfaces, because they can easily be added to existing content, and because prompts can help guide learners’ processing of information, while still letting learners take charge in interacting with the information being presented.

Related Work
While it might be more intuitive that people learn by receiving explanations, evidence from psychology and education suggests that certain ways of prompting people to explain and answer questions can help learning, even without feedback on correctness of learners’ explanations [1, 5]. Studies document the benefits of explaining broadly, in populations, tasks, topic ranging from five year olds learning math to professionals learning to use Excel [1, 3].

Helping learners realize their misconceptions by prompting for explanations is challenging, because people often ignore contradictory information [2]. Or, asking them to elaborate could lead them to entrench beliefs. How can prompts be designed that ensure users interact with and processes facts that contradict existing knowledge in a way that leads to productive learning and behavior? [3]

The Subsumptive Constraints Account [5] proposes that prompts to explain “why?” will be particularly effective, because they do not merely boost engagement, but selectively drive learners to subsume what is being explained as an instance of an underlying principle. We therefore focus on comparisons of “why?” to other prompts, and explore further questions about how the pattern-seeking constraints of “why?” prompts can be effectively leveraged by presenting anomalous information that guides learners to from misleading to reliable patterns.

Current Research
We conducted two experiments in the context of learning statistical rankings [4]. These experiments looked at how effects of explaining depend on amount of contradictory information, and whether the quantity of contradictory information is the dominant factor, or whether one designs the presentation of information to specifically rule out existing beliefs.

Our findings show that prompting learners for explanations help learners realize and correct their misconceptions, though the benefits of this intervention depend on the number and distribution of anomalies that users are asked to explain.

Experiment 1
The learning task in both experiments was adapted from [4]. Participants had to learn from observations of the relative ranking of five/six pairs of samples from different populations (grades of two students from different classes) what the basis for ranking was and
Tom was ranked more highly by the university than Sarah. Sarah got 85% in a Sociology class, where the average score was 79%, the average deviation was 8%, the minimum score was 67%, and the maximum score was 90%.

Tom got 69% in an Art History class, where the average score was 65%, the average deviation was 3%, the minimum score was 42%, and the maximum score was 87%.

Explain why this student was ranked higher. [Explain condition]
Write out any thoughts you have about this information. [Write Thoughts]

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Figure 1: (a) illustrates what participants saw as they observed each ranked pair and answered a question prompt. Only one prompt was shown, either the explain or the write thoughts prompt. Table 1 depicts how the ranked pair in (a) would have been ranked by each of the four principles. This reveals that the correct ranking for the pair in (a) is only consistent with the "more deviations above the average" principle, because (a) is an anomaly with respect to the "higher score", "greater distance from average", and "closer to maximum" rules.

As is discussed in Experiment 2, ranked pairs like (a) were used in the overlapping anomalies condition because the same observation is an anomaly to all three of the non-normative rules.
(b) shows how a near-identical ranked pair could be produced that was instead consistent with all four rules (and so not an anomaly with respect to any rule), simply by switching the class average deviations of the pair in (a). This was how number of anomalies was manipulated.

Learning Materials: Ranked Pairs of Students
Participants studied five pairs of students from different classes whose academic performance had been ranked by the university, and were told that their goal was to learn the ranking system employed. Figure 1 shows two ranked example pairs, detailing the information provided. Each pair stated which student was ranked higher by the university, and reported each student's score (e.g., 83%), as well as the class's average score (e.g., 73%), average deviation (e.g., 8%), and maximum & minimum scores. Participants were given the definition of mean and average deviation in the introduction.

Table 1: How different principles would rank students.

<table>
<thead>
<tr>
<th>Type of Information</th>
<th>Sarah</th>
<th>Tom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal Score</td>
<td>85%</td>
<td>69%</td>
</tr>
<tr>
<td>Class Average</td>
<td>79%</td>
<td>65%</td>
</tr>
<tr>
<td>Class Maximum</td>
<td>90%</td>
<td>87%</td>
</tr>
<tr>
<td>Class Deviation</td>
<td>8%</td>
<td>3%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ranking Rule</th>
<th>Use of rule</th>
<th>Higher ranked</th>
</tr>
</thead>
<tbody>
<tr>
<td>Higher score</td>
<td>85 &gt; 69</td>
<td>Sarah</td>
</tr>
<tr>
<td>Greater distance from average</td>
<td>(85 – 79) &gt; (69 – 65)</td>
<td>Sarah</td>
</tr>
<tr>
<td>Closer to maximum</td>
<td>(69 – 65) &lt; (87 – 69)</td>
<td>Sarah</td>
</tr>
<tr>
<td>More deviations above the average</td>
<td>(85-79)/8 &lt; (69-65)/3</td>
<td>Tom</td>
</tr>
</tbody>
</table>
Principles for ranking pairs of students
1 shows four ways in which participants could rank the
two students from Figure 1(a). The only principle that
was consistent with the observed rankings of all five
student pairs was the fourth one. This “more deviations
above the average” principle predicted that the higher
ranked student would be the one with a score that was
more deviations above their class mean. While the
other three non-normative principles (e.g., “higher
score” student is ranked higher) were consistent with
some of the observed rankings, they never correctly
applied to all. Moreover, these principles are termed
non-normative because while previous research has
found they are commonly used and consistent with the
intuitive statistical knowledge many people posses [4],
they are less reasonable as a basis for ranking from the
perspective of a correct understanding of statistics,
while the “more deviations above the average”
corresponds to core concepts like z-scores or
standardized normal scores.

Participants
The participants were adults recruited online through
the Amazon Mechanical Turk marketplace (659 in
Experiment 1 and 261 in Experiment 2). Participants
were asked to complete 1 HIT asking them to answer a
20-40 minute survey using an external platform, with
compensation around $3.00/hour.

Experiment Design & Procedure
EXPLAIN VERSUS WRITE THOUGHTS
To examine the effect of prompts to explain “why?”,
both Experiment 1 and 2 randomly assigned half of the
participants to have one of two kinds of question
prompts displayed below the ranked pairs. These are
shown in Figure 1. Responses were typed into a text
box below the prompt.

In the explain condition the prompt was to "Explain
why this student was ranked higher". In the write
thoughts condition the prompt was to "Write out any
thoughts you have about this information", so they
could use a range of strategies to engage with the
observation, while ensuring they paid attention and
engaged in comparable levels of verbalization.

NUMBER OF ANOMALIES
To explore how the effect of explaining “why?” was
enhanced by the way in which information contradicting
existing beliefs was presented, both Experiment 1 and
2 manipulated whether there were few or many
observations that contradicted or were anomalies with
respect to common misconceptions.

In Experiment 1, in the 1 out of 5 condition, for each of
the three non-normative principles, there was one
ranked pair that was an anomaly with respect to the
principle (and four ranked pairs consistent with the
principle). In the 4 out of 5 condition, there were four
ranked pairs that were anomalies with respect to each of
the principles, and one that was consistent with it.
All five ranked pairs were consistent with the "more
deviations above the average” principle. Also, note that
the anomalies with respect to the non-normative rules
were overlapping, meaning that each ranked pair
observation that was an anomaly with respect to one
non-normative principle was also an anomaly with
respect to the others, so the correct “more deviations
above the average” principle was the only one not ruled
out. In Experiment 2 we directly manipulated this
factor, using distributed anomalies.
Measure of belief revision
Participants had to rank four unranked pairs of students that pitted the “more deviations above average” principle against the three non-normative principles, both before (Pre-Test) and after (Post-Test) studying the ranked pairs. Scoring “accuracy” as a participant ranking in accordance with the “more deviations above average” principle, accuracy change from before or after study served as the main dependent measure of belief revision and is shown in the Figures as a function of experimental condition.

Explanation’s effects depended on number of anomalies
Figure 2 shows the change in accuracy, as a function of the two independent factors, which was analyzed using a 2 (task: explain vs. free study) x 2 (number of anomalies: single vs. multiple) ANOVA.

While both receiving multiple anomalies and engaging in explaining overall promoted learning, these main effects ($ps < 0.01$) were superseded by the interaction between explaining and number of anomalies, $F(1, 659) = 8.20, p < 0.01$.

Explaining was beneficial when multiple anomalies were present, so that it promoted revision of beliefs about the non-normative principles, and discovery and use of the correct relative-to-deviation principle.

Experiment 2
Experiment 2 further manipulated whether the participants worked with observations that were designed so that contradictions to all the misconceptions overlapped in the same observation, so that information was presented to strongly rule out all but the correct principle, or whether such contradictions were distributed across multiple observations.

Table 2: The difference between having anomalies be overlapping versus distributed in Experiment 2.
Table 2 shows how ranked pairs were consistent and anomalous with respect to the principles in both the overlapping and distributed anomaly conditions. In the Overlapping condition the same ranked student pair was anomalous with respect to all three non-normative rules, as shown in. In the Distributed condition a ranked student pair that was anomalous with respect to one non-normative rule was consistent with one or more of the other non-normative rules.

Results
Figure 3 shows the change in accuracy, as a function of the three independent factors, which was analyzed using a 2 (task: explain vs. free study) x 2 (number of anomalies: single vs. multiple) x 2 (distribution of anomalies: overlapping vs. distributed) ANOVA.

As in Experiment 1, receiving multiple anomalies boosted learning, $F(1, 261) = 8.94, p < 0.01$. There was also an interaction of task with the distribution of anomalies. Explaining benefited participants when the anomalies overlapped, but explaining was no longer beneficial when the anomalies were distributed, $F(1, 261) = 11.23, p < 0.01$.

The quantity of anomalous information was therefore not the key determiner in prompts to explain producing belief revision. Instead, it was critical that observations were designed so that prompts to explain could help people rule out the non-normative principles.

References