

On guided invention activities that support scientific reasoning and domain learning

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Introduction

Invention as Preparation for Learning (IPL) involves asking students to invent methods or solutions to challenging problems, prior and in addition to being taught the canonical solution through tell-and-practice methods (direct instruction followed by opportunities to practice the domain). It has been shown that students who engage in IPL activities perform better on domain-level transfer tasks than students who receive tell-and-practice methods alone (Schwartz & Martin, 2004; Roll, Aleven & Koedinger, 2009). It is unknown, however, through what cognitive processes these learning gains occur.

A study was thus carried out to answer the following research questions:
 -How does metacognitive scaffolding, which guides students to noticing the deep features in the data, affect the quality of students' inventions?
 -How does metacognitive scaffolding affect students' use of unsupported inquiry strategies, such as self-explanations?

Study Participants

Study conditions were applied to 134 freshmen science students, over half of whom were physics majors, across four sections of a first-year physics lab course at UBC. These students had been previously exposed to invention activities that covered topics such as least-squares residuals and uncertainty propagation.

Method

Students in each section were presented with an identical introduction and then worked through individual worksheets in randomly assigned pairs, with access to a spreadsheet program with which to implement their methods. Domain-level prompts were identical between groups, but two lab sections received "Guided Invention" activities with metacognitive scaffolding as outlined in Table 1. Contrasting cases were provided as in Figure 1 to highlight particular features of the domain, which was regarding uncertainty in the slope of a linear best-fit line that goes through the origin (Figure 2).

Invention stage	Instructions (given to all students)	Scaffold (given to Guided Invention only)		
		Exploratory data analysis	Self explanation	Peer critique
Task definition	Story problem: compare contractors			
Analysis		Engage in pairwise comparisons; Rank all data sets	Explain comparisons	Discuss with peers
Plan & design	Write down a formula for calculating σ_m			
Implementation & prediction	Calculate the uncertainty for each data set; Rank all data sets based on the invented methods			
Evaluation				

Table 1 : Metacognitive scaffolding through domain-independent prompts characterized the Guided Invention (treatment) and Unguided Invention (control) groups.¹

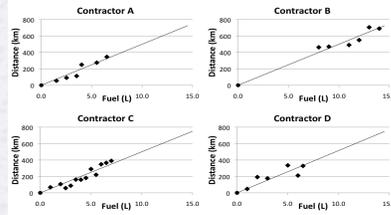


Figure 1 "Contractor Data" provided to the students during the invention task.
A vs B: Large range, gives low uncertainty
A vs C: More measurements lowers uncertainty
A vs D: High residuals increases uncertainty

$$\sigma_m^2 = \frac{1}{N} \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N x_i^2} = \frac{1}{N} \frac{\sum_{i=1}^N (y_i - \beta x_i)^2}{\sum_{i=1}^N x_i^2}$$

Higher variability \Rightarrow higher uncertainty
 Higher range \Rightarrow lower uncertainty
 More points \Rightarrow lower uncertainty

Figure 2 (left): Formula to calculate the uncertainty in the slope of a linear best-fitting line that goes through the origin.

Results and Conclusions

Students in the Guided Invention condition were 3 times more likely to include new features (Sample Size) in their invented methods, and also made correct predictions more often (Table 2). While there was no significant difference in technical, mathematical qualities of inventions, fewer students in the Unguided Invention condition produced formulae that could accurately predict the rankings of slope uncertainties for each case (ie $\delta m_A > \delta m_B$, $\delta m_A > \delta m_C$ and $\delta m_A < \delta m_D$).

	Guided Invention	Unguided Invention
Included features		
- Sample Size	42% (.50)	14% (.35)***
- Residuals	99% (.11)	98% (.13)
- Leverage	65% (.48)	71% (.46)
Correct predictions	69% (.25)	57% (.28)**
High-level comments		
- Any	56% (.50)	39% (.49)
- Focusing on features	56% (.50)	28% (.45)**
Multiple methods	13% (.34)	3.4% (.18)*

Table 2: Percentage of students who included each of the three features of the domain in their inventions, and whose inventions resulted in correct rankings of uncertainties in the cases.¹

Focus of high-level comments in either condition who made comments

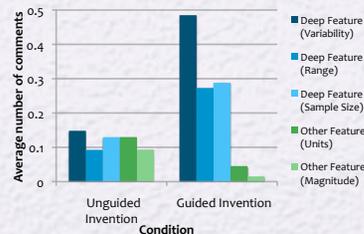


Figure 3: Distribution of student comments across surface and deep features.¹

While most students included unprompted self-explanations with their solutions regardless of condition, students in the Guided Invention condition included more deep-reasoning comments that focused on key features of the data, compared with unguided students (Figure 3, Table 2). Metacognitive prompts, therefore, improve the invention process and exploratory data analysis skills.

Slope of origin to each data point = m_i
 slope of the model = m
 number of points in data set = n
 $\sigma_m^2 = \frac{1}{n-1} \sum_{i=1}^n (m_i - m)^2$
 n is squared to reflect the fact that a data set with more data points will be more accurate.
 went with $\sigma_m = \frac{1}{n} \sum_{i=1}^n |m_i - m|$
 because the first model gave what we thought was an unrealistic uncertainty for Contractor D.

Factors $\rightarrow \sum_{i=1}^n (\text{Data point} - \bar{y})$
 $\rightarrow \sum_{i=1}^n (y_{\max} - y_{\min})$

$$\sigma_m = \frac{\sum_{i=1}^n y_i - \bar{y}}{N(\bar{m} - \bar{m})}$$

Figure 4: Sample inventions from 2 different students, demonstrating surface level comments, such as term definitions, and deeper reasoning, such as evaluation through multiple methods and explanations of features.

Current Work

We are currently examining the effect of faded metacognitive scaffold across 5 invention activities. In addition, we have implemented these tasks using intelligent tutoring systems. Figure 5 shows the Fuel Consumption activity as presented to students using the "Invention Lab 2.0"

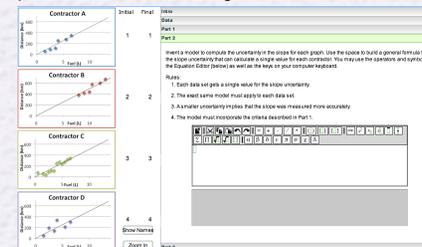


Figure 5: Screenshots of the "Invention Lab 2.0" demonstrating the equation editor and self-explanation space.

Scientific reasoning skills will be assessed through several methods:
 • Quality of reasoning and methods on invention tasks
 • Throughout the term's invention activities
 • On transfer activities
 • Performance on evaluation (or debugging) activities
 • recreating data from a previous task
 Domain-level knowledge will be assessed through a statistics assessment as developed by the researchers.

Acknowledgements

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References

¹Roll, I., Holmes, N., Day, J. & Bonn, D. (submitted). On guided invention activities that support scientific reasoning and domain learning. *Submitted to Instructional Science*.
 Roll, I., Aleven, V., & Koedinger, K. R. (2009). Helping students know "further" - increasing the flexibility of students' knowledge using symbolic invention tasks. In N. A. Taatgen, & H. van Rijn (Eds.), *Proceedings of the 31st annual conference of the cognitive science society* (pp. 1169-1174). Austin, TX: Cognitive Science Society. (32%)
 Schwartz, D. L., & Martin, T. (2004). Inventing to prepare for future learning: The hidden efficiency of encouraging original student production in statistics instruction. *Cognition & Instruction*, 22(2), 129-184.