Using causal networks to examine resource productivity and coordination in learning science

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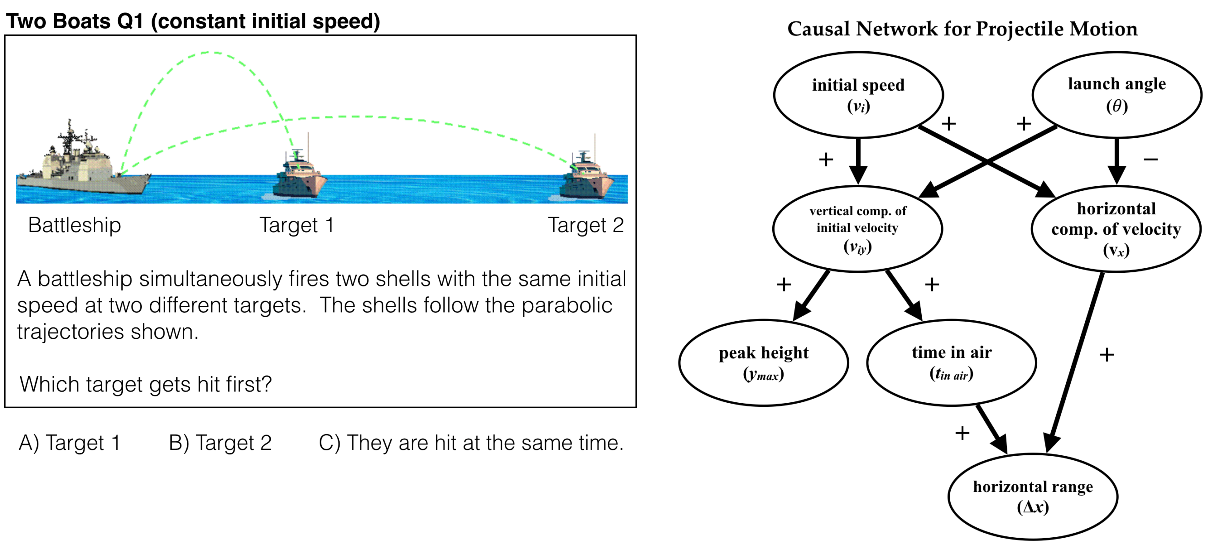
Abstract: We propose that *causal networks* representing canonical scientific models can be a useful analytic tool for specifying how student knowledge resources are aligned with canonical science as well as the ways that they need to be recoordinated in learning science. Using causal networks to analyze student-generated science explanations, we highlight three results that illustrate the ways in which student thinking can simultaneously align with and break from correct scientific reasoning. This initial study highlights the potential benefits of causal networks for specifying the role of student resources in learning science.

An analytic approach to characterize student resources for scientific reasoning

Understanding the processes by which people change their conceptual knowledge from naïve beliefs to expert knowledge is a longstanding goal of the cognitive and learning sciences. From a knowledge-in-pieces perspective, novice intuitions are resources for, rather than barriers to, learning canonical scientific concepts (Hammer et al., 2005; Smith et al., 1993). Although incorrect thinking can stem from the inappropriate use of these knowledge resources, learning is, in part, characterized by improved coordination and use of these productive existing resources in canonically correct ways.

We propose that *Bayesian causal networks* (Pearl, 2000) are analytic tools that can specify the role of student resources in learning science. Causal networks represent cause-effect relationships through a graphical representation of nodes and links. For example, the causal network representing projectile motion (Figure 1) shows the relations between seven key physical factors. In this study, we compare student reasoning to a causal network representing the canonical physical model. In doing so, we identify three ways in which student resources can be productively aligned with canonical physics while still needing to be recoordinated in learning science.



<u>Figure 1.</u> A sample physics problem, taken from FlipItPhysics (Gladding et al., 2015), and the causal network representing the underlying causal relations.

Method

One-hour interviews were conducted with 16 undergraduate students, who were either enrolled in or had completed at least one college physics course, at a large research university. On two focal multiple-choice physics questions (Two Boats Q1 and Q2), students were asked to: (i) for each choice (A, B, or C), *generate* the most convincing explanations for why someone might choose it and (ii) *rate* how likely they thought each choice was correct on a scale from 0 ("it's not likely at all") to 100 ("it's definitely correct"). Two Boats Q2 differs from Two Boats Q1

(Figure 1) in that the two projectiles do not have the same initial speed but instead reach the same peak height. The generate task was designed to elicit a range of student resources and inferences from those resources. The rate task indicated which explanations students found most plausible. Through multiple rounds of iterative coding, the first and second author developed and refined a coding scheme, coded all student explanations, and identified explanations that were well-modeled by the canonical causal network for projectile motion.

Result #1: correct explanations given were not viewed as the most plausible

One correct explanation relies on a subset of the causal network in Figure 1, that we denote by the shorthand $y_{max} \leftarrow v_{iy} \rightarrow t_{in\ air}$. This sub-network has a *common cause* structure, where v_{iy} is the common cause of two other variables, y_{max} and $t_{in\ air}$. Because these two effects have the same sole cause, they are correlated. For Q1, this means that, since y_{max} is smaller for projectile 2, it also has a smaller $t_{in\ air}$, so (B) *target 2 will be hit first*. Although seven students generated this explanation, only one of these students rated (B) as the most likely choice. For Q2, the two projectiles have the same y_{max}, so they have the same $t_{in\ air}$, and (C) *they are hit at the same time*. Three students gave this correct explanation, but none of these students rated (C) as the most likely choice. Although these students could generate the correct explanations, they largely did not believe in them.

Result #2: ignoring one factor in a common effect structure

One class of error ignored one factor in a common effect structure, where two causes influence a single effect. Four incorrect explanations fell within this class (Table 1). These errors show how student reasoning can rely on canonically valid factors, demonstrating students' productive resources for learning physics. They also show what ignored factors need to be integrated into student reasoning, demonstrating exactly how student thinking needs to be recoordinated for learning science.

Table 1: Incorrect explanations that ignore one causal factor in a common effect structure.

Incorrect Explanation	**Common effect structure**	**Factor considered**	**Factor ignored**	**Q1 # given (# most likely)**	**Q2 # given (# most likely)**
(A) Target 1; it is closer to the battleship	$t_{in\ air} \rightarrow \Delta x \leftarrow v_x$	$t_{in\ air} \rightarrow \Delta x$	$\Delta x \leftarrow v_x$	14 (0)	12 (9)
(B) Target 2; projectile 2 has a lower θ	$v_i \rightarrow t_{in\ air} \leftarrow \theta$	$t_{in\ air} \leftarrow \theta$	$v_i \rightarrow t_{in\ air}$	[*correct answer in Q1*]	2 (1)
(B) Target 2; projectile 2 has a greater v_i	$v_i \rightarrow t_{in\ air} \leftarrow \theta$	$v_i \rightarrow t_{in\ air}$	$t_{in\ air} \leftarrow \theta$	[*initial speeds equal in Q1*]	12 (3)
(C) Same time; they have the same v_i.	$v_i \rightarrow t_{in\ air} \leftarrow \theta$	$v_i \rightarrow t_{in\ air}$	$t_{in\ air} \leftarrow \theta$	5 (4)	[*speeds not equal in Q2*]

Result #3: invalid compensation arguments in a common effect structure

Another class of error highlighted by the causal network analysis is an invalid compensation argument: identifying changes in two factors, but incorrectly concluding that these changes exactly offset each other so that a third factor was unchanged. For Q2, one student gave a speed-distance compensation argument aligned with the common effect structure $t_{in\ air} \rightarrow \Delta x \leftarrow v_x$ to argue for (C) *They are hit at the same time.* They reasoned that although Δx is greater for projectile 2, this greater distance is offset entirely by projectile 2's greater v_x. Six other students gave a speed-distance compensation argument that had the same structure but did not explicitly refer to the horizontal component of speed or distance. These compensation arguments again illustrate recognition of valid scientific relationships while also showing how students need to recoordinate their use of these relationships for correct scientific reasoning.

References

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