Learning From Explanations: Diagrams can "Inhibit" the Self-Explanation Effect

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Abstract

Research shows that one can learn from self-explanations (Chi et al. 1989), but the influence of diagrams on this type of learning has not been assessed. This paper examines the role of spatial localization on the self-explanation effect. It is hypothesized that adjacency may blur feature discrimination, leading to inappropriate self-explanations. Ten subjects with naive conceptions about motion in a curved path were asked to think aloud while studying a chapter and a worked-out example. They were divided into Low-Benefit (LB) and High-Benefit (HB) learners, using a post-hoc median split on post-test measures (explanation, isomorphic, and transfer tests). Analyses of verbal protocols and drawings show that the LB learners self-explained without learning. They used diagrammatic representations extensively, relying on their features to make sense of the example lines, whereas the HB learners processed the text conceptually. Contrary to previous emphasis on the benefits of localization of information in a diagram (e.g., Larkin and Simon 1987), spatial localization inhibited the self-explanation effect because access to adjacent features propagated inaccurate comprehension *via* familiar diagrammatic knowledge. This research shows that learners in the process of acquiring new conceptual knowledge are not necessarily helped by local diagrammatic features because they can use them indiscriminately. It also suggests that the self-explanation effect may be tied to highly constrained learning situations.

Introduction

Considerable progress has been made in understanding how learning can arise from explanations (Armengol and Plaza 1995, deJong 1993, VanLehn and Jones 1993). An example of such progress is offered by the self-explanation effect: a correlation between the presence of explanations generated by a learner, and better learning (Chi 1996, Chi et al. 1989). Chi et al. (1989) analyzed verbal protocols of students studying examples and solving problems in introductory college physics. Using a post-hoc median split to define a group of Poor learners and a group of Good learners, they noticed two differences between these groups. One, the Good learners produced more self-explanations than their Poor learner counterparts, who typically reread and paraphrased the example sentences. And, two, the Good learners were able to articulate clearly their comprehension failures, whereas the Poor learners did not and commonly said that they understood the statements presented in the worked out examples. These results have been replicated, not only in physics (Ferguson-Hessler and deJong 1990), but in computer science (Pirolli and Bielaczyc 1989, Pirolli and Recker 1991), and in biology as well (Chi et al. 1994). Moreover, a simulation called "Cascade" has revealed that in the particular situation of the Chi et al. study, the self-explanation effect is caused by impasse-driven acquisition of small, rule-sized pieces of knowledge (VanLehn and Jones 1993). "Cascade" has also uncovered new learning strategies based on example use: Min and Max. The Min example-using strategy is tied to effective learning. It occurs when Ss try to solve the problems by themselves, refer to the examples only when they reach an impasse, and return to unaided problem solving as quickly as possible. The Max example-using strategy reflects less learning and occurs with extensive use of examples (VanLehn in press).

The motivation of the present paper stems from interest in the role of diagrams in knowledge acquisition. The contribution of diagrams to learning from explanations has received little attention so far. Yet, it represents an important research question. In machine learning, it is desirable to build intelligent systems that can learn from both linguistic and pictorial resources. Moreover, human learning often involves pictorial modalities. Therefore, it is natural to ask about the role played by diagrams in the self-explanation effect (interestingly, diagrams were used extensively in most of the previous self-explanation studies, yet their contribution to the effect is unclear). Finally, the paradigm used in self-explanations studies represents an interesting avenue to test existing theories of diagrammatic influence on cognition and to uncover cognitive properties of diagrams.

Given what precedes, the goal of this paper is not to offer a definite answer to the contribution of diagrams to learning from explanations. Rather, this paper seeks to open up an avenue of research. It does so by raising critical elements of analysis to help us understand the relationship between diagrams and the self-explanation effect.

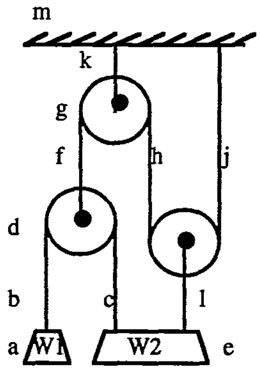
Diagrammatic Representations and Self-Explanation Effect

To begin uncovering the contribution of diagrams to learning from explanations, I have chosen to concentrate on the role of information adjacency in self-explanations. The reason for this focus is a seminal analysis of spatial localization (Larkin and Simon 1987) that remains one of the most cited when facilitative properties of diagrams are emphasized (e.g., Koedinger 1992; Cox and Brna 1995).

The above model proposes that one of the reasons for the usefulness of diagrams lies in the diagrammatic representations users build from them, in which they index information by location in a plane. Information at neighboring points can be accessed and processed at the same time. The search for information is facilitated by such indexing, allowing a single location to provide much of the information needed for making an inference. This search is regulated by an "attentional control mechanism" that makes available all information present at a given location and that switches its focus to any adjacent location specified by the elements currently under consideration. A pulley system (Figure 1) illustrates this mechanism in an example where the goal is to find the ratio of the weights such that the system is in equilibrium. The Figure shows the pulley system and the way it is encoded by a problem solver. Adjacency is defined by the content of each encoded element: the locations a and b are adjacent because they are both mentioned in the element (hangs a from b). Problem solving begins at location a, where a weight is found ((Weight a)), with associated value 1 ((value a 1), along with the fact that a hangs from something at location b ((hangs a from b)), which is a rope ((Rope b)). By applying an appropriate production rule, the rope at b is given 1 as an associated value. Then, since location a and b are adjacent, attention is focused at b, and the solution proceeds.

It is important to recognize that spatial localization may not necessarily exert a positive impact on learning. First, the above model considers the case of expert knowledge rather than that of novices. For instance, the analysis requires the existence of a correct program (rules of inference) to solve the problem. In addition, it assumes a normative theory of inference generation (e.g., problem solving progresses in a particular order). However, learners do differ in their ability to draw inferences. Importantly, the above emphasis on the benefits of spatial localization rests on the assumption that facilitation of problem solving results from making all information at a given location automatically available to the attentional control mechanism. However, simultaneous access to distinct features in a diagram may overwhelm novices and confuse them. This hypothesis is suggested by the finding, in the context of reading, that less-skilled readers have less efficient suppression mechanisms than more-skilled ones (Gernsbacher 1993). A similar situation may well operate with diagrams. If so, then spatial localization, and in particular feature adjacency, could actually be detrimental to less-skilled learners.

PULLEY SYSTEM



DIAGRAMMATIC ENCODING

(Weight a) (Rope b) (Rope c) (Pulley d)
(hangs a from b)
(pulley-system $b\,d\,c$)
(Weight e)
(hangs e from c)
(Rope f) (Pulley g) (Rope h) (Pulley i) (Rope j)
(Rope k) (Rope l) (Ceiling m)
(hangs d from f)
(pulley-system $f\,g\,h$)
(pulley-system $h\,i\,j$)
(hangs g from k)
(hangs k from m)
(hangs j from m)
(hangs l from i)
(hangs e from l)
(value a 1)

Figure 1. Spatial localization guides problem solving by making the problem solver move from one adjacent location to the next (Larkin and Simon 1987).

This research addresses the above concerns by studying learning in the context of inaccurate prior knowledge. I do so for two reasons: first, previous research on the self-explanation effect has recognized the importance of prior knowledge in the genesis of self-explanations. Second, powerful, inaccurate preconceptions are often implicated in science learning and the way learners manage these preconceptions plays an essential role in knowledge acquisition (diSessa 1993). Since these two reasons constitute key issues in learning, finding out the way learners use spatial localization to self-explain in the context of inaccurate prior knowledge should reveal valuable information on the hypothesized benefits of spatial localization in learning. In what follows, I have chosen the field of physics and in particular, physical motion (in a curved path) because it has been shown that naive beliefs in this domain are very common (McCloskey 1983, diSessa 1993).

The hypothesis guiding the present research is that the use of adjacent features can prevent identification, and hence correction, of inaccurate prior knowledge, by allowing self-explanations when the features share similar properties. Diagrams in the sciences are often made of simple adjacent elements with certain identical properties (e.g., a curve and a line both represent distances that can be measured). In the context of learning, such adjacency can lead to blurring the distinction between the features and can inappropriately foster the ability to self-explain. As a result, inaccurate prior knowledge is not necessarily identified and modified, and localization can inhibit the self-explanation effect.

Method

Subjects

Ten volunteers (three males and seven females), all undergraduate students from the University of California at Berkeley, who were paid $10.00 per hour for their participation. They had taken neither college-level physics, nor astronomy at the college or high school level. Four of them had taken physics in high school. Only one knew calculus, taken in college. They represented a range of abilities in terms of grade point average (GPA) and Scholastic Aptitude Test scores.

Materials

A three-page text entitled "Motion" was written by the author to introduce basic physics concepts: speed, average and instantaneous velocity, average and instantaneous acceleration, tangent, vectors and the addition of vectors. These concepts were presented with a definition, a brief explanation concerning their usefulness, a simple diagram, but no calculus. To illustrate the use of the concepts in the study of motion, the author wrote a seven-page text entitled: "An Example of Two Dimensional Motion: Motion in a Curved Path." The text discussed two balls falling, one along a straight line (ball A), and the other in a curved path (ball B) with uniform horizontal velocity and constant vertical acceleration. The trajectory of ball B was analyzed by studying the way its instantaneous velocity vector changed at successive times equally spaced. It was shown that by grouping the successive instantaneous velocity vectors, one can notice that these vectors change by a constant vertical vector. Finally, an equation was derived to express the instantaneous velocity in terms of the initial horizontal velocity and the acceleration. Diagrams were not provided at this stage (subjects were asked to draw their own).

Design and Procedure

The same experimenter tested all the subjects individually. Sessions lasted between 1 hour 30 minutes - 2 hours and were audio and videotaped. A fifteen question pretest was administered to measure the subjects' theoretical and physical understanding of the physics concepts. It asked subjects to distinguish between speed and velocity, and to define instantaneous acceleration. After the pretest, subjects were asked to read a two-page sheet of instructions about the verbal protocol procedure, and they watched the experimenter think aloud while reading a text about introductory statistics. Then, the students practiced the procedure with a two-page text about the study of light. After this training, subjects were asked to study the text presenting the basic concepts in the physics of motion, until they were able to answer a ten-question test correctly. Then, they studied the example by reading each statement aloud and explaining their understanding with verbalizations and drawings. Finally, they took an "explanation test" and were asked to answer a set of 10 isomorphic and 6 transfer questions. The explanation test prompted them to explain the physics of the two balls studied in the chapter, inviting them to make drawings along with their explanations, to avoid ambiguities of interpretation during the analysis of their performance. After completion of the postests, subjects were debriefed.

Results

The explanation test was coded as follows: thirteen facts that had been mentioned in the example were identified (see Appendix) and were counted as one point each, which made a possible total score of thirteen. A post-hoc median split based on performance on the postests (including the explanation test) was used to define two groups, Low-Benefit (LB) and High-Benefit (HB) learners. One "middle" subject was dropped from the analysis, so there was a total of 5 subjects in the LB learners' group and 4 in the other group. The mean success of the LB learners was 44.8% (26.1% for the explanation test, 60% for the isomorphic test, and 33% for the transfer test). The mean success of the HB learners was 82.7% (71.2% for the explanation test, 90% for the isomorphic test, and 66% for the transfer test). In terms of background, the number of LB and HB learners having had high school physics was the same (2). In addition, the subject having had college-level calculus turned out to be a LB learner.

Analysis of verbalizations accompanying the beginning statements of the example on motion in a curved path showed that all the students had an inaccurate conception of the fall. According to the most common naive conception, the ball was supposed to follow a straight line on the table, a little curve when leaving the table, and then a vertical line when falling. One student thought the ball should experience a straight line on the table and a vertical fall. Another naive conception that was built around the idea of a vertical fall was the case of a student who thought that the curve mentioned in the text was happening *while the ball was on the table*. Finally, a student also said that after a straight line on the table, the ball should follow a diagonal path.

Self-explanations were identified in the verbalizations, and their number was counted. A self-explanation was defined as a unit of one or several lines of protocol referring to the same idea, that was a comment about the physics of the situation but not a paraphrase. For instance, reading the statement: "The acceleration is therefore constant" and saying "Well, I guess that would have to be since the object is the same and gravity is the same" was counted as a self-explanation because the subject in this case was bringing his own knowledge to provide a coherent explanatory statement.

Self-Explanations and Learning. The respective mean numbers of self-explanations were computed (see Table 1). The null hypothesis that the two means are equal was not rejected ($p > .80$, two-tailed). This result, which should be interpreted with caution given the power limitation of this test, may indicate that HB learners do not necessarily self-explain more than LB learners. It is important to notice that the figures from Table 1 do not correspond to the ones that are typically found in self-explanation studies which have used similar sample sizes as the one in the present investigation. Such studies usually get a clear, significant effect with a higher number of self-explanations characterizing the HB learners' group.

HB Learners	LB Learners
15.2 (SD = 3.40; n = 4)	13.4 (SD= 7.70; n =5)

Table 1. Mean Number of Self- Explanations.

Perhaps a *qualitative* difference between HB and LB learners' self-explanations does exist? For instance, LB learners might generate more inaccurate self-explanations than their HB counterparts. This would represent a departure from previous studies of the self-explanation effect which have not reported such a differentiation between the two groups of learners. Chi and VanLehn (1991) have mentioned the occasional occurrence of incorrect elaborations, and Pirolli and Recker (1991) have noticed the rarity of incorrect explanations in their investigation (1.8%). To address this hypothesis, self-explanations were categorized as correct (such as the one above), or inaccurate. An example of the latter is provided by subject N's performance. In the paragraph analyzing the motion of ball B at successive time intervals, N read the following sentence: "In each successive interval, the instantaneous velocity vector increases by the same amount, $\Delta \mathbf{v}$." Instead of focusing on the *length* of that vector, N's attention was drawn to the *distances on the curve* between the successive instantaneous velocity vectors characterizing ball B's trajectory. N's explanation was that these vectors are separated by equal distances on the curve. In reality, the distances increase because of acceleration. By comparing the distribution of such inaccurate self-explanations and by contrasting them to correct ones, it was found that LB and HB learners do differ in terms of the quality of their self-explanations (see Table 2).

	HB Learners	LB Learners
Mean	0.5	4.6
Percentage	3.3	34.8**

**p< .01.

Table 2. Mean Number and Percentage of Inaccurate Self- Explanations.

It may be that self-explaining is nevertheless useful to LB learners, who could refine their thinking in an appropriate direction despite the fact that they are generating inaccurate self-explanations. This hypothesis was tested by considering the proportion of inaccurate self-explanations that were produced while working on the first and the last thirds of the example solution. The difference between the two proportions is significant ($z= 2.01$, $p= .02$, two-tailed) but it is in the direction opposite to that expected by the hypothesis. A greater number of inaccurate self-explanations was produced during the last part of the example than during the first (53.8% versus 21.9%). This result clearly shows that the LB learners of this study did not get any benefit from their self-explanations. Self-explaining does not seem to help remove inappropriate mental models, since all the ones that have been isolated in the problematic self-explanations were present during the postests.

A content analysis of the self-explanations reveal that most (91.3%) of the LB learners' inaccurate self-explanations relate to drawing connections from the text to the physical world ("kinematic" category) as opposed to applying a non-physical definition of a concept such as "acceleration equals difference in speed over time" ("formulaic" category) which accounts for the remaining 8.7%. Self-explanations were also categorized as "conservative" versus "liberal" when either a few or none of the knowledge pieces mentioned in the explanation had been presented in the text previously. For instance, an explanation involving the decomposition of an instantaneous velocity vector into a horizontal and a vertical component was "conservative" because addition of vectors had been presented in the introductory chapter and it was mentioned in the example that ball B had a uniform horizontal velocity. By contrast, saying that the instantaneous velocity vector was the product of a number X by a constant C was considered "liberal" because it introduced a way to analyze vectors that had not been mentioned in the text. It was found that LB learners' accurate self-explanations are strongly tied to the "conservative" dimension ($p < .05$, two-tailed) whereas their inaccurate self-explanations are not ($p > .05$, two-tailed). It is also interesting to note that HB learners' self-explanations tend to be "conservative" ($p < .05$, two-tailed) suggesting that LB learners make mistakes because they go *too much* beyond the text. As a result, four out of the five LB learners thought that the ball follows equal curved distances along the curve during successive equal time intervals. None of the HB learners came to this conclusion.

Diagrams and Self-Explanations. How did diagrammatic adjacency affect self-explanations? At the beginning of this paper it has been emphasized that diagrams such as curves and lines used in the study of motion are made of adjacent features which share similar properties (e.g., being measurable). By facilitating access to such features, a diagram also may contribute to blurring the discrimination between them, leading to an "inhibition" of the self-explanation effect by allowing learners to inaccurately self-explain.

This hypothesis was explored by developing a model (Figure 2) that makes use of adjacency to account for the way the LB learners generated their inaccurate kinematic explanations. The model was built by choosing at random one inaccurate kinematic self-explanation from each of the three LB learners and by analyzing the steps the subject took to generate each self-explanation given: the content of the example line; the subject's intuitive knowledge of the physical world; and her understanding as described in the preceding part of the protocol, by drawings and verbalizations. The model accounts for 65% of the inaccurate self-explanations. It does not account for any of the HB learners' explanations which relied on conceptual meaning rather than on a matching process between text and diagrams to process each example line.

The model has two major phases: a component analysis phase, where subjects work on the example line and on their diagrams in a piecemeal fashion; and an integration phase, where they put the different elements of their understanding together. The component analysis phase shows that LB learners typically used concepts of a line of text to create a diagrammatic representation based on previous verbalizations (step A). They then matched diagrammatic attributes and concepts from the new line using recognition or operators exploiting adjacency (step B), and finally took the remaining concepts of the new line that could not be explained this way as new attributes of the diagram (step C). This last step allowed the integration of ideas into an explanation.

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PHASE I. Component Analysis

A. Draw diagram to explain new example line, using understanding of previous lines.

B. Match attributes between diagrams and words in the example line to explain, using the "Recognition" operator and Adjacency Operators (e.g., "Transfer").

PHASE II. Integration-Explanation

C. Create diagrammatic attributes for remaining concepts in the example line to explain.

D. Generate explanation.

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Figure 2. The model that uses adjacency to account for LB learners' inaccurate explanations.

To understand how the model works, let us study the exact transcript provided by subject N (Figure 3):

Example line #24:

In each successive interval, the instantaneous velocity vector increases by the same amount, Δv.

Subject N:

[draws Curve 1 with arrows and segments]

"It just means to say that between each successive intervals the distance is the same

[draws Curve 2 with segments and labels A, B, C, D]

A would be at C if it were into three parts, B would be equal to A, would be equal to C

[writes the equalities and the sum]

and A+B+C would be equal to D."

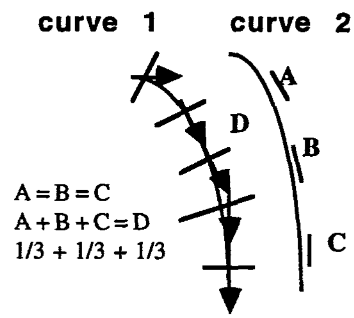

Figure 3. N's transcript.

In the above episode, N interprets the fact that the instantaneous velocity vector increases by the same amount as being reflected by equal distances on the curve between the successive vectors. First, let us notice that adjacency between the vectors and the curve plays a role in N's episode. It allows N to transfer a characteristic C mentioned in the sentence ("same amount") from the instantaneous velocity vectors to the curve. This is represented in the model by an "Adjacency Operator" called "Transfer", which is written as:

$$\text{Transfer}\ (C, a, b)/\text{Adj}(a, b)$$

where a characteristic C is transferred from the diagrammatic feature *a* to the diagrammatic feature *b*, given adjacency of *a* and *b*.

The model accounts for N's performance in the following manner (see Figure 4): First, N's prior understanding of instantaneous velocity vector is used to begin making sense of line #24. N had previously misunderstood that the successive instantaneous velocity vectors remain of the same length, so a corresponding diagrammatic representation is created (step A). However, this representation does not immediately explain the fact that these vectors "increase by the same amount," since the vectors are of the same length. In step B, attributes from the diagram and concepts of the example line are used the following way: using the Recognition operator, "each successive interval" is matched with the intervals on the curve, as is "the instantaneous velocity vector" with the vectors on the diagram. However, "the instantaneous velocity vector increases" cannot be matched with the equal length of the vectors, creating an impasse. At this point, the Transfer operator notices the adjacency of the vectors and the curve and transfers "same amount" from the instantaneous velocity vectors to the equal segments on the curve. Different knowledge pieces are now available, but

Example line: *"In each successive interval, the instantaneous velocity vector increases by the same amount, Δv."*
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PHASE I. Component Analysis

A. Draws Curve 1 (see Figure 3) from previous understanding: curved trajectory, equal segments on curve to represent time intervals, equal instantaneous velocity vectors (i.v.v.).

B. Matches:

Operators: REC: Recognition, TRA: Transfer
REC: ("in each successive interval", interval_curve)
REC: ("the instantaneous velocity vector", i_v_v)
Failed REC: ("increases", equal_length_i_v_v)
TRA: ("same amount", equal_curve_segments)

PHASE II. Integration-Explanation

C. Remaining concept: "increase". Create corresponding diagrammatic attribute: i.v.v. becomes more and more vertical.

D. Generate explanation: the successive i.v.v. are found at equal segments on the curve.
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Figure 4. How the Model from Figure 2 Accounts for N's Performance in Figure 3.

the occurrence of "increase" in the example line is left to be explained. So in step C, a new diagrammatic attribute is created (the fact that the vectors become more and more vertical) corresponding to "increase". This step allows one to integrate all the pieces into an explanation: the successive i.v.v. are found at equal segments on the curve.

What precedes illustrates the fact that adjacent features can foster the generation of inappropriate explanations. They function as a source of additional degrees of freedom for a learner in generating a self-explanation. This is so, in this paper, when particular properties/qualities are shared by the local features. In N's example, for instance, a vector had a "length" and an "amount," and such measurable entities were transferable to the curve.

In the present study, the qualities transferred were all highly familiar ones. That is, they corresponded to concepts that can be visualised automatically on a diagram because they are highly practiced. Indeed it may be that the Transfer operator should be written as:

$$\text{Transfer}\ (C, a, b)/\text{Adj}(a, b),\ \text{Fam}(C)$$

where Fam stands for Familiarity. In N's example, we can see this familiarity at work with "same amount". The equal segments on the curve, initially drawn to represent equal time intervals, were readily seen as representing "same amount": they became terribly tempting to explain why the instantaneous velocity vector increases by the same amount. In this case, N needed strong suppression mechanisms to reject this automatic knowledge and to decide to increase the length of his instantaneous velocity vectors. Why did this not happen? The answer to this question lies in the relationship between highly familiar diagrammatic knowledge and mental models. We know little about this critical issue, which I have begun investigating.

Discussion And Conclusion

The purpose of the present paper was to explore the role played by diagrammatic representations in the self-explanations effect. It has been shown that learners do not necessarily become HB learners if they self-explain: no significant difference was found in terms of the number of self-explanations in the LB learners and the HB learners' groups, contrary to what previous self-explanations studies have found for similar sample sizes; self-explaining does not seem to have helped the LB learners of this study to refine their comprehension appropriately; and the LB learners' self-explanations tended to be inaccurate.

It was found that, among the key variables influencing the LB learners' performance is the use of spatial localization. The LB learners' inappropriate use of this diagrammatic property played an important role in their ability to generate inaccurate self-explanations. Access to adjacent features sharing common, familiar properties led to the propagation of inaccurate comprehension, inappropriately fostering self-explanations (e.g., N used an adjacent feature to the instantaneous velocity vector -- the curve ---, which is also measurable, to end up saying that equal distances separated the vectors on the curve). As a result, the use of these features prevented identification and correction of inaccurate prior knowledge.

This exploration of the role of spatial localization in explanations shows that, contrary to what has been previously emphasized (Larkin and Simon 1987), the organization of information by location in diagrams does not turn out to be a strong, beneficial quality of diagrams, at least in the present context. It also shows that it is important to consider the *properties* of local elements, rather than localization per se. When doing so, one finds that subjects in the process of acquiring new conceptual knowledge are not necessarily helped by local diagrammatic features that share similar, familiar properties/qualities (such as being potentially referred to by their length) because they can use them indiscriminately. The overwhelming benefits of localization emphasized in Larkin and Simon's analysis hold for subjects who are experts already, rather than novices. Experts can break down the elements of a diagram according to their relevant properties in a given problem, but novices in the early stage of learning have not yet acquired the skills to do so. As such, the present results extend previous analyzes on perceptual inference (Scaife and Rogers 1996).

Finally, this paper shows that a correlation between the presence of self-explanations and poor learning will be observed when diagrams provide low-ability learners with a high number of degrees of freedom. Such a case occurs in particular when adjacent features share a relevant, common property, leading to a lack of discrimination of these features. This situation tends to "inhibit" the self-explanation effect by providing learners with the flexibility to generate inappropriate explanations of their own. This analysis suggests that the self-explanation effect may be tied to highly constrained situations.

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Appendix: The Coding Scheme for the Explanation Test

Presence or absence of the following ideas: Uniform horizontal motion/ Application of the velocity concept in the horizontal direction/ Uniform velocity can be seen by equal horizontal distances of the ball falling in a curved path/ There is uniform vertical motion/ The acceleration is uniform/ Acceleration can be seen by increasing vertical distances/ The motion of the ball can be analyzed by studying successive instantaneous velocity vectors/ An instantaneous velocity vector is tangent to the path/ It can be decomposed in two vectors/ The decomposition is an addition of vectors/ One of these initial vectors (horizontal) is the initial horizontal velocity vector of the ball/ The vertical component shows a constant vertical change/ This change is acceleration.

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