# DISTRIBUTED LEARNING AND MUTUAL ADAPTATION


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Abstract

If distributed cognition is to become a general analytic frame, it needs to handle more aspects of cognition than just highly efficient problem solving. It should also handle learning. We identify four classes of distributed learning: induction, repurposing, symbiotic tuning, and mutual adaptation. The four classes of distributed learning fit into a two-dimensional space defined by the stability and adaptability of individuals and their environments. In all four classes of learning, people and their environments are highly interdependent during initial learning. At the same time, we present evidence indicating that certain types of interdependence in early learning, most notably mutual adaptation, can help prepare people to be less dependent on their immediate environment and more adaptive when they confront new environments. We also describe and test examples of learning technologies that implement mutual adaptation.

## DISTRIBUTED LEARNING AND MUTUAL ADAPTATION

If distributed cognition is to become a general analytic frame, it needs to handle more aspects of cognition than just highly efficient problem solving. Thus far, distributed cognition has mainly described how environments and people are components of larger systems that have been designed to accomplish specific informational tasks. Another critical aspect of most cognitive systems, however, is that they learn. Does it make any sense to consider distributed learning where both individuals and their environments learn, or shall we restrict learning to a non-distributed analysis and relegate distributed cognition to narrow application?

To make this a fair question, we should probably describe learning as functional adaptation, so it can apply to both humans and the environment. Given an adaptation definition of learning, a strong case for distributed learning will require instances of individual adaptations that are difficult to describe if we ignore adaptations to the environment (whether physical or social). Furthermore, to make the case, it should be possible to generate and test learning predictions that stem from a distributed framework. Finally, if the idea of distributed learning has practical value, then it needs to guide the design of environments to support learning. In the following, we try to provide a preliminary analysis, empirical evidence, and learning technologies to make the case for distributed learning and a fuller account of distributed cognition. Our basic point is simple. Most cognitive research has been silent about the signature capacity of humans for altering the structure of their social and physical environment. Nevertheless, the adaptation of the environment is a powerful catalyst for learning and self-adaptation, and instructional designers should capitalize on this capacity so as to improve learning experiences.

## Distributed Learning and Education

Our interest in distributed learning grows from our interest in education. Cognitive research in education has faced a difficult problem. Educators need to prescribe environments that orchestrate specific learning processes. The demands of educational research may be contrasted with those of cognitive psychology and neuroscience, where the focus is usually on the internal mechanisms of thought. Here, the methods of research use a particular environment to trigger internal processes, but the environment is not part of the theory about how people think. Unfortunately, it is difficult to design learning experiences solely on a theory of internal process. It rarely works to say, “People will learn using mental process X in an environment that is like the one they used in Bob’s study, all things being equal.” All things are rarely equal. Environments differ across classrooms. They also change over time. This is one of the appeals of research on distributed cognition. It is working towards theories that encompass how individuals and environments interact.

A theory of distributed cognition relevant to education *must* consider learning. Most of the work in distributed cognition has focused on problem solving. Researchers examine how information processing and storage are distributed across people and contexts (for a review, see Pea, 1993). This has been useful for exploring how people efficiently accomplish familiar tasks with the aid of smartly constructed environments. Improved computer interfaces, for example, can help people off-load the demands of recalling how to initiate a spreadsheet process. This type of research does not explain learning, or how these environments became distributed the way they are. Though learning and problem solving strongly influence one another, learning yields lasting change, while problem solving does not. Thus, we distinguish distributed *problem solving* from distributed *learning*.

## Four Types of Distributed Cognition for Learning

To help clarify situations that involve distributed learning, we created Figure 1. The figure characterizes types of learning by the relative degree of stability or adaptability of individuals and their environments.

| | | | |
|---|---|---|---|
| Individual | Adaptable | (1) Induction | (4) Mutual Adaptation |
| | Stable | (2) Symbiotic Tuning | (3) Repurposing |
| | | Stable | Adaptable |
| | | Physical & Social Environments | |

**Figure 1**. Four Quadrants of Distributed Cognition (Adapted from Martin & Schwartz, 2005)

In Quadrant 1 – Induction – people do not have stable, mature ideas, but they are operating in well-structured and stable environments. By induction, we do not mean a specific psychological process or learning algorithm. Rather, we mean it more broadly in the sense that a current in one wire can induce a current in another wire. Abacus masters, for example, have expansive digit spans and arithmetic abilities because they have induced a mental model that can simulate the structure of an abacus (Hatano & Osawa, 1983). In Quadrant 1 people induce the regularities of a stable environment. In physical environments, the learning interaction often involves probing an environment to infer its structure. In social environments like a classroom, the induction might involve trying to infer the meaning behind a teacher's words. Glenberg et al. (2004) provides an excellent example of Quadrant 1 learning. Early readers learned to create mental models of text passages by moving characters in a physical scene. In Quadrant 1, learning involves changes to the individual. The environment does not change its basic structure, though it can be moved around.

In Quadrant 2 – Symbiotic Tuning – people operate in stable and often specialized environments and they have stable ideas. For example, highly trained pilots operate in the well-designed environment of a cockpit. They form a system that succeeds at achieving complicated feats such as remembering airspeeds (Hutchins, 1995). Activity in this quadrant has been the mainstay of the distributed cognition literature, where the question is how people off-load intellectual work to the environment (Norman, 1988; Zhang & Norman, 1994). In the symbiotic quadrant, learning is characterized by an increase in the efficiency of the system and the interdependence of its components. Because the components become increasingly interdependent, the learning is often bound to the context. Pilots cannot transport their specialized reliance on the cockpit to another environment, nor can a highly specialized cockpit transport to another setting; hence, the label "symbiotic tuning." Adaptations to the individual and environment depend on one another to manifest themselves.

In Quadrant 3 – Repurposing – people have stable ideas, but the environment does not have an ideal form. If people's ideas are mature enough, they can repurpose the environment to serve their functions (Kirsh, 1996). For example, people might repurpose a knife to turn a screw, or invent a screw in the first place. Repurposing involves adapting the environment to implement one's ideas. Once the environment stabilizes, individuals can move into a more symbiotic mode and improve the efficiency of the system.

In Quadrant 4 – Mutual Adaptation – people do not have stable ideas nor do they operate in a fixed environment. While ideas and environments do not change constantly, people often need to adapt their environments and ideas. A home gardener may need to switch from roses to shade-loving plants. In the process of adapting the garden, the gardener will learn more about shade-loving plants. Mutual adaptation involves the co-evolution of the individual and the environment.

## A Hypothesis about Mutual Adaptation

In the following, we provide several examples of distributed learning to indicate why we think it is relevant to education. In the first examples, we consider physically distributed learning. We consider cases where children manipulate physical objects to help them learn math concepts. In the second examples, we consider socially distributed learning. We consider cases where learners adapt with other people.

For both physically and socially distributed learning, we have a special interest in Quadrant 4: Mutual adaptation. One reason is that we have found examples of learning that would be incompletely characterized if we only focused on individual adaptations (described below). A second reason is that we have found that opportunities for mutual adaptation provide important benefits to students compared to the more canonical situation where the environment is fixed and only the student can change. In particular, we will show that mutual adaptation prepares learners to transfer their adaptations to new environments. We end each section below with an example of how our perspective on mutual adaptation leads to implications for learning technologies.

## Physically Distributed Learning

For our discussion of physically distributed learning, we consider the case of hands-on manipulation in mathematics learning. This is an interesting test case for two reasons. First, students often use hands-on materials (manipulatives) in early mathematics, but there is quite a bit of academic and political confusion about how to conceptualize their role in learning. Second, it is not a trivial question how children can work with concrete materials to learn abstract ideas, as opposed to just learn more concrete operations.

Our particular case involves children learning about ratio. Ratio is a common bottleneck in arithmetic learning. When children meet formal treatments of ratio around 8-years old, they already have highly efficient whole-number schemas for counting and other basic number operations. Children often interpret ratio problems in terms of these schemas. When asked to solve symbolic problems, like 1/2 + 1/4, children often answer 2/6 (Carpenter, Corbitt, Kepner, Lindquist, & Reys, 1980; Kerslake, 1986). Given pictures or hands-on materials, they make similar mistakes. For example, if children are shown eight pieces and asked to indicate one-fourth, they often indicate one piece, four pieces, or both.

For ratio problems, children need to develop new interpretations of quantity. For example, to solve 1/4 of 8 pieces, they need to reinterpret the pieces as groups, so they can map the “4” of the problem into four equal groups. They can then map the “1” of the fraction into one group, and count the number of items within the group. This level of reinterpretation is difficult to do mentally, especially if one does not know that such an interpretation exists (Chambers & Reisberg, 1985). This is where physical objects may be useful; children can easily and quickly rearrange manipulatives, and this reorganization of their environment could lead to adaptations in their interpretations.

Most applications of manipulatives fall into Quadrant 1 (Induction) where ideas are adaptable and the environment is taken as stable. The cognitive assumption is that manipulatives provide children direct access to quantitative structures. Once induced, children will be able to map the structures from the physical domain into the symbolic domain (e.g., Piaget, 1953; Dienes, 1973). Instructionally, the idea is that manipulatives provide a concrete and easily accessible analogy for symbolic procedures (e.g., Hall, 1998). Base-10 blocks are a good example. A ten-rod equals 10 unit-blocks, a hundred-plate equals 10 ten-rods and 100 unit-blocks, and so on. The base-10 blocks have a stable structure that mirrors the base-10 notational system. Using base-10 blocks, children are supposed to learn to map each operation they take on a concrete object directly into a comparable operation on symbolic objects. Here, children are not changing their environments. Their environments provide stable structures, which can guide the development of their ideas.

Learning in Quadrant 2 (Symbiotic Tuning) is ideal for some abilities. Reading, for example, occurs in a highly stable environment of textual conventions – words are left-to-right, punctuation delimits sentences, and so forth. For reading, we want students to become highly tuned to a specific and recurrent environment. For abilities that need to transfer from one situation to another, symbiotic tuning is not ideal. In fact, one of the concerns of learning in Quadrant 1 (Induction) is that it can yield an unwanted symbiotic relation once student understanding stabilizes. For example, over time, children become more efficient at using base-10 blocks, and they become dependent on the blocks for that efficiency. Experimental studies indicate that learning with base-10 blocks does not transfer very well to symbolic tasks. The children's understanding is symbiotic on the base-10 blocks, and it does not survive when the blocks are removed.

In Quadrant 3 (Repurposing), learners' ideas are stable but their environments are adaptable. When children have stable ideas, they can adapt physical environments to support their problem solving. For example, 10-year-olds are familiar with multiplication, but they cannot always do complex problems in their heads. Nevertheless, the children have a sufficient grasp of multiplication that they can use just about any physical material to help solve multiplication problems they cannot solve mentally (Martin & Schwartz, 2005). When people have strong ideas, they can repurpose many environments to support their continued learning.

## The Case for Considering Mutual Adaptations in Physical Environments

In Quadrant 4 (Mutual Adaptation) children and their manipulatives both change form. A series of studies can help clarify what this means and why it is theoretically important (Martin & Schwartz, 2005). In the first study, 10-year-olds tried to solve four problems of the form "indicate 1/4 of these 8 pieces". Each child tried two problems using plastic pieces spread across a table. They could move the pieces. Each child also tried two problems that showed pictures of pieces on a sheet of paper. The children had a pencil and paper to draw on the paper. The exact same children were three times more successful when they could manipulate the pieces (regardless of the order in which they completed the tasks). The children did not have a plan for how to solve the problems.

Instead, they pushed the pieces rather haphazardly, sometimes one at a time and sometimes in groups. By adapting their environment, they began to reinterpret the meaning of the pieces; they realized that instead of counting each piece, they could count groups of pieces. For example, they might sort out four equal groups of pieces, and pick one group, solving the problem of what 1/4 means.

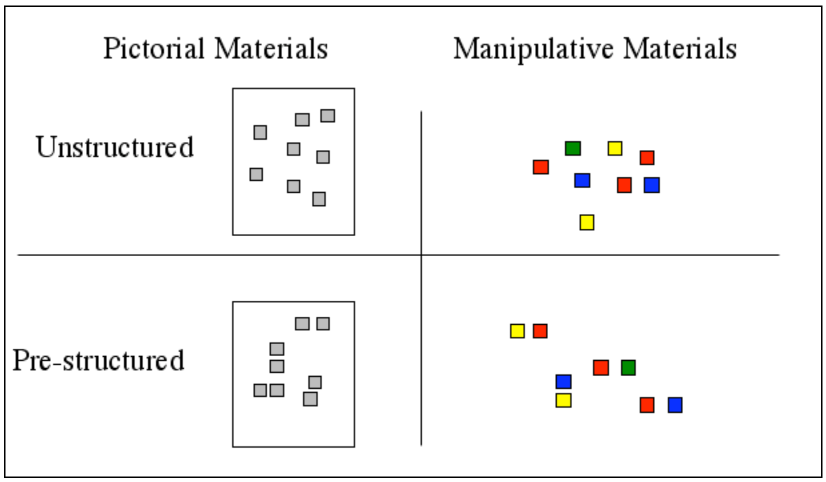


**Figure 2**. Unstructured and pre-structured materials.

In the second study, we wanted to confirm that the children were learning by adapting their environment. An alternative might be that the children already had an algorithm to solve the problems, and they used the environment to help off-load the cognitive burden of executing the algorithm in their head. We gave children tile pieces in unstructured or pre-structured configurations. Figure 2 provides an instance. If the children already had an algorithm for solving these problems, then the pre-organized pieces should make the problem trivial. Children also received manipulative or picture versions of the materials. Again, when children could move the pieces, they were more accurate, even compared to when the pieces were pre-organized into the penultimate answer in a picture.

The take home point of these examples is that adapting the environment was critical to children's own abilities to reinterpret the environment and solve these ratio problems. It seems like a theoretical mistake to treat the environment as fixed and only look at changes to the individual learners. The structure of the environment, from single units to groups, co-evolved with children's abilities to see groups in the environment.

Predictions about the Learning Benefits of Mutual Adaptation in Physical Environments

While the study of distributed learning requires an analysis of how individuals and their environments change with one another overtime, educators have a rightful concern for what individuals learn and can use once they leave a specific context. Thus, it becomes important to identify which quadrants of distributed learning are likely to yield individual learning that can transfer to new contexts. Our hypothesis is that mutual adaptation in Quadrant 4 is particularly beneficial for transfer. As people adapt their environments, they can learn which structures are adaptive and central to completing a given task. The hypothesized consequence is that they will be able to find or impose these structures in new environments that differ from the original context of learning.

Learning in Quadrant 4 may be contrasted with inductive learning in Quadrant 1, where the environment does not require any restructuring. To take the case of manipulatives in Quadrant 1, children induce how to rely on the given structure of the manipulative to solve problems. But, the children may never notice what structures in the environment made their manipulations effective. As an analogy, it might be something like using a calculator – one can learn what buttons to press, but this does not mean one will learn the structure of arithmetic that makes the button pressing effective. The consequence of this Quadrant 1 learning is that students may be less able to work in new environments that do not include all the structures built into their original environment.

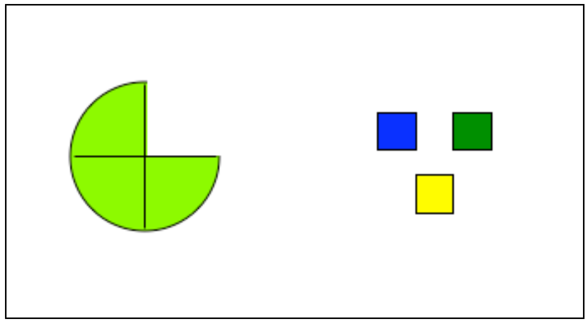

**Figure 3**. Pies indicate part-whole structure, whereas tiles require adaptation.

To test our prediction that Quadrant 4 has special benefits for transfer compared to Quadrant 1, we conducted a teaching study with 9- and 10-year-olds. Over three days, children learned to solve problems like 1/4 + 1/2. Half of the children used tiles and half used pie pieces. We chose these two types of materials because pie pieces have a part-whole structure built into their design. In Figure 3, one can readily see that the three pie-wedges do not make a whole. Tile materials do not manifest this part-whole structure, and it is much harder to see that the 3 tiles in the figure are parts of a whole. Thus, the pie pieces cause the learning to fall in Quadrant 1, where the environment has a stable structure, and students are expected to induce and use this structure. In contrast, the tile pieces require Quadrant 4 learning, because they do not manifest a part-whole structure. Children have to learn to adapt them into a part-whole structure to solve the problems. We thought this mutual adaptation would have benefits when the children had to transfer their learning to new environments. They would have a more complete interpretation of the structure of physical fractions, and they would be able to repurpose new environments into a useful structure.

The results indicated that both groups learned to do the fraction problems with their original learning material equally well. The difference between the two groups of children appeared when they had to transfer their embryonic understanding of fractions to new materials. At the end of each of the three days, we asked the children to solve similar problems to the ones they had solved earlier, except we gave them new materials (e.g., beans, fraction bars). The Tile students were more successful on the transfer problems than the Pie students were. They were able to figure out how to use the new materials to help them solve the problems.

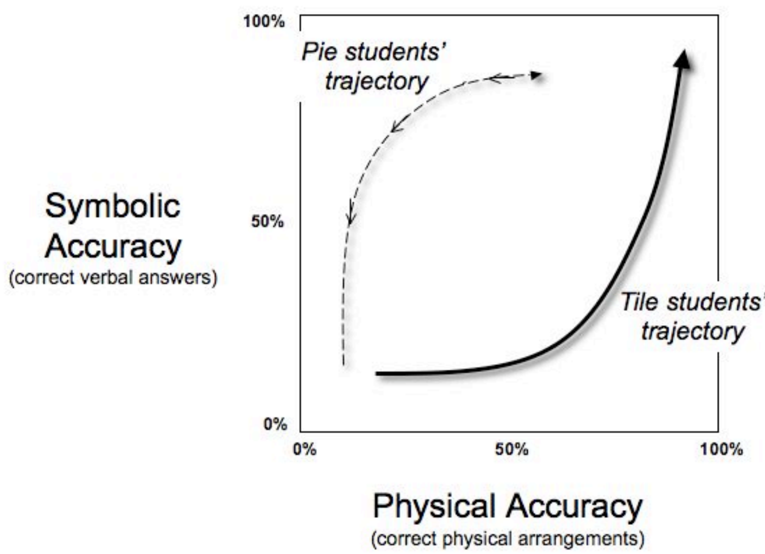


**Figure 4**. Learning trajectories as a function of physical and symbolic adaptations (Adapted from Martin & Schwartz, 2005).

To describe this transfer effect, we found it valuable to consider adaptations to the environment and the children's symbolic responses. Figure 4 shows a schematic of the results. The vertical dimension indicates student accuracy at giving the correct symbolic answer to a problem. The horizontal dimension indicates whether the materials were accurately grouped for the problem. The arrows indicate the average trajectory of learning over the three days. Analyzing how the environment and the children's symbolic responses co-evolved reveals some interesting patterns. First, the Tile students were more likely than the Pie students to reach the top right corner of perfect performance. Second, the Tile students had a much more stable trajectory, whereas the Pie students often regressed from one day to the next. Third, the Tile children correctly adapted the physical materials slightly ahead of their abilities to give correct symbolic answers. In contrast, the Pie children tended to give correct symbolic answers before they could make correct physical adaptations. As the Tile students were more successful than the Pie students by the end, this result suggests that adaptations to the environment can lead to symbolic learning that has positive benefits for student understanding.

In summary, children learned to solve problems using their physical environment that they could not do in their heads (or with paper and pencil). Children depended on making structural changes to their environment to support learning. It was the opportunity to adapt their environment in the Tile condition that led to their subsequent abilities to adapt new environments. Had we ignored how the children distributed their learning with the environment, we would have no evidence as to why Pies were less useful than Tiles. However, by considering how children distributed their learning to the materials, it appears that the opportunity and ability to adapt the environment led to superior student learning that followed a more stable trajectory and could move from environment to environment.

## Technological Application of Mutual Adaptation in a Physical Domain

Technology can enhance the benefits of mutual adaptation. We created virtual manipulatives that children move like real manipulatives, for example, one-by-one or in groups. There are many virtual manipulatives available on-line, and they can provide many of the same benefits as real manipulatives do (Martin & Lukong, 2005). Our improvement has been to include a history feature. Children's behaviors are maintained in a database, and the children (and teacher) can replay their actions and see their answers. The value of this replay is that children can reflect on their adaptations to the environment.

The addition of a replay features makes it easier for children to notice how the environment has been changing, and by hypothesis, they will learn more from their adaptations. For example, a first grader used our virtual manipulatives to solve the problem, "Sally has 5 apples. She eats some of them. Then she has 2 left. How many apples did she eat?" This problem uses an unknown intermediate quantity, which is harder for children than problems that use a final quantity as the unknown. The student made a collection of 5 pieces on the computer screen, then she removed pieces until there were two left. Next, she replayed her actions and counted the pieces that disappeared to get the answer "3". Being able to see her adaptations helped her decompose the task. She distributed her memory to the tool, so she could focus on getting to the target of two apples, and afterwards, she counted the number of apples she had removed. For students, the opportunity to observe their adaptations in process (and not just as finished products) can help them develop novel and appropriate interpretations of their actions sooner.

## Socially Distributed Learning

We can extend the four quadrants of distributed learning to social interaction. For expository purposes, we will restrict our analysis to face-to-face interaction. The environment in this case is another person. Examples of Inductive learning might be an infant who realizes that his mother appears each time he cries in pain, or a student who learns that he is about to be scolded when his teacher begins with "Mr." An example of Quadrant 2 (Repurposing) might be a mother who uses the infant's crying to tire him out, or a teacher who trains her students to be attentive when she says "Mr."

The Symbiotic quadrant refers to situations where individuals refine stable patterns of interaction with one another. For example, partners may develop a particularly shorthand method of reference or emotional support, and they may learn to apportion chores in ways that are efficient given the peculiar structure of their lives. Symbiotic learning like this does not travel very well to new situations involving new people, though people do often try to impose a set of stable behaviors into new situations with varying degrees of success.

## The Case for Considering Mutual Adaptation in Social Environments

In Quadrant 4, individuals adapt with one another and what emerges can be different than what either individual would learn without mutual adaptations. In these situations, it is difficult to describe learning by focusing solely on individual cognition. For example, we asked 15-year-olds to solve simple problems about gear movement such as, "Imagine there are four gears in a row that are touching like a row of quarters. If you try to turn the gear on the left end clockwise, what will happen to the gear on the right end?" We investigated whether the children spontaneously learned a parity rule – the first and last gears turn the same direction for an odd number of gears (Schwartz, 1995). The children either worked alone or in pairs. The individuals learned the rule 14% of the time. Given this base rate, we can estimate how well the dyads should do if they communicate what they know perfectly and without "process loss." We do this by estimating the percentage of pairs that should include an individual who would have induced the rule working alone, and we assume this individual can convince his or her partner to accept the rule. This estimate is 26.5%. In fact, the pairs learned the parity rule 58% of the time. It is difficult to explain this level of learning in terms of individual cognition given that an analysis of individuals only predicts, at best, that 26.5% of the groups would learn the parity rule.

The members of the pairs somehow changed one another so they became more than the sum of two individual heads. This provides a parallel to the example of the young children who could only learn the meaning of "1/4 of 8" by pushing the pieces around. In both cases, the children's learning depended on an interaction with an environment that they were simultaneously modifying.

## Evidence on the Learning Benefits of Mutual Social Adaptation

We think many cognitive analyses of learning through social interaction have neglected the significance of mutual adaptation. A case in point involves the research on learning-by-teaching, where one student teaches another student and learns in the process of teaching. Learning-by-teaching should be an ideal instance of mutual adaptation, because the teacher learns by teaching, and the pupil learns by being taught. Both are adapting.

Even so, the cognitive explanations for the benefits of teaching have typically been reduced to individual cognitive processes. Chi, de Leeuw, Chiu, and Lavancher (1994), for example, summarize the literature on learning-by-teaching:

> Citing 19 published studies… Webb found that giving elaborate explanations was positively related to individual achievement, whereas receiving elaborate explanations had few significant positive relationships with achievement… Such findings are consistent with the self-explanation effect because the advantages gained by explaining to others and to oneself are comparable (p. 441).

While these findings are true as described, the authors have separated the learning of the teacher and the learning of the student into two separate, individual cognitive phenomena, giving and receiving. They do not treat teaching as a case of mutual adaptation, and we believe this oversight misses important causal elements in learning. For example, imagine a situation where teachers can teach and elaborate their ideas, but they never get to see how their students adapt in response. Would they learn so well?

Okita and Schwartz (in press) conducted a study to demonstrate that mutual adaptation is an important ingredient of learning-by-teaching. They showed that knocking out the opportunity for teachers to see how their student adapts reduces learning, even compared to teacher self-study. In the first phase of the experiment, college students read a passage on the mechanisms that cause people to heat up when they have a fever (e.g., a reduction in sweat production). They heard that they would be tutoring another student about the passage and should read the passage accordingly. The participants then taught Student X, a confederate, in a one-on-one session. Student X asked 5 questions, and the participants helped her with those questions. Student X followed a script to ensure she did not introduce any new information that would favor some participants over others.

In the next phase of the experiment, half of these participants received a new set of 5 questions. They were told that they would shortly be tutoring on the five questions and to consult the passage if they wanted. The other half of the participants saw Student X answer the same set of 5 new questions in an interview setting. The interviewer was another confederate who simply asked the questions without providing feedback. These participants saw a videotape of Student X answering the questions, and they were told that the video was a live feed. This way, every participant who observed Student X saw the same videotape, though they thought Student X's responses were her own adaptations of what they had taught her. Finally, all the participants took a surprise test of 5 new (and harder inference) questions.

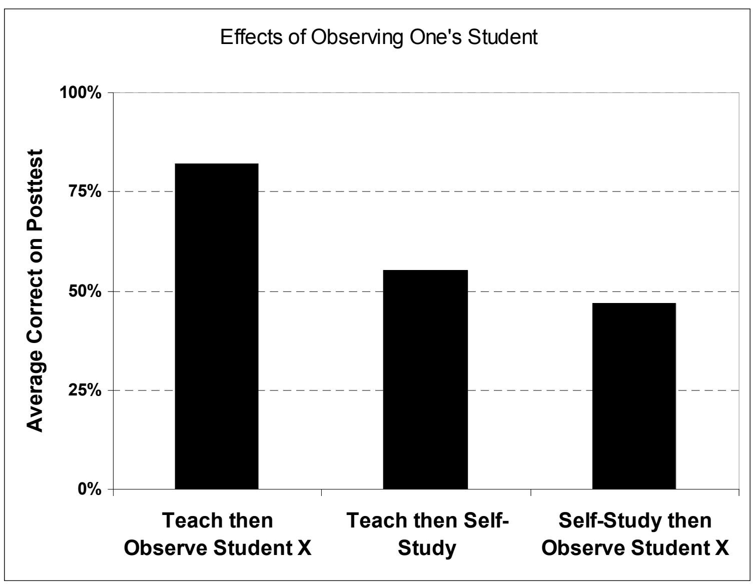


**Figure 5.** Participants learn more when they see their student answer questions (in uninformative ways) than when they answer the same questions themselves.

Figure 5 shows how much the participants learned as measured by the final inference test. The participants who taught and observed Student X learned the most. Participants who taught Student X, but then did self-study on the second set of questions, were 27% less accurate. Evidently, the opportunity to passively observe how one's student adapts to what she has been taught is quite valuable for adapting one's own understanding – even more valuable than teaching and then doing it oneself. Moreover, we know that Student X did not introduce any special information when she answered questions in the faux-interview. A third group of students studied the first five questions in preparation for tutoring, and then they observed Student X answer the second set of five questions (as a "live feed" of a student answering questions). The figure shows these participants also did relatively poorly.

There are many useful results in this study. For example, the study provides a counter-example to the common wisdom that doing something oneself is better than observing. Observing can be extremely valuable in a context of mutual adaptation.

For our current purposes, however, the most important finding is that the participants who taught and observed their student learned the most. They learned more than the participants who taught but never observed how their student adapted their instruction. These latter participants also explained and elaborated their ideas when they taught. Therefore, the difference between the conditions cannot be reduced to the individual process of explaining or elaborating ones ideas. As fits our overall story, to make sense of a situation of mutual adaptation, like learning-by-teaching, it is useful to consider the overall system of distributed learning and not just individual processes.

## Implications of Mutual Social Adaptation for Technology

We have transported the idea of mutual social adaptation into an educational technology called Teachable Agents (Schwartz et al., in press). Teachable Agents are computerized agents that students teach. Once they have been taught, the Teachable

Agent can answer questions and solve problems using simple artificial intelligence techniques. Students observe their agent’s answers, and, depending on the quality of the answer, students can revise the agent’s knowledge (and their own). Thus, Teachable Agents begin from the assumption that by adapting another social agent, students can adapt their own understanding. We have created several different classes of Teachable Agent to help students learn how to reason in different content areas (see <AAALab.Stanford.Edu>).

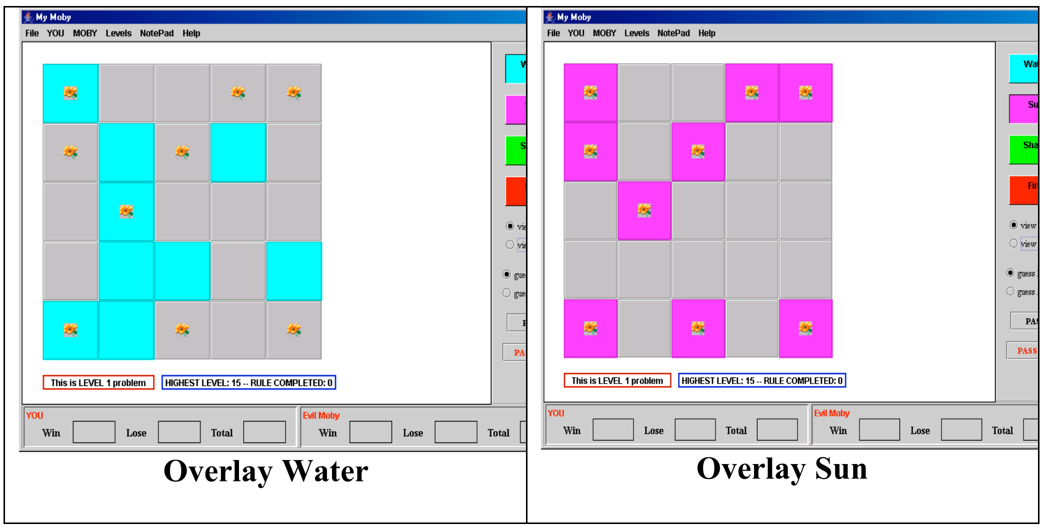


**Figure 6.** An interface for inducing how various factors influence a given outcome. Students can overlay factors (shown by colored cells) on a given outcome (shown by little flowers in the cells) to help induce the rule that regulates where the flowers will appear. Once they induce the rule, they teach a computer agent who then uses the rule to solve new problems.

We conducted a study with a Teachable Agent, named Moby, to directly compare the inductive learning of Quadrant 1 with the mutual adaptation of Quadrant 4 (Schwartz et al., in press). Moby is a game context where students learn hypothetico-deductive reasoning. Students play a game that shows a given outcome (e.g., flowers growing). They have to induce the logical combination of factors that regulate the appearance of the outcome (e.g., “sun” is necessary and sufficient for flowers to appear).

Figure 6 provides an example of the interface for inducing a rule. Students overlay different factors on the grid by clicking on buttons that represent the factor. The right panel of Figure 6 shows what the interface looks like if students pick the correct factor for this particular problem. The rules can get quite complex; for example, "Sun and Not Water are necessary for the absence of the Flower."

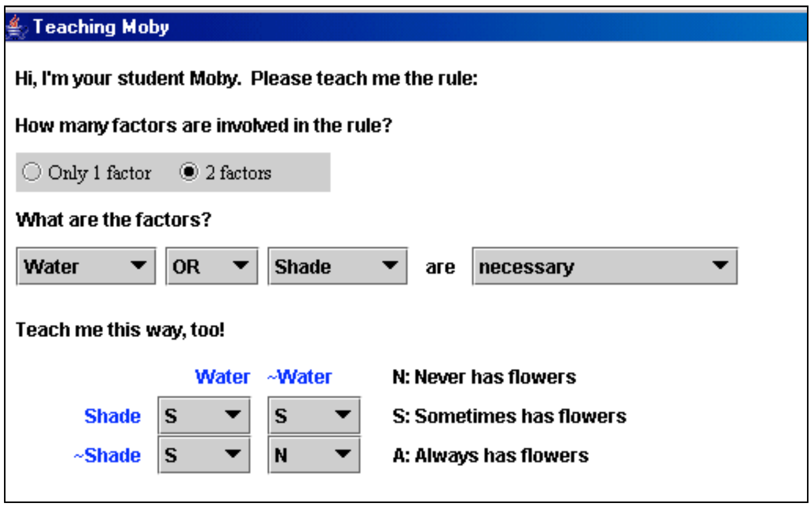


**Figure 7**. Students teach their agent by using propositional and matrix formats.

Once players have induced a rule, they teach Moby by filling in the representations shown in Figure 7. Moby then plays a game based on the rule it has been taught; it tries to make predictions about where the flower will appear in a new grid (that follows the same underlying rule). Moby competes against "an evil agent" who also plays the prediction game. If Moby wins, students progress to the next level and a more difficult logical rule.

This particular Teachable Agent permits a nicely matched evaluation of induction (Quadrant 1) versus mutual adaptation (Quadrant 4). The study involved over a hundred high school seniors. Two conditions are of special relevance. In the Inductive condition, the students played the game themselves. In the Teach condition, the students saw their agent perform based on how it had been taught. Specifically, the Induction students induced rules, played against the evil agent to progress to the next level, and created a knowledge representation of each rule (per Figure 7). The Teach students also induced rules, created the same knowledge representation of the rule (to teach Moby), and then watched Moby play against the evil agent based on the rule. Thus, students in both conditions completed the same activities with the exception that the students in the Teach condition adapted an agent and watched its independent behavior, whereas the students in the Inductive condition used the rules themselves so there was no mutual adaptation.

Over the course of the study, there were no apparent differences between the conditions; both groups progressed through increasingly difficult problems at an equal rate of success. Students in both conditions adapted to the demands of the specific environment. However, as we have argued, the effects of mutual adaptation often show up in transfer situations when participants need to operate in a new environment. To test this claim, we gave the students a test of hypothetico-deductive reasoning a week later. The paper-and-pencil questions took several new forms that did not look like the original computer environment. Students in the Teach condition significantly outperformed the students in the Induction condition on every type of question. Thus, like the study with Student X, distributed learning can be more effective in helping students learn to handle new situations than simply doing things oneself.

## Conclusion

In The Lives of a Cell (1978), Lewis Thomas points out the difficulty of determining the boundary of a living organism. Cells, for example, are often considered the fundamental unit of life. But, within every cell are mitochondria that produce the cell's usable energy. Mitochondria have a different genetic make-up from the cell, and they appear to be "separate" living entities with their own reproductive mechanisms. This is an excellent example of the inextricable interdependence of living organisms, and the difficulty of identifying any single "unit" of life. Thomas ultimately concludes that the earth itself should be considered a single organism.

Distributed cognition brings up similar issues, because it raises the question of how we should locate the "unit" of cognition. Harnad (2005), for example, rejects an information processing definition of cognition. Instead, he proposes that the unit of cognition should be identified phenomenologically by the introspective feeling of thought. In this solution, distributed cognition does not exist, because cognition can only be felt by individuals. He proposes "cooperative cognition" as a better way to think about dependencies between individuals and an intelligently designed environment.

In our own work, we have tried another approach to the boundary problem. We begin with the assumption of interdependence instead of singular cognition. Our question is how people and their environments adapt such that they become more or less interdependent over time. Our finding has been that people and their environments can be highly interdependent during initial learning. At the same time, certain types of interdependence in early learning, most notably mutual adaptation, can help prepare people to be less dependent on their immediate environment and more adaptive when they confront new environments.

Although we have made some headway in our analysis of distributed learning, there are some notable omissions. Perhaps the most glaring omission is that we have not offered a solid metric for evaluating the degree to which the elements of a distributed learning system are stable or amenable to adaptation. In our examples, we have relied on intuitively different situations, but this can only take us so far. At some point, it will be necessary to define which changes constitute an adaptation and which changes simply reflect the usual processes of a stable environment. This applies to both individuals and environments.

Cognitive research has made some headway in distinguishing incremental changes from larger adaptations in individual cognition (e.g., automaticity versus conceptual change; for a review, see Schwartz, Bransford, & Sears, 2005). The work of Hatano and Inagaki (1986), for example, distinguishes routine expertise from adaptive expertise. Routine experts are highly efficient in their usual tasks, whereas adaptive experts seek out new challenges and sources of learning. We hope that cognitive science begins to see a similar value to making headway in distinguishing "stable" and "adaptive" environments. The appearance of adaptive expertise, for example, is surely a function of whether an environment allows for individual adaptation.

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