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Learning by Teaching Human Pupils and Teachable Agents: The Importance of Recursive Feedback

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Feedback is important for learning. However, there are different types of feedback, and not all feedback is effective. Here we introduce recursive feedback (RF), which occurs when tutors observe their pupils use what they have been taught. Two experiments examined the value of RF during learning by teaching. In the first study adults taught another adult face to face about human biology. Those participants who observed their pupil interact with an examiner exhibited superior learning relative to individuals in several control conditions that included elements of learning by teaching but not RF. The second study examined whether RF benefits extend to teaching computerized teachable agents in regular classrooms. High school students played games in which they induced logical rules. Students taught their agent the governing rules. They received RF when they observed their teachable agent play a prediction game against a second competitor agent. On a posttest, these students exhibited greater abilities to use logic to solve novel problems compared to students in control conditions who received direct feedback by playing against the competitor agent themselves. RF may further generalize to nonteaching situations that also involve a production–appropriation cycle, such as do-it-yourself projects in which people have a chance to learn from how other people take up their handiwork.

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Teaching is ubiquitous across age, culture, and setting. The modal case involves a more knowledgeable person purposefully communicating accumulated experience by word and deed. Teaching is a basic building block for the transmission of culture (Tomasello, Kruger, & Ratner, 1993). Even 4-year-old children distinguish teaching from other forms of intentional communication (Butler & Markman, 2012). Within a broader instructional arrangement of opportunities and supports, teaching is the element that is directly communicative.

Teaching is central to human development, and Premack (2004) argued that it is also strictly human. Premack pinned his argument on the observational role of the teacher: "Unlike imitation, in which the novice observes the expert, the teacher observes the novice—and not only observes, but also judges and modifies" (p. 318). Though young animals may imitate older animals, only human teachers observe whether their pupils have learned. Premack proposed that only humans teach, because humans have the unique capacity of recursive thought—the capacity to constitute a thought as a function of itself. Teachers try to communicate what they know to their students—they constitute their students' thoughts as a function of their own. Humans can further reflect on the successes and failures of this recursive move. For example, if a student is confused about a particular problem, that student's confusion is feedback that the teacher receives. Through this feedback, the teacher may discover that the problem was not with the teaching method or student, but rather the problem was with the teacher's own understanding of the concept in the first place. This loop in which the student's understanding and performance becomes feedback for the teacher's understanding is called *recursive feedback* (RF).

RF supports effective teaching. Formative assessments, for instance, make student thinking visible so that teachers can make better instructional decisions (Black & Wiliam, 1998). Despite the centrality of RF to teaching and its unique standing in human thought, the learning literature has not examined the effects of RF on learning in general or on teacher learning specifically. RF has not been isolated as a specific class of feedback, nor has it been evaluated for its potential contribution to learning. The current article attempts to redress this oversight by experimentally isolating the effects of RF during learning by teaching (LBT).

In LBT, students teach other students. The desired side effect is that students learn especially well when they take on the role of the teacher (e.g., Palincsar & Brown, 1984). In the first experiment reported here we demonstrate a large positive effect of RF when teaching a human pupil, and in the second experiment we demonstrate that the benefit extends to teaching a computerized agent. To avoid confusion going forward, we use the terms *teacher* or *tutor* when referring to students or others engaged in teaching. We use the term *pupil* to refer to the student, person, or computer-controlled agent receiving the instruction.

We begin with a review of the empirical literature on LBT, including an analytic separation of LBT into three phases. From there we discuss research on feedback to help clarify why RF is unique and how it may ameliorate some of the documented risks of using feedback to enhance learning. We then outline the experimental studies and present them in turn, including a description of a computerized agent called a *teachable agent* (TA; Biswas, Leelawong, Schwartz, Vye, & TAG-V, 2005). The General Discussion widens the focus to locate RF within a larger cycle of production and appropriation. We propose that RF is a significant contributor to many formal and informal learning activities besides LBT, including hobbies and project-based learning.

EFFICACY OF PEER TUTORING

The practice of students teaching one another has yielded strong results. In a meta-analysis of 81 peer tutoring studies in elementary school, Rohrbeck, Ginsburg-Block, Fantuzzo, and Miller (2003) found a positive 0.33 effect size for peer tutoring compared to control groups. Peer tutoring has also penetrated a broad range of educational practices. In a study with medical students (Nnodim, 1997), one group completed the initial 18 dissections of a cadaver and then demonstrated their accomplishments to a second group. The second group then completed the remaining 18 dissections and showed their accomplishments to the first group. On an extensive posttest, both groups of peer tutoring students demonstrated greater learning than otherwise equivalent students who completed all 36 dissections on their own and without peer exchange. There are many variations of peer tutoring that mix and match ability groupings, ages, and genders, as well as the degree of support students receive to tutor well.

Of special interest are the effects of teaching on the tutor's own learning. LBT is an old idea. Gartner, Kohler, and Riessman (1971) attributed the first explicit mention to John Comenius, the reputed father of education, in 1632. In a seminal report, Cohen, Kulik, and Kulik (1982) conducted a meta-analysis of 65 peer tutoring studies. For the pupils, they found an average effect size of 0.4 compared to control pupils who had not received peer tutoring. Of particular relevance here is that 38 of the studies also measured the learning gains of the tutors. The average effect size was 0.33 compared to control students who did not tutor. The effect was robust. In all, 87% of the studies showed a benefit for the tutors. Moreover, the benefits were not detectably influenced by moderating variables that ranged from tutor achievement to tutor training to structured versus unstructured tutoring. Professional teachers can also learn their subject matter more deeply by teaching. Sherin (2002) detailed how in-service teachers who implemented a new curriculum negotiated student understandings to improve their own mathematical knowledge as well as their pedagogical content knowledge.

THREE PHASES OF LEARNING BY TEACHING

To understand the cognitive benefits experienced by tutors, we decompose LBT into three phases: preparing, teaching, and observing. The analytic separation helps to pinpoint possible causes. In practice, these three phases can be comingled over various time frames, and there are many different ways in which students might teach each other. The LBT literature has highlighted the positive effects of the preparation and teaching phases. However, there is no direct evidence regarding the observation phase that generates RF.

Preparing to Teach

When preparing to teach, tutors consider what knowledge to deliver and how to deliver it in advance of interacting with pupils. In isolation, the preparation phase has demonstrable benefits for learning (Annis, 1983). Bargh and Schul (1980) found that people learn better when they prepare to teach a pupil who will take a test than when they prepare to take the test themselves. Similarly, Benware and Deci (1984) conducted a 2-week intervention and found no difference for learning rote material but did find a benefit for high-level items. There are three aspects that seem especially important: motivation, generation, and metacognitive vigilance.

Preparing to teach other people introduces motivations that range from a sense of responsibility to the anticipation of a public performance. Chase, Chin, Oppezzo, and Schwartz (2009) described a *protégé effect.* They found that both fifth- and eighth-grade students spent more time learning in advance of teaching a computer agent than they spent learning for themselves, even when the alternative activity was a motivating game. Renkl (1995) pointed out that the strong motivational aspects of LBT need to be used judiciously, because they can elevate into performance anxiety.

Preparing to teach is also a generative activity that depends on frequent retrieval and elaboration of information from memory. As teachers think about what they will convey, they need to actively rehearse what they know. This effort at retrieval creates a *generation effect* (Slamecka & Graf, 1978) that improves future retrieval. Karpicke and Blunt (2011), for example, showed that the retrieval involved in taking a test improved students' subsequent ability to draw inferences, because the students could more easily remember the facts needed for the inferences. One can further surmise that in the preparation phase, teachers elaborate and organize the facts for themselves, which further enhances retrieval and future coherence.

Finally, preparing to teach can engage metacognition, because teachers are motivated to anticipate the needs and questions of their pupils. Teachers need to organize the information for communication (Zajonc, 1960), and they need to explain it to themselves so that they are prepared for the questions of their pupils.

Self-explaining and self-generated questions can help learners identify conflicting or incomplete understandings that they might otherwise gloss if they did not take the time and effort to explicitly integrate what they have learned (Chi, Deleeuw, Chiu, & Lavancher, 1994).

For example, Biswas, Schwartz, Bransford, and TAG-V (2001) found that college students who thought they were preparing to teach a class engaged an empirical article more deeply than students who thought they were preparing for a test. The students preparing to teach were better able to graph results and explain how the reported experiments related to one another. They had to prepare themselves for any question that might arise when teaching. In contrast, when students in the test preparation condition received the graphing task they frequently commented to the effect that "I didn't think *that* would be on the test." Of course, if tutors do not have appropriate metacognitive skills, then increased metacognitive activity can have deleterious effects (Mandl & Ballstaedt, 1982), unless there are specific scaffolds to support the development of metacognition during LBT (Okita & Jamalian, 2012).

The Act of Teaching

The same principles that regulate the benefits of cooperative learning largely apply to interactive teaching. Broadly speaking, these principles include the benefits of explanation, question answering, and physiological arousal. Explanation effects (e.g., Ploetzner, Dillenbourg, Praier, & Traum, 1999) refer to the benefits of explaining ideas rather than just receiving them. The benefits are similar to those found for preparing to teach, except that they occur in real-time interactions. In a classic correlational study of in situ cooperative interactions, Webb (1989) found that students who provided explanations learned more than those who received them.

In addition to explanations, tutors often answer questions. The pupils' questions have an effect on tutor learning. Borko et al. (1992) provided a canonical example. A preservice teacher was asked by a student why fractions get inverted for multiplication and realized that she did not know the conceptual reason. Questions asked by pupils can lead teachers to recognize and repair gaps in their own understanding or to consider new extensions to their understanding. This is one reason that the quality of questions asked by students has a measurable effect on tutor learning (Uretsi, 2000). Roscoe and Chi (2007) concluded that tutees' questions were responsible for about two-thirds of tutors' reflective knowledge-building activity. Tutoring sessions should be arranged to limit the natural tendency of tutors to slip into didactics, which can eliminate opportunities for pupils to ask questions (Fuchs, Fuchs, Bentz, Phillips, & Hamlett, 1994; Graesser, Person, & Magliano, 1995). Chi, Roy, and Hausmann (2008) found that the didactic tendency had a negative effect on the tutor relative to situations in which a more interactive dialogue permitted the development of deep questions (see also Craig, Sullins, Witherspoon, & Gholson, 2006).

Finally, the process of teaching can increase in-the-moment engagement (Chi, Siler, & Jeong, 2004). Though this has not been directly tested in the literature, one can easily imagine that even lecturing has positive effects on teacher learning, because teachers tend to be "activated" when presenting to students. It is likely that lecturing moderately increases both arousal and attention, which have been found to improve learning in more interactive settings (Lim & Reeves, 2010; Okita, Bailenson, & Schwartz, 2008).

Observing Recursive Feedback

In the full cycle of teaching, tutors observe their pupils apply what they have been taught. Our hypothesis is that this is an important but neglected source of tutor learning. This activity differs in important ways from observational learning (e.g., Bandura & Jeffery, 1973). Unlike in observational learning, pupils do not normally serve as models that the tutors imitate. Instead, the pupils are providing feedback on how well the tutors have taught.

To help situate RF, we can differentiate it from the existing literature on feedback. There are many refined characterizations and categorizations of feedback, and we cannot do justice to them all (e.g., Hattie & Timperley, 2007; Kluger & DeNisi, 1998; Lawton et al., 2012; Mory, 2004; Narciss, 2008; Nicol & Macfarlane-Dick, 2006). A brief review, however, can help locate the uniqueness of RF.

Because feedback is ubiquitous and takes so many forms, different theoretical traditions delimit the complexity by deciding what to include and exclude. For cybernetics and control theory (Powers, 1973), feedback is conceptualized as a signal that marks a deviation from a standard or goal state (e.g., a thermostat). From this perspective, only negative feedback is of interest, because it indicates a discrepancy from the goal state and a need for change. In contrast, the behaviorist feedback tradition, spawned by Thorndike's law of effect, emphasizes both positive (reward) and negative (punishment) feedback in the form of behavioral reinforcements. The cognitive tradition, unlike behaviorism, embraces feedback that provides information about the structure of the task at hand and not just one's behavior (e.g., "reach for the bolt under the sink, not on top"; e.g., Blazer, Doherty, & O'Connor, 1989). The metacognitive tradition goes even further away from behaviorism because it does not require external information at all. Feedback can result from internally monitoring one's thoughts (Mory, 2004). Lastly, socially oriented theorists may restrict feedback to supervised learning, in which a second agent intentionally provides feedback to the learner (Kluger & DeNisi, 1996).

Regardless of how scholars partition the space of feedback, all current theories share the common restriction that feedback is a direct consequence of the agent's

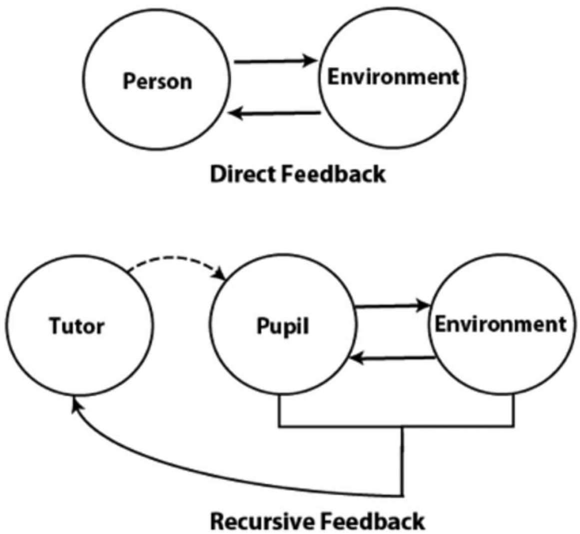

FIGURE 1 Schematic of the differences between direct and recursive feedback. With recursive feedback, the tutor gains feedback by observing how the pupil applies what has been learned in a new performance context.

thoughts or actions. In the top half of Figure 1, we refer to this as the *direct feedback* loop. The information or reinforcement can come from another person, a computer program, a book, or, more generally, any change to the internal or external environment that can be interpreted as a consequence of a person's actions or thoughts. In all cases, the feedback is always a direct consequence of the person's behaviors, words, or thoughts.

The bottom half of Figure 1 shows RF that is not a direct consequence of tutor behavior. There are two key criteria. The first is that the feedback is generated by the independent interactions of the pupil with the environment. The second criterion is the recursive mapping. Teachers need to map the behaviors of their pupils back to their own understanding of the task.

For instance, when a professor sees how her graduate student performs during a dissertation defense, this satisfies the first criterion for RF. The feedback generated by the candidate's interactions with the dissertation committee is a consequence of the candidate's performance and not the professor's performance. To satisfy the second criterion, the professor needs to interpret the pupil's answers with respect to her own teaching and understanding of the topic (as opposed, e.g., to discounting the feedback by blaming the student). By hypothesis, the professor can learn a great deal about the strengths and limitations of her own understanding as it is revealed through the student's interactions with the committee. It is important to note that in our thought experiment, the professor might also learn something about the effectiveness of her mentoring. But here we concentrate on the benefit of RF for teachers in terms of learning about a topic rather than learning to be a better teacher (for this latter topic, see Putnam, 1992).

HOW RECURSIVE FEEDBACK MAY ADDRESS TWO PROBLEMS WITH DIRECT FEEDBACK

Feedback is not always effective. In a meta-analysis of 131 studies, Kluger and DeNisi (1998) found that feedback interventions have an average effect size of 0.4 compared to providing no feedback. They also found that fully one third of the studies exhibited significant negative effects of feedback compared to no feedback at all. Despite prevailing beliefs that feedback is always good, it can cut both ways. For example, the delivery of praise for having exceeded a standard can demotivate student learning. Praise often does not provide specific information for improvement, and it may also cause students to decrease their effort because they have already exceeded the standard. In general, there are two major threats to feedback success.

The first threat is affective. Students often interpret feedback with respect to themselves rather than as a way to improve at a task (Graham & Golan, 1991; Kluger & DeNisi, 1996). Hattie and Timperley (2007) explained that when a student perceives feedback episodes as directed at the self, the episodes "have a negative effect on learning because they include or lead to self-handicapping, learned hopelessness, or social comparison. The related [task] feedback itself is usually discounted or dismissed, and goals of low challenge are adopted" (p. 97). It is a natural inclination for feedback to trigger ego involvement. Students like positive feedback precisely because it makes them feel good about themselves, even if it has little effect on learning (Hattie & Timperley, 2007). Dweck and colleagues have also extensively documented how pupils frequently attribute negative feedback to a fixed intelligence rather than consider it an informative signal for how they can improve (e.g., Mangels, Butterfield, Lamb, Good, & Dweck, 2006).

The second threat involves cognitive complexity and the challenge of interpreting the implications of feedback for one's performance or understanding. This challenge often appears in the literature under the moniker of "task complexity," but it should be understood as complexity relative to one's prior knowledge. When a task is relatively familiar, students can track down the implications of the feedback. In contrast, for an unfamiliar task, it is more difficult for learners to determine the precise implications of the feedback for improving performance. For example, a novice cook may only detect that the meat in his stew tasted tough, whereas an expert can use this feedback to diagnose that the novice did not sear the meat first. Based on their meta-analysis, Kluger and DeNisi (1998) suggested that feedback interventions "grow more positive either as the task becomes more subjectively familiar or as it becomes objectively familiar" (p. 71).

The recursive aspect of feedback during LBT may help mitigate both threats. On the affective side, RF may circumvent ego involvement, because tutors focus on their pupils rather than solely themselves. In their studies of the *protégé effect,* Chase et al. (2009) described how students were likely to acknowledge their TAs' errors and to express negative affect (e.g., "Oh no! I'm sorry I didn't teach you that"). In contrast, students who answered the same questions themselves were inclined to show little affect upon errors. They suppressed uptake of the negative feedback presumably because it had implications for their selves. The authors proposed that teaching creates an *ego-protective buffer,* because the pupil rather than the tutor takes the immediate responsibility for being wrong. Moreover, teaching brings a sense of responsibility, so tutors are motivated to pay attention to the task-level feedback to improve their own understanding so they can teach better.

On the cognitive side, LBT can help students develop the prior knowledge that mitigates the deleterious effects of task complexity for interpreting feedback. In the preparation and teaching phases, tutors have a chance to develop their knowledge of the topic and of what they taught. As a result, tutors can make better sense of the implications of RF for their own understanding. Also, because the goal is to improve the tutee, tutors ideally respond to the feedback by reorganizing their teaching (and understanding) so they can teach better.

OVERVIEW OF THE TWO STUDIES

There is no theoretical guarantee that RF is effective for learning. On a purely cognitive analysis, the effectiveness of RF requires that tutors maintain representations of their own understanding, of what they taught, and of the understanding of their pupils. Moreover, these representations need to be entertained simultaneously so that the tutors can sort out which aspects of the pupils' performance relate to which level of representation. The high cognitive load could be detrimental to learning compared to a more direct feedback loop. However, recursive thinking may be a privileged cognitive and affective domain for humans. Recursive thought is usually assigned to language, problem solving, and theory of mind (e.g., Corballis, 2007), but it may also be a powerful but unrecognized mechanism of learning.

The first experiment reported here is laboratory based and demonstrates the added value of RF. The primary treatment uses all three phases of LBT. Three control conditions use LBT models that do not include RF. In one control condition, for instance, tutors prepare and teach, but they do not observe their pupil. Thus, the first experiment addresses the question of whether RF rises above those one third of cases in which feedback has a negative effect (Kluger & DeNisi, 1998). This is also the first study to demonstrate that RF is an important component for maximizing the benefits of LBT on tutor learning. The experiment involves college students, and the topic of learning involves the causal pathways by which humans maintain a fever.

The second experiment was conducted in regular high school classes and provides a more stringent test of RF. Rather than showing the added value of RF compared to no feedback, it shows that RF is more effective than direct feedback that otherwise holds identical information and reinforcement. The topic of learning is also more demanding, because the study evaluates whether RF helps students learn and transfer logical reasoning, a notoriously difficult instructional goal (e.g., Moshman, 1990; Moshman & Franks, 1986). For this experiment, we also wanted to demonstrate that the RF of LBT could be effectively rendered to a process (i.e., an instructional technology). Therefore, we used a TA that incorporated RF as part of its core mechanic. Thus, the second experiment also serves as a test of the effectiveness of one instantiation of TA technologies in a regular classroom environment.

EXPERIMENT 1: THE ADDED VALUE OF RECURSIVE FEEDBACK

In the first study, we isolated the potential value of RF through an ablation research design that systematically removed various phases of the full LBT cycle. The tutors in the study were graduate students. The topic of learning was the mechanisms by which humans maintain a fever, which the graduate students initially learned from a written passage (see the online supplement). If the students constructed a strong mental model of fever mechanisms, they should have been able to explain, among other things, how people can have a fever yet feel chills, why sweat does not cool down a fever, why skin often feels irritated during a fever, and why a dog's nose is dry when it has a fever. We measured how much they learned using a posttest (see the Appendix).

Figure 2 shows a graphic representation of the research procedure and experimental design. The first branch at the top of the procedure panel represents the full LBT condition. Tutors in this condition completed all three phases, Prepare–Teach–Observe, so we refer to it as the *PTO condition.* The other three branches describe the various control conditions. We describe the PTO condition first. In Session 1 (P), the tutors read the passage and prepared to teach its content. In Session 2 (T), they taught a pupil whom we call Pupil X. Pupil X was a confederate who provided the same quality of interaction and information for all of the tutors. The tutors received five questions (Set A) that guided what they should teach about. In Session 3 (O), the tutors watched a video monitor that showed Pupil X orally responding to five new questions (Set B) that were asked

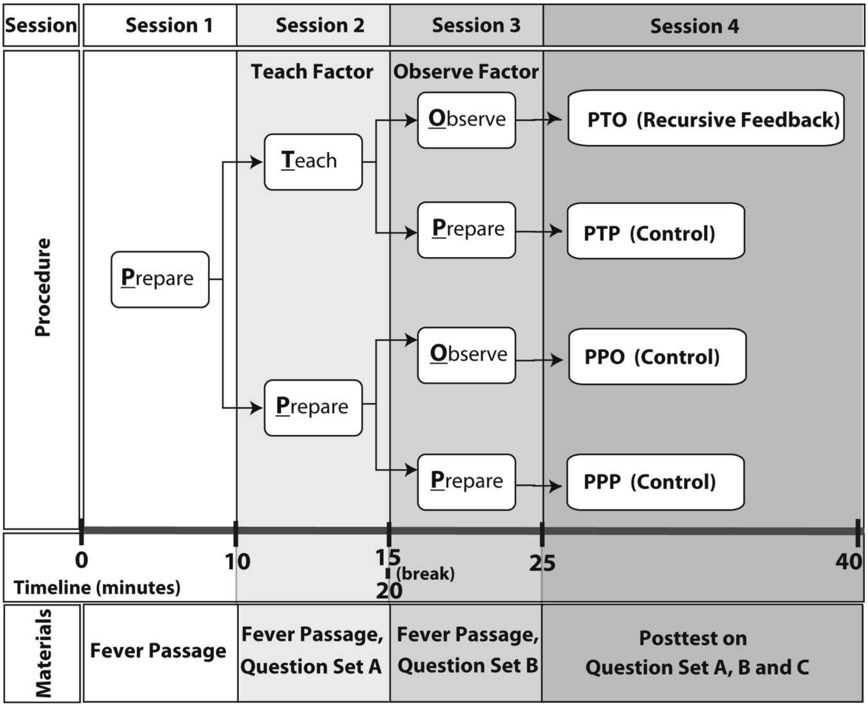

FIGURE 2 Research design and procedure for Experiment 1.

by an outside interviewer who was also a confederate. The tutors thought they were watching a postinstruction video recording of Pupil X. In reality, it was a recording made days earlier. (Pupil X wore the same outfit in the video that she wore during all of the teaching sessions.) Finally, in Session 4, the tutors took a posttest that included all of the questions in Sets A and B, plus five new questions (Set C).

The use of the three question sets (A, B, and C) requires some explanation. There were four reasons for using these. The first was to help keep the teaching interactions comparable across conditions by using the questions to focus the interactions. The second was to ensure that the quality of questions was constant across all four conditions. The quality of questions raised by a pupil can have an effect on tutor learning (Roscoe & Chi, 2008), so we wanted to control the questions so that they were not a factor in the results. The third reason we introduced questions at different points in the study was to gain some purchase on how the different phases of LBT influence learning. We predicted that the tutors in the full LBT condition would begin to show their learning advantage for Set

B (not Set A), because the Set B questions drive the RF when the tutors observe their pupil. Finally, Set C provided a test of the tutors' general mental model of fever mechanisms, because these questions were never broached during the learning phases. We also predicted that participants in the PTO condition would do relatively well on Set C, because their overall mental model would have improved as a result of the RF earlier.

The baseline control condition (PPP) appears as the fourth branch at the bottom of the top half of Figure 2. Rather than teach or observe, these tutors only prepared to teach. They received the passage and prepared to teach. They then received Question Set A and then Question Set B to help them further prepare and to maintain the same time on task as in the other conditions. As reviewed earlier, preparing to teach can have strong benefits for learning, so this condition made for a stronger control than simply asking the graduate students to learn on their own.

The most important control condition involves the second branch from the top (PTP). Tutors in this condition prepared and taught, but they did not observe their pupil, so they did not receive RF. Instead, for Session 3, they prepared for another teaching session with the help of Question Set B. One might reasonably predict that these students would exhibit the greatest learning. After interacting with Pupil X, they would have a chance to concentrate on improving their own understanding and to prepare in light of the prior interactions. In contrast, the PTO tutors who received the RF of the video recording did not receive a subsequent chance to restudy, which could have put them at a relative disadvantage for learning. Our prediction, however, was that the benefits of RF would be stronger than the opportunity to restudy.

Finally, the third control condition is represented by the third branch from the top (PPO). In this condition students prepared twice, and then they observed Pupil X. They had not taught Pupil X, so observing the video recording did not serve as RF, although it did include an opportunity to learn through observation. If the students in this condition do not perform as well as those in the PTO condition, then we can conclude that the benefit of watching the video was not simply the result of the video holding important information or models of thinking.

In terms of experimental design, the conditions created a 2 × 2 between-subjects factorial design in which preparing to teach served as the control condition for each of the factors. The factor in Session 2 is whether students prepared or taught (P vs. T). The factor in Session 3 is whether students prepared or observed (P vs. O). This creates the four conditions of PTO (RF condition), PPP (baseline prepare condition), PTP (no RF condition), and PPO (control for video content condition). Crossed with these between-subjects factors is the within-subjects factor of question set on the posttest. Set A is associated with the comparison of preparing versus teaching. Set B is associated with preparing versus observing. Set C asks novel questions as a measure of overall understanding.

Methods

Participants. Forty graduate students from Stanford University voluntarily participated in the study (average age = 29.8 years). The students' areas of study education (57.5%), humanities (20%), and engineering (22.5%). Students were randomly assigned to one of the four conditions with the constraint that area of study and gender were balanced across conditions. (Pupil X was female, and the confederate examiner in the video recording was male.)

Design. Figure 2 shows the time spent in each of the four conditions, which were created by crossing the factors of Teach (Teach vs. Prepare) and Observe (Observe vs. Prepare). In Session 1, all participants prepared to teach using the fever passage (see the online supplement). In Session 2 for the Teach factor, participants were divided so that half taught Pupil X and half continued to prepare, both using Question Set A. In Session 3 for the Observe factor, participants were further divided so that half observed Pupil X answer questions and half prepared to teach, both using Question Set B. Participants never received feedback on any answers generated from the question sets. All participants completed a posttest by answering Question Sets A and B and the new Set C (see the Appendix).

Procedure. All sessions were video recorded. Participants completed the study one at a time. The participants were told that they would eventually tutor a student about fever based on the passage and that they should prepare to teach. Students retained the passage for consultation until the posttest. In Session 2, the Teach participants met Pupil X, who was referred to by a proper name. Pupil X was a confederate used for all participants. Pupil X studiously avoided providing any new information or asking targeted questions in response to her tutors (see "Coding" for more detail). The participants were told that Pupil X had "some questions [Set A] that she needs to be tutored on, but also reflect on other issues that seem important from the passage. Please feel free to look at your notes and the passage while you tutor." In the Prepare version of Session 2, participants also received Question Set A. They were told to study the questions because "these are examples of some questions that you will need to address when you tutor. Please feel free to look at the passage as you examine the questions."

After completing Session 2, participants were given a brief restroom break. This was useful for maintaining the ruse that Pupil X was being tested during that time. Participants then began Session 3. In the Prepare condition, participants received Question Set B, and they were asked to use the questions to prepare for subsequent teaching. In the Observe condition, participants observed Pupil X, who tried to answer Set B. Participants who had taught Pupil X were told that their student had been video (and audio) recorded answering some questions. They were now going to watch the recording, and they could consult the passage as they watched. Participants who had not taught Pupil X were told the following: "Now you will watch a student answer some questions about fever. Her answers can be right or wrong. Please feel free to consult the passage as you watch." Thus, participants who had taught Pupil X thought that they were seeing *their*student answer the questions. Participants who had not taught thought that they were seeing *any* student answer the questions. As Pupil X answered the questions, she stated that she was not sure whether she was right or wrong. In fact, Pupil X gave relatively vague answers that were neither incorrect nor completely correct, and the interviewer provided no hints as to the quality of the answers. (See "Coding" for more detail.)

After finishing the treatments, the participants completed a posttest in which they answered Question Sets A, B, and C (15 questions). The posttest was administered orally and transcribed for analysis.

Coding. Table 1 provides a sample coding for one of the questions. A primary coder scored the answers to each question on a 2-point scale: 0 indicated an incorrect answer; 1 indicated a partially correct but incomplete answer; and 2 indicated a precise, detailed answer. To ensure the reliability of the coding system, a secondary coder scored 20% of the transcripts with 97% agreement.

We applied the coding scheme to three separate data sets. The first data set was the answers to the 15 posttest questions making up Sets A, B, and C. Thus, for each set of five questions, the maximum score was 10 points. The second data set came from the teaching session, which used Question Set A. First we coded the information introduced by the participant for each question using the same coding scheme. Then we coded any additional relevant information that Pupil X introduced beyond what the participant had told her. The third data set came from the video the participants observed that showed Pupil X answering the Set B questions. We coded the quality of the answers given by Pupil X. The coding

TABLE 1
Sample Coding

"Why is shivering not enough to create a fever?"	
Scoring	*Sample Response*
0 points: Incorrect, no answer	Because it is not enough, you need more.
1 point: Partially correct, incomplete	Because shivering alone creates heat, but the brain is not involved so it doesn't set the temperature set point.
2 points: Precise and detailed	You can create heat with shivering, but you also need a mechanism that doesn't let that heat escape, so you need the hypothalamus to raise the set point.

of the videotapes permitted a more careful consideration of how any information provided by Pupil X may have influenced what the participants learned.

Results

Participants who received RF—the PTO condition—did better on the overall posttest than participants in the other three conditions. The PTO condition had a mean accuracy score of 24.4 ($SD = 3.5$) out of a possible 30. This was substantially higher than all three control conditions: $M_{\mathrm{PPP}} = 16.0$ ($SD = 4.0$), $d = 2.2$; $M_{\mathrm{PTP}} = 19.2$ ($SD = 4.3$), $d = 1.3$; $M_{\mathrm{PPO}} = 17.5$ ($SD = 3.8$), $d = 1.9$. We conducted an analysis of variance with the four conditions making up the independent factor and the total posttest score as the dependent measure. There was a significant effect of condition, $F(3, 36) = 8.69$, $MSE = 15.4$, $p < .001$. A priori, we contrasted the PTO condition to each of the other three conditions pairwise. PTO outperformed each of the control conditions at $p < .01$.

Separating the results by question set further supports the positive effects of RF. Figure 3 shows that the strongest learning outcomes for the PTO condition appeared once the participants received RF (Question Sets B and C). We conducted a repeated measures analysis. Teach (Teach vs. Prepare) and observe

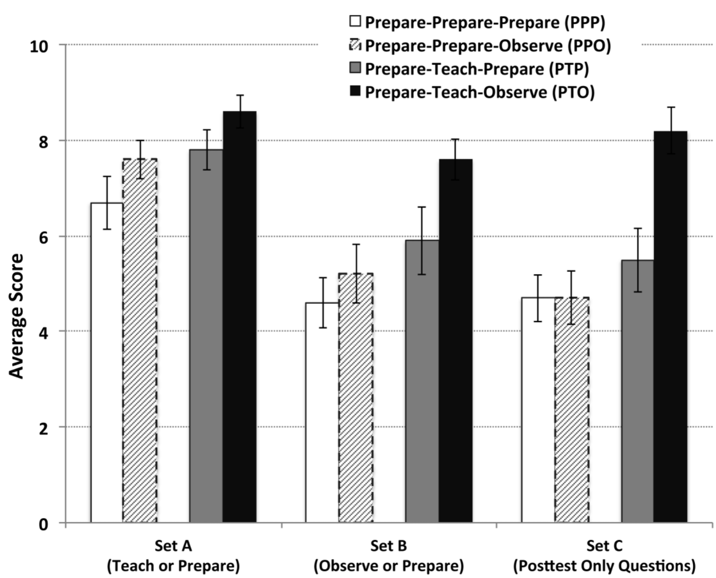

FIGURE 3 Average posttest scores for Experiment 1 broken out by condition and question set (max = 10). The error bars shown in the figure are the standard errors of each mean taken in isolation.

(Observe vs. Prepare) were crossed between-subjects factors. Question sets (A, B, C) were repeated measures that created the within-subjects factor of question set. There was a significant three-way interaction of Teach × Observe × Question Set, $F(2, 35) = 3.32$, Hotelling's $T = .19$, $p = .048$. Given the umbrella effect, we conducted a planned contrast to test a precise prediction. This prediction was that the PTO advantage would be mostly located in Question Sets B and C, which occurred during and after the RF. The relevant contrast tested for a three-way interaction between the teach factor, the observe factor, and Set A versus the aggregated Set B and C scores. The interaction was significant, $F(1, 36) = 4.88$, $MSE = 73.75$, $p = .034$, indicating that the advantage of the PTO condition was greater for combined Question Sets B and C than for Set A. This effect can be seen by noting that in Figure 3, the relative advantage for the PTO condition increases for Question Sets B and C relative to Question Set A.

Independent of the benefits of observing one's pupil, a final question for the main analyses was whether teaching (and preparing) provides an advantage over simply preparing. We compared the condition in which students only prepared to teach (PPP) versus the condition in which students prepared and taught but did not observe Pupil X's performance (PTP). Although the teaching participants did better descriptively (see Figure 3), the advantage did not reach significance, $F(1, 18) = 2.96$, $MSE = 17.3$, $p = .103$. This null effect should not be taken as strong evidence that under other circumstances teaching would not provide a benefit over simply preparing to teach. The effect size favoring teaching was relatively strong ($d = .41$), but the sample size was small.

The remaining analyses addressed the issue of whether Pupil X introduced question-relevant information that inadvertently helped those participants who either observed or taught her. The results for Question Set C, which no participants saw prior to the posttest, provide one indication that the benefit of RF was not simply a result of Pupil X introducing question-specific information. For a more refined look, we analyzed the information that Pupil X actually introduced in the sessions.

We begin with Question Set A, which was the focus of the teaching session. Using the same coding scheme used for the posttest, we coded the answers that the participants taught to Pupil X during the teaching session, and we coded the information that Pupil X introduced during the session over and above the participants. Participants and Pupil X received a coding from 0 to 2, for a maximum possible score of 10 points across the five questions in Set A. Table 2 shows the mean scores from the teaching sessions (not the posttest), broken out by those participants who subsequently observed Pupil X and those who did not. As may be seen, Pupil X was quite artful at not introducing information. She said things such as "I think I understand" and "Oh, I didn't know that." T tests indicated that the amount of information introduced by the participants or by Pupil X did not differ significantly by condition. To further determine whether the information provided by Pupil X had an effect on posttest scores, we conducted a multiple regression with

TABLE 2
Average Information Introduced During the Teaching Session

Condition	*Participant (SD)*	*Pupil X (SD)*
Teach (+ Observe)	7.8 (1.5)	0.3 (0.5)
Teach (+ Prepare)	7.5 (1.7)	0.1 (0.3)

the Question Set A posttest score as the dependent measure. Predictor variables included a main effect term for the two conditions (PTO vs. PTP), the participants' scores during the teaching session, Pupil X's scores during the respective teaching session, plus the two-way interaction terms of condition by each of the other predictor variables. The score of the participant during the teaching session was the only significant predictor of how the participant performed on the posttest ($\beta = .64$), $t(19) = 3.46$, $p < .01$. Thus, the advantage of the PTO condition over the PTP condition on the posttest was not due to any differences in the information provided by Pupil X in the teaching session.

We also coded the answers that Pupil X gave in the video-recorded interview with the examiner (who asked Question Set B). For four of the questions Pupil X received a score of 1 point, and for the remaining question she received 0 points. Pupil X did not introduce any incorrect information—she was simply incomplete or vague. We examined participants' scores on the posttest for the four questions on which Pupil X received a score of 1. Here the relevant treatment comparison is between those participants who observed Pupil X (PTO vs. PPO). On the posttest, the PTO participants gave answers that included Pupil X's information 72.5% of the time, whereas the PPO participants included Pupil X's information 57.5% of the time, $F(1, 18) = 3.6$, $MSE = 0.03$, $p < .075$. Thus, there was a marginally significant difference between the two treatments for whether participants repeated what Pupil X said. The bigger difference was that the PTO participants were more likely to build on the information they heard from Pupil X. When we compared those answers for which the participants included information introduced by Pupil X, the PTO participants went beyond the information 70% of the time (received 2 points for their posttest answer) compared to 30% for the PPO participants, $F(1, 18) = 5.0$, $MSE = 0.11$, $p < .05$. Thus, the PTO participants appeared to have been somewhat more likely to take up direct information from Pupil X, and they were much more likely to elaborate upon what Pupil X had to offer compared to those participants who had observed but not taught Pupil X.

Discussion

This experiment demonstrates that RF is useful for conceptual learning and that it should be an integral component of instructional models that include LBT. Tutors who received RF by observing their pupil's subsequent performance (PTO) outperformed tutors in three control conditions who did not receive feedback. The advantage was strong, with the PTO condition performing 2 *SD* above the prepare only condition (PPP) and more than 1 *SD* above the more closely matched prepare and teach condition (PTP). The RF promoted a better understanding of the mechanisms of fever, so PTO participants were able to answer new questions that had not been broached during the learning experiences. This learning effect cannot be attributed to any extra information that Pupil X introduced in the teaching or observation sessions. The amount of information from Pupil X was small and equivalent across conditions. Finally, the greatest positive advantage for the PTO condition did not appear until the participants had gone through the RF phase of LBT. This selective effect further identifies RF as a cause of learning. This pattern of results has been recently replicated in a virtual reality study that was otherwise identical, except that the teaching and observation activities took place in Second Life (Okita, Turkay, Kim, & Murai, 2013).

This study was not designed to isolate specific psychological factors that might have contributed to the effect, but it is still possible to detect hints of why RF was successful. Our leading interpretation is that the feedback loop enabled the participants to invest themselves in Pupil X's performance, while their memory of what they had previously taught enabled them to map the feedback recursively to their own understanding of fever mechanisms. The most direct evidence for this is that the recursive participants built on Pupil X's answers 70% of the time compared to 30% for those participants who observed Pupil X but had not taught her. This implies that the tutors were willing and able to use the feedback to figure out what was missing, which they then integrated into their understanding of the mechanisms of fever. Another possible explanation is that people find it easier to monitor someone else who is doing their thinking for them compared to having to fully generate, formulate, and monitor their own thoughts (Okita & Jamalian, 2012).

This study did not include a condition in which participants taught Pupil X and then observed a different Pupil Y answer questions. A condition that involves teaching one pupil and monitoring another would have helped to test the importance of the social connection between the tutor and the pupil. For example, participants who observe their own pupils may learn better than participants who observe another tutor's pupil, because they have a strong connection by which to make the affective and cognitive recursion. This would make a good follow-up line of research, now that the basic effect has been established. Our prediction is that the benefit of watching someone else's student is a function of the degree to which tutors project their original teaching into the pupil they subsequently observe. More generally, it would be worthwhile to identify those things that help tutors continue to think about their pupils even when they are out of sight. Such research may have useful implications for professional development courses, in which teachers presumably need to think through how their students might respond to gain the full benefit of the professional development activities.

There are alternative interpretations of the results. One alternative is that the recursive condition simply included more task variation. The recursive condition (PTO) included preparing, teaching, and observing. Compared to participants in the other conditions, the PTO participants had more varied tasks to keep things fresh and provide more contexts for thinking about the topic. Combined, these could explain the benefit of the PTO condition. For example, this could explain why the learning benefit increased during Session 3, when the participants observed their pupil. This is the time when the PTO condition uniquely introduced a third activity compared to the other three conditions. To address this concern, the next experiment held the number of distinct tasks constant across treatments.

Another alternative account of the overall results is that there is nothing special about RF. The PTO condition is simply the only condition that received feedback. For instance, the PPO students who observed Pupil X may have taken it as a pure case of vicarious learning (Fox Tree, 1999). So, despite the fact that these participants received exactly the same information as the PTO participants, they may not have interpreted it as feedback. Under this interpretation, the prudent conclusion is that feedback in LBT is better than no feedback. The next study addresses this concern. The students received identical feedback that they necessarily interpreted as feedback. The difference was whether it was direct feedback or RF.

EXPERIMENT 2: RECURSIVE FEEDBACK VERSUS DIRECT FEEDBACK

Experiment 1 provides the first demonstration that RF provides added value to learning conceptual material compared to no feedback. Experiment 2 compares RF to direct feedback to show that it is a special class of feedback. Direct feedback occurs when it comes as a direct result of a person's actions, whereas RF occurs when the feedback is a result of the independent behavior of one's pupil.

The current experiment leaves the paradigm of face-to-face human interaction in a laboratory setting. Instead, high school students tutored a TA as a way to learn logical reasoning. There were several reasons for reaching so far beyond Experiment 1. First, the move from the laboratory to classroom was to determine whether the benefits of RF would hold up in a school setting. The study was conducted with calculus students in their regular class. Second, the use of logical reasoning instead of fever mechanisms enabled a test of whether RF can support other types of learning besides declarative networks of causal relations. Third, the use of a TA enabled us to carefully match direct feedback and RF for informational content while also ensuring that all conditions received the same degree of task variation. Fourth, the TA implementation also demonstrated one way to build RF into learning technologies. Finally, we wanted to test a hypothesized key ingredient of TA, namely, the independent behavior of the agent and the RF that behavior produces.

Teachable Agents

A TA is a type of pedagogical agent (Baylor, 2007) in which students teach the computer rather than the computer teaching the student or serving as a learning companion (Chou, Lin, & Chan, 2002). TAs have been used to teach qualitative causal relations in science (Biswas et al., 2005; Chin et al., 2010), taxonomies (Chin, Dohmen, & Schwartz, in press), and mathematical topics (Blair, Schwartz, Biswas, & Leelawong, 2007; Matsuda et al., 2012; Pareto, Haake, Lindström, Sjödén, & Gulz, 2012). Each agent has a different teaching interface designed to help organize the domain content according to key relations. For instance, to teach causal relations with the TA called Betty's Brain (Biswas et al., 2005), students make a directed graph that shows how entities influence each other (e.g., "sweat → decreases → fever"). As the agent reasons, it highlights links in the graph to show how it reaches its conclusion. A major purpose of TAs is to help students learn key relational predicates and how to reason with them. For instance, Chin et al. (2010) found that using Betty's Brain for one science topic (e.g., living systems) transferred to prepare students to spontaneously learn causal relations in a different science topic (e.g., the water cycle), even after the technology had been withdrawn.

Across the different TAs and their varied interfaces and instructional goals a common property is that the agent independently uses what it has been taught, for example, in response to a mentor agent that asks questions or when deciding what to do in a game. In this way, the TA provides RF to the tutor. The current study is the first rigorous test of whether RF is an important ingredient of the technology.

Moby: A Teachable Agent for Hypothetico-Deductive Reasoning

The TA designed for this study was named Moby. Students can teach Moby to solve problems in a game-like environment, or they can solve the same problems themselves in the same game environment. This permits a tightly matched comparison of direct feedback and RF. Moby was designed to help students learn the process of hypothesis formulation and the subsequent testing of the hypothesis's implications. Hypothetico-deductive reasoning is notoriously problematic for children and adults (Johnson-Laird, 1983; Kuhn, Schauble, & Garcia-Mila, 1992), so scaffolds that support reasoning and improve performance after those scaffolds are removed would be a positive outcome. In the following study, we did not include meaningful content (e.g., true science hypotheses).

We wanted to help students learn foundational logical concepts for hypothetico-deductive reasoning, including conjunction, disjunction, negation, and the distinction between necessity and sufficiency. There is evidence that topical content can cause people to reason intuitively rather than formally (e.g., Wason & Johnson-Laird, 1972), which can block their appreciation of the subtleties of formal reasoning. Fortunately, removing topical content does not reduce the appeal of logic games, given the success of logic software programs such as Zoombinis (Higgins, 2000), Hyperproof, and Tarski's World (Barwise & Etchemendy, 1998).

Moby is played in rounds. Each round has three primary activities. The first activity involves inducing the rule that regulates the appearance of flowers. Students receive a grid in which some cells show a flower and some do not. Students can overlay four different factors and their combinations to induce the rule. In the left panel of Figure 4, a student has overlaid a single factor (water) that is not responsible for the outcome (flowers). In the right panel, the student has overlaid the correct factor (sun). The underlying rule for this grid is "Sun is necessary and sufficient for a flower to appear." A rule, however, can be more complicated; for example, "Fire or shade is sufficient but not necessary for the absence of a flower."

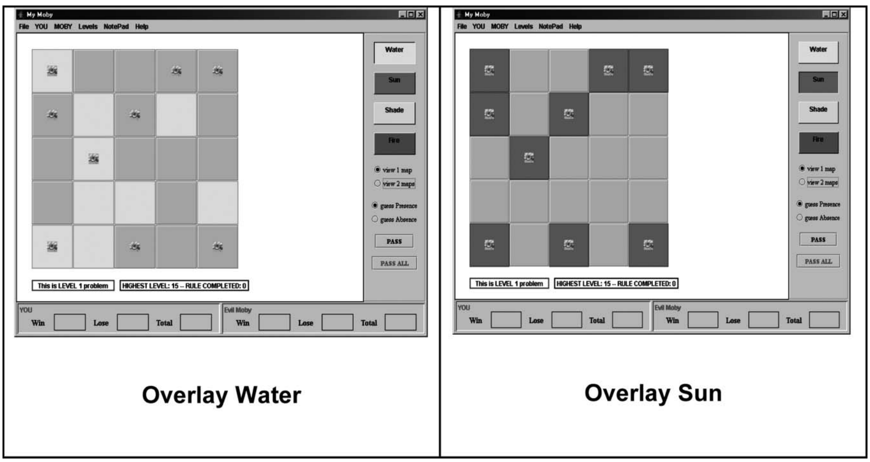

FIGURE 4 Two examples of a student overlaying a factor to help induce conditions that cause an outcome. For each game, students need to induce a rule about the factors that determine where flowers appear on a grid. Students click the buttons to the right of the grid to toggle an overlay that shows the locations of various factors. In the left panel, the student has clicked on "water," and the lighter squares show where water is present. In the right panel, the student has clicked on "sun," and the darker squares indicate where it is sunny. The perfect correspondence of the dark squares and the flowers indicates that the rule for this game is as follows: Sun is necessary and sufficient for a flower to appear.

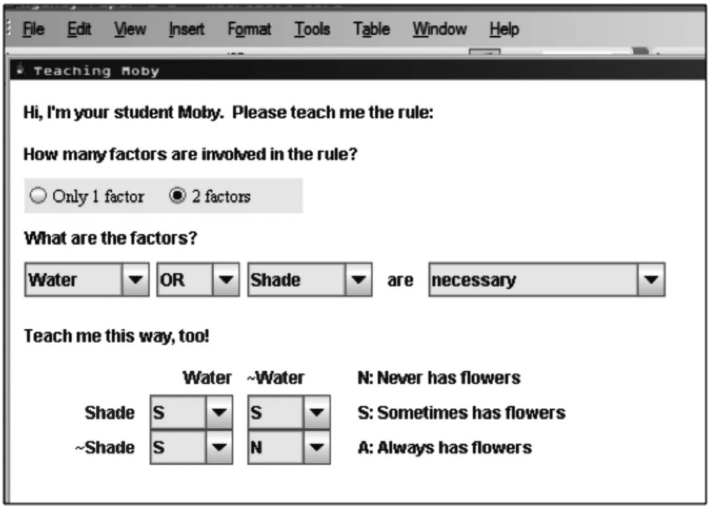

FIGURE 5 Students teach Moby using propositional and matrix formats. Once students believe they have induced the rule, they need to teach Moby using one of two formats or both. Here, the student has determined that the rule depends on two factors. In the propositional format, the student uses pull-down menus to indicate the factors (water and shade), the logical connective (or), and the governing relation (necessary). The matrix format shows the four possible combinations of the two factors (water vs. ∼water by shade vs. ∼shade). The student uses a pull-down menu to indicate whether a flower appears for each combination (never, sometimes, always). The matrix expresses the rule: Water or shade is necessary (but not sufficient) for a flower to appear.

Once students believe they have induced the rule, they move to the second activity of teaching Moby. To teach Moby, students formally describe their hypothesis. Figure 5 shows that there are two representations that students use. The students use the pull-down menus at the top of the figure to specify a propositional representation of the rule. They specify the relevant factor(s), their logical combination, and the governing qualifier (Necessary, Sufficient, Necessary & Sufficient). The students teach using a matrix representation, shown at the bottom of the figure. After choosing the factor(s), the students fill the cells with (A)lways, (S)ometimes, (N)ever, indicating when flowers appear in these cells. The software randomly presents one or the other teaching interface or both. When students have to use both representations simultaneously to teach a rule, the software alerts them to inconsistencies between the two specifications and prompts the students to try again until the two forms are consistent.

In the final activity, students observe Moby playing a prediction game. In this activity, a new grid is generated. The flowers are hidden, and Moby needs to guess where the flowers are by using the rule it was taught. Moby lays down the factors specified by the rule and chooses one cell at a time to predict either the presence or absence of a flower. Feedback consists of a yellow smiling face in the cell if Moby is correct and a yellow frown if it is not. After Moby takes a turn predicting a cell, a second agent named Evil Moby takes a turn predicting a cell of its choosing. Feedback for Evil Moby appears in red. Evil Moby receives a rule from the underlying computer code to make its predictions. Evil Moby's rule is correct about 20% of the time, and in the other instances, it is a randomly generated rule. A scoreboard keeps a tally after each turn. To win the round, the Moby needs to score more points than Evil Moby. Figure 6 shows Moby and Evil Moby midway through a prediction game. The game ends when all of the cells have received predictions.

To move up a level, the TA needs to win two rounds in a row. Each round within a level uses the same logical form, but the factors change (e.g., A & ∼B

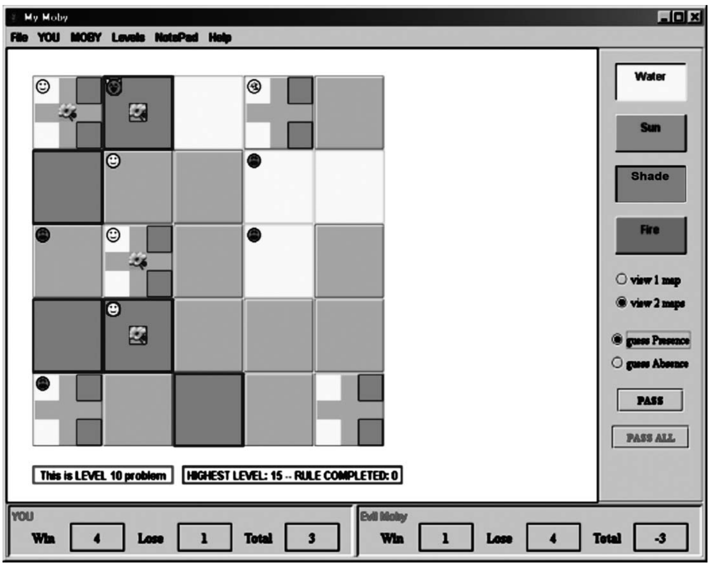

FIGURE 6 The teachable agent Moby plays against Evil Moby to see who better predicts where flowers appear. The student taught Moby that water and shade are necessary for a flower to appear. (This rule is incorrect.) Using the rule, Moby shows its reasoning by first toggling the water and shade overlays. Cells with water appear in white, and cells with shade appear in dark grey. Squares in the corners indicate that both are present. Moby takes a turn predicting where a flower will appear or not. If there is a flower, it appears. Moby's predictions are scored as correct or incorrect with a smiling or frowning yellow face (in light gray). After Moby's turn, a competitor agent (Evil Moby) makes a prediction. Its accuracy is indicated with a red smiling or frowning face (darker gray). Moby and the competitor take turns until all of the flowers have been revealed. The game has not finished, but Moby is winning so far.

are necessary for a flower; B & ∼C are necessary for a flower). If Moby fails at a round, students can reteach Moby for that round (and go back to the induction activity if they wish), or they can simply let Moby try again to win two rounds in a row. Each level of the game uses increasingly complex rules.

Overview of the Study Design

To compare direct feedback and RF, we created a second version of the game that provided direct feedback. There was no TA (Moby). Instead, for each round, students induced the rule and then played Evil Moby themselves in the prediction game. The feedback was to their own actions instead of their agents' actions. Afterward, students explicitly formalized their rules using the interface in Figure 5, or they explained their rules in free text. Thus, these students also had a chance to formalize their rules. The difference from the TA condition was that their formalization was for expressing their ideas rather than teaching an agent.

All told, there were four conditions. In the Control condition, students never used the software and simply took a reasoning posttest. For the other three conditions, students played the game for about 75 min. In the Teach condition, students taught an agent who played the game. In the Represent condition, students played the prediction game themselves, and after beating Evil Moby in a round, they used the same sentential and matrix interfaces as the Teach students to describe their hypothesis (see Figure 5). Finally, in the Explain condition, students played the game themselves, and after they beat Evil Moby, a text window appeared asking them to explain the rule they used. In the Explain condition, students did not see the sentential or matrix representations and simply had to find a way to express their ideas. If RF is a unique type of feedback, then we should expect the students in the Teach condition to do the best on the posttest, even though students in the Represent and Explain conditions had to induce and formulate rules and received direct feedback.

To assess the effects of the different conditions, we had students complete a reasoning posttest. There were three classes of questions (see the online supplement). The first type of question, induction questions, asked students to infer a rule given a set of factors and an outcome presented in tabular form. They had to describe the rule and answer a question to confirm that they understood the rule. The second type of question required drawing implications given a rule. These problems required hypothetico-deductive reasoning. For example, one question was a variant of the selection task (Wason & Johnson-Laird, 1972), in which people need to choose an empirical test to check if a rule is being followed:

> Mrs. Smith thinks that the famous Brazil Cockroach needs a wet climate or warm nights to breed. The Brazil Cockroach will destroy her corn crop. If you want to see if she is right, where would you check and what would you look for?

This is a notoriously difficult type of question because people tend to exhibit a confirmation bias and choose those situations that are consistent with the rule (i.e., look for cockroaches in wet or warm climates) rather than those situations that would falsify the rule (i.e., cockroaches in a cold and dry climate). If students in the Teach condition exhibit an advantage on the implication problems, this would be a promising finding given the difficulty of improving logical reasoning (Nisbett, Fong, Lehman, & Cheng, 1987). Finally, the third type of assessment item asked students to translate between sentential and matrix/tabular expressions of a logical rule. This was intended to evaluate whether students learned to interpret the formal representations and whether this differed between the Teach and Represent conditions.

Methods

Participants. A total of 94 high school students from four calculus classes at a public high school participated in the study. Each class participated at a separate time spread over 2 days. Students within each class were randomly assigned to one of the four conditions. To provide the best possible glimpse of students using the full system, we did not assign students in equal numbers to each condition. The Teach condition, which used the full TA system, had 40 students. The Represent and Explain conditions had 27 students and 12 students, respectively. We had intended 20 students for the Represent and Explain conditions, but there was an experimenter error. However, this error did not undermine the goal of having roughly equivalent samples of those who received RF and those who received direct feedback. The Control condition had 15 students.

Design and procedure. When students arrived at the computer lab with their class, they received a password that determined which condition would appear when they logged on. Students in the Control condition completed other activities. Students worked for roughly 75 min, and a day or two later, they completed a paper-and-pencil posttest as an in-class assignment.

Students who used the software progressed through a series of increasingly difficult logical rules, all of which used flowers as the outcome and the same four factors (sun, fire, water, soil). Recall that we wanted students to focus on logic rather than content. The first five rule levels used single-factor rules and progressed as follows: Factor X is necessary and sufficient, Factor not-X is necessary and sufficient, Factor X is necessary, Factor X is sufficient, and finally a randomly chosen single-factor rule from all possibilities. The next five rule levels used two factors. They began simply, as in Factor X and Factor Y is necessary and sufficient, but progressed to complex rules, as in Factor not-X or Factor Y is necessary. The final five levels were randomly generated for each student from all possible 1-factor and 2-factor rules.

To move from one level to the next, students (or their agent) had to beat Evil Moby at predicting flowers twice in a row for a given rule. For each level, the system generated a specific instantiation of a rule by randomly selecting which factors were involved. For example, for Rule Level 3 students might first have to induce “Fire is necessary” to beat Evil Moby, and then for the next game they might have to induce “Soil is necessary.” If they beat Evil Moby for both rules in turn, they moved to Rule Level 4. If they failed to beat Evil Moby, they started over for that level.

For the Explain condition, whenever students beat Evil Moby in a round, a text window appeared that asked them to explain the rule. Students had to type in a free-text response before the system would provide the next problem. For the Represent condition, whenever students beat Evil Moby, the sentential menus, matrix menus, or both appeared (with equivalent odds). Students had to fill in a rule to proceed to the next game. (If students entered conflicting rules when they received both the sentential and matrix formats, the system would tell them to make them consistent.) For the Teach condition, the process was similar, except that Moby, whom they had taught, had to beat Evil Moby twice in a row instead of the student beating Evil Moby.

After completing the instructional phase, the students completed a paper-and-pencil posttest in a regular classroom setting. The posttest had two 1-factor and two 2-factor induction problems, five 1-factor and five 2-factor implication problems, and two 1-factor and two 2-factor translation problems (see the online supplement for examples). We included a larger sample of implication problems because they did not depend on any familiarity with specific formalisms that students may have acquired during the game.

Results

Students appeared to enjoy the game and worked steadily from the beginning of the 75-min period to the end. The students in the three game-playing conditions reached about the same rule level in the game with no significant differences (max = 15): $M_{\text{Explain}} = 10.4$, $M_{\text{Represent}} = 10.3$, $M_{\text{Teach}} = 11.4$, $F(2, 48) = 0.77$, $MSE = 8.9$, ns. Thus, all groups had similar levels of exposure to instances and complex rules.

Each question on the posttest was coded as correct or incorrect. Scores were aggregated by question type to make a percentage of correct answers for the induction, implication, and translation problems. Figure 7 displays the condition averages for each question type. The Teach condition did best across all three question types.

To analyze the data, we entered each student’s performance for the three question types into a Question Type × Condition multivariate analysis. Overall, there was a significant effect of condition across the aggregated measures, $F(3, 90) =$

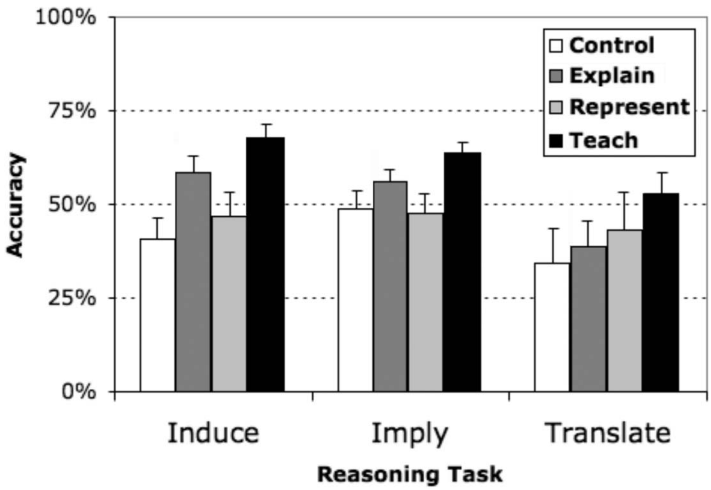

FIGURE 7 Posttest performance broken out by question type and condition for Experiment 2. Error bars represent the standard error of the condition mean for the question type.

4.9, $MSE = 0.04$, $p < .005$. A priori, we had predicted the following order of outcomes for the aggregate measures: Teach > Represent = Explain > Control. Therefore, we completed the following planned contrasts. The Teach advantage over Represent was significant ($p < .05$). The Explain and Represent conditions were not different ($p = .43$). However, contrary to our hypothesis, the Control and Explain conditions were not significantly different ($p = .12$). Given the rejection of the a priori hypothesis that Explain would do better than Control, we expanded the analysis. A post hoc LSD analysis compared all of the conditions pairwise at $p < .05$. The nonconservative LSD test increased sensitivity to possible differences among the three control conditions. None of the control conditions were significantly different from one another at this sample size, although the Teach condition led to significantly better performances than either of the other three conditions. The effect sizes of the Teach condition versus each other condition were as follows: Control, $d = 0.95$; Represent, $d = 0.75$; Explain, $d = 0.47$.

It is surprising that there was no Question Type × Condition interaction, $F(6, 180) = 0.73$, ns. This means that the Teach condition did significantly better on all three types of questions compared to the other conditions, and the other conditions exhibited no significant differences among themselves on any of the question types. We had expected the Represent and Explain groups to do better than Control on the induction and implication problems, because they had just played the game and leveled up. We also expected the Represent group, which had used the formal representations, to do better than the Explain and Control conditions on the translation problems. Figure 7 shows a trend in this direction, but the trend does not reach significance. With a larger sample, it is possible the contrast would have reached significance.

When we look at the specific questions, we find that the Teach condition did better on each question. For example, on the difficult (cockroach) selection task, 25% of the Teach students gave the correct answer compared to 10%–13% of students in the other three conditions.

Discussion

Working with the TA significantly improved students' abilities to induce hypotheses, test deductive implications, and translate between different forms of logical assertion as compared to otherwise similar students who simply took the posttest. The novel posttest questions had low surface similarity to the game itself, so the students made a transfer beyond the game. However, TA students also knew that the posttest was relevant to what they had done before. Such a cued transfer test is unlikely to predict whether these students will spontaneously use logical reasoning in their everyday lives. Nevertheless, the students learned an important distinction between necessary and sufficient, as well as how to reason about negations and disjunctions. Presumably, these concepts will be explicitly cued as students move into more advanced curricula, so the students should be able to apply them and learn the curricula more deeply.

The Teach condition also performed better on the posttest than the two game conditions, Represent and Explain. The advantage is notable because students in the other game conditions not only received feedback (direct) but also had to explain or represent their correct answers, which is known to enhance learning (e.g., Siegler, 2002). Also, across the conditions, participants achieved equal levels in the game. This indicates that the differences in outcomes were not due to the level of problem exposure or success at mastering the game. The fact that the conditions achieved similar levels in the game but exhibited strong differences on the posttest serves as a cautionary note for designers of learning games. Leveling up in a game may not be a satisfactory assessment of learning, because gains within the game may not predict how well students will perform when the specific formats and supports of the game disappear. Although the Represent and Explain students leveled up by solving increasingly complex problems, their posttest scores were not significantly above those of the Control students, who never played the game.

The Teach and Represent conditions were most closely matched. When playing against Evil Moby, both groups received feedback and filled out the formal representations to express their induced rule. The principal difference was that the feedback for the Teach group was recursive, whereas the feedback for the Represent group was direct. Why did RF work better?

One possibility involves the independence of TA behavior. To generate RF, the agent needs to perform independently of the tutor. Moby plays the game, not the tutor. This means that students need to teach rules that Moby can use for any relevant situation. In contrast, the Represent students could get by with situational problem solving, for example, by taking advantage of a particular detail of opponent play. So, rather than producing a general explanation and viewing the formal representation as the embodiment of that explanation, the Represent students could produce unique solutions that were good enough for the game at hand, which Martin and Schwartz (2009) demonstrated is a characteristic of novices. By this account, one explanation of the results is that the non-TA students never had to think about the general implications of their rules, because they were solving each move in each game without necessarily referencing any rules they formulated. Although gaming the system is clever, it may not be the best way to learn general logic.

GENERAL DISCUSSION

In the current research, RF was operationalized as a situation in which teachers observe their pupils use what they have been taught in an independent performance context. In this section, we first review the immediate implications of the two studies while considering some limitations and next steps. We then situate RF more broadly to clarify other compelling forms of learning that do not involve LBT but still involve gaining feedback from the embodiment of one's thoughts. For example, when people design a product, they put their ideas into an artifact, and they receive RF when they see other people engage their artifact.

Review of Findings and Possible Applications

In the first study, college students learned when they taught and received feedback by observing their pupil. The effect was large. Compared to students who only prepared to teach, students who received RF performed 2 *SD* better on the posttest, and compared to students who taught without feedback, the gain was a full standard deviation. Although explaining is a powerful way to learn, and it has been identified in numerous publications (e.g., Chi et al., 1994; Ploetzner et al., 1999), seeing the subsequent use of those explanations substantially amplifies the positive effects.

The immediate implication is that collaborative pedagogies like peer tutoring can be augmented by ensuring that tutors see how their pupils perform after instruction. The implication also extends to instructional models that include an implicit LBT component. For instance, students may conduct research and then present (teach) the rest of the class. Presumably, these students would learn even more if they could subsequently read their classmates' answers to a relevant posttest.

A limitation of the study was that the confederate, Pupil X, was not blind to condition. Data analyses indicated that Pupil X did not introduce more information to one condition than another. Nevertheless, it is still possible that Pupil X differentially engaged the students in subtle ways. There are also numerous generalization issues that follow from a study designed as an existence proof: Would the effects hold up with other topics, with students who are not enrolled at an elite university, with younger students, with pupils whom the tutor does not like, in classrooms, without scripted questions, with less interactive teaching, and so on? We hope that the strength of the current results merits research into these questions and others.

In the second study, high school students who taught a TA improved their hypothetico-deductive reasoning by a standard deviation over students who never played the game. This finding complements two other TA findings. The TA called Betty's Brain helped fifth-grade students learn causal reasoning, which they subsequently transferred to learn new science content better (Chin et al., 2010). A TA that modeled hierarchical reasoning helped fourth-grade students learn to reason about class inclusion (e.g., a ladybug inherits the properties of insects; Chin, Dohmen, & Schwartz, in press). Combined, the evidence suggests that teaching an agent that makes thinking visible in transparent, consistent, and circumscribed ways can help students learn important reasoning schemas.

Regarding LBT, the study isolated the value of RF compared to direct feedback. Students who taught the TA did better than students who played the same logic games and received feedback for how well *they* played. Some of these latter students were even required to express their rules using the same formalism as the TA students. We can speculate that in their case, the formalisms lacked representational force—the expression of the rules had no effect on the world and did not generate feedback. The immediate implication is that when students are asked to organize their knowledge, for example as a graph, paragraph, or symbolic notation, it is valuable for them to see how other people use that organization to solve new problems.

The second study raises an interesting question about the value of feedback toward one's rules versus one's actions. Students' interpretation of the TA's behavior was presumably with respect to the rules the TA had been taught. In contrast, in the Represent condition, the feedback was about students' actions in the game and not the rules they filled out. A useful next study could include a condition in which the Represent students also receive direct feedback about their rules (e.g., right/wrong feedback). This would help determine whether direct feedback toward one's rule formulation is as valuable as RF about the rules one has taught.

The Production–Appropriation Cycle (PAC)

Research on feedback often makes a hard distinction between a malleable agent and a regulatory environment that influences that agent. The separation of roles is simple and empirically tractable. It also neglects a major characteristic of human learning. People do not just adapt to or learn from the environment. People also adapt the environment to suit their needs (Kirsh, 1996). Moreover, when they transform their environment, they receive feedback that causes them to change yet again and learn from unforeseen consequences. This creates a system of adaptive exchanges between people's intents and the environmental changes. For instance, humans changed their environment by creating cars, and in turn people have had to adapt to cars, which continue to bring about a host of unanticipated issues, good and bad, from which people learn.

When one moves to the interpersonal level in which people exchange and adapt ideas, the cycle of adaptations becomes the dialectic of production and appropriation (see Engeström, 1999). When a person, say Doris, produces ideas for other people, Doris can appropriate or learn from how those other people use her ideas. More to the point, the students who taught the TA produced its rules, and in turn they appropriated the logical reasoning the agent used. The RF made this possible. Without the RF, the dialectic was broken and students did not learn very well.

For clarity, instead of *dialectic* we use the expression *production–appropriation cycle* (PAC). The current studies concentrated on the appropriation side of the PAC. The studies took the tactic of breaking the appropriation loop to show that RF is important. In the first study, for example, one group of students taught but did not get to observe their pupil subsequently answer questions, so there was no chance for appropriation. They did more poorly than the students who did observe their pupil. Studies can also be designed to break the production side of the loop to show that the full cycle is important. The first study included an example of how this might be done. Students prepared to teach and then observed a pupil whom they had never taught. Thus, they never produced ideas in a pupil, but they did have a chance to observe and appropriate from a pupil. These students did not learn any more than students who never observed the pupil, so they appropriated very little. It would be worthwhile to conduct more targeted studies of the hypothesis that production facilitates appropriation.

Recursive Feedback More Broadly

RF should arise for any PAC, not just for teaching. In the current studies, the chain of influence comprised tutor → pupil → tester. We propose that this chain effectively generalizes to situations in which people embody their ideas in artifacts and not just a pupil. The more general chain might be described as person → embodiment → other person (e.g., maker → product → consumer). The first part of this chain (production) is explicit in numerous product-focused pedagogies, including constructionism (Kafai & Resnick, 1996), design-based learning (Kolodner et al., 2003; Penner, Lehrer, & Schauble, 1998), project-based learning (Barron, 1998), and reflective practice (e.g., Schön, 1983). The latter part of the chain, however, is often left implicit.

When feedback arises for the first part of the chain, it may be called *first-order* RF. By first-order RF, we mean that students are observing their artifact or intervention without any direct social mediation; for example, they might observe whether their computer program, mousetrap, or electrical circuit works as intended. First-order RF should be useful for learning because a student "contemplates himself in a world that he has created" (Marx 1844/1972, p. 62). For instance, Etkina et al. (2010) demonstrated that college students who produced their own experiments coupled with a reflection rubric developed more scientific abilities than those who followed a research script.

The latter part of the chain—observing what other people make of one's embodied ideas—creates *second-order* RF. Papert (1991), the originator of constructionism, provides a helpful quote:

> Constructionism . . . shares constructivism's connotation to learning as building knowledge structures irrespective of the circumstances of learning. It then adds the idea that this happens especially felicitously in a context where the learner is engaged in constructing a *public* entity whether it is a sand castle on the beach or a theory of the universe. (p. 1, italics added for emphasis)

The word *public* should not simply be interpreted as "external." Public includes a social component. The ideas need to be taken up by others. This is how learners can appropriate and learn from the ways in which others use their ideas. The practical implications for formal instruction are straightforward. If there are lessons that give students the opportunity to produce (and not just reproduce), then those lessons will be more effective if students have an opportunity to see what other people do or think with their products.

Many instances of informal learning appear to engender a PAC, because many activities involve design, do-it-yourself projects, and, more generally, the creation of products and performances. Halverson (2013), for instance, described media arts programs that support the development of representational abilities. If it is true that these activities create a PAC, then it should be possible to find evidence for the role RF contributes to learning and motivation within informal environments.

Pfaffman (2003) provided promissory evidence. He interviewed and surveyed hobbyists (e.g., beer brewers, model rocketeers, musicians) about their satisfactions. Uniformly across hobbies, the top satisfaction was seeing the fruits of their labor. This captures the production half of the PAC and first-order RF. Two other satisfactions were also consistently in the top five. One was sharing their products or performances with others. This captures the second-order RF and appropriation side of the PAC; the hobbyists wanted to see and learn from how other people used and responded to the fruits of their labor. Finally, people rated highly the opportunity to learn more so that they could produce further, which points to the spiral or expansive (Engeström, 1999) nature of the PAC. It is interesting that when Pfaffman asked high school students about the satisfactions of their favorite classes, they also gave top ratings to producing and sharing. For formal education, a key question is whether students would better engage in topics they might otherwise not choose if the classes included more PAC experiences.

CONCLUSION

There are a number of formal and informal learning arrangements in which learners incorporate their ideas into external entities, whether other people, products, or performances. These arrangements can be beneficial for both learning and motivation. Much of the relevant educational literature emphasizes the significance of constructing, explaining, or contributing. We have tried to highlight the special nature of the feedback that arises from these productive arrangements. By using the term *productive* we do not mean useful, although utility for learning is a likely side effect (Kapur & Bielaczyc, 2012). Rather, we mean producing something, which can involve design, fabrication, orchestrating, or simply teaching another. RF from production activities is unlike feedback that simply indicates good or bad or how one should think or do. RF shows how other people have taken up one's ideas. Seeing how people use one's ideas is an affirmation of one's productive agency (Schwartz, 1999), and evidently it is also powerful for learning.

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APPENDIX

TABLE A1
Experiment 1, Question Sets A, B, and C

Set	*Questions*
Set A	1. Does a fever usually do good or bad to your body? If so how? 2. Why do your hands and feet get cold when you have a fever? 3. What processes cause the body to increase temperature? 4. What does aspirin/Tylenol do? 5. When you have a fever, does your body's cooling mechanism shut down or does the heat production kick in?
Set B	1. How is the brain involved with the fever? 2. What is the relation between TRH (thyrotropin-releasing hormone) and TSH (thyroid-stimulating hormone)? What is the main purpose of the two? 3. How does the body get rid of the fever? 4. Why is shivering not enough to create a fever? 5. Birds do not have hair and they do not sweat. But piloerection also helps them have a fever. How?
Set C	1. Why does a dry nose mean a dog might have a fever? 2. When do you know that your body is recovering, and why? 3. Imagine that there are no pathogens in your body and your body temperature is normal. If you take an aspirin, your body will not cool down. Why not? 4. Here is a common situation: People wake up all sweaty, and they are finally cured from their flu. Does the sweating help them to cure their flu? 5. Why do you get fatigued when you have a fever? Is it helping the body? Or is it a side effect?