In the full proposal, we will describe research that supports the common intuition that people learn when they teach. Our agents have been designed to capitalize on three significant phases of teaching, each with complementary benefits. In the teaching phase, students teach the agent. The representational structure of the agent shapes student thinking about the domain. In the performance phase, students watch their agent perform based on how well it has been taught. Much like a coach whose child is playing in soccer, students find this autonomous performance highly motivating and engaging, and they want their agent to do well. Moreover, students receive important feedback about their own understanding. In the revision phase, students improve the agent’s understanding (and their own) by consulting additional resources and improving the agent’s knowledge structure. We describe how each agent implements this three-phase cycle.

Betty’s Brain is our initial effort. Betty was designed to meet three challenges that we considered significant for all subsequent agents. First, we wanted to see if we could make a domain independent agent that could be used for multiple topics and adapted by teachers. Unlike intelligent tutors, we wanted Betty to be flexible and easily adapted by classroom teachers who might generate activities we had not foreseen. Second, we wanted to create an agent that incurred low startup overhead for students. When learning by programming, students need to learn a programming language. With TAs, we wanted students to focus on teaching domain content immediately. Third, we wanted to create an agent that made thinking visible. Unlike computer simulations in which the underlying domain rules are often hidden, we wanted Betty’s reasoning about a domain to be readily open to inspection.

In the teaching phase, students teach Betty by drawing qualitative causal graphs. These graphs are similar to concept maps except they have a more constrained semantics that organizes student thinking and that permits generic AI techniques to draw inferences based on the concept map. For example, in a simple map of a pond ecosystem, students might teach Betty that fertilizer increases algae, algae produce oxygen, algae increase bacteria greatly, and that bacteria consume oxygen. In the performance phase, students (or teachers) can ask Betty text questions; for example, what happens to oxygen if fertilizer increases. Betty answers by animating the links that she traverses to find the solution. Betty also describes her answer in text and text-to-speech; in this case, oxygen decreases when fertilizer increases. Students can “unpack” Betty’s reasoning so that she explains each of her chains of reasoning. (For example, how algae increase oxygen, but decrease oxygen through the mediator of increased bacteria.) In the revise phase, students can modify and add new
concepts and links to Betty’s concept map. In initial studies, secondary-school students were able to teach Betty after 5 minutes of instruction, and they found her very motivating. In a study with college students, students had to teach Betty about cell metabolism based on a text chapter on exercise physiology. As a comparison, another group of students wrote a 1- to 2-page paper under otherwise identical conditions. Students who taught Betty discovered that they were thinking in terms of correlation rather than causation, whereas the summary students did not. The Betty students also exhibited more complex chains of reasoning at posttest, and they learned more when they read the passage a second time.

We designed Orbo based on research we have been conducting under an NSF grant that is teaching secondary school students descriptive statistics. Orbo meets the challenges we set for designing Betty. For example, in the figure, students have taught Orbo how to find the average. The image shows how we made thinking visible. We also set the design challenge of having students teach by showing. This introduces an interesting problem, because Orbo has to infer what students mean to show. For example, when showing a young child a can of Coca-Cola and saying “coke,” the child needs to infer the intended referent. Does “coke” mean the color red, the liquid inside, the can being held, and so forth? Similarly, Orbo needs to infer what students have in mind when they demonstrate an operation over a set of numbers. For example, if students subtract the first and last numbers from a distribution to find the range – do the students mean the first and last numbers, or the smallest and the largest? The challenge for Orbo is doubly complex, because the students often do not precisely know what they should mean. After all, they are learning. Our solution to this “double grounding problem” is to turn it into a natural mechanism for learning. Orbo helps clarify his understanding of what students mean in the same way that Orbo helps students learn what they mean. For example, students may teach Orbo a range formula to find the spread of a group of numbers. Orbo then provides a contrasting case. For example, he presents the distributions \{1, 3, 5\} and \{1, 3, 5, 7, 9\}. Students notice that he gets the same answer to both problems. At the same time, they realize that their spread formula did not take into account the middle numbers of the distribution. This leads them to reteach Orbo and clarify to themselves what the “spread” refers to. We have tested the approach of asking students to invent formulas over contrasting cases without Orbo. Comparisons between 150 9th-grade students who completed the activities and college students who had taken a semester of statistics showed that the approach is very successful. Orbo permits us to improve on this instruction; for example, students can teach Orbo as homework on the web, which prepares them for the next day’s class.
Our last agent is Moby. Moby is a teacher-extensible agent that includes personalities. It has been designed to meet the daunting challenge of helping students learn the logical force of scientific hypotheses. Children, as well as adults, have trouble thinking about evidence that would falsify a hypothesis and in revising their hypotheses in the face of negative evidence. Moby may provide some help by visualizing the negative case, as well as offering a vehicle for teaching domain-specific science concepts. Students begin by inducing a hypothesis of the factors that are necessary and/or sufficient for the presence or absence of an outcome. Students see a map that shows the locations of a particular outcome (e.g., a flower). Students choose factors to overlay on the map. These factors represent tentative hypotheses. Once students believe they have induced the underlying rule, they teach Moby with one of several different representations (e.g., a 2 x 2 table, a sentence, etc.). Afterwards, Moby uses the rule to play several prediction games against Evil Moby. Based on the results, students can revise the rule they have taught Moby, or they can attempt to induce the rule again or consult text resources that provide explanations of the phenomenon under study.