Predicting Students' Need For Help Using Pre-test Data

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Abstract

This paper proposes a methodology for using information about student ability based on pre-test data to predict when a student is likely to need help in advance of the student requesting it. The methodology differs from approaches commonly used in interactive learning environments because it proposes to derive information from a pre-test of the students to scale their ability in the domain being taught. It then scales the difficulty of problems they will tackle in the learning environment, using the same metric. By comparing the two, useful information about how difficult an individual is likely to find a particular problem can be derived. This will enable the learning materials to be sequenced in a way that progresses smoothly for that student and allow the tutor component to predict when the student will need help, and be ready to give it. This paper addresses a traditional form of interactive learning environment, Intelligent Tutoring Systems (ITS), but the principles discussed could be applied to any system making decisions about when to give help.

The problem to be addressed

One of the persistent challenges in the development of intelligent learning environments is how to determine accurately when a student needs help, and then determine what is the best help for that individual student. To do this, many systems make estimations of the probability that a student has gained a particular knowledge or skill. The estimates are usually based on whether or not the student gets a series of problems, or steps in a problem, correct. For example, in the PACT Geometry Tutor, which was developed at the PACT Center at Carnegie Mellon University (Aleven, Koedinger, Sinclair, & Snyder, 1998), as in many systems, a hint is given to a student when an incorrect response is given, or when the student requests help. Then, the procedure is often to offer a series of progressively more helpful hints until, hopefully, the student gives a correct response.

The basic approach of such systems is to model the learning of the student as is illustrated in a model proposed by John Self (1999) that is reproduced in figure 1. In this model, a student using an Intelligent Tutoring System (ITS) passes through a series of situations (s_1, s_2 .. s_m) via a sequence of events. When a student has reached situation s_m there are several events ($event_1$ .. $event_m$) that could possibly follow. Each event leads to a different updating of the student model s_{m1} .. s_{mn}. An ITS must make this decision repeatedly as it models the learning of a student. One could examine each possible event in turn and, using the Model of Learning, determine which student model would exist if that event happened. Then, the optimal student model could be determined and the student could be directed or prompted to the best course of action.

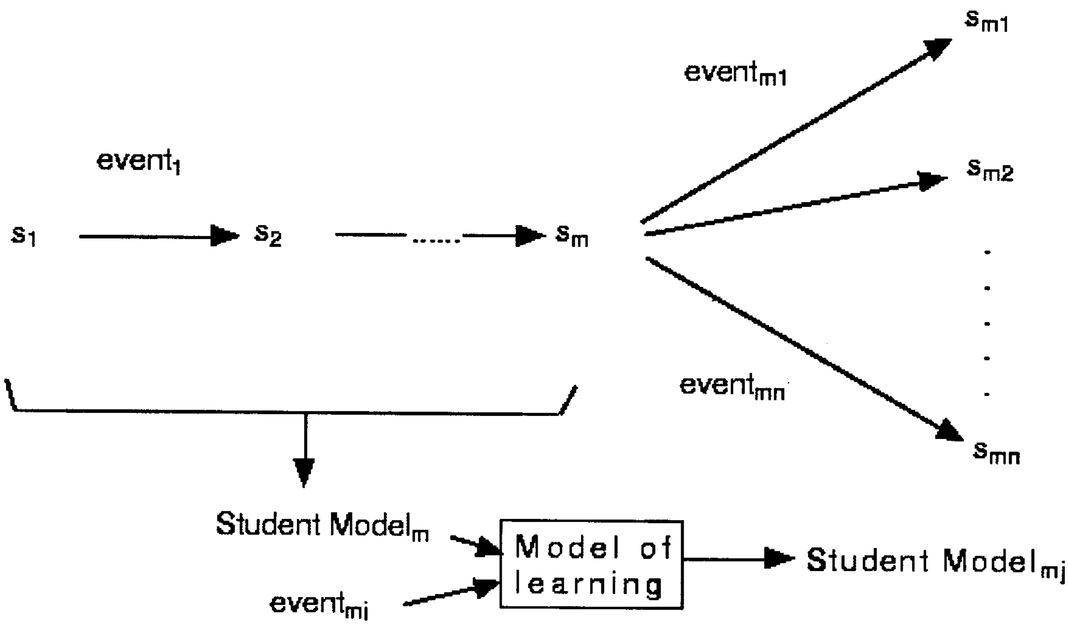

Figure 1. Model of adaptation through student modeling (Self, 1999)

The development of ITSs has generally been based upon an information-processing approach to knowledge representation. This had great appeal in the 1960s and '70s at the time that development in the field of computer technology was beginning to gain pace. It relies on a detailed analysis of cognitive process, in a way that parallels how computer programs deal with processes step-by-step (Kail & Bisanz, 1992). So, when early ITS systems were being developed, information-processing seemed to hold promise for helping to analyze cognitive developmental processes, although critics thought it overly mechanistic and misleading (Brown, 1982). A major assumption of the approach is that information is represented inside the brain and manipulated in real time by mental process, and it follows that these processes can be represented. Information processing theory seeks to describe and explain the process between the observable stimuli (input) and observable responses (output). These processes get represented in algorithms and flow charts that model the cognitive process. For example, Siegler and Shrager (1984) developed a computer-based algebraic model of simple addition problems. This approach is attractive in planning ITSs because it enables the cognitive process to be modeled in the computer.

By contrast, the constructivist view of learning is founded on the belief that knowledge cannot be objectively defined and statistically represented. This is an approach that is apparently in conflict with the way that most ITSs operate. Self (1999), who was concerned at this weakness in the field of AIED, proposes an alternative approach. Instead of modeling what the student **knows**, the alternative approach focuses on the **process** of learning. Figure 2 shows such a model. The upper part of Figure 2 is the same as in Figure 1, but the lower part of the diagram shows how the focus is now on the **interaction** of the student and the tutor. Again, the student passes through a series of situations that result from a series of events, and this is considered a 'course of interaction'. The aim of the tutor now becomes choosing a future event that will optimize the learning opportunity for the student. This is a different focus to the traditional student model that would be evaluating what a student has learned up to that point. The focus on optimizing the learning for the student requires more information than simply what the student knows so far.

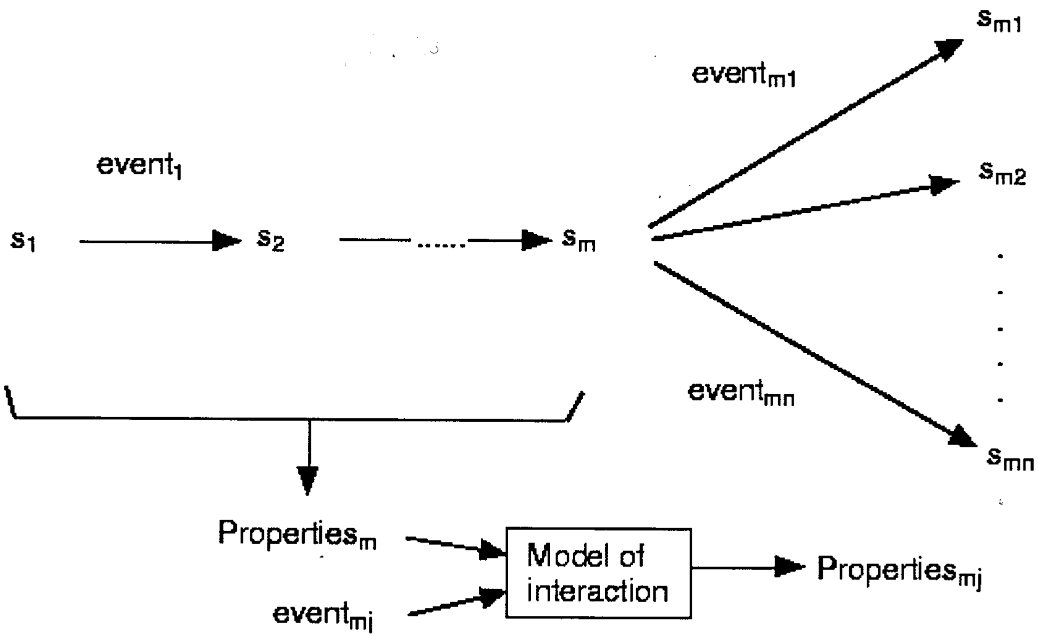

Figure 2. Model of adaptation through interaction (Self, 1999)

For an ITS to take the interaction approach rather than the traditional student model approach may not be easy. AIED systems suffer from certain constraints. They are constrained in the number of measurement points they can observe. We may know nothing about the student's knowledge or skills when a student begins to use a tutor. Only after the student has completed several tasks do we begin to build a clearer picture of the student's abilities. It may take a while for the system to build up sufficient data upon which judgments can be made that will lead to effective tutoring. Even then, the number of measurement points may be small and the measurement reliability may be low. Another constraint for AIED systems as they are currently configured is that usually the inputs to the diagnosis system of an ITS are all related to the individual student. One way of increasing the information used by the tutor in its diagnosis is to make use of data that is derived from the whole population of students using the ITS instead of individuals alone. For example, the difficulty of particular questions and the prior ability level of the student calculated from data for the group of students. Knowing about a student's prior ability in the domain being taught allows the ITS to do two things. First, the tutor can ensure that a student is set problems that go beyond their current ability. The Soviet psychologist L.S. Vygotsky proposed as early as 1934 that instruction creates a "zone of proximal development" (Wertsch & Kanner, 1992). The zone of proximal development (ZPD) was defined by Vygotsky as the distance between a child's "actual development level as determined by independent problem solving" and the higher level of "potential development as determined through problem solving under adult guidance or in collaboration with more capable peers." In the case of the

Geometry Tutor, the adult guidance is embedded in the domain module of the tutor and the tutorial process. There is an interaction between the student and the tutor in a way that can be regarded as part of the sociocultural action.

The second thing that a tutor can do when a student's prior ability in a domain is known is to predict the performance of a student on a problem, assuming that the difficulty of the problem is known. An example of an ITS that successfully used knowledge from a pre-test to set problems that are consistently in the ZPD was DynoMath, which tutored special education students in multi-digit multiplication (Gerber, Semmel, & Semmel, 1994). DynoMath pretested students on their multiplication tables before they used the tutor to learn how to do multi -digit multiplication. The difficulty of a multi-digit multiplication problem can be predicted from the number of digits in the numbers being multiplied. For example, an *n* X *nn* problem is easier than an *nn* X *nn* problem. Knowing this, and knowing from the pre-test data which parts of the multiplication tables the student had mastered, the tutor could predict which problems would be in the student's ZPD.

Unfortunately, few domains are as simple to define as multidigit multiplication. Linking information from a student's pre-test to the tutoring process in an ITS is not as straightforward as the obvious link made in DynoMath. In more complex domains it is harder to determine how a particular part of a student's pre-knowledge is likely to influence their work with an ITS. It may be because of this that few artificial intelligence in education (AIED) researchers have used pre-knowledge to shape the actions of the tutor. This is unfortunate because, according to the literature on individual differences in skill acquisition, previous knowledge in a domain together with cognitive skills is a strong predictor of success in learning new skills (Ackerman, 1988; Kyllonen & Woltz, 1989).

A proposed methodology

It is proposed that a Rasch item response model could be applied to data from a pre-test of students before they engage in the interactive learning environment. In this way, estimates of initial ability could be obtained for the students who use the tutor. The Rasch item response model is one of a family of models from a branch of measurement called Item Response Theory (IRT). In the simple Rasch model the probability that a student will give a correct response to a problem with a right/wrong answer format is conditional on the ability of the student and the difficulty of the item. After estimating the beginning ability, estimates of item difficulties will be obtained from an item response theory modeling of the data on the number of errors made in solving the problems posed in the learning environment. Item response models have the advantage that they place estimates of student ability and item difficulty on the same scale, measured in logits. This means that the difference between a student’s ability estimate and the item difficulty has a direct meaning for performance (Embretson and Reise, 2000). Since both the estimates of student abilities and the estimates of item difficulty are expressed in logits, they can be meaningfully compared. Say, for example, that a student has an estimated ability level of 1 logit. If that student were to be posed a problem with a difficulty equal to 1 logit, then there is a 50% chance that the student will get the problem correct without help. But, if the same student encounters a problem that has a difficulty of 2 logits, then the probability that they will get it correct are much less than 50%. Similarly, if that student tackles a problem with a difficulty of -1 logits, then it is highly likely that the student will be able to complete the problem successfully. So, knowing the pre-test estimates of ability of the students and the estimates of difficulty of the problems, predictions can be made as to which problems a student is most likely to need help on. When the difference in logits between the student ability and the item difficulty is great, the tutor can be more ready to intervene. When the difference is small, the tutor might give lower levels of help. The data on the use of the tutor includes records of the number of hints that students sought and this can be used to check the predictive accuracy of this method of deciding when a student most needs help. The predicted number of hints needed can then be correlated with actual numbers of hints used. The hints offered by the tutor are graduated from offering a little help, through to the maximum level of hints that actually lead the student to the correct answer. Refinements of this prediction method might include predicting the actual hint that a student is most likely to need.

In the example of the PACT Geometry Tutor, each occasion that a student attempts an item is logged separately. This means that it is possible to calculate difficulty estimates for items at different occasions. The student abilities calculated from the pre-test scores will, obviously, reflect only their ability at the point before they engage with the Geometry Tutor. As a student participates in the curriculum and uses the Tutor, their geometry ability will change. In fact, the evaluation study from which these data come showed that there is a significant growth in student's geometry ability as a result of using the tutor. So, student geometry ability is changeable and, although the pre-test estimates should be useful as a student begins with the tutor, their usefulness will diminish.

Proposed research

At this point, this is just a proposed methodology that has yet to be tested. The author proposes to conduct a study to answer a series of research questions. One question is, "How useful are the pre-test estimates in predicting the level of help a student needs?" A question that leads on from that is, "How often should ability estimates be updated to continue to be useful in predicting when a student needs help?" It is possible to recalculate ability estimates at many points during the time a student uses a learning environment. In the proposed the ability estimates for each student will be calculated at different points in time over the period they use an interactive learning environment and then plot these graphically. Then, those results will be examined to see if there are patterns of performance that might be generalized. If this is possible, then beginning estimates of ability might be predictive of a pattern of increasing ability. If so, it would not be necessary to recalculate student abilities frequently as the tutor is being used, but maybe just track them periodically.

Conclusion

If a method can be developed that will allow pre-test performance to be scaled and used to anticipate student performance in the use of an ITS (or other interactive learning environment), this would be useful in two ways. First, the problems posed by the tutor can be aligned to meet the needs of the student. This study aims to use pre-test ability estimates to allow the tutor to build an optimal path through the problems for every student that ensures that they are constantly in their personal ZPD. This should maximize the learning for each student by individualizing the curriculum. Second, the information from the pre-test ability estimates can be used by the tutor to anticipate how challenging a problem is likely to be and then be ready to give hints at the level that is most appropriate for each student. It might be possible to refine the predictive process by recalculating the estimates of student abilities as the student completes problems assigned by the tutor because their ability level will improve as they proceed through the tutoring process.

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