Presentation Summary Megan Tarter Bridgette Parsons

 The paper we did our presentation on was called *Bayesian Networks for Student Model Engineering*, written by Eva Millan, Tomasz Loboda and Jose Luis Perez-de-la-Cruz. The purpose of their paper is to provide a basic understanding of Bayesian Networks to teaching personnel so that they might use it to teach and tutor in the best way for their students.

A student model stores all the information about the student and the way the student learns, so that it can be used by the system. When creating a student model, you must consider the questions “How will the student model be updated and initialized?” and “How will the student model be used?” A student model can be used to look at the cognitive, conative, and affective attributes of the student, which can affect how they learn. There are four types of networks: overlay model, differential model, perturbation model and constraint-based model. Each has its own positive and negative characteristics. Overlay models consider the student’s knowledge versus perfect knowledge. Differential models are similar to overlay models, but break knowledge into necessary and unnecessary knowledge. Perturbation models keep track of common student mistakes, breaking the student’s knowledge into “correct” or “incorrect.” Constraint-based models allow for different methods of problem-solving, using a set of constraints to identify solutions and comparing the student model to this set. Student models use either knowledge tracing, which focuses on what the student knows, or model tracing, which focuses on how the student learns.

 When building a student model, the types of variables needed are target variables, observation variables, factor variables, and auxiliary variables. Target variables are used to represent student features. They include the student’s knowledge, cognitive features, and affective attributes. Observation variables are evidence variables. They include observable student behavior, such as the pages the student has accessed, answers to questions, and unconscious behavior, like eye movements. Factor variables affect other variables, and represent the student’s current state. The variables involved in the model can be either global, meaning they are linked to many other nodes, or local, linked to only a few. Generally, the network needs to be updated as new evidence is received, so a Dynamic Bayesian network is needed to address this issue.

 The most common types of links used in the student model have prerequisite, refinement, or granularity relationships. Prerequisite relationships require one or more nodes to be known before another is known, such as requiring the knowledge of addition before multiplication. Refinement relationships refer to the level of detail of knowledge. Granularity has to do with the way the sets of knowledge are broken down. Coarse-grained models contain a smaller number of knowledge areas that encompass larger knowledge components. Fine-grained models contain a larger number of knowledge areas with smaller knowledge components. Granularity should be decided before student modeling begins.

 Because the student’s knowledge state changes over time, Dynamic Bayesian networks can be a good approach to student modeling. Machine learning techniques can also be used to update the student model automatically by using structural constraints. These techniques, and the using of log data, make it possible to find the most appropriate student model for a given situation.

 More complex student models model a wider range of features, such as problem-solving, metacognitive skills, and emotions. The ANDES physics tutor, for example, models problem-solving by keeping track of knowledge, goal, strategy, and rule application variables. It builds a separate Bayesian Network containing up to 200 nodes for each physics problem a student attempts. The same approach has also been used to model medical problems, using medical hypotheses instead of physics rules. These models are used to analyze a student’s problem-solving approach and knowledge. It can then provide appropriate assistance to the student in order to achieve a specific goal.

 Metacognitive models attempt to classify a student’s learning process. Models using Analogical Problem Solving divide students into two categories: Min-analogy and Max-analogy. Min-analogy students try to solve problems on their own, consulting examples only when necessary. Max-analogy students copy as much as possible. As the Explanation Based Learning of Correctness (EBLC) is considered a good method of problem-solving when a student has insufficient knowledge, the ANDES program was adjusted to add EBLC and APS variables.

 As emotions have a great impact on a student’s performance, there has been a recent interest in adding them to the student model. The program Prime Climb, a game that helps children learn factorization, is a good example. Along with goals, actions, and goal satisfaction, it also has variables to model 6 emotional states: joy and distress and pride or shame, which are user states, and admiration or reproach, which are states of the game A.I. The game attempts to improve students’ learning by increasing how much they enjoy playing.

 In conclusion, student models are very useful in education. Bayesian Networks are a powerful and practical tool for modeling knowledge, and are therefore a good tool for student modeling. The concepts and examples in this paper should be helpful for those desiring to use Bayesian Networks as a student modeling tool.