Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 13

Oct, 6, 2017

How many samples? (Hoeffding's inequality)

- > p can be the probability of any event for random variable $X = \{X_1, \dots, X_n\}$ described by a Bayesian network
- Suppose p is the true probability and s is the sample average from n independent samples.

$$P(|s-p| > \varepsilon) \le 2e^{-2n\varepsilon^2}$$

- > If you want an infinitely small probability of having an error greater than $\mathcal{E}_{,}$ you need infinitely many samples
- > But if you settle on something less than infinitely small, let's say δ , then you just need to set

$$2e^{-2n\varepsilon^2} < \delta$$

So you pick

- the error \mathcal{E} you can tolerate,
- the frequency δ with which you can tolerate it
- And solve for *n*, i.e., the number of samples that can ensure this performance $\int_{1-\delta}^{\delta}$

$$n > \frac{-\ln\frac{\delta}{2}}{2\varepsilon^2} \qquad (1)$$

Hoeffding's inequality

> Examples:

- You can tolerate an error greater than 0.1 only in 5% of your cases
- Set ε =0.1, δ = 0.05
- Equation (1) gives you n > 184

$$n > \frac{-\ln\frac{\delta}{2}}{2\varepsilon^2} \qquad (1)$$

- If you can tolerate the same error (0.1) only in 1% of the cases, then you need 265 samples
- If you want an error greater than 0.01 in no more than 5% of the cases, you need 18,445 samples

Hoeffding's inequality

> Examples:

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- If you want an error greater than 0.01 in no more than 5% of the cases, you need 18,445 samples
 so it should be clear that
 J goes down
 J goes down
 A goes down

Cited by 561

<u>Using Bayesian networks to manage uncertainty in</u> <u>student modeling</u>

- <u>C Conati</u>, <u>A Gertner</u>, <u>K Vanlehn</u> User modeling and user-adapted …, 2002 Springer
- When a tutoring system aims to provide students with interactive help, it needs to know what knowledge the student has and what goals the student is currently trying to achieve. That is, it must do both assessment and plan recognition. These modeling tasks involve a high level...

Some recent (2017) citations

IRT-based adaptive hints to scaffold learning in programming

M Ueno, Y Miyazawa - IEEE Transactions on Learning ..., 2017 - ieeexplore.ieee.org

35 days ago – Over the past few decades, many studies conducted in the field of learning science have described that scaffolding plays an important role in human learning. To scaffold a learner efficiently, a teacher should predict how much support a learner must have <u>Leveraging CPTs in a Bayesian Approach to Grade Open Ended Answers</u>

M De Marsico, A Sterbini ···· - ··· (ICALT), 2017 IEEE 17th ···, 2017 - ieeexplore.ieee.org

52 days ago - Here we discuss a framework (OpenAnswer) providing support to the teacher's activity of grading answers to open ended questions. OpenAnswer implements a teacher mediated peer-evaluation approach: the marking results obtained from peer assessments

Classification and prediction of port variables using Bayesian Networks

BM Serrano, N González-Cancelas, F Soler-Flores··· - Transport Policy, 2017 - Elsevier

58 days ago – Abstract Many variables are included in planning and management of port terminals. They can be economic, social, environmental and institutional. Agent needs to know relationship between these variables to modify planning conditions. Use of Bayesian

Learner Modeling for Integration Skills

Y Huang, J Guerra-Hollstein, J Barria-Pineda···· - Proceedings of the 25th ···, 2017 - dl.acm.org

83 days ago – Abstract Complex skill mastery requires not only acquiring individual basic component skills, but also practicing integrating such basic skills. However, traditional approaches to knowledge modeling, such as Bayesian knowledge tracing, only trace

Predicting Learner's Deductive Reasoning Skills Using a Bayesian Network

<u>A Tato</u>, <u>R Nkambou</u>, <u>J Brisson</u>, S Robert - International Conference on ..., 2017 - Springer

92 days ago – Abstract Logic-Muse is an Intelligent Tutoring System (ITS) that helps improve deductive reasoning skills in multiple contexts. All its three main components (The learner, the tutor and the expert models) have been developed while relying on the help of experts

Exploring Learner Model Differences Between Students

M Eagle, A Corbett, J Stamper, BM McLaren… - … Conference on Artificial …, 2017 - Springer

92 days ago – Abstract Bayesian Knowledge Tracing (BKT) has been employed successfully in intelligent learning environments to individualize curriculum sequencing and help messages. Standard BKT employs four parameters, which are estimated separately for

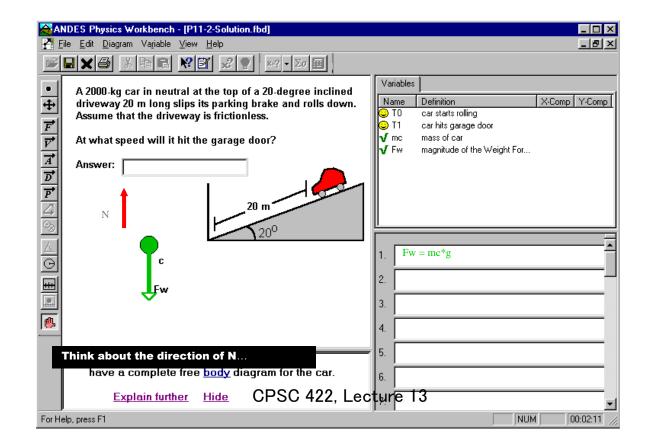
Slide 6 CPSC 422, Lecture 13



- Representing the instructional domain (expert model)
- Understanding the student (student model)
- Providing adequate help and instruction (tutoring model)

ANDES: an ITS for Coached problem solving

- The tutor monitors the student's solution and intervenes when the student needs help.
 - Gives feedback on correctness of student solution entries
 - Provides hints when student is stuck



Slide 8

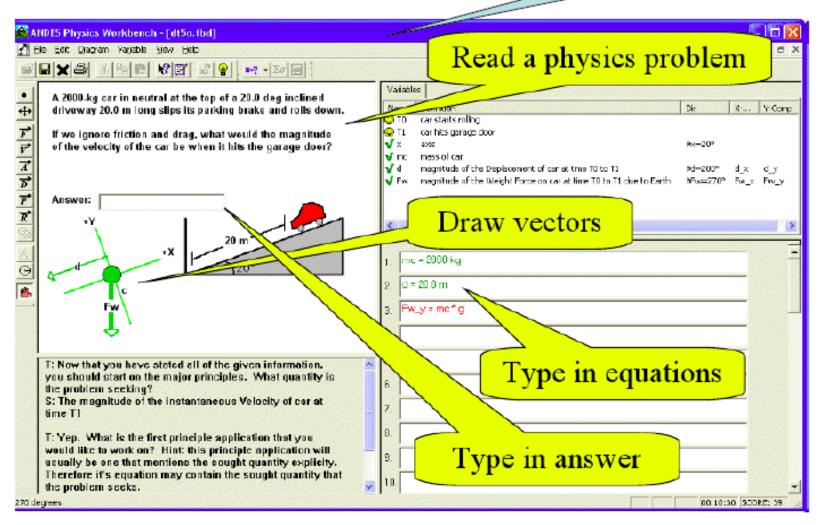
Student Model for Coached Problem Solving

Three main functions

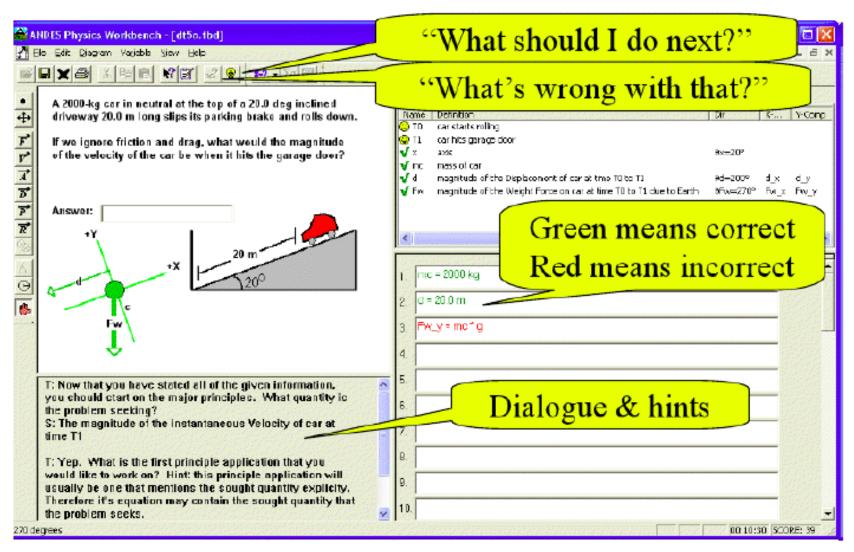
- Assess from the student's actions her domain knowledge, to decide which concepts the student needs help on (*knowledge tracing*)
- Infer from student's actions the solution being followed, to understand what the student is trying to do (*plan recognition*)
- Predict what further actions should be suggested to the student, to provide meaningful suggestions (*adaptive procedural help*)

Andes user interface

Problem solving interface



Andes feedback and hints

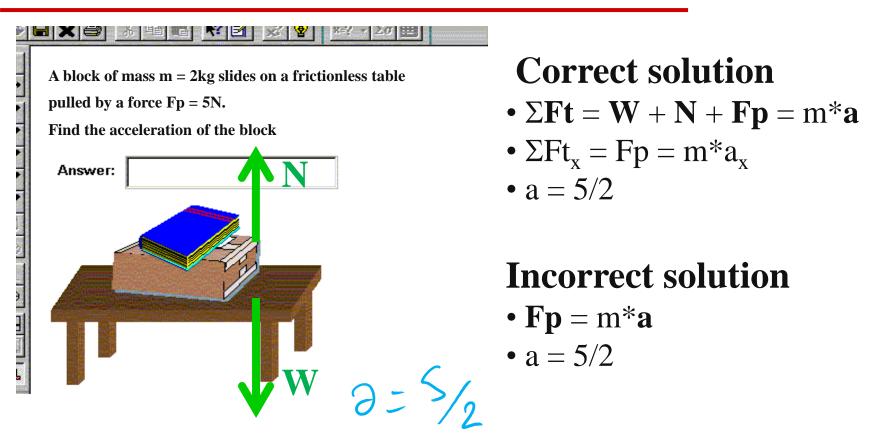


Several sources of uncertainty

- Same action can belong to different solutions
- Often much of the reasoning behind the student's actions is hidden from the tutor
- Correct answers can be achieved through guessing
- Errors can be due to slips
- System's help affects learning
- In many domains, there is flexible solution step order

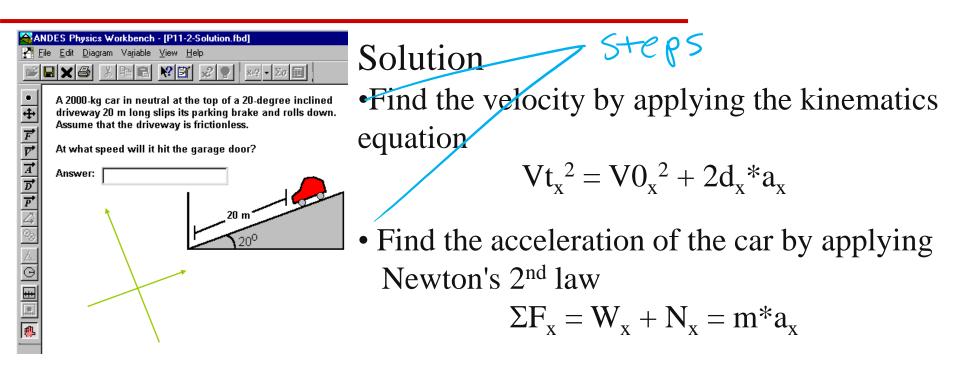
Andes deals with this uncertainty by using Bayesian Networks

Example 1



If the student only types a = 5/2 m/sec, what line of reasoning did she follow?

Example 2

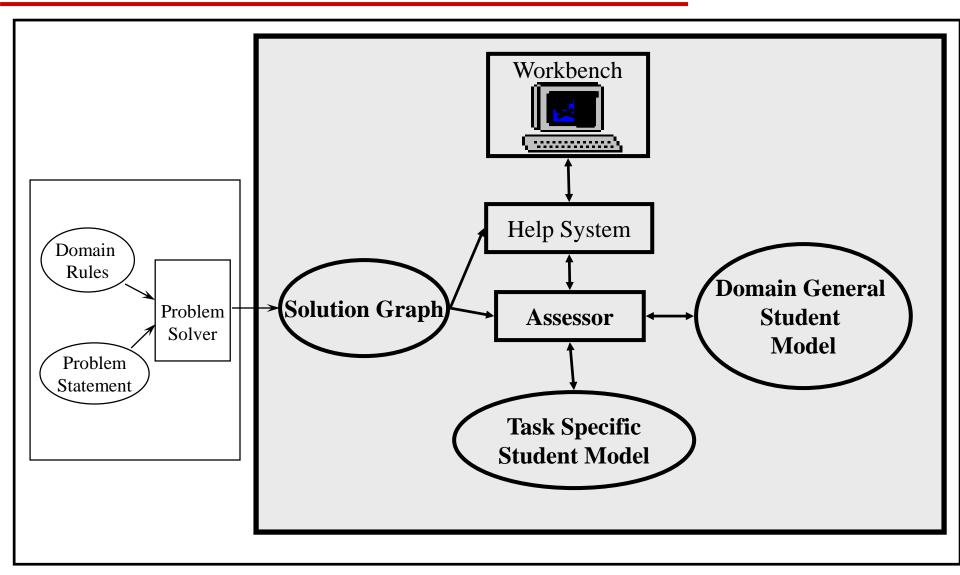


If the student draws the axes and then gets stuck, is she

trying to write the kinematics equations to find V?
trying to find the car acceleration by applying Newton's laws?
term ble Solution step order

Architecture





Components of Andes' Student Model

Domain General

- Reflects the content of Andes' rules
- Defined once along with Andes' KB
- Maintained across problems
- Assesses the student's domain knowledge

Task Specific

- Automatically built when a new problem is opened
- Assesses the student's task specific knowledge and problem solving behavior

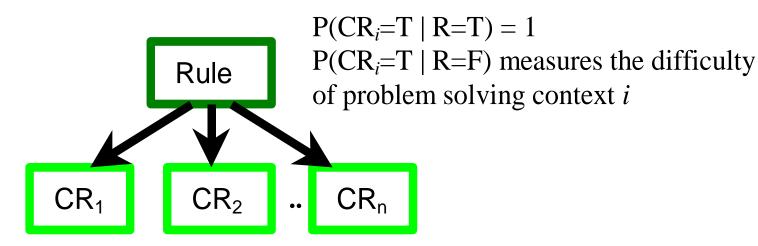
Domain General Bnet

• Rule nodes

- represent knowledge of generic physics and planning rules
- P(R = T): probability that the student knows the rule (how to apply it in any context)

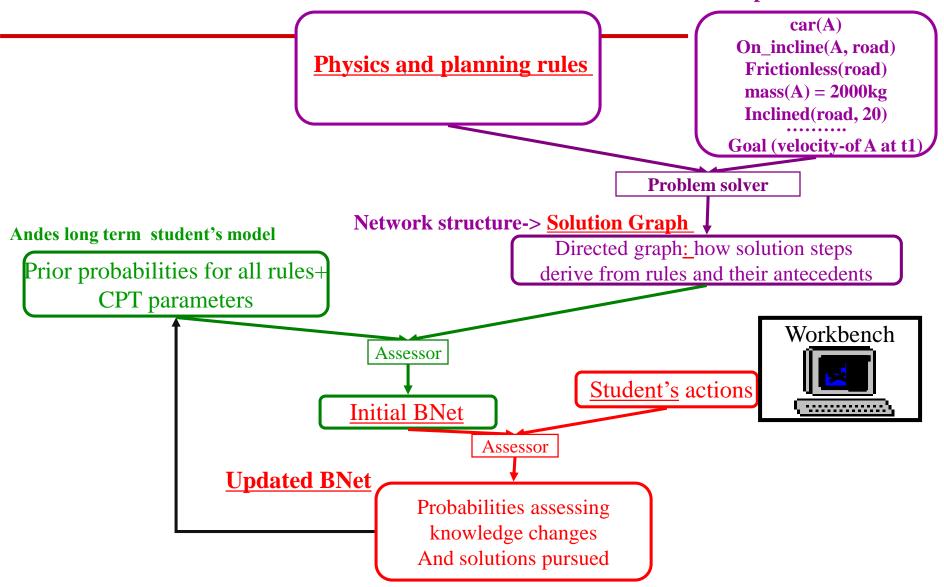
Context rule nodes

- Represent rules in specific problem solving contexts
- P(CR = T): probability that the student can use the rule in the corresponding context

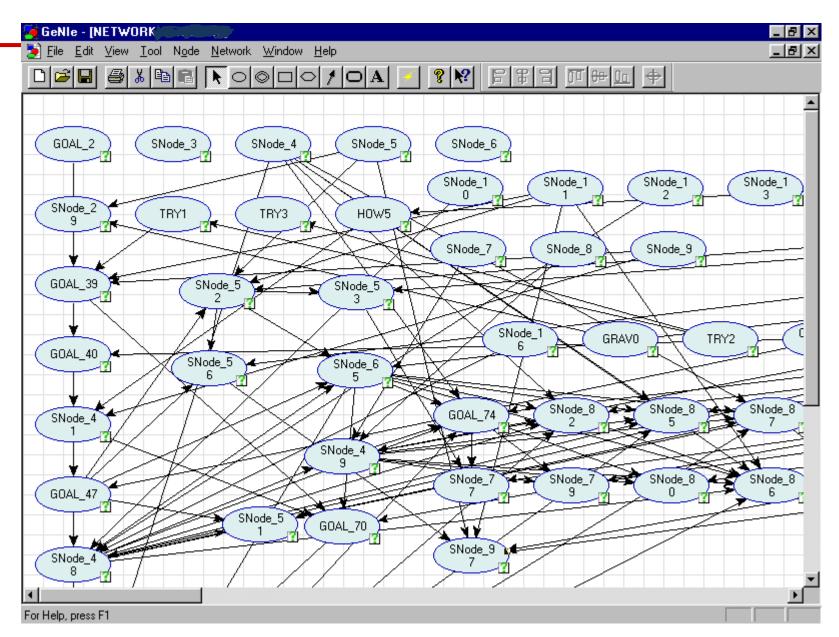


Construction of the task specific BNet

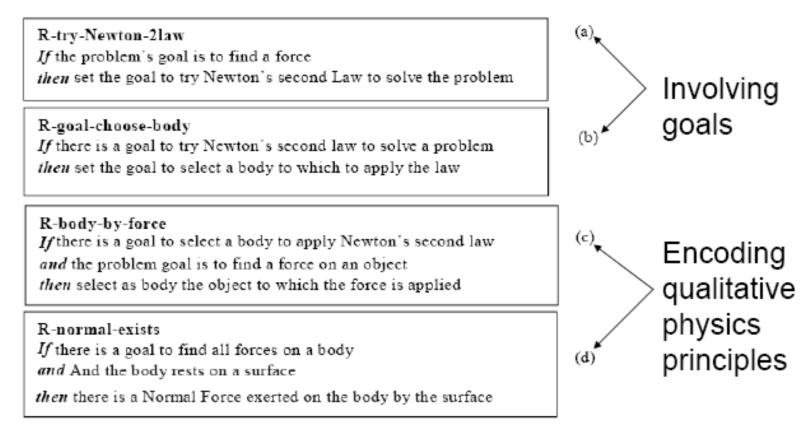
problem definition



Importance of Automatic Generation



Andes rules: encode a solution approach





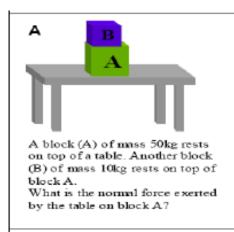
Andes problem solver generate a solution graph There is a block A, which has a magnitude of 50kg

1. Encode the problem to Andes problem solver as:

(SCALAR (KIND MASS) (BODY BLOCK-A) (MAGNITUDE 50) (UNITS KG))

2. Encode the problem goal to Andes problem solver as

(GOAL-PROBLEM (IS FIND-NORMAL-FORCE) (APPLIED-TO BLOCK-A) (APPLIED-BY TABLE) (TIME 1 2))



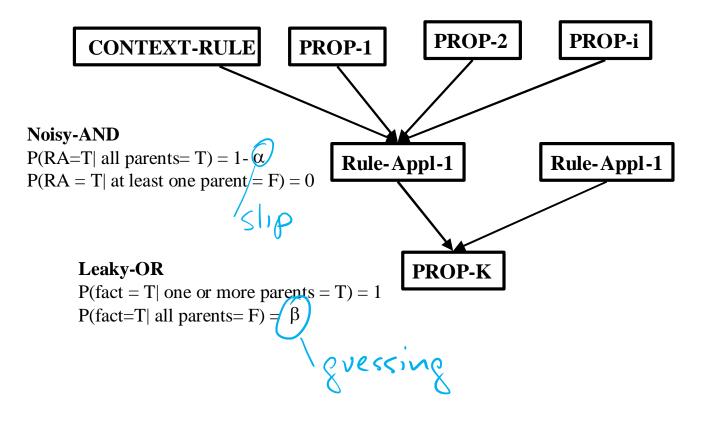
Find the normal force on block A applied by table

- 3. Find the sub-goals and apply rules until to solve the sought quantity
- 1. choose a body/bodies to which to apply the law,
- 2. identify all the forces on the body,

3. write the component equations for $\Sigma \mathbf{F}_i = \mathbf{m}^* \mathbf{a}$.



Conditional Probabilities in the Task Specific BNet

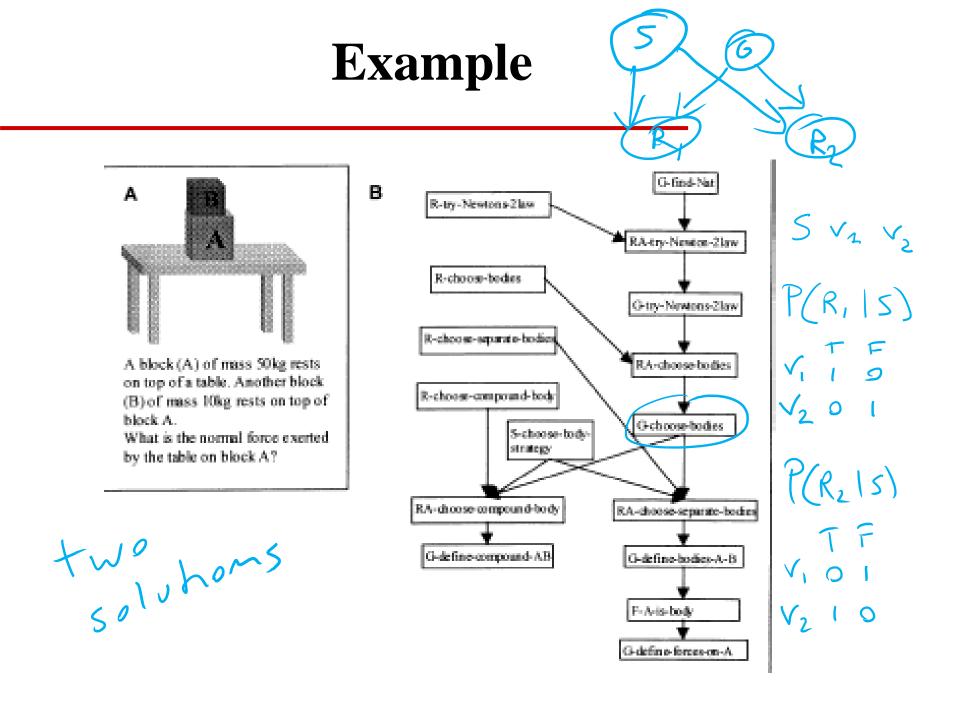


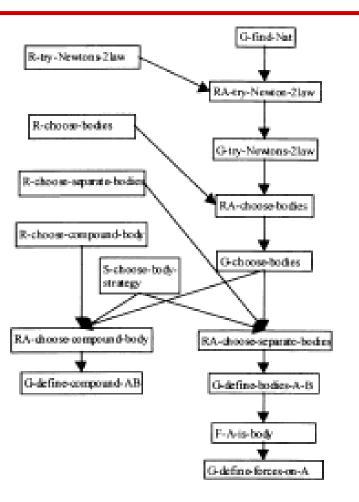
Strategy Nodes

- If a given goal is involved in generating two alternative solutions, evidence that a student is following one solution should decrease the probability of the other solution
- ◆ This does not happen with the basic Andes' Bnet. Actually, evidence of a solution would increase the probability of any other alternative solution that shares a charge Anchise of BNCT BNCT BOAL RULE to avoid RULE APPLICATION RULE APPLICATION RULE APPLICATION RULE APPLICATION RULE APPLICATION goal with it

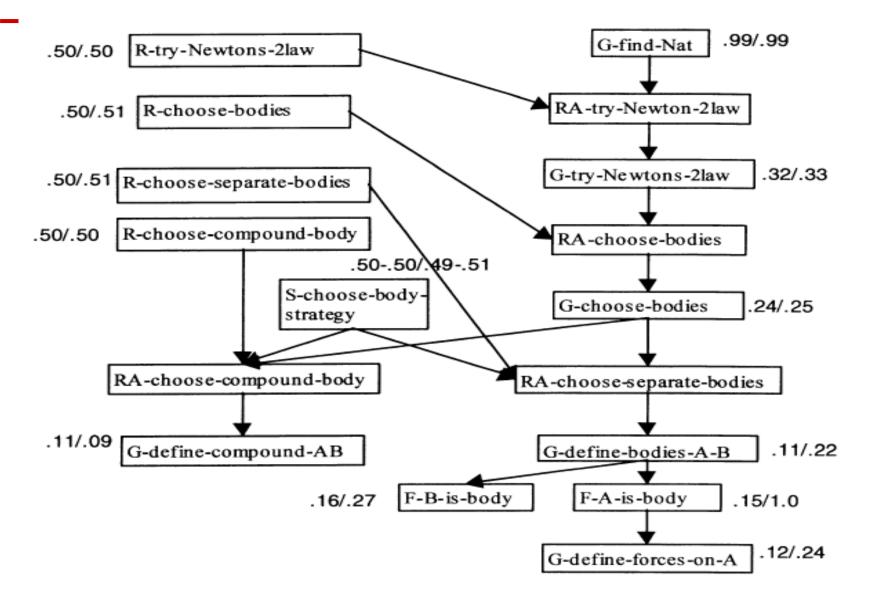
RULE

RULE APPLICATION





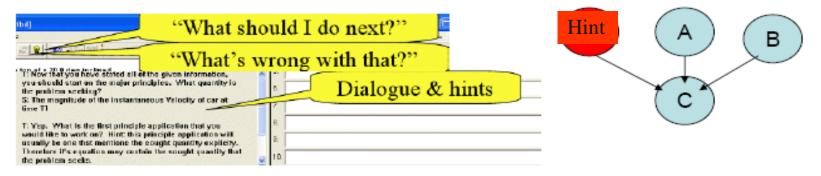
The network before and after observing F-A-is-a-body



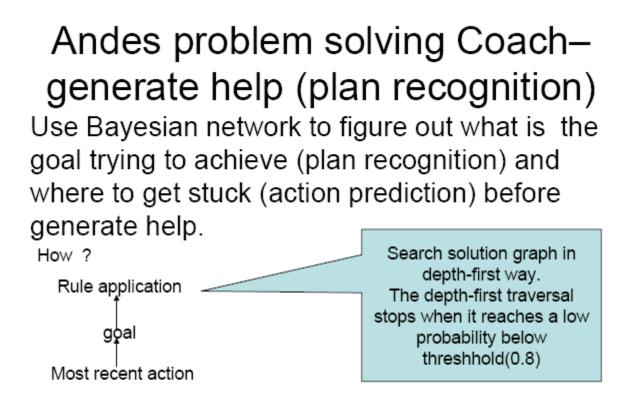
Andes problem solving Coach– handle Errors

- Two type errors:
 - Errors of omission :missing actions
 - errors of commission: disbelieve a certain correct fact or not clear what a correct action is
- Omission errors : rarely clamps nodes to F because Andes does not require explicit actions ordering
- Errors of commission:
 - Implies to disbelieve a certain correct fact, clamps nodes to F
 - otherwise not (more common)

Andes problem solving Coach– handle hint issue

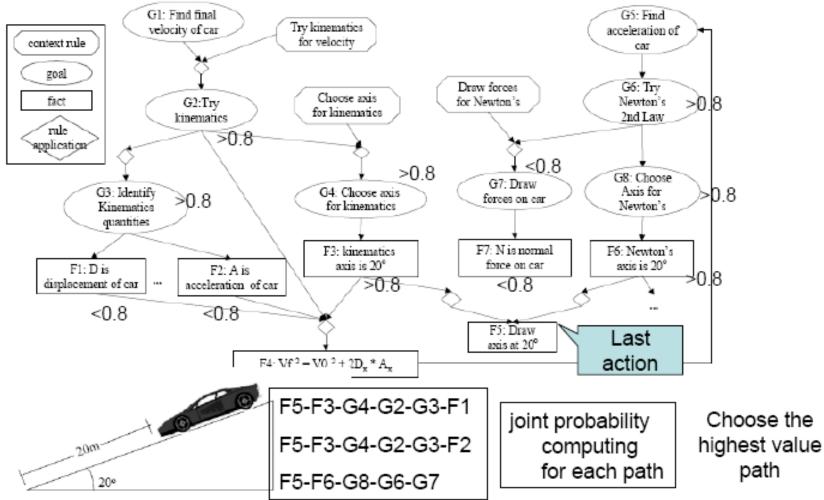


- Andes hints affect actions not domain knowledge
 - Hints just reminds knowledge not teaches it;
 - Hints increases the chance of guessing the next action.
- Hint node is added as a parent node of the proposition node



The result of this traversal is a set of paths through the solution graph beginning with the most recent action, and stopping with a node whose probability is below 0.8

Reference: procedural help in Andes: generating hints using Bayesian network student model



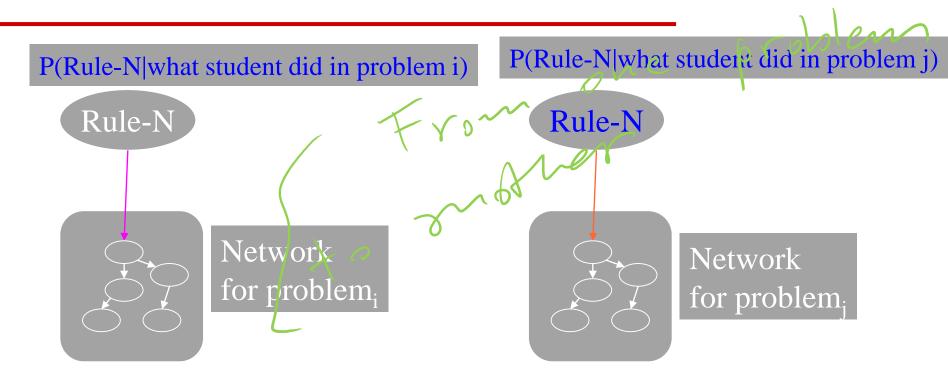
A 2000kg car at the top of a 20° inclined driveway 20m long slips

its parking brake and rolls down. Assume that the driveway is

frictionless. At what speed will it hit the garage door?

Reference: procedural help in Andes: generating hints using Bayesian network student model

Andes Dynamic Bayesian Network



What is the granularity of a time-slice in Andes?

Evaluation

 Andes tutor for physics is currently in use at the US Naval Academy

Informal studies have shown positive effect on learning

Continuously updated through students' feedback

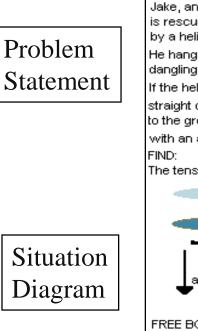
Outline

- ◆ ILE, background.
- Probabilistic student modeling for coached problem solving.
- Probabilistic student modeling to support learning from examples.

ILE - a step beyond

- Most ILE targets problem solving and domain specific knowledge
- Andes' SE-Coach a framework to
 - support learning from examples
 - coach self-explanation(SE)
 - » generate explanations to oneself to clarify an example solution

Sample physics example



Free Body

Diagram

EXAMPLE 1: Boy rescued by a helicopter Jake, an 80Kg undergrad, is rescued from a burning building by a helicopter. He hangs at the end of a rope dangling beneath the helicopter. If the helicopter accelerates, straight downward with respect to the ground, with an acceleration a = 2m/s^2, The tension T exerted by the rope. $a = 2m/s^{2}$ n = 80Ka FREE BODY DIAGRAM: a = 2m/s^2 +X· Jake (m = 80Kq)

w

SOLUTION

Because we want to find a force, we apply Newton's 2nd law to solve this problem.

We choose Jake as the body to which to apply Newton's 2nd law.

The helicopter's rope exerts a tension force T on Jake.

The tension force T is directed upwards.

The other force acting on Jake is his weight W.

The weight W is directed downwards.

To apply Newton's 2nd law to Jake, we choose a coordinate system with the Y axis directed downward.

```
The Y component of Jake's weight VV is 
VV_y = VV.
```

The Y component of the tension T on Jake is $T_y = -T$.

The net force acting on Jake along the Y axis is Net-force_y = W_y + T_y.

Therefore, substituting W_y = W, and T_y = -T into the net force equation, we obtain Net-force_y = W - T.

If we apply Newton's 2nd Law to Jake, along the Y axis, we obtain:

```
Net-force_y = m*a_y
```

The Y component of Jake's acceleration a is a_y = a. Therefore, if we substitute a_y and

```
Net_force_y = VV - T
into
Net force-y = m*a y
```

```
we obtain:
W - T = m*a = (80*2) Newtons.
Solving the preceding equation for T gives:
```

Worked out solution

Why examples and self-explanation?

Students who self-explain learn more

Many students do not self-explain

- Fail to detect their lack of understanding
- Unable to use knowledge to self-explain

Human tutors can guide self-explanation

SE-Coach: individualized support to SE

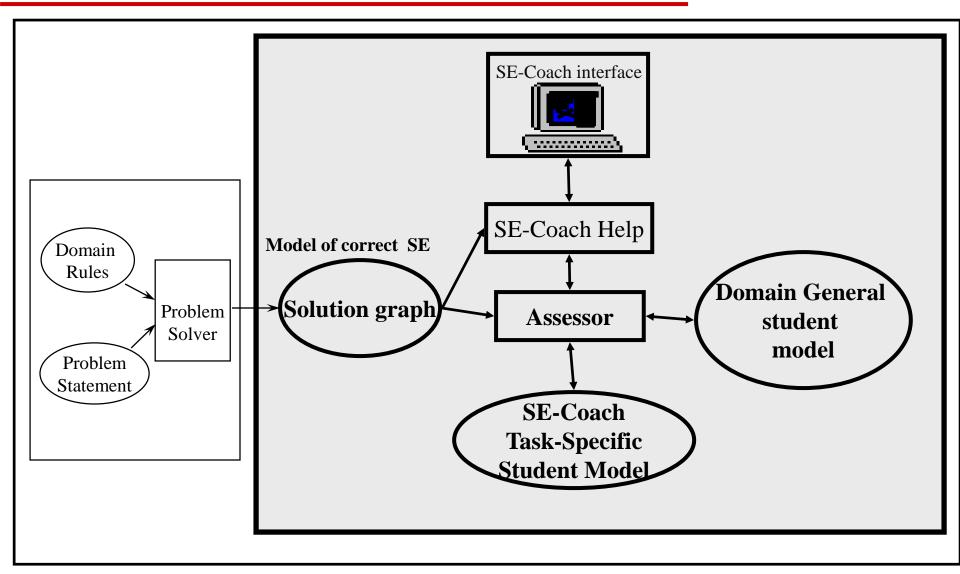
• Monitor students as they study examples

• Guide self-explanation to improve students' understanding

 Challenge: only prompt self-explanations that improve students' understanding

SE-Coach Architecture





The SE-Coach Workbench

- Masking interface
 - Helps students focus attention and SE-Coach monitor it
- Prompts for relevant self-explanations
 - Justify solution steps in terms of domain principles
 - Explain role of a step in the underlying solution plan
- Menu based tools to generate self-explanations

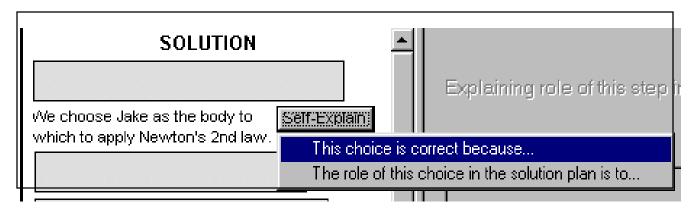
The Workbench - Masking Interface

Helps students focus attention and SE-Coach monitor it

<mark>全 E</mark> ile ⊻iew <u>H</u> elp		
EXAMPLE 1: Boy rescued by a helicopter	SOLUTION VVe choose Jake as the body to Self-Explain which to apply Newton's 2nd law.	Explaining role of this step in the solution
REE BODY DIAGRAM:		
↓a = 2m/s^2 +X		Submit Done
$ \int_{+Y}^{\text{Jake (m = 80Kg)}} VV $		Click on the [+] to expand a step Double click on a step to submit it.

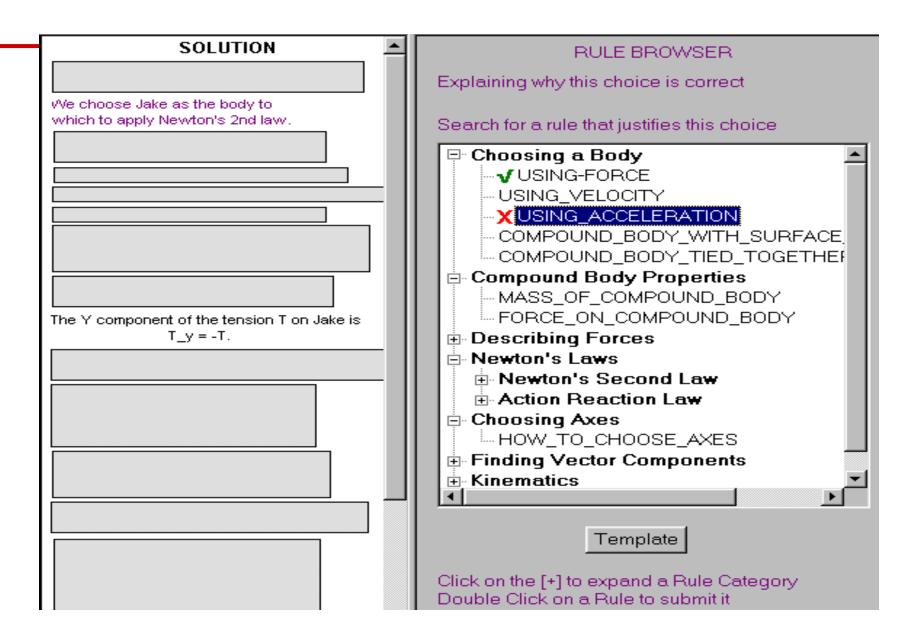
Prompts to Self-Explain

Stimulate self-questioning on relevant explanations



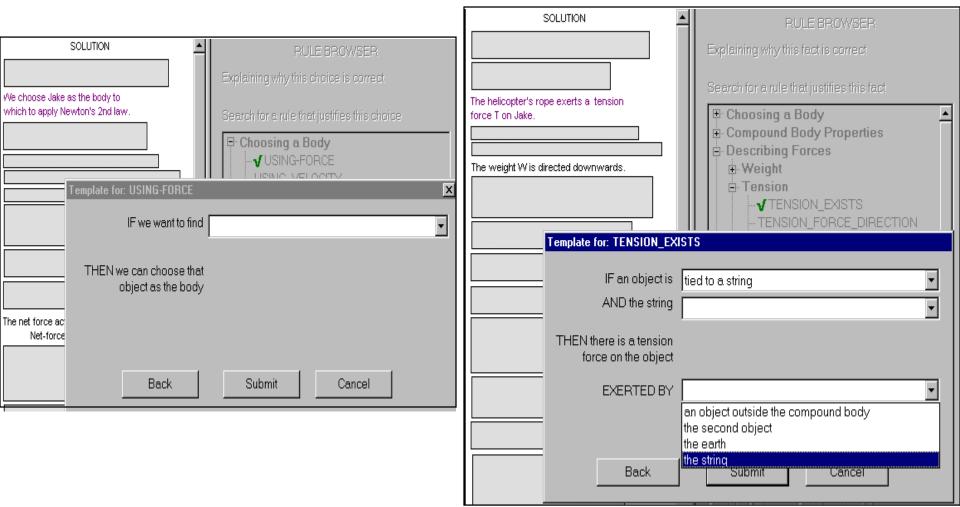
SOLUTION	
	Explaining role of this step in
The helicopter's rope exerts a tension force T on Jake.	
	This fact is true because The role of this fact in the solution plan is to

Justify Solution Steps: Rule Browser



Justify Solution Steps: Rule Templates

Help students generate principle definitions



Identify Goal Structure - Plan Browser

Encodes abstract solution plan

SOLUTION	PLAN BROWSER
The helicopter's rope exerts a tension force T on Jake.	PLAN BROWSER Explaining the role of this fact in the solution plan Plan for Newton's 2nd Law - Apply Newton's Second Law - Choose body - Describe body's properties - Describe body's acceleration - Describe body's mass - Identify all forces on the body - Write component equations - X Choose coordinate axes - Find vector components - Write equations for Newton's 2nd law - Find quantities algebraically - Find remaining unknowns - Solve for desired quantities
	Done Click on the [+] to expand a step Double Click on a step to submit it

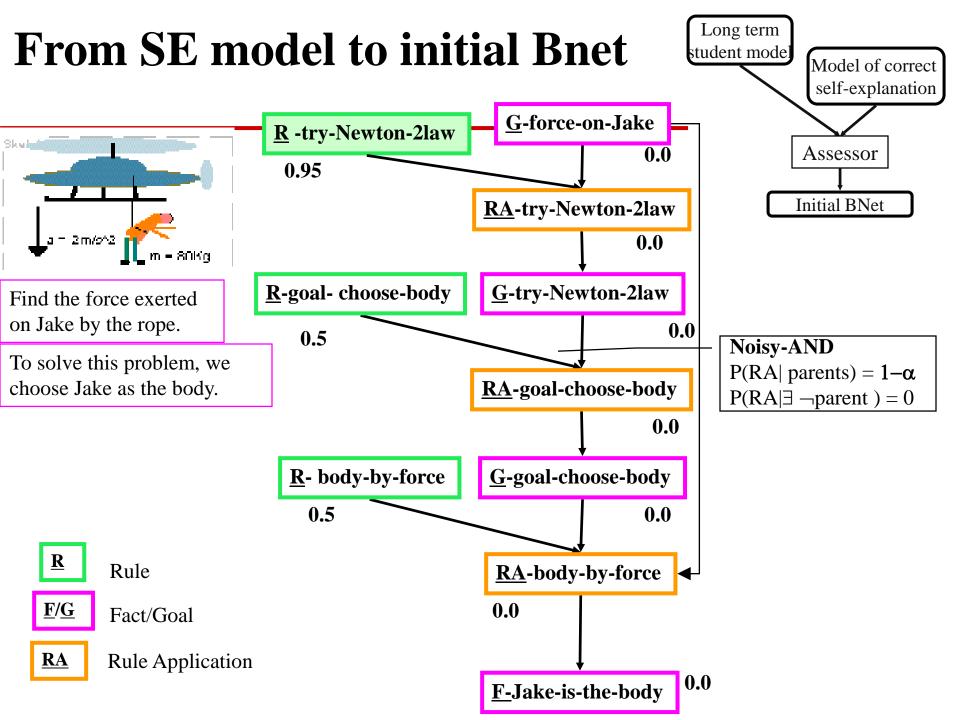
SE-Coach Hints

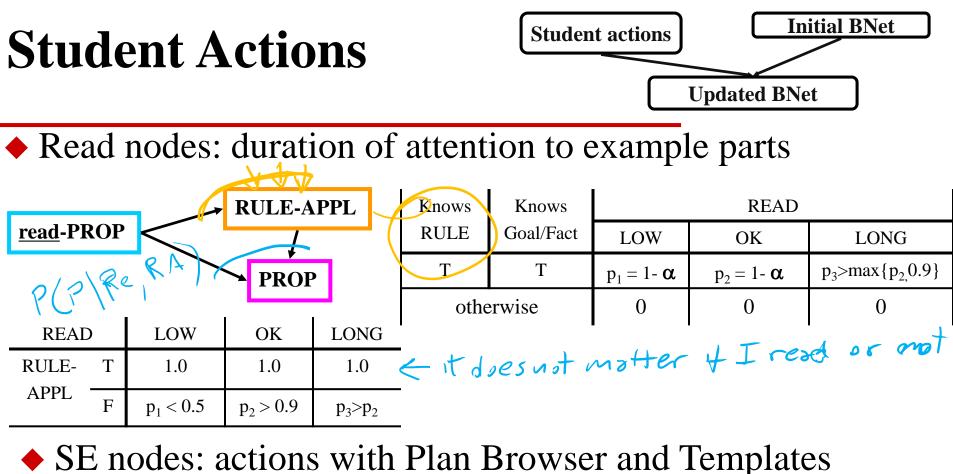
SOLUTION	Expl	SOLUTION	Explain
We choose Jake as the body to Self-Explain with the which to apply Newton's 2nd law. Window	e Plan		Plan for
		The helicopter's rope exerts a tension force T on Jake.	Self-Explain with the Rule Browser

Probabilistic Student Model

Based on a Bayesian network to deal with various sources of uncertainty involved in the modeling task

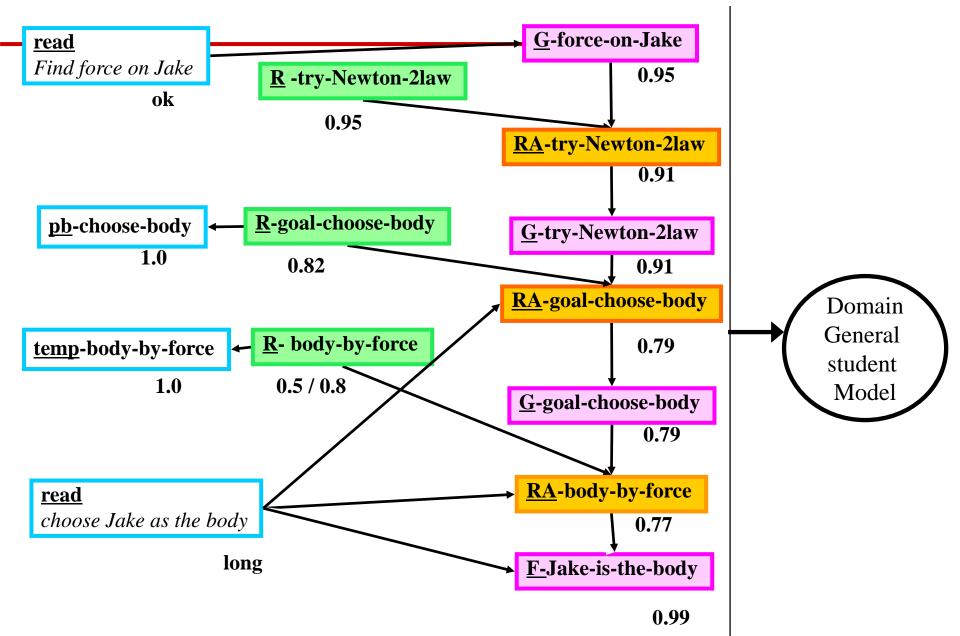
- Detecting spontaneous self-explanation from
 - Reading time
 - Student's knowledge
- Some students study examples by reasoning forward.
- Assessing learning from using the interface menubased tools



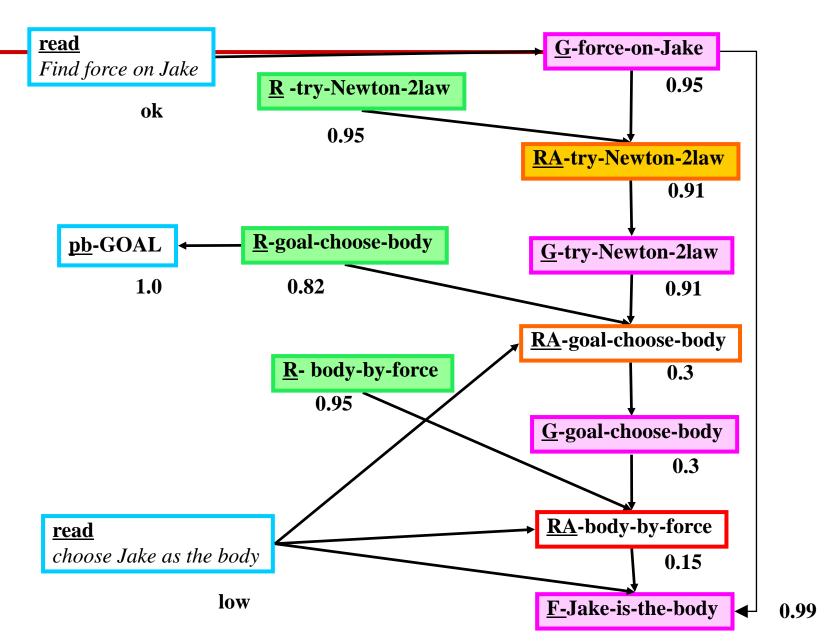




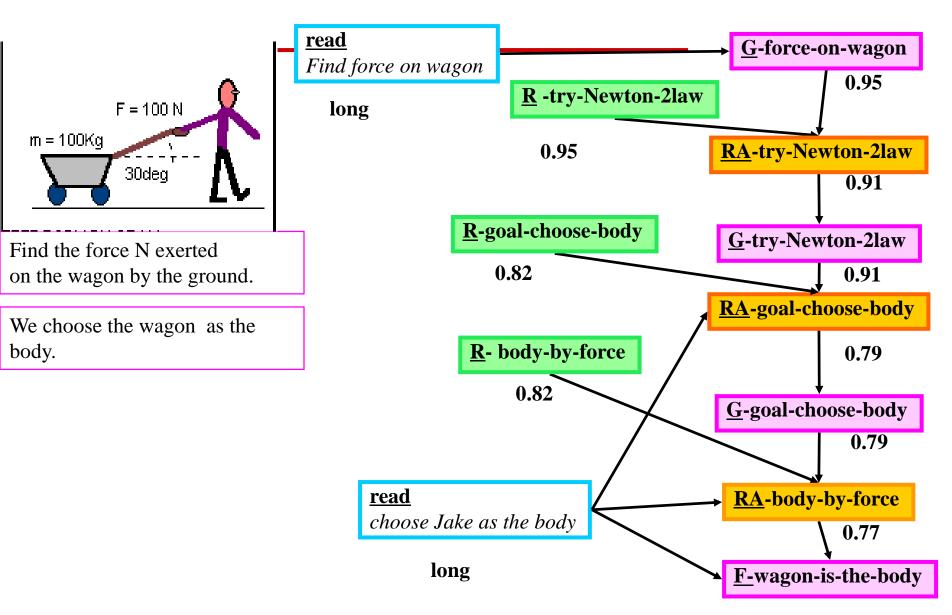
After Filling Template and Closing



After Reading and Plan Browser Selection



Transfer to a new example



Empirical Evaluation

- Subjects 56 students taking Introductory Physics
- Pretest 4 problems on Newton's second law
- Treatment
 - Experimental (29): studied examples with complete SE-Coach
 - Control (27): studied examples with Masking interface and Plan Window, no feedback nor coaching
- Posttest 4 problems analogous to pretest

Evaluation of the SE-Coach

- Interface easy to use and generally successful at stimulating SE.
- Overall effectiveness seems to depend on learning stage
 - The SE-Coach was more effective for the subjects that had just started learning the examples topic (late-start subjects).
- Student model: guides interventions that positively correlate with learning (p < 0.05)

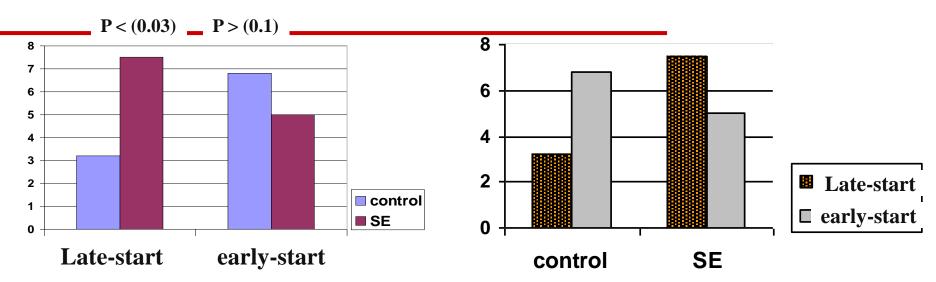
Prompt Type	Max.	Generated	Followed
Use Rule Browser/Templ.	43	22.6	38.6%
Use Plan Browser	34	22.4	42%
Read More Carefully	43	7	34%

Results: Hints to self-explain

Prompt Type	Max	Generated	Followed
	•		
Use Rule Browser/Templ.	43	22.6	38.6%
Use Plan Browser	34	22.4	42%
Read More Carefully	43	7	34%

• All hints positively correlated with posttest (p < 0.0.5)

Results: Learning



• Late-start subjects in SE condition more motivated to learn from Workbench tools?

- Significantly more (p = 0.01) attempts before abandoning template explanation
- Larger correlation (r = 0.3 vs. r = 0.03) between learned rules and posttest
- Early-start subjects control spontaneously self-explained?
 - Mean and St.Dev. # of line accesses correlate with posttest (p < 0.08)
 - Pitt-USNA classes started semester earlier => More recall to self-explain spontaneously

Conclusions

Probabilistic student modeling for

- Coached problem solving
 - On-line knowledge tracing, plan recognition and action prediction to improve the effectiveness of the tutor's interventions

Learning from examples

- Assessment of the understanding of written instructional material
- Takes into account student's attention patterns

Andes Bnet inference

- Andes' networks include anywhere between 100 and 1000 nodes
- > Update needs to happen in real time
 - Starts each time a student performs a new action
 - Needs to be done when the student asks for help

- Exact when feasible
- > Otherwise Approximate

Several questions about...

Why Bnets and not MDPs or POMDPs?

Actions of the agent and action of the student

What would be a state?.....

reason for not modelling it as a planning problem because there would be a **large number of states** due to fact that Andes stresses that the order of solving the problem is not strict

Inference

Can the model be extended to **Reinforcement learning model** based on the observations of user behaviors in the practice questions?

Is the paper using Approximate Inference at all? It may be implied somewhere but I can't find a concrete example.

Yes exact inference in some cases was taking seconds… too much for an interactive system

Selecting the problem

As a first/second year physics tutor for many years, I' ve seen a lot of students becoming completely lost when the problem incorporate more than 2 or more physics theories/concepts. In the paper, it says Andes will choose a problem with an appropriate complexity that involves only a few rules that the student has not yet mastered, how exactly does Andes generate such problem and how does it know what is the appropriate complexity for the student?

Student modeling....

At what point will the Andes Student model determine that a Student has mastered a rule?

- How does this model handle with **different difficulty levels** of questions with same rule applied to decide the **mastery** of this rule? For example, two questions might use the same rule but one of them is extremely tricky and students may fail to do this one while it cannot say they do not master the rule.
- Was the approach able to predict the effect of outside knowledge affecting students answers? In the case of a student having sufficient knowledge in calculus and linear equations the majority of Newtonian mechanics is simplistic, but would not provide diagramming skills.

No

What happens if a student interacts with the system and the network learns about the student but then the student completely changes his behaviour in some wayWill it take a long time for the system to readapt to this? CPSC 422. Lecture 13

Yes... probably the same for a human ;-)

Student modeling.....

What happens if a rule of some sort is created by the teacher (e.g. these two are mutually exclusive strategies to solve a problem), realizes it's incorrect after some students

It seems as if the probability of knowing a rule is based on the student's reading ability. However since the AI tutor is using time as the only reference, how will it take into account if the student had opened the application and did not immediately start reading?

Self explaining

Error due to input mistake: there is a prob for that Error due to language mistake: ESL student might ... Not covered by Andes

Problem Solving Interface

Can the students view information the system has on them, such as how likely the system thinks they are likely to self-explain, or what topics they are likely to not yet have mastered?

No but this is an interesting possibility

- How do students actually use the "hint" feature? The hint is encoded so that the probability of mastery is not raised as much when a hint is given but perhaps students use the hint to confirm their solutions as opposed to solely for when they have not mastered the rule. Is there evidence that the "hint" feature is encoded in the way that is actually used by students?
- **??** Given that mutual exclusivity is a big issue with Newtonian physics, how does the system handle this when **presenting problems to students** and generating the probability distribution?

Bnet structure

Many of the nodes are described to have binary domains. Although the paper provides reasoning for this choice, is it common practice to do this for Bayesian networks due to the increase in complexity with having to maintain bigger probability tables if more domain values are available?

No I would say you try to model your domain as close as possible

Domain-general part

Is there a problem with making general rule nodes observable with perhaps a simple question about a definition?

No, could be an interesting extension

 How are Context-rule nodes corresponding to a template for student's selfexplanation created and how does their input get translated into Bayesian Network probabilities required for building their student model?

This is encoded in the Bayesian network by linking the SE node for a template filling action with the Context-rule node corresponding to that template's content.

Dependencies among rules

Not captured in Andes

Task / Probabilities

 ……. It would be very useful if particular dominant strategies could be identified – e.g. if a problem can be solved in multiple ways, but those who solved it in one particular way were more or less likely to solve a separate problem.

Not sure this analysis was ever done. But it would be interesting and possible for similar systems

- On page 387, then definition of a slip is presented. Would something still be considered a slip if all preconditions were known and two rules were mastered, but one was chosen instead of the other? (i.e. is there an idea of a "best" action to take, or are all the correct actions really just as good as each other?). No
- The approach to implement Leaky-OR relationship to address the case where the student might be guessing is really interesting. What are other potential or actual usage for this in the industry? to make them seem more random and human like?

I would say yes.

 How are alpha and beta determined in 'slipping' and 'guessing' (i.e., Leaky– OR and Noisy–AND)?
 Slide 65

Conditional/ Prior Probability Where do prior probabilities come from? Default to 0.5? Are there better starting values? Learn probabilities from more data on the student (Educational Data Mining)

Task / Probabilities

series of correct guesses? Wouldn't the model have no way to know/recover from that?

What about humans?

Reading latency

How did they end up tackling the problem of deciding what is happening during the student latency time period?

Student modeling for example studying

It is discussed that reading latency is used to evaluate the probability of selfexplanation without requiring self-explanation explicitly, and an equation modeling this was provided. How is this probability value scaled compared to explicit self-explanation?

Student learning in practice

"Has this tutoring system had an impact on student learning in practice?"

Adaptation to new tasks/domains

How difficult would it be to add more physics problems to Andes system?

- Could this model be applied to different learning domains such as language learning, literature analysis or history?
- What are the limitations of expanding this system to other problem domains?
- How difficult is it to extend the system? For example, by adding new rules and problem types.
- other applications exists for the Andes? Is it possible to use it in a literature class environment? Since there are multiple interpretation of a book/paragraph/essay/paper, how would Andes handle such high level of variety in the student's response? strictly model for student in mathematics and theorem related courses?
- The ITS, Andes, studied in this paper is using in the subject of physics. Physics involves a lot of problem solving and formula applying, and it is a good field to apply ITS to improve self-learning. However, this tutoring model may not be good for other subject such as **Philosophy and Business** where the answer can be various due to different point of view. These could cause a even ^{Slide 67} higher uncertainty and hard to make a educated guess.

What about **chemistry**, assess comprehension in the **arts**?

Future Directions

- NLP: There has been huge advancement in natural language processing since the year this paper was accepted in 2002. How would expressing selfexplanations work if we were to replace the interface discussed in this paper with current available natural language processing technology? Still not "easy".... Very specific, simple proposal....
- Lehman, B., Mills, C., D'Mello, S., & Graesser, A. (2012). Automatic Evaluation of Learner Self– Explanations and Erroneous Responses for Dialogue–Based ITSs. In. S. A. Cerri, & B. Clancey (Eds.), *Proceedings of 11th International Conference on Intelligent Tutoring Systems (ITS 2012)* (pp. 544–553). Berlin: Springer–Verlag.
- NLP: What parts of the system can be changed with better natural language processing?
 - **Eye tracking:** With today's eye tracking technologies, can we train a separate model which is able to classify whether student is confused or satisfied on a particular problem from student's eye movement? Then, we can integrate this feature as a prior probability to student's actions in the bayesian network, as it may provide accurate information for the student model to infer student's action and generate help. Yes
- Does taking into account other student's tendencies and patterns help create a better algorithm for future students?

It could

TODO for Mon

• Start Reading Textbook Chp. 8.5

• Keep working on assignment-2 (due on Fri, Oct 20)