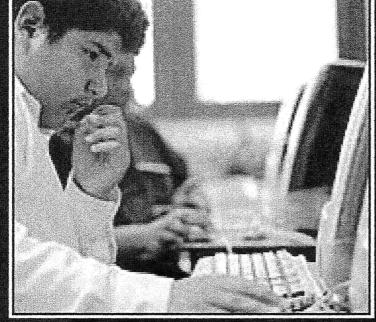
### Simulated Students and Classroom Use of Model-Based Intelligent Tutoring

by

Kenneth R. Koedinger

# Simulated Students & Classroom Use of Model-Based Intelligent Tutoring Systems



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CMU Director of the Pittsburgh Science of Learning Center

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# Modeling & simulation to enhance education

- Two paths:
  - 1. Students create models & use simulations
  - 2. Researchers create models of learners to guide materials development
- #1 is great way to potentially enhance learning, however,
- Understanding student learning (#2) is critical to effective design & use

# Real World Impact of HCI & Learning Technologies

Algebra Cognitive Tutor

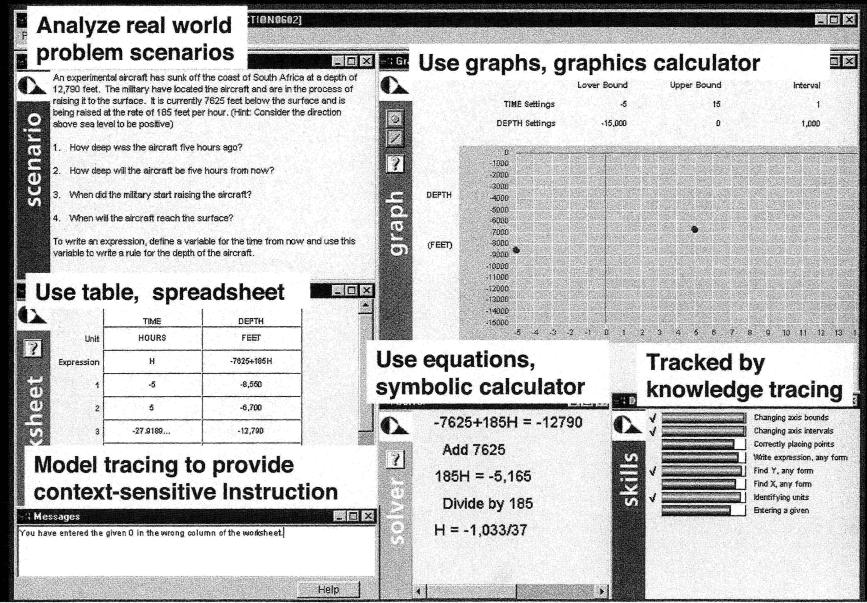
- Based on computational models of student thinking & learning
- Course used nation wide
  - Over 4000 schools, 35 states, 475K students use for 80 minutes per week
- Spin-off:



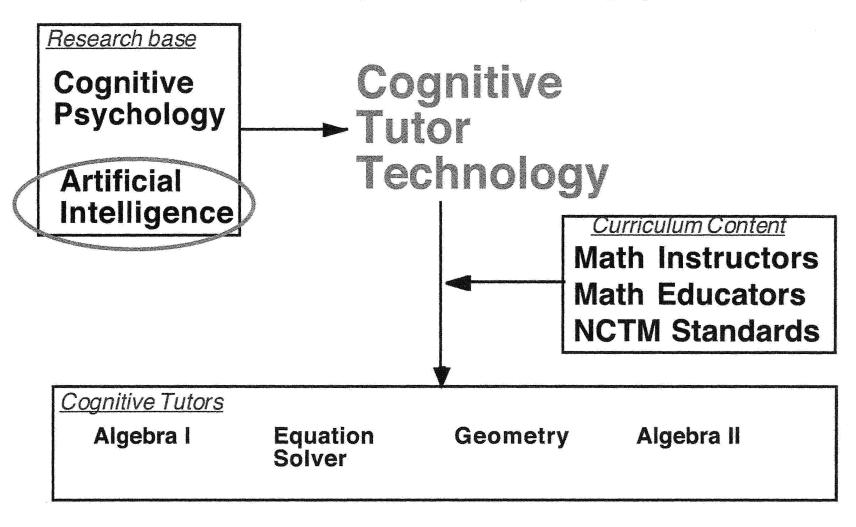
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- Background: Cognitive Tutors
  - Simulating tutoring
  - Data crucial to create accurate model
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  - Generalizing learning science & technology
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### Algebra Cognitive Tutor Sample



## Multi-Disciplinary Approach



#### 53

# Cognitive Tutor Technology: Use ACT-R theory to individualize instruction

 Cognitive Model: A system that can solve problems in the various ways students can

Strategy 1: If the goal is to solve a(bx+c) = d

THEN rewrite this as abx + ac = d

Strategy 2: If the goal is to solve a(bx+c) = d

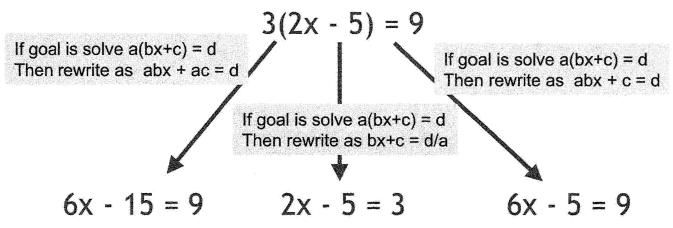
THEN rewrite this as bx + c = d/a

Misconception: If the goal is to solve a(bx+c) = d

THEN rewrite this as abx + c = d

# Cognitive Tutor Technology: Use ACT-R theory to individualize instruction

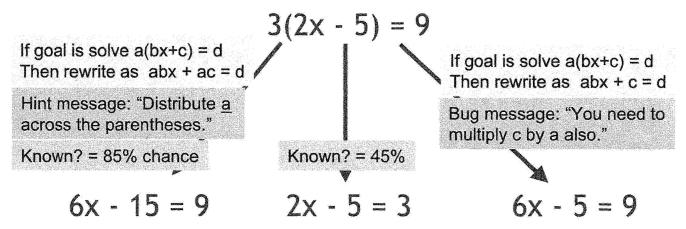
 Cognitive Model: A system that can solve problems in the various ways students can



 Model Tracing: Follows student through their individual approach to a problem -> context-sensitive instruction

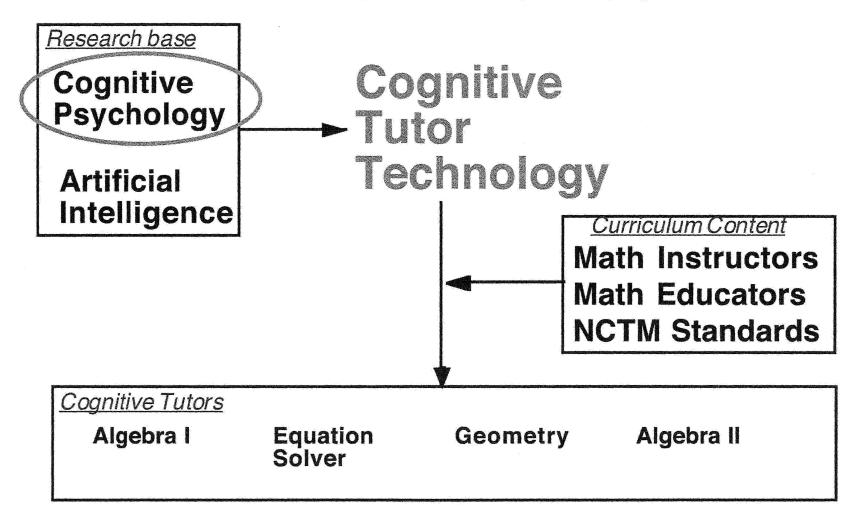
# Cognitive Tutor Technology: Use ACT-R theory to individualize instruction

 Cognitive Model: A system that can solve problems in the various ways students can



- Model Tracing: Follows student through their individual approach to a problem -> context-sensitive instruction
- Knowledge Tracing: Assesses student's knowledge growth -> individualized activity selection and pacing

## Multi-Disciplinary Approach



# What prior knowledge do algebra students have?

Which problem type is most difficult for beginning Algebra students?

#### Story Problem

As a waiter, Ted gets \$6 per hour. One night he made \$66 in tips and earned a total of \$81.90. How many hours did Ted work?

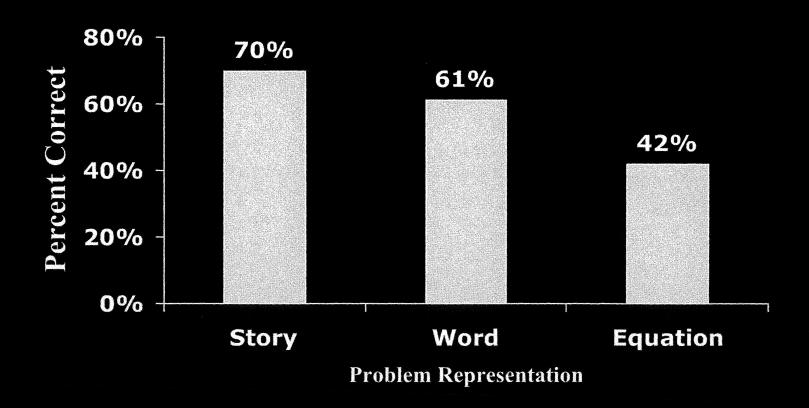
#### Word Problem

Starting with some number, if I multiply it by 6 and then add 66, I get 81.90. What number did I start with?

#### Equation

x \* 6 + 66 = 81.90

## Algebra Student Results: Story Problems are Easier!



Koedinger, K. R. & Nathan, M. J. (2004). The real story behind story problems: Effects of representations on quantitative reasoning. *The Journal of the Learning Sciences*, 13 (2), 129-164.

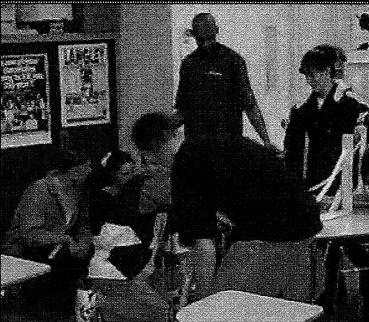
# Practical & Theoretical Implications of Surprising Results

- Guided Cognitive Tutor Algebra design
  - Success due in part to smoothly bridging from students' existing common sense
- Inspired basic cognitive modeling work to explain these results
  - Coded student solutions for alternative strategies & errors
  - Model could generate both & fit student data on frequency of both

# Cognitive Tutor Algebra Course

- Integrated tutor, text, and teacher training
- In computer lab 2 days/week, classroom 3 days/week
- Learn by doing:
  - Project-based
  - Student-centered
  - Cooperative learning
  - Teacher as facilitator





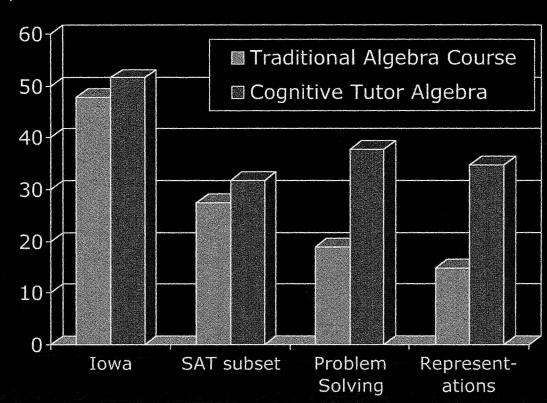
## Original Field Study Results

- Full year classroom experiments with comparison classes
- Replicated over 3 years in urban schools
- In Pittsburgh & Milwaukee
- Results:

   50-100% better on problem solving & representation use.

15-25% better on standardized tests.

Koedinger, Anderson, Hadley, & Mark (1997). Intelligent tutoring goes to school in the big city. International Journal of Artificial Intelligence in Education.



# Many other studies of Cognitive Tutor Algebra

- 11 study reports available
  - From 1994 to present, 11 different districts
  - More than 8000 students in these studies
  - Most run independently of Carnegie
- Significant positive results in all but 1 case (which was a tie)
- See www.carnegielearning.com/results/reports

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# Transition to Pittsburgh Science of Learning Center

#### Past Success:

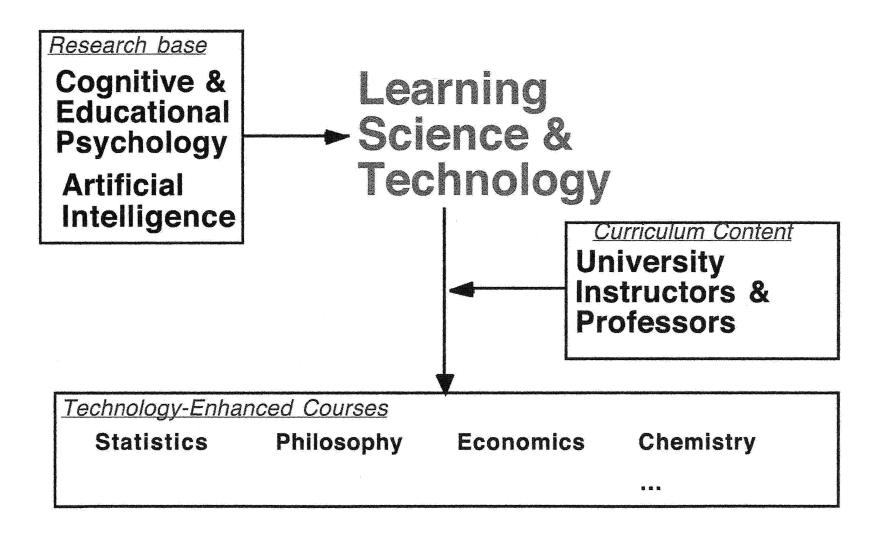
- Cognitive Tutors as delivery vehicle
  - Bring existing Learning Science to classroom

#### New Goal:

- Cognitive Tutors as research platform
  - Create new Learning Science & Technology
- 5 year, \$25 million research center:



# Generalizing Cognitive Tutor Approach



# Pittsburgh Science of Learning Center (PSLC)

- *Problem*: Inadequate theory to engineer courses to be provably effective in raising student achievement
- Solution: PSLC's theory & facility development
  - Theory: Unified effort toward *robust learning* theory
  - Facility: LearnLab's courses, technology, DataShop
- Scientific merit & broad impact
  - Advance a practical learning theory, evidence-based education, fast & natural dissemination



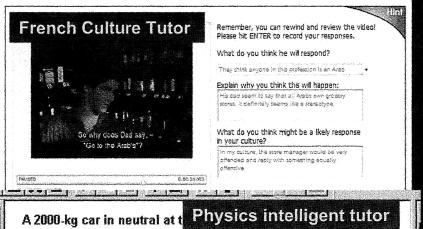
# PLSC Focus on Robust Learning

- Other Intelligent Tutoring Systems yield better learning on immediate post-tests
  - Woolf, Graesser, VanLehn, ours ...
- Push to address robust learning
  - Transfer beyond isomorphic probs
  - Long term retention
  - Preparation for better future learning
- Address both sides of ed wars
  - Basic fluency & deep conceptual understanding
- Tutor at meta-cognitive level

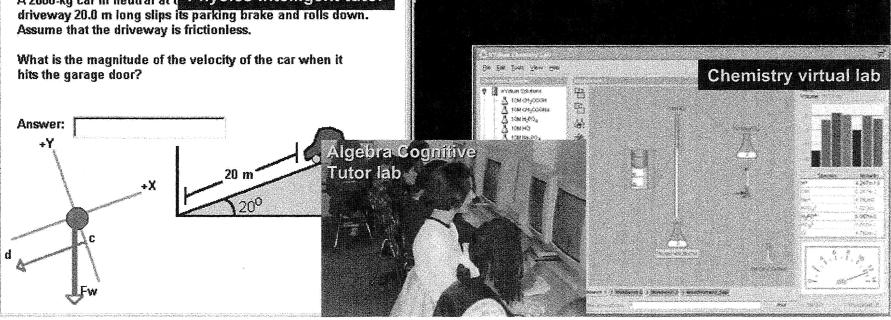
### PSLC's Resources

- 7 Technology-enhanced courses where researchers can run studies
  - Algebra, Geometry, Chemistry, Physics, French, Chinese, English
- Data Shop
  - A repository of student learning data sets
  - Reporting, export, & analysis tools
- Tools for authoring tutors ...

# LearnLab: 7 testbed courses open for studies



- Technology-enhanced courses:
  - 2 math, 2 science,3 language courses
- Tutors, simulations, video, chat rooms, multimedia ...



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# Cognitive Tutor Authoring Tools (CTAT)

- Easier authoring of Tutoring Systems
  - Non-programmer methods
  - General plug-and-play architecture
- Tutors created in a variety of domains:
  - Chemistry, Thermodynamics, Genetics, Law, French culture ...



#### ☐ Getting Started

- Introduction
- Tutor Types
- ▶ □ Download CTAT
- □ Building Tutors
- Tutorials
- Tutor Examples

Cognitive Tutors have been successful in raising students' math test scores in high school and middle-school classrooms, but their development has traditionally required considerable time and expertise. With the Cognitive

Total Authorina Tools (CTAT)



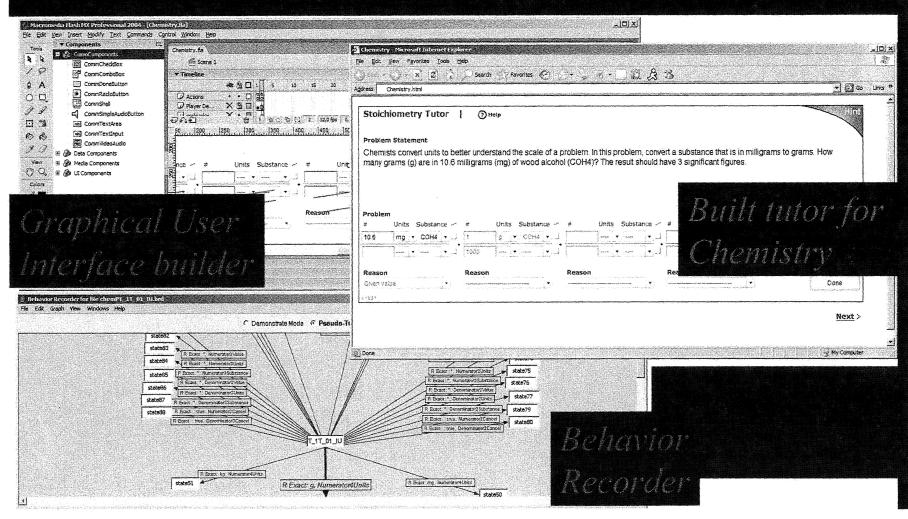
# Aids for Building Cognitive Tutors

- Iterative design-&-test for GUI
  - Building, testing, and modifying a prototype
  - Cycling quickly and easily
- Cognitive Modeling
  - Generating a cognitive model without programming
  - Human friendly testing & debugging

### Solution

- Integrated intelligent authoring environment
  - CTAT: Cognitive Tutor Authoring Tools
  - Simulated Student: Machine learning agent that learns cognitive skills

# CTAT: Cognitive Tutor Authoring Tools



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### SimStudent

- Work with Noboru Matsuda & William Cohen
- Learn production rules by demonstration
- 3 parts: What, how, and when
  - What to operate on
  - How to operate
  - When to do it

### Structure of a Production Rule

If

such and such *constraints* hold *When* 

among this and that GUI elements

What

Then

do actions with the GUI elements

How

Left Hand Side (LHS)

Right Hand Side (RHS)

### Structure of a Production Rule

```
(defrule trans-lr-lhs
                                                                       GIII elements
                                        Working Memory Element (WME)
    ?problem <- ((problem (interface-elements ?table1 ? ? ?))</pre>
                                                                       WME path
    ?table1 <- (table (columns ?column1))</pre>
    ?column1 <- (column (cells $?m1 ?cell0 $?))</pre>
    ?cell0 <- (cell (value ?val0&~nil))</pre>
    ?problem <- (problem (interface-elements ? ?table2 ? ?))</pre>
    ?table2 <- (table (columns ?column2))</pre>
    ?column2 <- (column (cells $?m2 ?cell1 $?))</pre>
    ?cell1 <- (cell (value ?val1&-nil))</pre>
    ?column1 <- (column (cells $?m3 ?cell2 $?))</pre>
    ?cell2 <- (cell (name ?selection) (value ?input))</pre>
    (test (consecutive-row ?cell0 ?cell2))
                                                     Topological
                                                                    WME
    (test (same-column ?cell0 ?cell2))
                                                     constraints
                                                                    conditions
    (test (distinctive ?cell0 ?cell2))
    (test (consecutive-row ?cell1 ?cell2))
    (test (same-column ?cell1 ?cell2))
    (test (distinctive ?cell1 ?cell2))
                                                     Feature
    (test (polynomial ?val0))
                                                     constraints
    (test (not (has-var-term ?val1)))
                                                                   Constraints
=>
    (bind ?input (first-var-term ?val0))
                                                                                   RHS
                                                   Actions
```

(modify ?cell2 (value ?input)) )

## Learning Techniques

(defrule trans-lr-lhs Focus of attention Working Memory Element (WME) ?problem <- (problem (interface-elements ?table1 ? ? ?))</pre> WME path ?table1 <- (table (columns ?column1))</pre> ?column1 <- (column (cells \$?m1 ?cell0 \$?))</pre> ?cell0 <- (cell (value ?val0&~nil))</pre> ?problem <- (problem (interface-elements ? ?table2 ? ?))</pre> ?table2 <- (table (columns ?column2))</pre> ?column2 <- (column (cells \$?m2 ?cell1 \$?))</pre> ?cell1 <- (cell (value ?val1&~nil))</pre> ?column1 <- (column (cells \$?m3 ?cell2 \$?))</pre> ?cell2 <- (cell (name ?selection) (value ?input))</pre> (test (consecutive-row ?cell0 ?cell2)) Topological WWE(test (same-column ?cell0 ?cell2)) constraints conditions (test (distinctive ?cell0 ?cell2)) (test (consecutive-row ?cell1 ?cell2)) (test (same-column ?cell1 ?cell2)) (test (distinctive ?cell1 ?cell2)) Feature (test (polynomial ?val0)) constraints (test (not (has-var-term ?val1))) ROH=>

(bind ?input (first-var-term ?val0))
(modify ?cell2 (value ?input))

\*\*Brute Force Search\*\*

\*\*RHS\*\*

## SimStudent demo ...

## SimStudent Goals & Progress

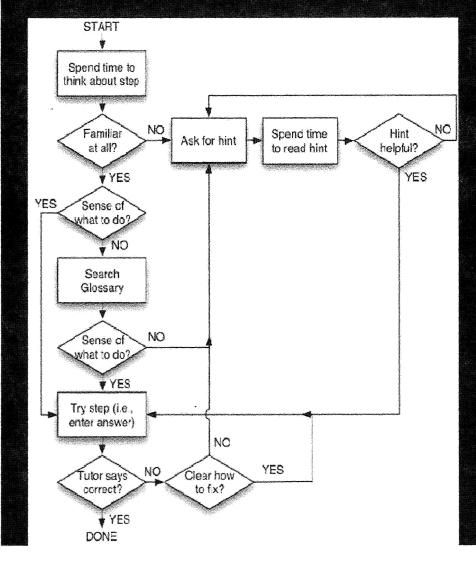
- Improving tutor authoring
  - Works in multiple domains
    - Past: Multi-column addition & multiplication, Tic-Tac-Toe, fraction addition
    - Current: Equation solving, Stoichiometry
    - Future: Scientific reasoning
- Simulating human learning
  - Studies varying:
    - Alternative curriculum sequences
    - Human-like memory limitations
  - Surprising result: Hard-to-easy curriculum sequence better than easy-to-hard

# Tutoring Help-Seeking



Roll, Aleven, McLaren, Ryu, Baker, & Koedinger, (2006). The help tutor: Does metacognitive feedback improve students' help-seeking actions, skills and learning? In *Proceedings of the 8th International Conference on Intelligent Tutoring Systems*.

# A model good student helpseeking behavior

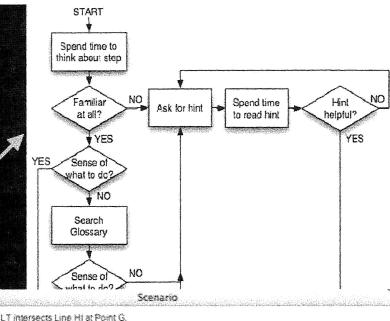


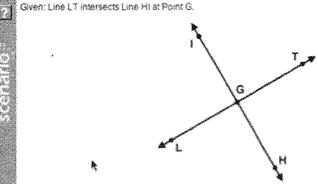
- Production system implementation
- About 50 rules
- Use same model tracing technique
- But at the "metacognitive" level
  - In addition to geometry tutor at cognitive level

#### Tutoring Help-Seeking

- Goal: Foster long-term learner independence
- Model of desired learning & help-seeking behaviors

Provide tutoring relative to this model





1. If the measure of Angle LGH = 77 degrees, find the measures of Angles IGT and TGH.

m./LGM 77 Reason Given

Router 77 Reason Vertical Angles

THE TIGH Reason

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# Another example of using ML

Adapting to When Students Game an Intelligent Tutoring System

Former Phd student Ryan Baker

## Gaming the System

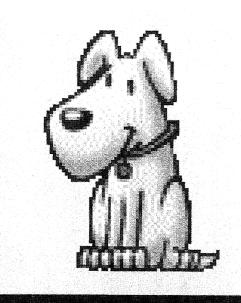
"Attempting to get correct answers and advance in a curriculum by taking advantage of the software's help or feedback, rather than by actively thinking through the material"

#### For instance

- Systematic Guessing (cf. Mostow et al 2002)
- Drilling through Hints (cf. Wood & Wood 2000, Aleven 2001)

### "Scooter the Tutor"

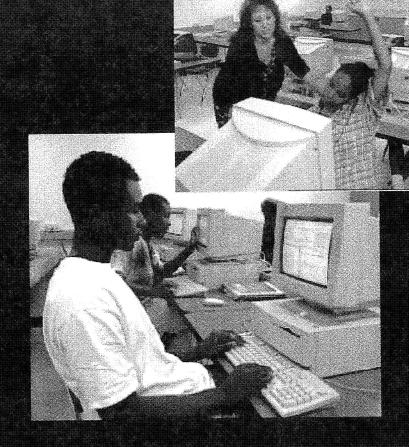
- A tutor agent
- Uses a machine learning "detector" to recognize student gaming behavior
- Intended to reduce gaming & negative consequences for learning



# Gaming detector construction

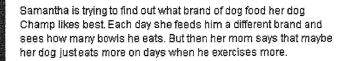
#### 1. Collect data

- Observe students in computer lab
  - Code off-task behaviors
- Get tutor interaction log data from same sessions

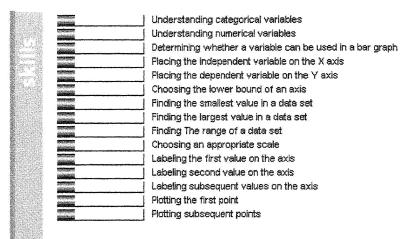


#### 2. Train a machine learning system using data

- Techniques: Fast correlation-based filtering, forward selection on log data variables & interaction terms
- Generalized & cross-validated across four tutor domains

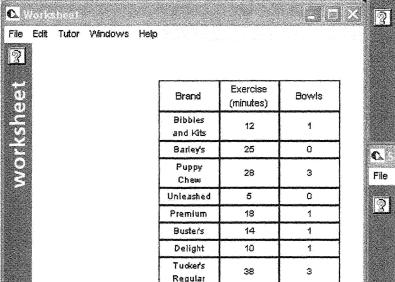


Please draw a scatterplot to show how many bowls the dog eats, given the dog's level of exercise that day.



 $\boldsymbol{c}$ 

File Edit Tutor Windows Help



Mad Dog

No Bones

About It

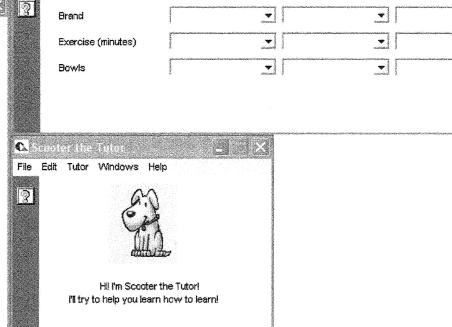
2

2

19

27

Problem SPLOT-DB-C-0-10-0-10



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# During the Student's Tutor Use

- Scooter responds to gaming in two ways
  - Emotional expressions
  - Supplementary exercises

# **Emotional Expressions**

If the student never games, Scooter looks happy



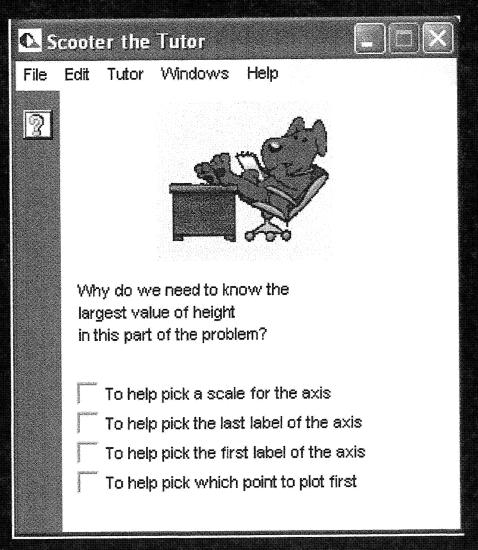
## **Emotional Expressions**

 If the student appears to be gaming, Scooter looks increasingly displeased and becomes redder and redder





## Supplementary exercises



- Multiple Levels
- If a student is wrong, receives another question

# Scooter demo video ...

#### Scooter results

- Reduces gaming behavior
- Supplementary exercises increase learning
- Emotional responses do not

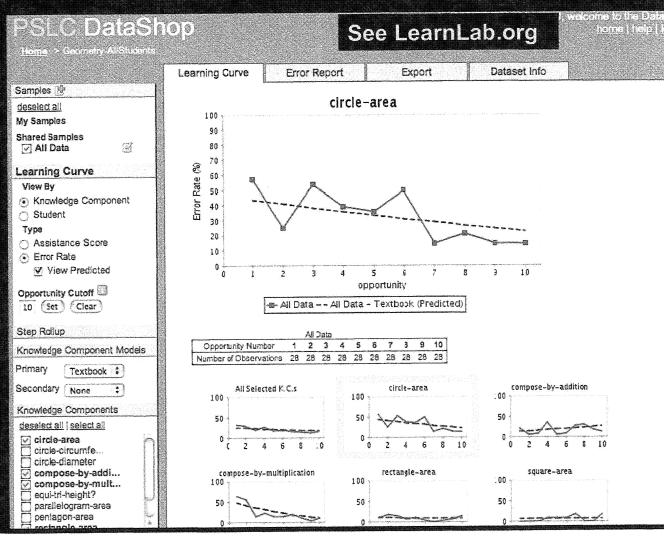
Baker et al. (2006). Adapting to When Students Game an Intelligent Tutoring System (*Best Paper at ITS06*)

# Two kinds of student modeling approaches

- 1. Rational approach
  - Analyze domain & code model that "makes sense"
  - Example: Help-seeking model
- 2. Empirical approach
  - Collect human data driven & use statistical machine learning to learn model
  - Example: Gaming detector
- Remember PSLC's resources
  - One is DataShop
  - It provides data needed for empirical approach

# DataShop: Get data to build or test models of learning!

- Microgenetic log data of student learning over semester
- Data from math, science, language courses

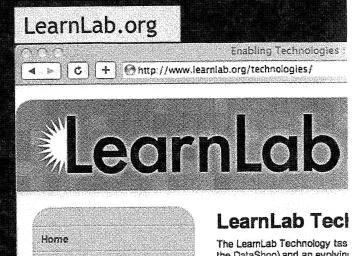


## Summary

- Two educational uses of models & simulations
  - 1. Students create models & use simulations
  - 2. Researchers create models of learners to guide development of reliably effective materials
- Cognitive Tutors simulate & support tutoring
  - Data is crucial to create effective model
- Pittsburgh Science of Learning Center
  - Resources for modeling, authoring, experimentation
  - Repository of data & theory
- Examples of advanced modeling efforts
  - SimStudent learns rule-based model
  - Help-seeking model: Tutors metacognition
  - Scooter uses machine learning detectors of student engagement

# Pittsburgh Science of Learning Center opportunities

- Propose a classroom study or attend summer school
- Analyze student data
  - TagHelper: Verbal data coding software
  - DataShop: Data sets, reporting & analysis tools
- Author a tutor or on-line activity
  - Cognitive Tutor Authoring Tutors
  - TuTalk: Authoring tutorial dialog
  - Open Learning Initiative
  - On-line assessments



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Taghelper TuTalk the <u>DataShop</u>) and an evolving finite duration. There are two I develops new kinds of data ar tools for advanced educationa

Some projects may produce to These tools are intended to mexperimental materials and to been developed and refined we which provides user support a

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assistment.org