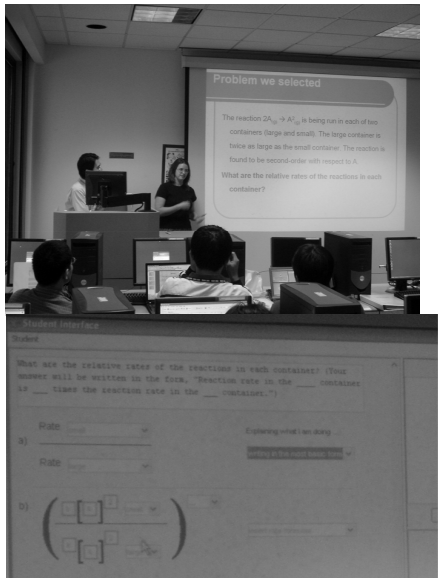
This is the 5th Annual PSLC Summer School

- 9th overall
  - ITS was focus in 2001 to 2004
- Goals:
  - Learning science & technology concepts
  - Hands-on project you present on Fri



Studying and achieving robust learning with PSLC resources

LearnLab
Pittsburgh Science of Learning Center

Ken Koedinger
HCI & Psychology
CMU Director of PSLC

National Science Foundation
WHERE DISCOVERIES BEGIN

Vision for PSLC

"rigorous, sustained scientific research in education" (NRC, 2002)

- Why? *Chasm* between science & practice
  Indicators: Ed achievement gaps persist,
  Low hit rate of randomized controlled trials (<.2!)
- Underlying problem: Many ideas, too little sound scientific foundation
- Need: *Basic* research studies in the *field*

=> PSLC Purpose: Identify the conditions that cause robust student learning
  - Field-based rigorous science
  - Leverage cognitive & computational theory, educational technologies

The Setting & Inspiration

- Rich tradition of research on Learning and Instruction at CMU & University of Pittsburgh
  - Basic Cognitive Science from CS & Psych collab
  - Learning in academic domains
    - Science, math, literacy, history …
    - Many studies, but not enough cross talk
  - Theory inspired intelligent tutors:
    - Andes physics tutor in college classrooms
    - Cognitive Algebra Tutor in 2500+ US schools
- **A key PSLC inspiration: Educational technology as research platform to launch new learning science**

Overview

Next

- Background
  - Intelligent Tutoring Systems
  - Cognitive Task Analysis
- PSLC Methods, Resources, & Theory
  - *In vivo* experimentation
  - LearnLab courses & enabling technologies
  - Theoretical framework
- Summary & Future

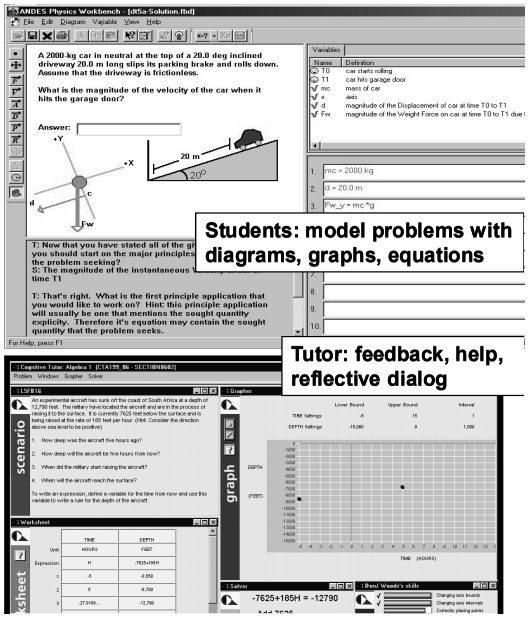
PSLC is about much more than Intelligent Tutors

But tutors & course evaluations were a key inspiration

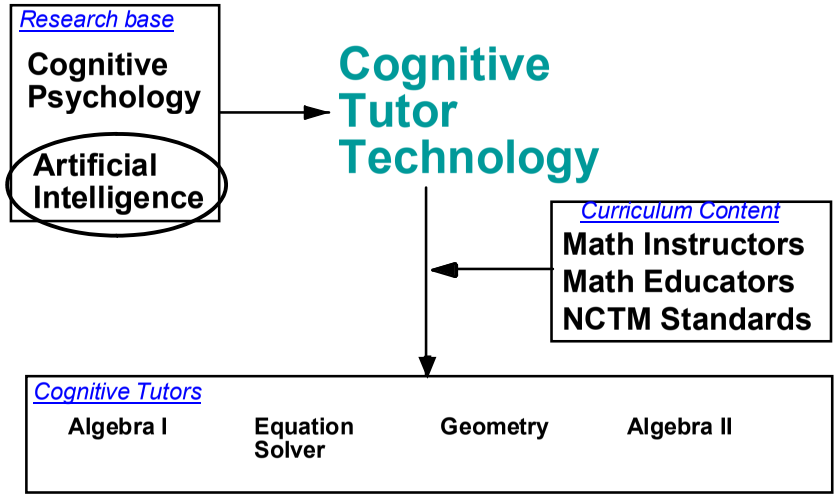
Quick review …

Past Success: Intelligent Tutors Bring Learning Science to Schools!

- Intelligent tutoring systems
  - Automated 1:1 tutor
  - Artificial Intelligence
  - Cognitive Psychology
- Andes: College Physics Tutor
  - Replaces homework
- Algebra Cognitive Tutor
  - Part of complete course



Cognitive Tutor Approach



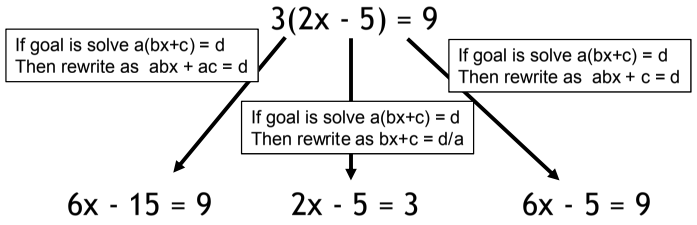
Cognitive Tutor Technology

- 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

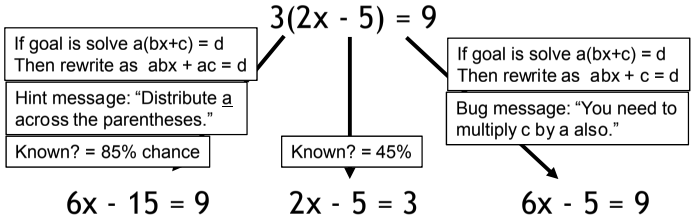
- Cognitive Model: A system that can solve problems in the various ways students can



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

Cognitive Tutor Technology

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

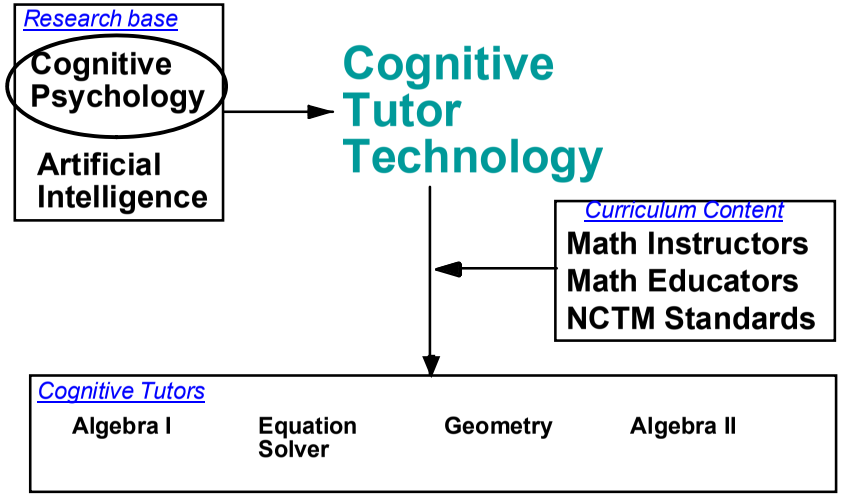


- Model Tracing: Follows student through their individual approach to a problem -> context-sensitive instruction
- Knowledge Tracing: Assesses student's knowledge growth -> individualized activity selection and pacing

Cognitive Tutor Course Development Process

1. Client & problem identification
2. Identify the target task & "interface"
3. *Perform Cognitive Task Analysis (CTA)*
4. Create Cognitive Model & Tutor
   a. Enhance interface based on CTA
   b. Create Cognitive Model based on CTA
   c. Build a curriculum based on CTA
5. Pilot & Parametric Studies
6. Classroom Evaluation & Dissemination

Cognitive Tutor Approach



Difficulty Factors Assessment:

Discovering What is Hard for Students to Learn

Which problem type is most difficult for 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

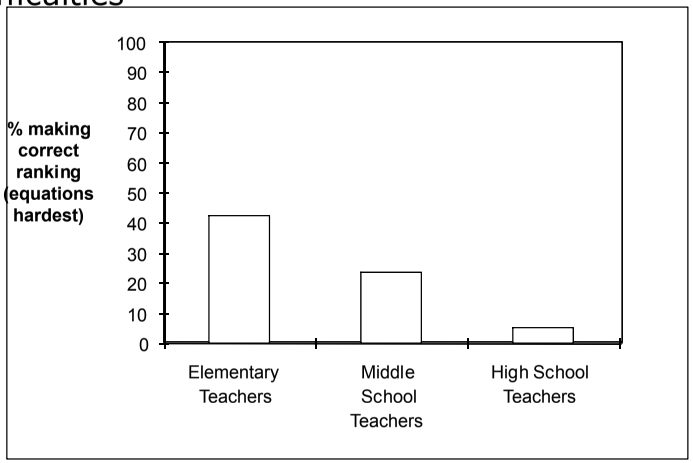
Algebra Student Results: Story Problems are Easier!

Koedinger, & Nathan, (2004). The real story behind story problems: Effects of representations on quantitative reasoning. *The Journal of the Learning Sciences*.

Koedinger, Alibali, & Nathan (2008). Trade-offs between grounded and abstract representations: Evidence from algebra problem solving. *Cognitive Science.*

Expert Blind Spot:

Expertise can impair judgment of student difficulties



Nathan, M. J. & Koedinger, K. R. (2000). An investigation of teachers' beliefs of students' algebra development. *Cognition and Instruction, 18*(2), 207-235

"The Student Is Not Like Me"

- To avoid your expert blindspot, remember the mantra:

  "The Student Is Not Like Me"

- Perform Cognitive Task Analysis to find out what students *are* like

Cognitive Tutor Course Development Process

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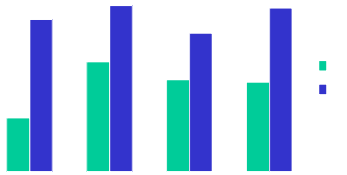
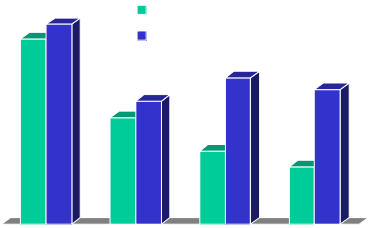
6. *Classroom Evaluation & Dissemination*

Tutors make a significant difference in improving student learning!

- Andes: College Physics Tutor
  - Field studies: Significant improvements in student learning
- Algebra Cognitive Tutor
  - 10+ full year field studies: improvements on problem solving, concepts, basic skills
  - Regularly used in *1000s of schools* by *100,000s of students*!!





President Obama on Intelligent Tutoring Systems!

"[W]e will devote more than three percent of our GDP to research and development. …. Just think what this will allow us to accomplish: solar cells as cheap as paint, and green buildings that produce all of the energy they consume; *learning software as effective as a personal tutor;* prosthetics so advanced that you could play the piano again; an expansion of the frontiers of human knowledge about ourselves and world the around us. We can do this."

http://my.barackobama.com/page/community/post/amyhamblin/gGxW3n

Prior achievement:
Intelligent Tutoring Systems bring learning science to schools

A key PSLC inspiration:
Educational technology as research platform to generate new learning science

Overview

- Background
  - Intelligent Tutoring Systems
  - Cognitive Task Analysis
- PSLC Methods, Resources, & Theory
  - *In vivo* experimentation
  - LearnLab courses & enabling technologies
  - Theoretical framework
- Summary & Future

Next

PSLC Statement of Purpose

Leverage cognitive and computational theory to identify the instructional conditions that cause *robust student learning*.

What is Robust Learning?

- *Robust Learning* is learning that
  - transfers to novel tasks
  - retained over the long term, and/or
  - accelerates future learning
- Robust learning requires that students develop both
  - conceptual understanding & sense-making skills
  - procedural fluency with basic foundational skills

PSLC Statement of Purpose

Leverage cognitive and computational theory to *identify the instructional conditions that cause* robust student learning.

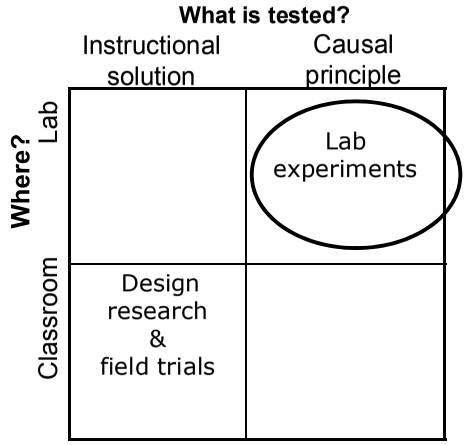
In Vivo Experiments

Principle-testing laboratory quality in real classrooms

In Vivo Experimentation Methodology

Methodology features:

- What is tested?
  - Instructional solution vs. causal principle
- Where & who?
  - Lab vs. classroom
- How?
  - Treatment only vs. Treatment + control
- Generalizing conclusions:
  - *Ecological validity*: What instructional activities work in real classrooms?
  - *Internal validity*: What causal mechanisms explain & predict?



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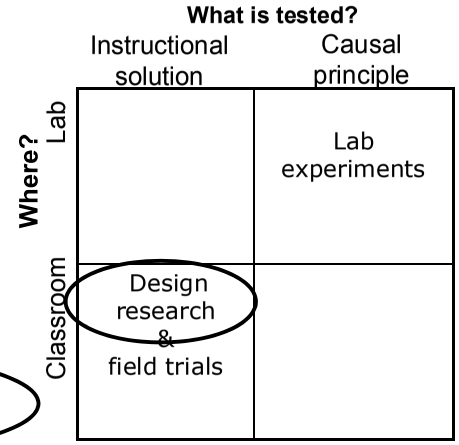

In Vivo Experimentation Methodology

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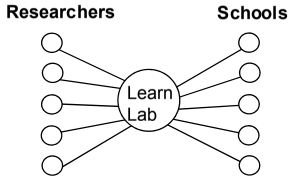
  - *Internal validity*: What causal mechanisms explain & predict?

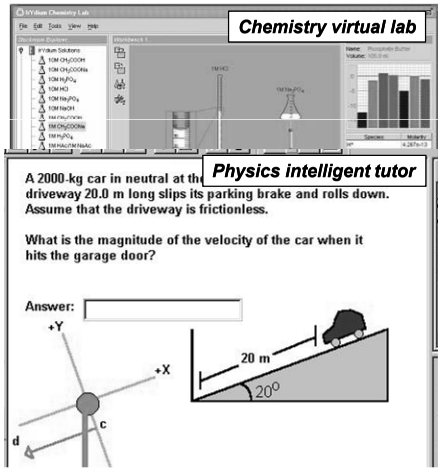
Where?	What is tested? Instructional solution	What is tested? Causal principle
Lab		Lab experiments
Classroom	Design research & field trials	***In Vivo* learning experiments**

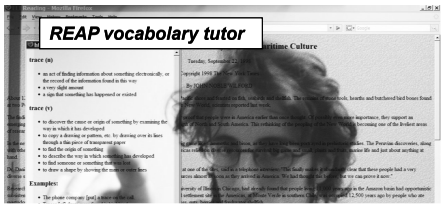
LearnLab
A Facility for Principle-Testing Experiments in Classrooms

LearnLab courses at K12 & College Sites



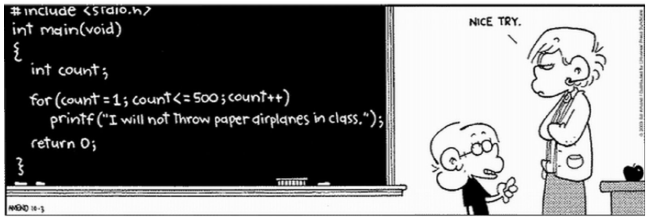
- 6+ *cyber-enabled* courses: Chemistry, Physics, Algebra, Geometry, Chinese, English
- Data collection
  - Students do home/lab work on tutors, vlab, OLI, …
  - Log data, questionnaires, tests → DataShop





PSLC Enabling Technologies

- Tools for developing instruction & experiments
  - CTAT (cognitive tutoring systems)
    - SimStudent (generalizing an example-tracing tutor)
  - OLI (learning management)
  - TuTalk (natural language dialogue)
  - REAP (authentic texts)
- Tools for data analysis
  - DataShop
  - TagHelper



LearnLab Products

Infrastructure created and highly used

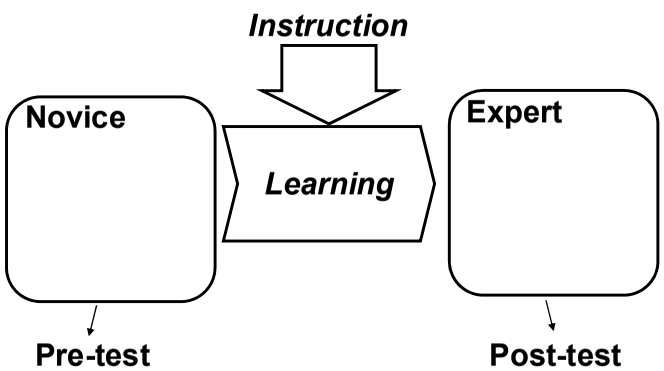
- LearnLab courses have supported over 150 *in vivo* experiments
- Established DataShop: A vast open data repository & associated tools
  - 110,000 student hours of data
    - 21 million transactions at ~15 second intervals
  - New data analysis & modeling algorithms
  - 67 papers, >35 are secondary data analysis not possible without DataShop

PSLC Statement of Purpose

Leverage cognitive and computational theory to identify the instructional conditions that cause robust student learning.

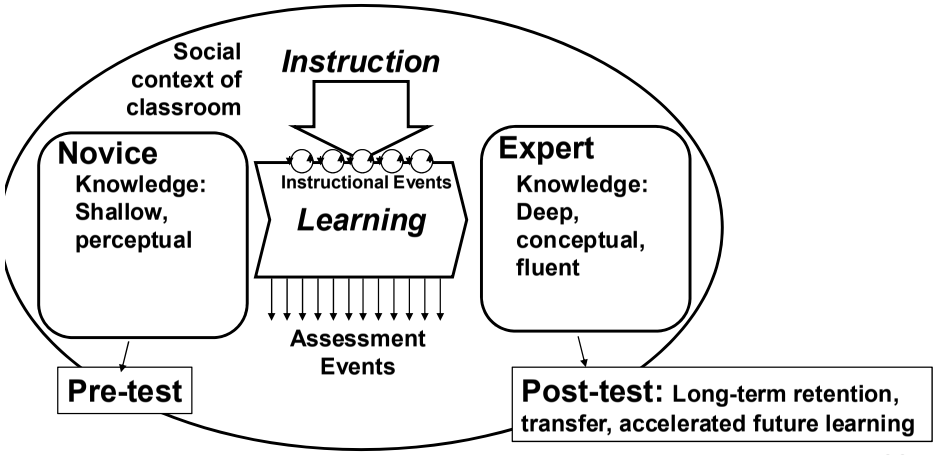
Typical Instructional Study

- Compare effects of 2 instructional conditions in lab
- Pre- & post-test similar to tasks in instruction



PSLC Studies

- Macro: Measures of robust learning
- Micro analysis: knowledge, learning, interactions
- Studies run *in vivo*: social & motivational context



Develop a research-based, but practical framework

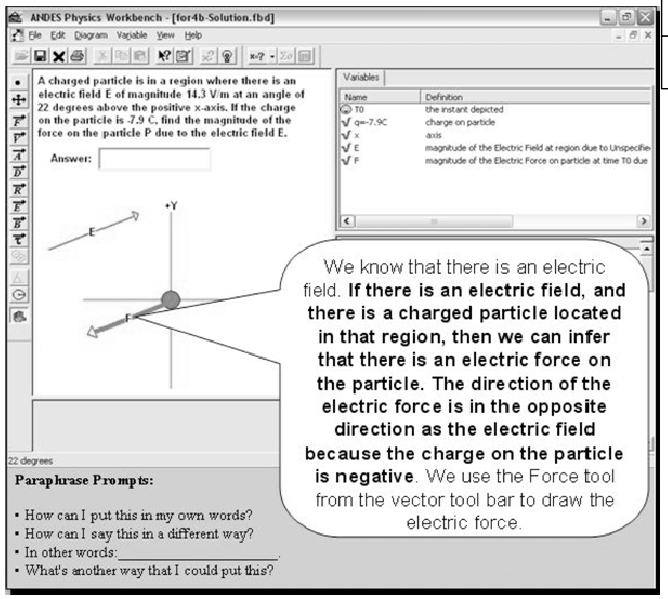
- Theoretical framework key goals
  - Support reliable generalization from empirical studies to guide design of effective ed practices

Two levels of theorizing:

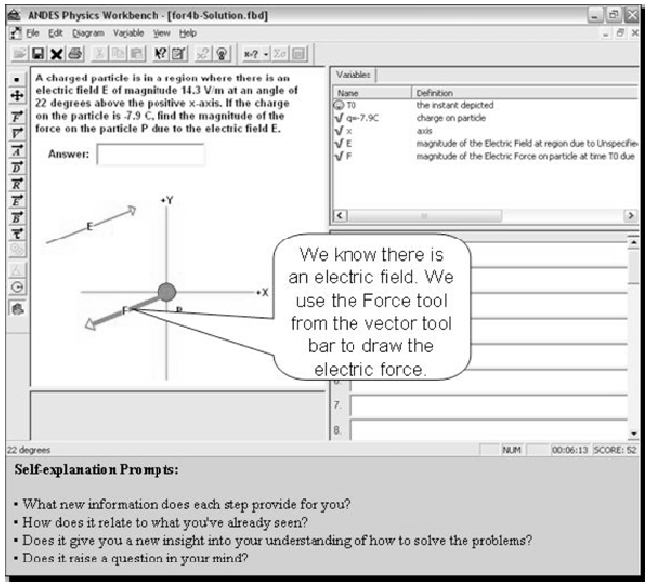
- Macro level
  - What *instructional principles* explain how changes in the instructional environment cause changes in robust learning?
- Micro level
  - Can learning be explained in terms of what *knowledge components* are acquired at individual *learning events*?

Example study at macro level: Hausmann & VanLehn 2007

- Research question
  - Should instruction provide explanations and/or elicit "self-explanations" from students?
- Study design
  - All students see 3 examples & 3 problems
    - Examples: Watch video of expert solving problem
    - Problems: Solve in the Andes intelligent tutor
  - Treatment variables:
    - Videos include *justifications* for steps or do not
    - Students are prompted to "*self-explain*" or paraphrase



	Para-phrase	Self-explain
Explan	X	
No explan		

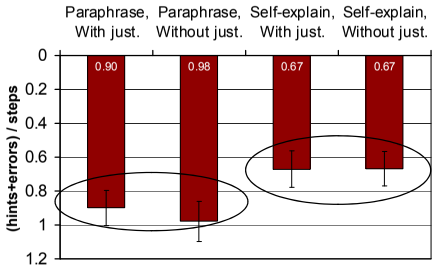


	Para-phrase	Self-explain
Explan		
No explan		X

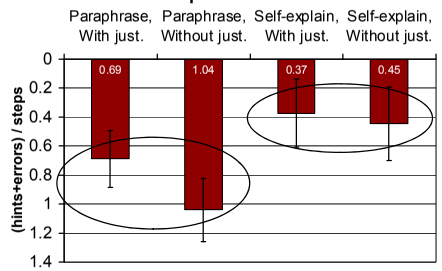
Self-explanations => greater robust learning

- Justifications: no effect!

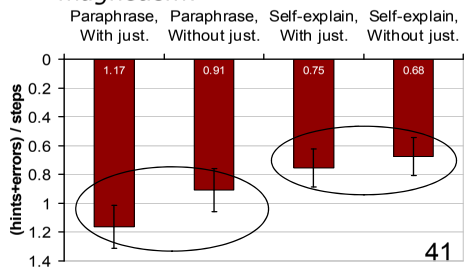
- Immediate test on electricity problems:



- Transfer to new electricity homework problems



- Instruction on *electricity* unit => accelerated future learning of *magnetism*!



Key features of H&V study

- *In vivo* experiment
  - Ran live in 4 physics sections at US Naval Academy
  - Principle-focused: 2x2 single treatment variations
  - Tight control manipulated through technology
- Use of Andes tutor
  => repeated *embedded assessment* without disrupting course
- Data in DataShop (more later)

Develop a research-based, but practical framework

- Theoretical framework key goals
  - Support reliable generalization from empirical studies to guide design of effective ed practices

Two levels of theorizing:

- Macro level
  - What *instructional principles* explain how changes in the instructional environment cause changes in robust learning?
- Micro level
  - Can learning be explained in terms of what *knowledge components* are acquired at individual *learning events*?

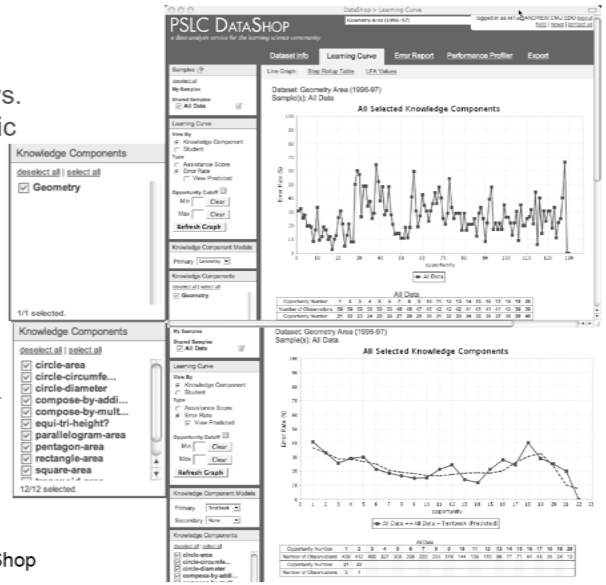
Knowledge Components

- Knowledge Component
  - *A mental structure or process that a learner uses, alone or in combination with other knowledge components, to accomplish steps in a task or a problem*-- PSLC Wiki
- Evidence that the Knowledge Component level functions in learning …

Knowledge Components vs. curriculum topic

Single Topic (Area) as unit

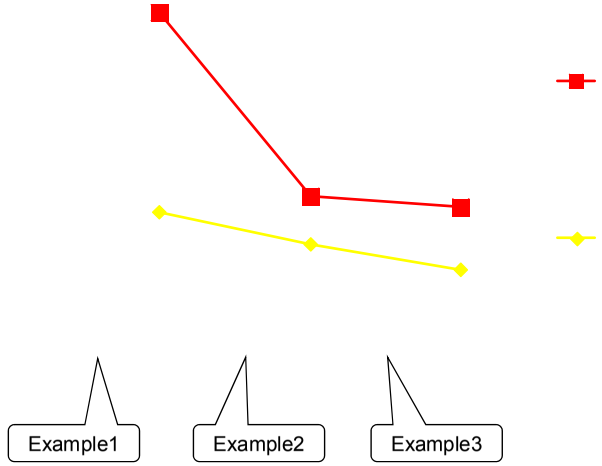
12 separate KCs as units



Enabled by Data Shop

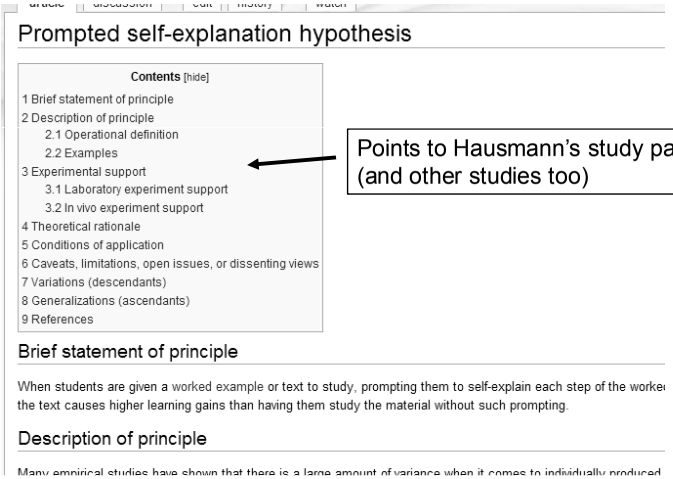
Back to H&V study: Micro-analysis

Learning curve for main KC
Self-explanation effect tapers but not to zero



PSLC wiki: Principles & studies that support them

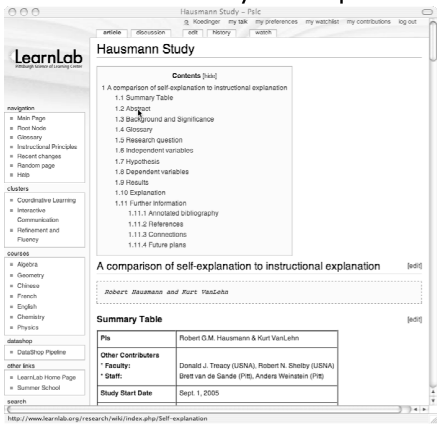
Instructional Principle pages unify across studies



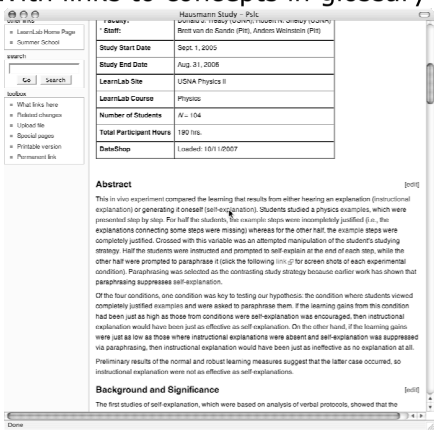
Points to Hausmann's study page (and other studies too)

PSLC wiki: Principles & studies that support them

Hausmann's study description:

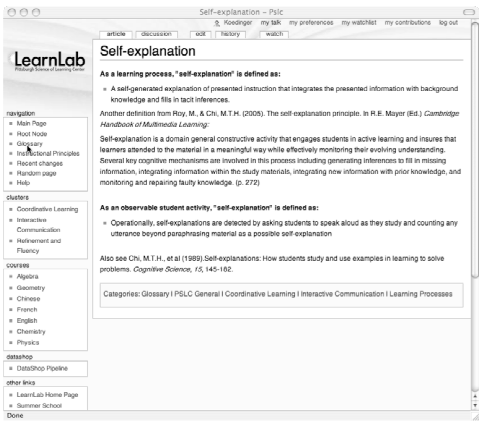


With links to concepts in glossary

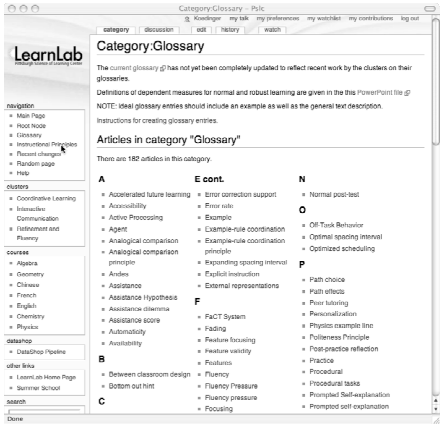


PSLC wiki: Principles & studies that support them

Self-explanation glossary entry



~200 concepts in glossary



Research Highlights

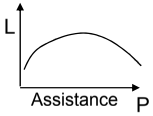
- *Synthesizing worked examples & self-explanation research*
  - 10+ studies in multiple 4 math & science domains
  - New theory: It's not just cognitive load!
    - Examples for deep feature construction, problems & feedback for shallow feature elimination

  This work inspired new question: Does self-explanation enhance *language learning?* Experiments in progress …
- *Computational modeling of student Learning*
  - Simulated learning benefits of examples/demonstrations vs. problem solving (Masuda et al., 2008)
    - Theory outcome: problem solving practice is an important source of negative examples
    - Engineering: "programming by tutoring" is more cost-effective than "programming by demonstration"
  - Shallow vs. deep prior knowledge changes learning rate (Matsuda et al., in press)

Research Highlights (cont)

- *Computational modeling of instructional assistance*
  - Assistance formula: Optimal learning (L) depends on right level of assistance

$$L = \frac{P*Sb+(1-P)Fb}{P*Sc+(1-P)Fc}$$



  - Relevant to multiple experimental paradigms & dimensions of instructional assistance
    - Direct instruction (worked examples) vs. constructivism (testing effect)

      Kirschner, Sweller, & Clark (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist*
    - Concrete manipulatives vs. simple abstractions

      Kaminski, Sloutsky, & Heckler (2008). The advantage of learning abstract examples in learning math. *Science*.
  - *Formula provides path to resolve hot debates*

Research Highlights (cont)

- *Synthesis paper on computer tutoring of metacognition*

  Koedinger, Aleven, Roll, & Baker. (in press). *In vivo* experiments on whether supporting metacognition in intelligent tutoring systems yields robust learning. In *Handbook of Metacognition in Education*.
  - Generalizes results across 7 studies, 3 domains, 4 populations
  - Posed new questions about role of motivation
- *Lasting effects of metacognitive support*
  - Computer-based tutoring of self-regulatory learning
    - Technologically possible & can have a *lasting effect*
  - Students who used help-seeking tutor demonstrated better learning skills in later units after support was faded
    - Spent 50% more time reading help messages
- *Data mining for factors that affect student motivation*
  - Machine learning to analyze vast student interaction data from full year math courses (Baker et al., in press a & b)
  - Students more engaged on "rich" story problems than standard
  - *Surprise*: Also more engaged on abstract equation exercises!

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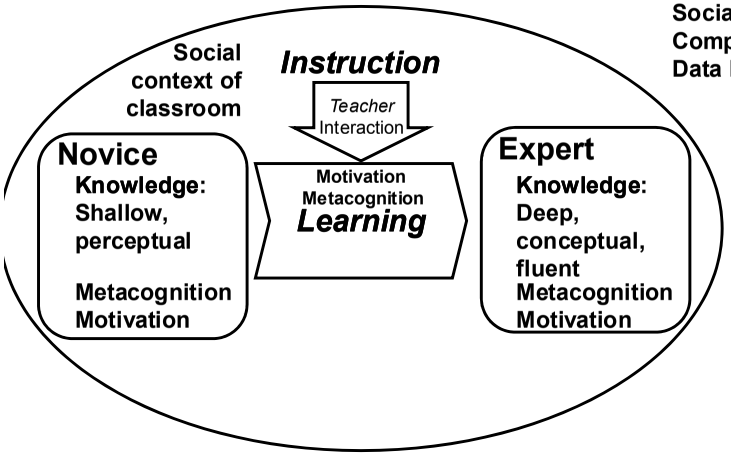
"rigorous, sustained scientific research in education" (NRC, 2002)

Summary

- Why? *Chasm* between science & practice
- PSLC Purpose: Identify the conditions that cause robust student learning
  - Field-based rigorous science
  - Leverage cognitive & computational theory, educational technologies
- Results: Sound evidence & deeper theory behind principles to bridge chasm
- Impact: Principles, methods, tools, & data in wide-spread use

Thrusts investigate overlapping factors

THRUSTS
Cognitive Factors
Metacognition & Motivation
Social Communication
Comp Modeling & Data Mining



Thrust Research Questions

- ***Cognitive Factors***. How do instructional events affect learning activities and thus the outcomes of learning?
- ***Metacognition & Motivation***. How do activities initiated by the learner affect engagement with targeted content?
- ***Social Communication***. How do interactions between learners and teachers and computer tutors affect learning?
- ***Computational Modeling & Data Mining***. Which models are valid across which content domains, student populations, and learning settings?

4th Measure of Robust Learning

- Existing robust learning measures
  - Transfer
  - Long-term retention
  - Acceleration of future learning
- New measure:
  - Desire for future learning
    - Is student engaged in subject?
    - Do they chose to pursue further math, science, or language?

END