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

Ken Koedinger
HCI & Psychology
CMU Director of PSLC

Vision for PSLC

• 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

• 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

Research base

Cognitive Psychology

Artificial Intelligence

Cognitive Tutor Technology

Curriculum Content

Math Instructors

Math Educators

NCTM Standards

Cognitive Tutors

Algebra I  Equation Solver  Geometry  Algebra II
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

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

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
Cogntive Tutor Approach

Research base
Cognitive Psychology
Artificial Intelligence

Cognitive Tutor Technology

Curriculum Content
Math Instructors
Math Educators
NCTM Standards

Cognitive Tutors
Algebra I
Equation Solver
Geometry
Algebra II

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
\[ x \times 6 + 66 = 81.90 \]

Algebra Student Results: Story Problems are Easier!

Expert Blind Spot:
Expertise can impair judgment of student difficulties


“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

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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

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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
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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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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

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Novice

Learning

Expert

Instruction

Pre-test

Post-test

Novice

Knowledge: Shallow, perceptual

Instructional Events

Learning

Expert

Knowledge: Deep, conceptual, fluent

Assessment Events

Pre-test

Post-test: Long-term retention, transfer, accelerated future learning
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

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<td>X</td>
</tr>
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**Example:**

We know that there is an electric field. If there is an electric field, and there is a charged particle located in that region, then we can infer that there is an electric force on the particle. The direction of the electric force is in the opposite direction as the electric field because the charge on the particle is negative. We use the Force tool from the vector tool bar to draw the electric force.
Self-explanations => greater robust learning
- Justifications: no effect!
- Immediate test on electricity problems:

Paraphrase, Paraphrase, Self-explain, Self-explain, With just, Without just, With just, Without just.

Paraphrase, With just.

Paraphrase, Without just.

Self-explain, With just.

Self-explain, Without just.

Justifications: no effect!

Immediate test on electricity problems:

Paraphrase, Paraphrase, Self-explain, Self-explain, With just, Without just, With just, Without just.

Paraphrase, With just.

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Self-explain, With just.

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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

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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...
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

### Prompted self-explanation hypothesis

**Contents**

1. Prompt statement of principle
2. Description of principle
   1. Operational definition
   2. Examples
3. Experimental support
4. Theoretical rationale
   1. Conditions of application
   2. Variations (ancestral)
   3. Generalizations (ancestral)
5. References

**Brief statement of principle**

When students are given a worked example or text to study, prompting them to self-explain each step of the worked text causes higher learning gains than having them study the material without such prompting.

**Description of principle**

Many empirical studies have shown that there is a large amount of variance when it comes to individually-validated...
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
  \[ L = \frac{P*S_b+(1-P)*F_b}{P*S_c+(1-P)*F_c} \]
  - Relevant to multiple experimental paradigms & dimensions of instructional assistance
    - Direct instruction (worked examples) vs. constructivism (testing effect)
    - Concrete manipulatives vs. simple abstractions
  - Formula provides path to resolve hot debates
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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

**THURSTS**
- Cognitive Factors
- Metacognition & Motivation
- Social Communication
- Comp Modeling & Data Mining

**Instruction**

Novice
- Knowledge: Shallow, perceptual
- Metacognition
- Motivation

Expert
- Knowledge: Deep, conceptual, fluent
- Metacognition
- Motivation

Social context of classroom

Teacher Interaction

Learning Metacognition Motivation

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?