

The Center for Innovative Research in Cyberlearning



CIRCL• Our purpose

The **Center for Innovative Research in Cyberlearning** seeks to amplify research-based voices by:

- Nurturing community among projects, investigators and those new to the field
- Addressing common needs
- Planning for the future
- Creating broader impact together

SRI Leads, EDC brings best practices, NORC evaluates









CIRCL • **Priority Activities**

- Events: annual major meetings, working groups, webinars
- Brokering: helping connect investigators, projects and newcomers to knowledge and resources
- Synthesis and Web Site: creating a public space to highlight contributions, share findings, build community and capacity
- Portfolio Analysis: understanding the funded projects
- Sharing Data: as needed by NSF and others
- **Broadening Participation:** in the cyberlearning CoP to include institutions and individuals currently underrepresented



CIRCL • What can CIRCL do for you? http://circlcenter.org

Perspectives

Learn about researchers, teachers, industry, informal learning and other stakeholders in the cyberlearning community, what drives their work, and what they think the community should be doing.





Projects

CIRCL Spotlights illuminate some of the different cyberlearning projects across NSF, including projects funded by the NSF Cyberlearning Program and projects funded by other NSF programs whose work has a cyberlearning theme. A tag map of funded projects is also available.



Want us to spotlight your project? Contact us to contribute your story.





COMPUTATIONAL THINKING AND SCIENTIFIC MODELING

Resources

Browse CIRCL Synthesis statements, watch NAPLeS webinars, search the digital collection of education resources from Informal Commons, and see other resources below



Synthesis Statements

CIRCL synthesis statements summarize effective use of advanced learning technologies that are integrative, innovative, empirically grounded, and widely useful. Want to contribute? Let us know.



AI APPLICATIONS IN EDUCATION

EDUCATIONAL DATA

LEARNING SCIENCES

IMPLEMENTATION

Events

Learn about upcoming CIRCL events like the 2015 Synthesis & Envisioning meeting, and access archives from past events, including the 2014 Cyberlearning Summit and the 2012 Cyberlearning Summit.

Browse our calendar of other cyberlearning-related conferences and events. Please let us know about other cyberlearning events in the community.

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Newsletter

Subscribe to the CIRCL newsletter to get updates 6 times a year on cyberlearning-related news

Have some news to share with the community?

CIRCL NEWSLETTER -ISSUE 6, JULY 2014

CIRCL NEWSLETTER -ISSUE 5, MAY 2014

CIRCL NEWSLETTER -ISSUE 3, JANUARY 2014

CIRCL NEWSLETTER -ISSUE 2, NOVEMBER





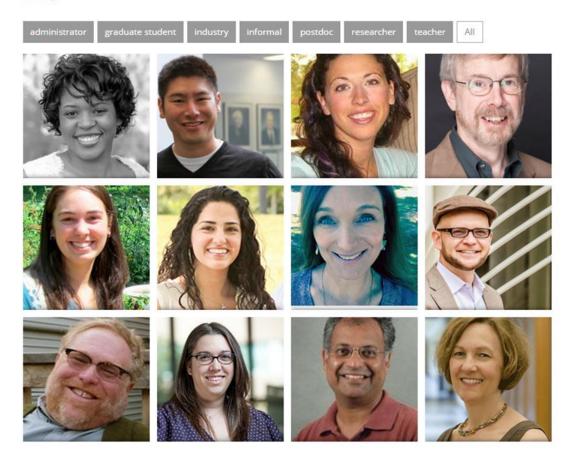
CIRCL • Connect, collaborate, create

Perspectives

Learn about researchers, teachers, industry, informal learning and other stakeholders in the cyberlearning community, what drives their work, and what they think the community should be doing.



What's your view on Cyberlearning? Use this quick form to let us know.





CIRCL • Identify synergistic projects

Projects

CIRCL Spotlights illuminate some of the different cyberlearning projects across NSF, including projects funded by the NSF Cyberlearning Program and projects funded by other NSF programs whose work has a cyberlearning theme. A tag map of funded projects is also available.



Want us to spotlight your project?

Contact us to contribute your story.

spotlight

All

LEARN ABOUT OUR COMPLEX WORLD THROUGH MAP-BASED GAMES!

CIRCL Spotlights illuminate some of the different projects...

HEAD-MOUNTED DISPLAYS IN DEAF EDUCATION

CIRCL Spotlights illuminate some of the different projects...

REVOLUTIONIZING EDUCATION IN HAITI

CIRCL Spotlights illuminate some of the different projects...

UNDERSTANDING SUSTAINABILITY THROUGH DISCOVERY AND PLAY

CIRCL Spotlights illuminate some of the different projects...

LINKING SUPERHEROES AND TECHNOLOGY TO STEM ASPIRATIONS

CIRCL Spotlights illuminate some of the different projects...

SYNERGISTIC TEACHING OF COMPUTATIONAL THINKING AND SCIENTIFIC MODELING

CIRCL Spotlights illuminate some of the different projects...

MIXED REALITY BRINGS SCIENCE CONCEPTS TO LIFE

CIRCL Spotlights illuminate some of the different projects...

ACTIVITY MONITOR GAME INCREASES YOUTH FITNESS

CIRCL Spotlights illuminate some of the different projects...



CIRCL • Access integrative, empirically grounded resources

Big Ideas

Read CIRCL synthesis statements, review resources for writing strong proposals to the NSF Cyberlearning Program, watch NAPLeS webinars, subscribe to edSurge, read the Cyberlearning Educators blog, search the digital collection of resources from Informal Commons, browse NSF project and program data in DIA2, and more.



Have ideas or resources to suggest? Contact CIRCL

Synthesis Statements

CIRCL synthesis statements summarize effective use of advanced learning technologies that are integrative, innovative, empirically grounded, and widely useful. Want to contribute? Let us know.

THE CUTTING-EDGE OF INFORMAL LEARNING: MAKERS, MOBILE, AND MORE!

Cyberlearning spans inschool and out-ofschool learning -- and these days, a lot of meaningful learning is...

COLLABORATIVE LEARNING

Learning to explain, justify, critique, etc. are essential skills for today's citizens, for scientists, and in...

GAMES AND VIRTUAL WORLDS

Computer-based games and virtual worlds provide opportunities for players to think about choices, take action, and...

EDUCATIONAL DATA MINING AND LEARNING ANALYTICS

EDM is the use of multiple analytical techniques to better understand relationships, structure,

PARTNERING FOR IMPACT: INCREASING CYBERLEARNING'S INFLUENCE IN

EDUCATION

MARKETS

Many Cyberlearning researchers know that their work could make

AI APPLICATIONS IN EDUCATION

Al techniques can enable educational technologies to better track, adapt to, and support individual learners.

TECHNOLOGY ENABLED FORMATIVE ASSESSMENT

Formative assessment occurs when teachers check student understanding and guide decision making to improve learning.

LEARNING SCIENCES

The Learning Sciences is a field of scientific research that developed in the 1980s, from influences...



CIRCL • Join a vibrant community of practice

Events

Learn about upcoming CIRCL events like Cyberlearning 2015, and access archives from past events.



Browse a calendar of other cyberlearning-related conferences and events. Please let us know about other cyberlearning events in the community.





CYBERLEARNING 2015: CONNECT, COLLABORATE, AND CREATE THE FUTURE

January 27-28, 2015 in Arlington, VA A gathering of participants with a...

CYBERLEARNING SUMMIT 2014

On June 9-10, 2014, CIRCL hosted the 2014 Cyberlearning Summit at the...

NSF CYBERLEARNING INTEGRATION (INT) PROPOSAL WEBINAR

Monday, June 2nd from 3pm – 4pm ET An informational webinar on...

PARTNERING FOR IMPACT 2014

On March 26 and 27, 2014, SRI hosted an intensive two-day workshop...

NSF CYBERLEARNING SOLICITATION INFORMATION WEBINAR

Tuesday, February 18th from 1pm – 2:30pm ET An informational webinar on ...

SYNTHESIS AND ENVISIONING 2013

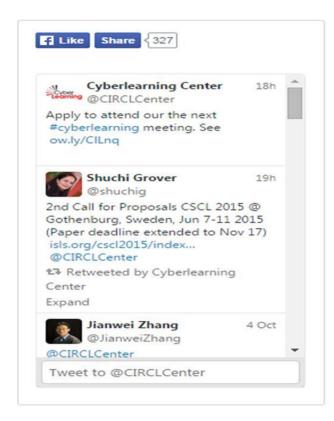
A gathering of NSFfunded cyberlearning projects to synthesize what is known and...

CYBERLEARNING SUMMIT 2012

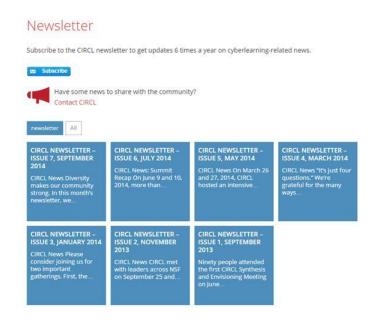
The 2012 Cyberlearning Research Summit was a high-profile gathering in Washington DC...



CIRCL • Follow us, contribute, stay connected!







http://circlcenter.org

circl-info@sri.com



Cyberlearning Data Sharing and Privacy

Ken Koedinger Professor of Human-Computer Interaction & Psychology Carnegie Mellon University

Director of





LearnLab Researchers: Charles Perfetti (Psych), Vincent Aleven (HCI), Geoff Gordon (Machine Learning), David Klahr (Psych), Tim Nokes-Malach (Psy), Lauren Resnick (Psy/Ed), Carolyn Rose (Language Tech) + some 200 others!

CIRCL Webinar: May 20, 2015

Outline

- Why data sharing?
- Data curation & privacy management
 - LearnSphere: DataShop, MOOCdb, DataStage, DiscourseDB
- Future of Cyberlearning data partnerships

Big Data for Cyberlearning

More important than "big"

- Collected as part of natural activities
- Affords experimentation, "A/B testing"

Big Data for Cyberlearning

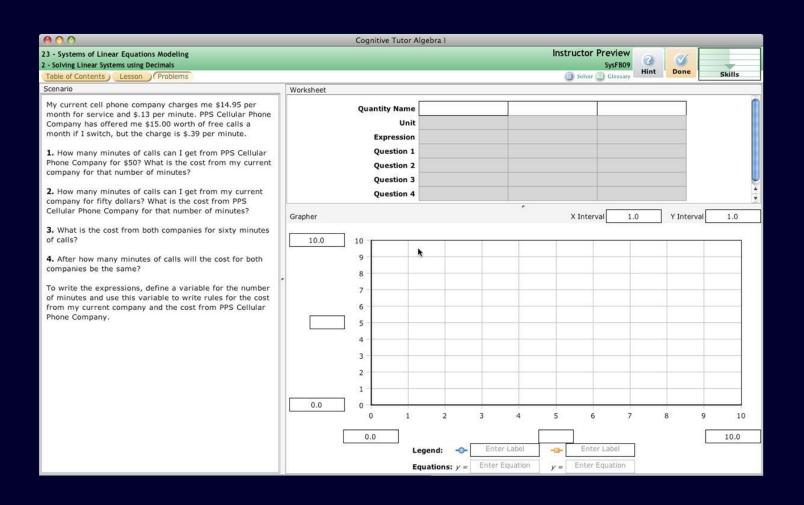
More important than "big"

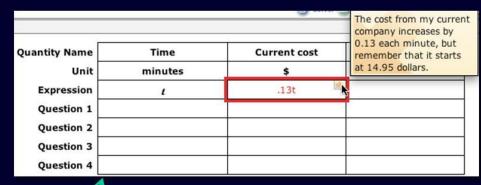
- Collected as part of natural activities
- Affords experimentation, "A/B testing"

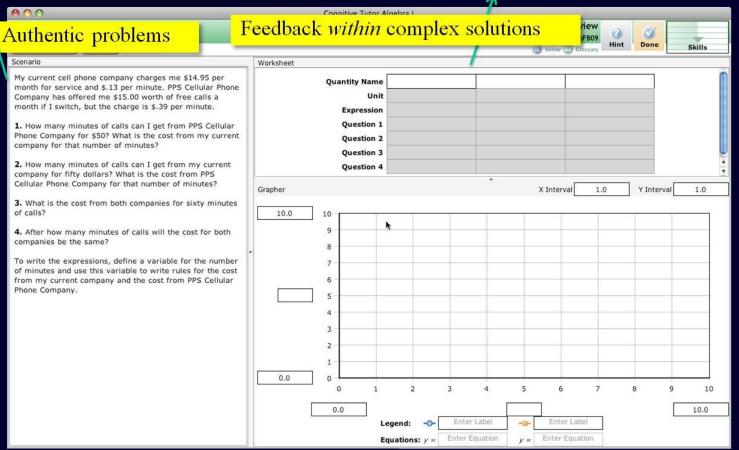
Many dimensions of "big"

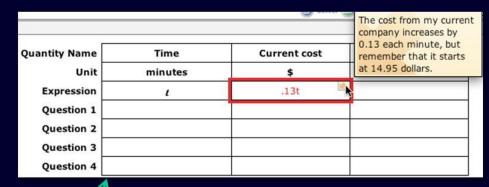
- Tall in number of participants (students)
- Wide in observations per participant (student)
- Fine in frequency of observation
- Long in spanning months or years
- Deep in theory-relevant variables

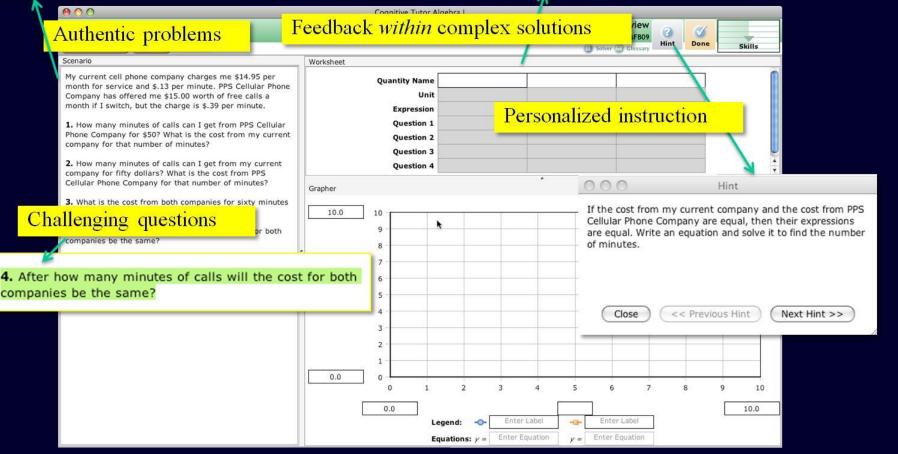
Privacy protection is a distinct challenge

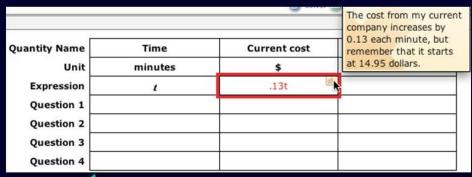


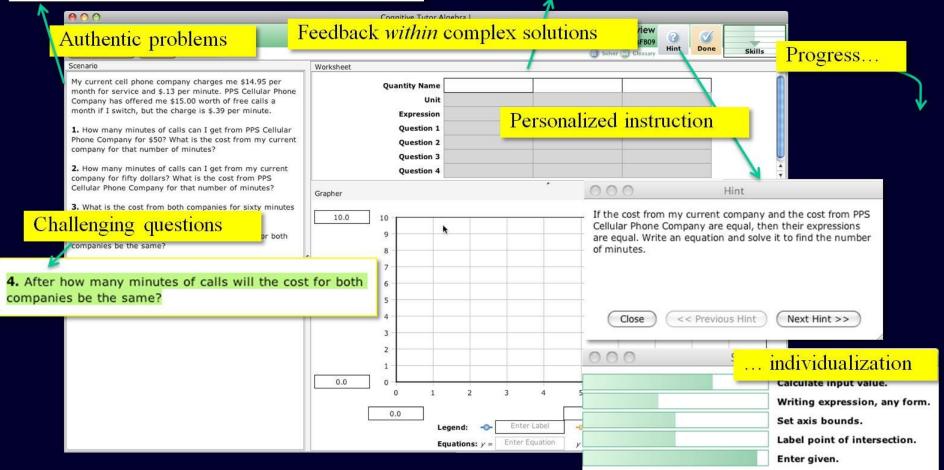




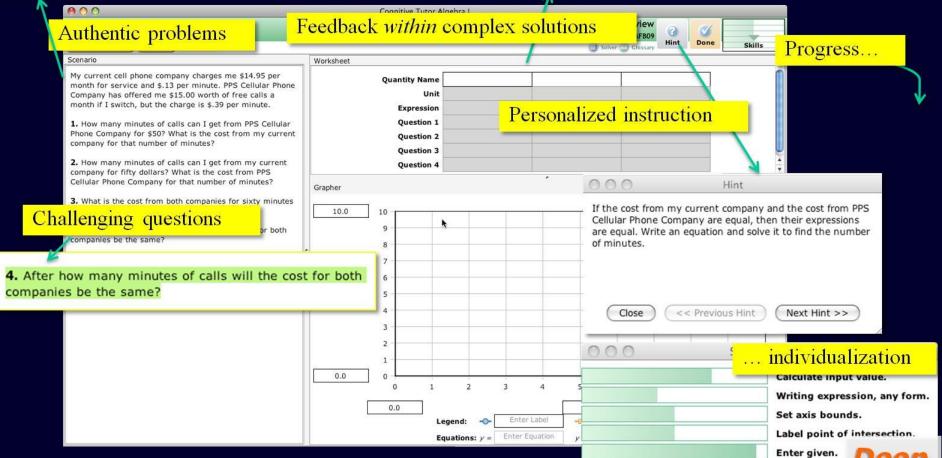






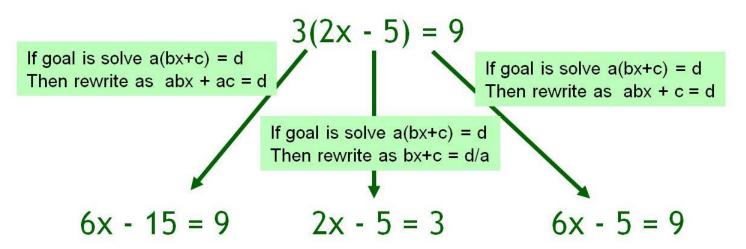






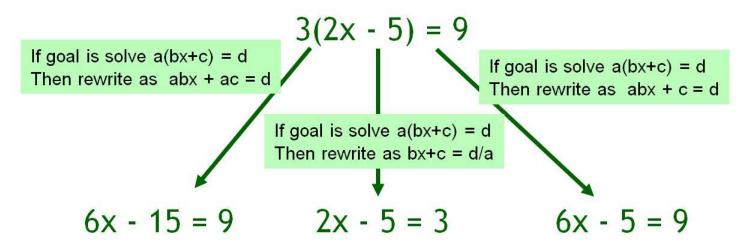
Cognitive model => adaptive support of learning by doing

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



Cognitive model => adaptive support of learning by doing

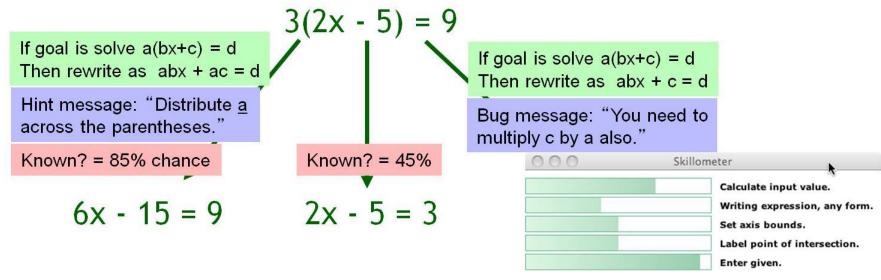
 Cognitive Model: A system that can solve problems in the various ways students can



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

Cognitive model => adaptive support of learning by doing

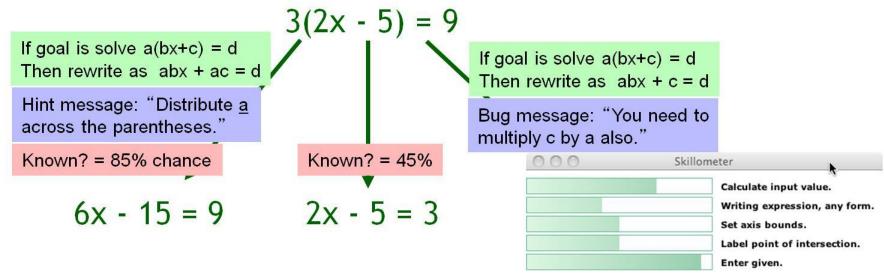
 Cognitive Model: A system that can solve problems in the various ways students can



- 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 model

- => adaptive support of learning by doing
- => deep theory-coded data stream
- 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

Use data to develop models of learners

Which is harder 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?

Answer question online!

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

$$x * 6 + 66 = 81.90$$

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

Use data to develop models of learners – because intuition is faulty!

Which is harder for algebra students?

Story Problem

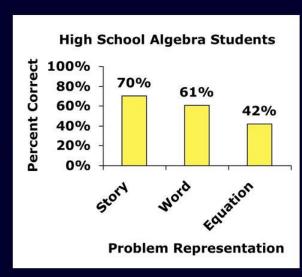
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Word Problem

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

Math educators say: story or word is hardest

Students: equations are hardest



Equation

x * 6 + 66 = 81.90

Expert blind spot!

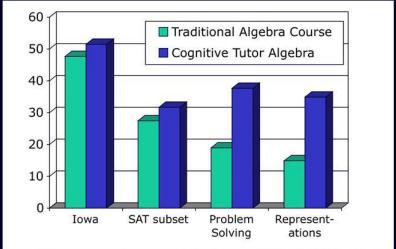
Algebra teachers, especially, incorrectly think equations are easy

Cyberlearning in use

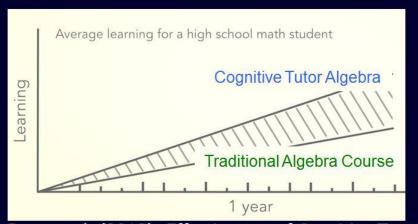


Algebra Cognitive Tutor

- Widespread intensive use
 ~600K students per year
 ~80 minutes per week
- Many field trials =>
 Student learning
 is 2x better



Koedinger, Anderson, Hadley, & Mark (1997). Intelligent tutoring goes to school in the big city.



Pane et al. (2013). Effectiveness of Cognitive Tutor Algebra I at Scale. Santa Monica, CA: RAND Corp.

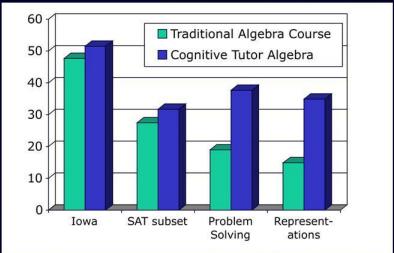
Cyberlearning in use: Good, but can do much better

Long

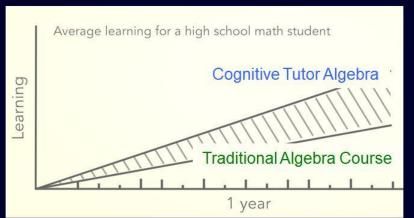


Algebra Cognitive Tutor

- Widespread intensive use
 ~600K students per year
 ~80 minutes per week
- Many field trials =>
 Student learning
 is 2x better
- Still:
 Could do better
 Too many decisions
 driven by intuition



Koedinger, Anderson, Hadley, & Mark (1997). Intelligent tutoring goes to school in the big city.



Pane et al. (2013). Effectiveness of Cognitive Tutor Algebra I at Scale. Santa Monica, CA: RAND Corp.

LearnLab: Use fielded Cyberlearning systems to advance learning theory

Ed tech + wide use = "Basic research at scale"







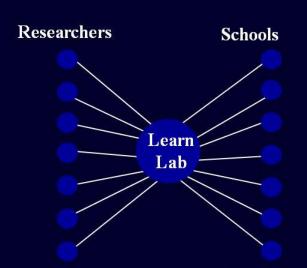
LearnLab: Use fielded Cyberlearning systems to advance learning theory

Ed tech + wide use = "Basic research at scale"









Since 2004

- 680 ed tech data sets in DataShop
- > 360 *in vivo* experiments

Koedinger et al. (2012). The Knowledge-Learning-Instruction (KLI) framework: Bridging the science-practice chasm to enhance robust student learning. *Cognitive Science*.

PSLC DataShop a data analysis service for the learning science community

http://learnlab.org/datashop

Help

Explore

Public Datasets

Private Datasets

External Tools

What can I do?

Learn More

Documentation

About DataShop

FAQ

Welcome to DataShop, the world's largest repository of learning interaction data.

Create an account

L

or

Log in

to start analyzing data.

What can I do with DataShop?

I'm a

Data miner/computer scientist

Cognitive scientist

ITS/AIED researcher

User modeling researcher

Educational psychologist

Course developer

Psychometrician

Learning analytics researcher

Here are topics of interest

(show all)

Test a theory of performance or learning

Applications of Bayesian modeling

Multiple skills

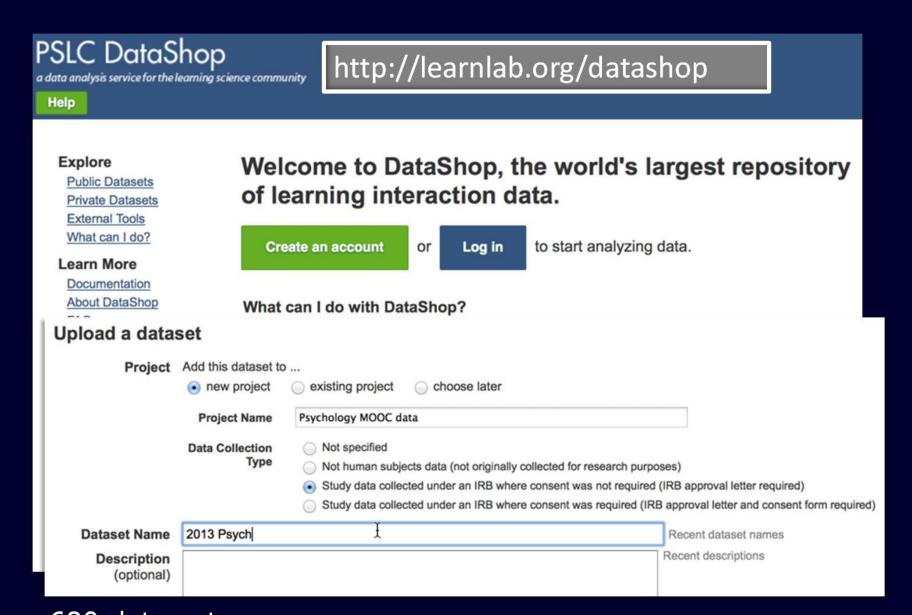
Modeling the rate of learning

Detecting motivation or engagement

Discovering knowledge component/skill/cognitive /student models

What is DataShop?

680 data sets math, science, language ... K12 & college



680 data sets math, science, language ... K12 & college



http://learnlab.org/datashop

Help

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Public Datasets

Private Datasets

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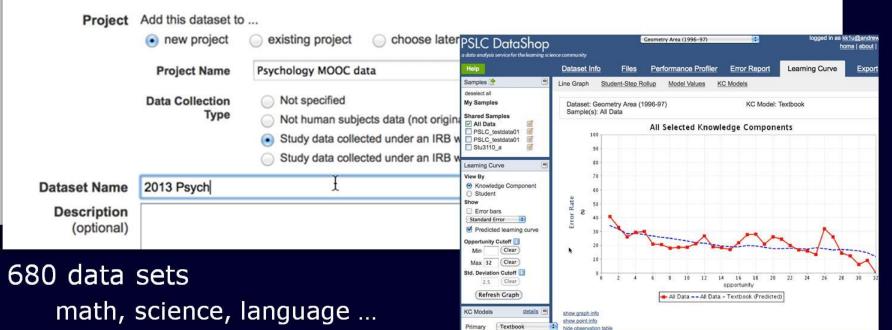
or

to start analyzing data.

What can I do with DataShop?

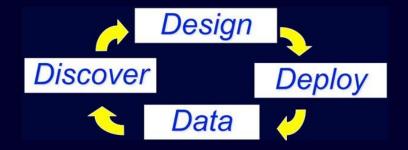
Upload a dataset

K12 & college

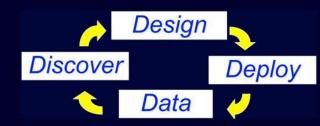


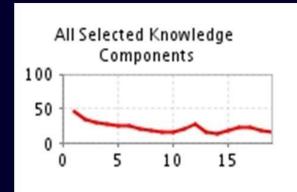
Closing the loop Data-driven continuous improvement

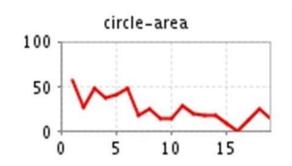
- Deploy v1 of online course
 - Use data to make discoveries
 - Make *design* changes
- Deploy v2 vs. v1 in randomized controlled experiment
 - Use data to evaluate improvement

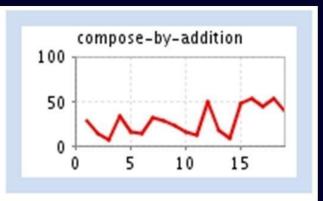


Visualizing learning curves to find opportunities for improvement

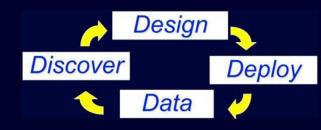


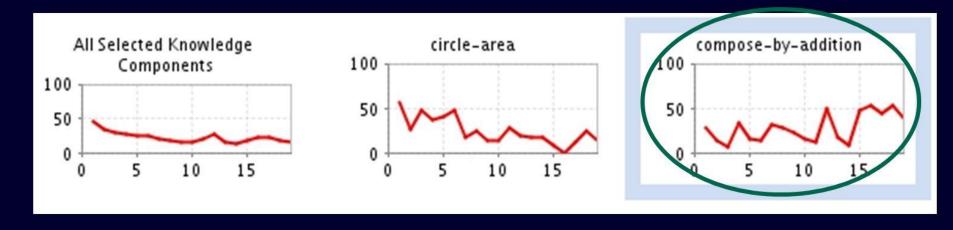






Visualizing learning curves to find opportunities for improvement





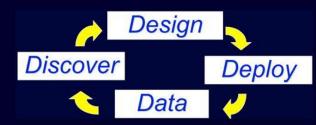
High rough curve

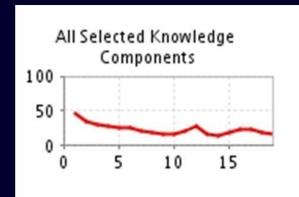
- => revise skill model
- => redesign instruction
- => do A/B test

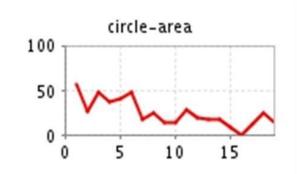
Better student learning!

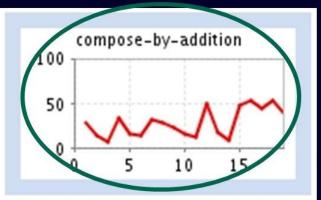
Koedinger, Stamper, McLaughlin, & Nixon. (2013). Using datadriven discovery of better student models to improve student learning. *Proceedings of Artificial Intelligence in Education*.

Visualizing learning curves to find opportunities for improvement







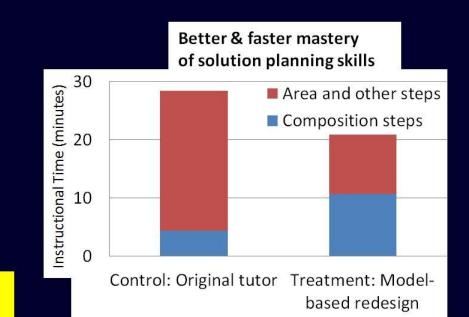


High rough curve

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Better student learning!

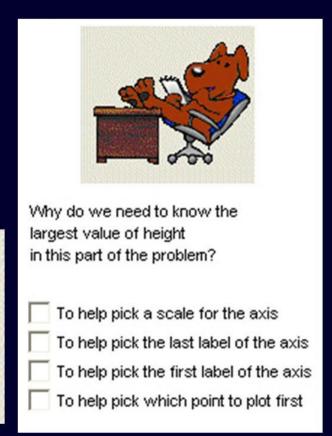
Koedinger, Stamper, McLaughlin, & Nixon. (2013). Using datadriven discovery of better student models to improve student learning. *Proceedings of Artificial Intelligence in Education*.



Machine learning on clickstream => diagnose engagement, "gaming the system", & effectively respond





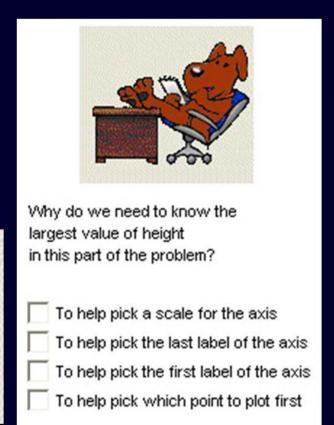


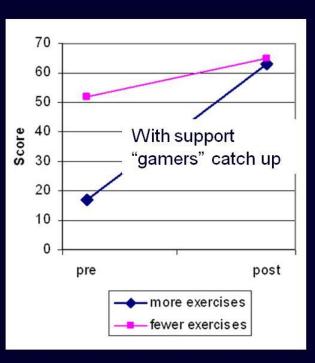
(Baker et al., 2006; Rodrigo et al., 2011)

Machine learning on clickstream => diagnose engagement, "gaming the system", & effectively respond





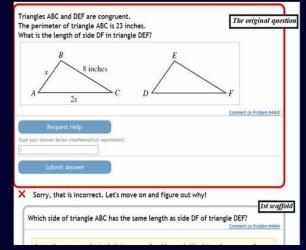


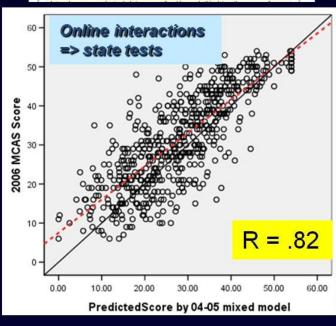


(Baker et al., 2006; Rodrigo et al., 2011)

Tech-based formative assessment: Aids learning & informs teachers

- Assess during learning
 - Data from Oct-Nov predicts end-of-year tests
 - Student effort matters
- Student feedback
 - Learning is better than traditional homework
- Teacher use
 - Low use students benefit from high use teachers





Feng, Heffernan, & Koedinger (2009). Addressing the assessment challenge in an online system that tutors as it assesses. In *User Modeling and User-Adapted Interaction:* The Journal of Personalization Research.

MOOC Analysis:

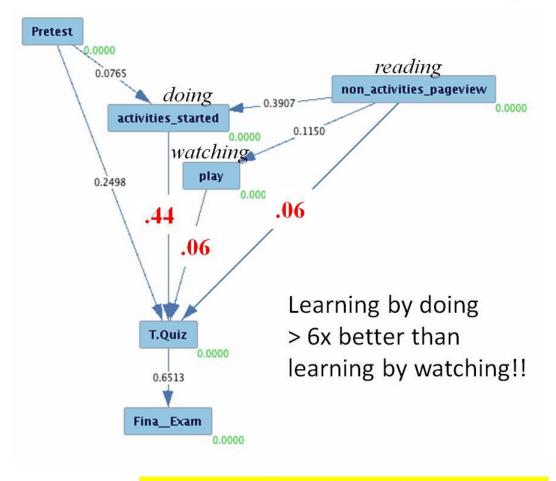
What student choices associate with most learning?

Watching lecture video **Psychology Brain & Behavior** Sensation & Perception Learning & Memory Cognition & Language 0058 YO - -Introduction to Psychology (Open + Free) Reading web pages Unit 12:: Personality Module 34 / Personality as Traits 173 Personalities are characterized in terms of traits, which are relatively enduring characteristics that influence our behavior across many situations. Personality traits such as introversion, friendliness, conscientiousness, honesty, and helpfulness are important because they help explain consistencies in The most popular way of measuring traits is by administering personality tests on which people self-report about their own characteristics. Psychologists have investigated hundreds of traits using the self-report approach, and this research has found many personality traits that have important implications for behavior You can see some examples of the personality dimensions that have been studied by psychologists and their Doing online activities learn by doing with hints & feedback You can try completing a self-repor Five-Factor Personality Test). There 20 minutes to complete. You will receive feedback about your personality after you have finished the test. Complete the table below by dragging each of the major factors of personality based on the Five-Factor (Big Five) Model of Personality to their proper location, between the corresponding traits of both extremes. Note that each factor represents a dimension, or range, between two extremes Low Extreme Traits **High Extreme Traits** Calm, even-tempered, Worrying, temperamental unemotional, hardy emotional, vulnerable Reserved, loner, quiet Down-to-earth, conventional, Imaginative, original, creative ncreative, prefer routine Sympathetic, softhearted, Antagonistic, ruthless. Lazy, aimless, quitting Hardworking, ambitious Agreeableness Conscientiousness Extraversion Openness to experience

Koedinger et al. (2015). Learning is Not a Spectator Sport: Doing is Better than Watching for Learning from a MOOC. *Proceedings of Learning at Scale.*

MOOC Analysis:

What student choices associate with most learning?



Koedinger et al. (2015). Learning is Not a Spectator Sport: Doing is Better than Watching for Learning from a MOOC. *Proceedings of Learning at Scale.*

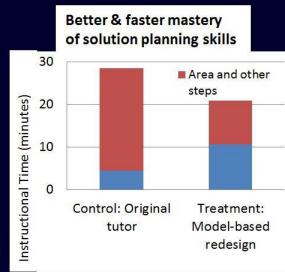


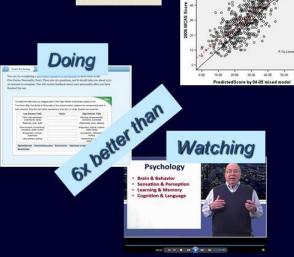
Summary So Far & Questions?

Why data sharing?

- Discover better models of learners
 - Data >> intuition alone
 - Design & deploy better learning activities
- Detect & remediate disengagement
- Improve assessment
- Improve MOOCs

Sharing leverages interdisciplinary interaction

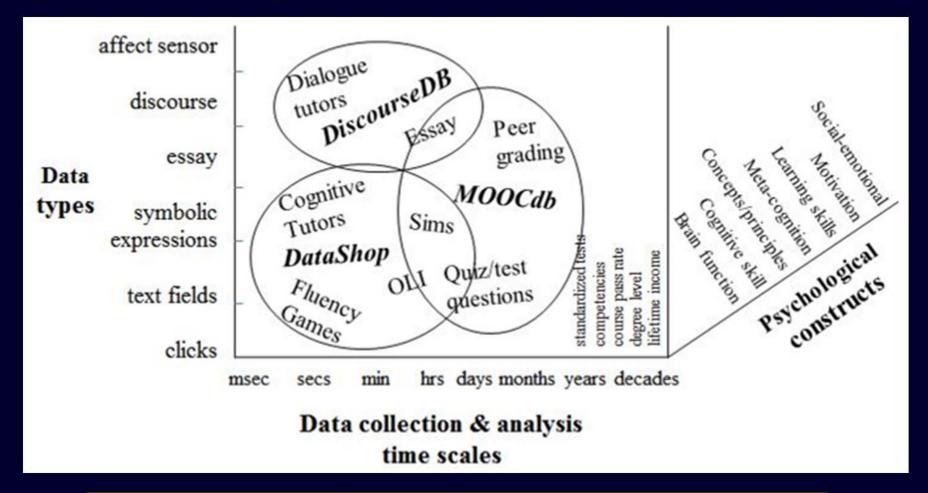




Outline

- Why data sharing?
- Data curation & privacy management
 - LearnSphere: DataShop, MOOCdb, DataStage, DiscourseDB
- Future of Cyberlearning data partnerships

Many kinds of data, time scales, and goals of analysis



We need a CyberLearning data infrastructure to integrate analytic methods => produce discoveries not possible within current data silos







About Explore

A community data infrastructure to support online learning improvement.



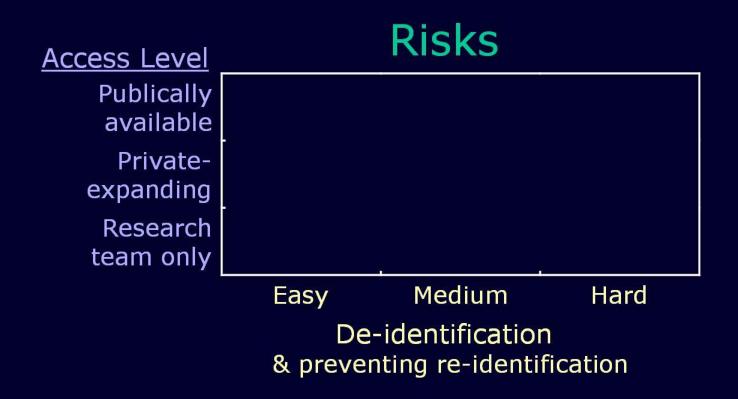
Existing Resources



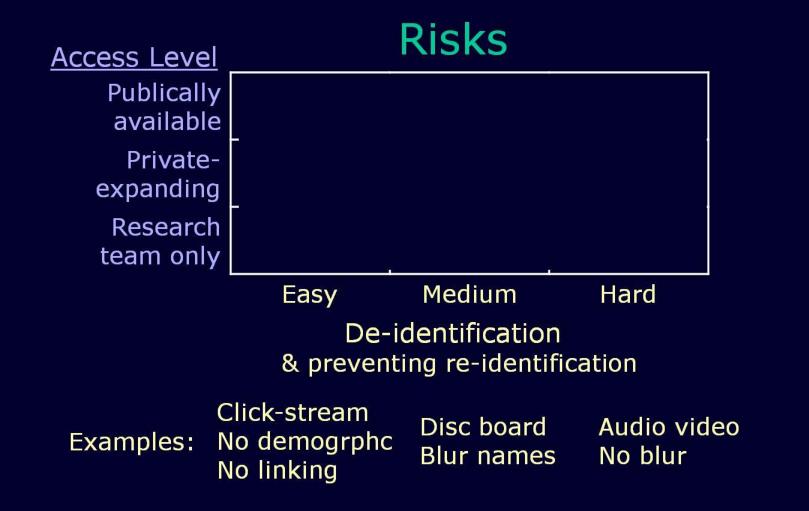




Privacy risks of kinds of data & availability



Privacy risks of kinds of data & availability



Privacy risks of kinds of data & availability

Access Level

Risks

Publically available	Little	Lots	Too much
Private- expanding	Little	Some	Lots
Research team only	Little	Little	Little

Easy Medium Hard

De-identification & preventing re-identification

Click-stream
Examples: No demogrphc

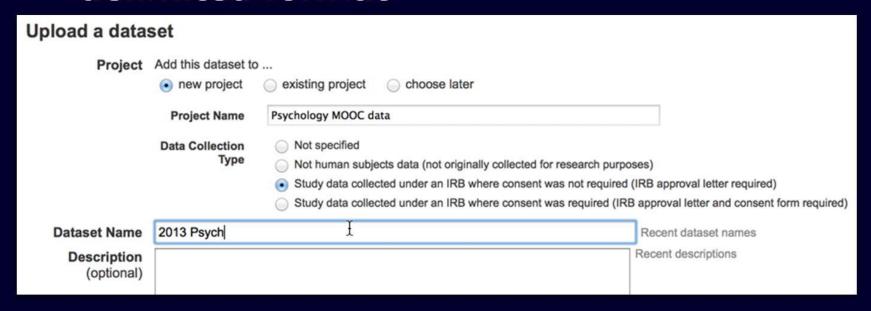
No linking

Disc board Blur names

Audio video No blur

Review process starts when data is uploaded

- Automatic upload for some courses
- By-hand upload is easy using tabdelimited format



Data Management Distinctions

- Shareability--determined by shareability review*
 - Not-Shareable = DataShop does not give the data owner the option of sharing their project outside their research team
 - Shareable = DataShop gives the data owner the option of sharing their project with people outside their team
- Private vs Public--determined by data owner, if shareable
 - <u>Private</u> = registered DataShop users cannot access project without data owner approval
 - Public = registered DataShop users may freely access project without owner approval (only "shareable" projects may be made public).

^{*}Research manager conducts *shareability review* according to shareability criteria (see below)

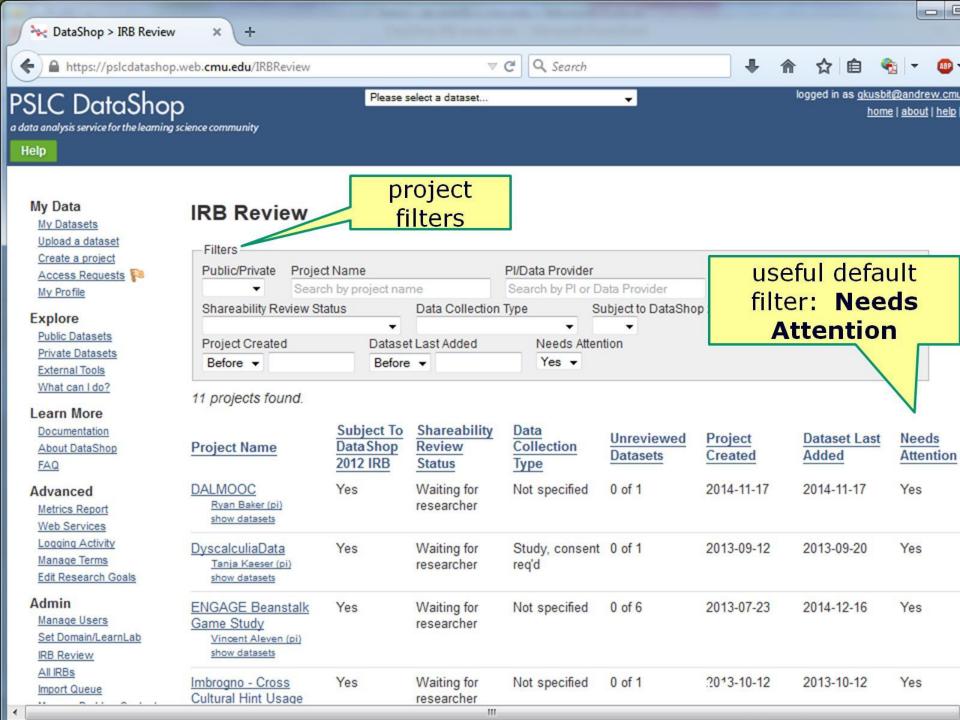
Data Sharing Procedures in DataShop

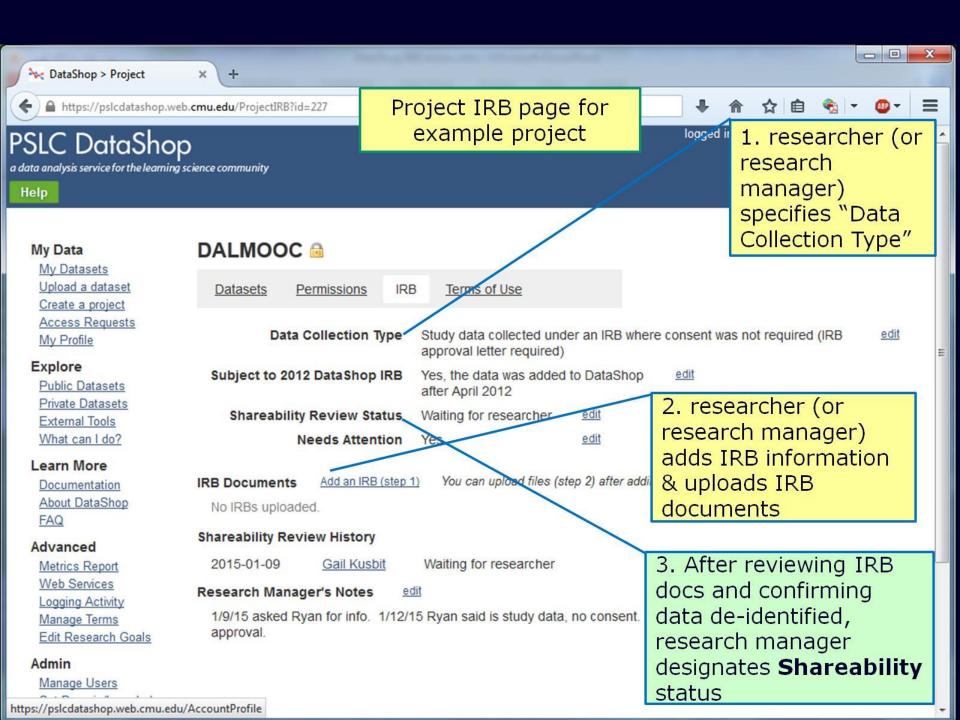
	Private	Public
Not- Shareable	Only PI/data owner may access	
Shareable	PI/data owner decides on case by case basis whether to share with non-team members	Any registered DataShop user may access project freely

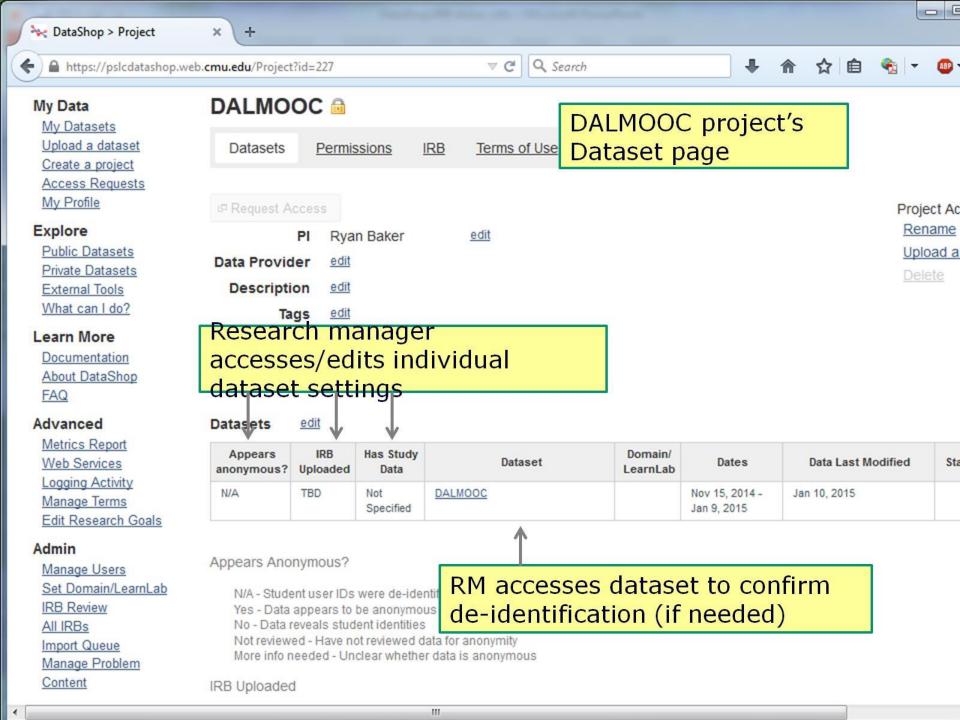
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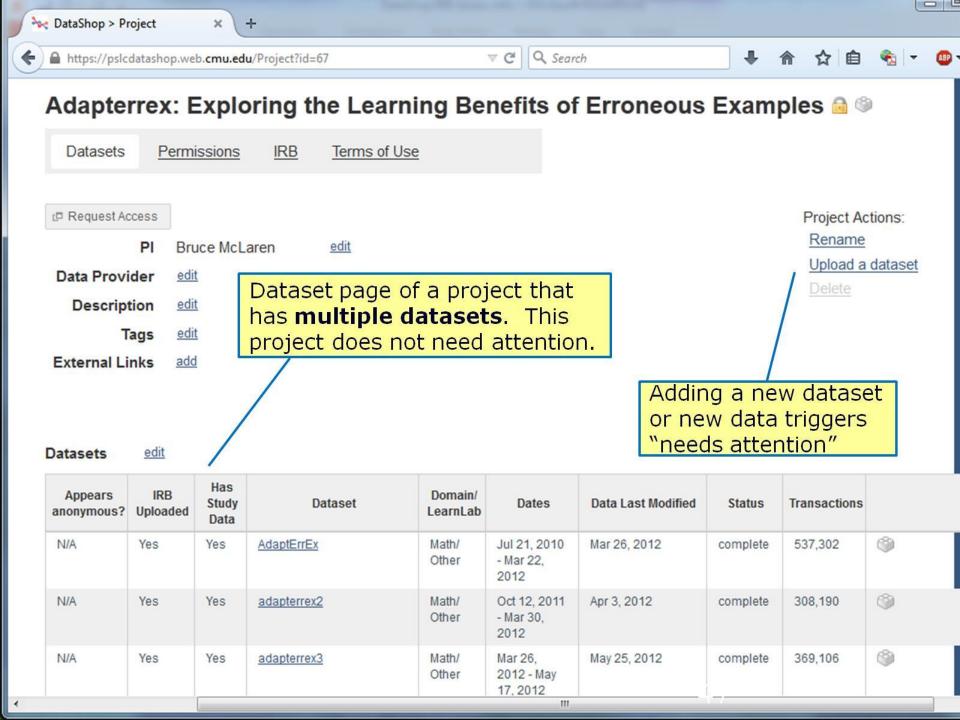
	Research Manager		Data Owner determines Private/Public			
determines Shareability			Private		Public	
	Not- Sharea	ble		ly PI/data owner ay access Default State: Private and Not-Shareable		
	Sharea	ble	on wh	data owner decides case by case basis ether to share with n-team members	Any registered DataShop user may access project freely	

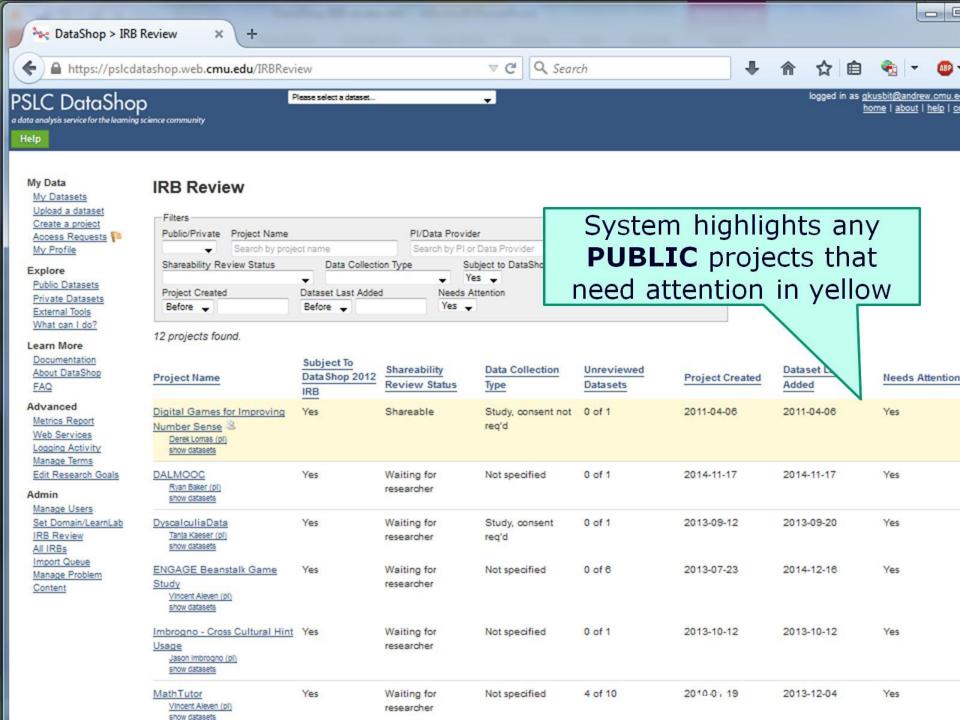
Cyberinfrastructure supports for data privacy review & access management ...









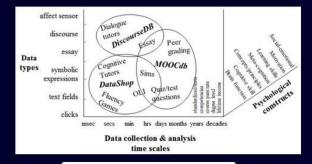


Summary So Far & Questions?

 Avoid data silos to facilitate multi-disciplinary discovery

 Privacy protection depends on data & access

 Cyberinfrastructure helps manage privacy protection









Outline

- Why data sharing?
- Data curation & privacy management
 - LearnSphere: DataShop, MOOCdb, DataStage, DiscourseDB
- Future of Cyberlearning data partnerships

Where to go from here?

Possible partnerships/collaborations/relationships to pursue Cyberlearning advances through data sharing?

Analyses that span levels of analysis

Where to go from here?

Possible partnerships/collaborations/relationships to pursue Cyberlearning advances through data sharing?

Analyses that span levels of analysis

Key needs to be both effective & legal

- Data sharing cyberinfrastructure
 - Easy to use
 - Layered & managed access
 - Rigorous privacy review: IRB+
- Researcher incentives for sharing
 - Sticks: Funder requirements, journal requirements
 - Carrots: Data citation, badges, shared data/analytics counts toward tenure

What's needed in Cyberlearning data partnerships?

As many as possible of:

- Shared datasets with
 - long-term robust learning & life outcomes
 - multiple assessments: performance, standardized, future learning
 - fine-grain, wide, & deep *click* data
 - fine-grain, wide, & deep verbal data
 - embedded experiments: 1 or more random variations

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- Analytics sharing with easy to
 - access existing analytics
 - apply analytics to full space of Cyberlearning data sources
 - Online courses, simulations, games, tutors, inquiry, class video, ubiquitous computing...
 - recombine existing analytics without programming
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 - recombine existing analytics without programming
 - contribute new analytics & new workflows
- Teams with compatible goals
 - interdisciplinary: education, computer science, psychology, economics ...
 - instructors drive research goals
- OTHERS???

Big Data for Learning Conclusions

- Big data can help unlock mysteries of human learning
 - Science & technology to support learning will transition from Model T to Jet Airplane
- Not the "big" that is important
 - Natural collection: tall, wide, fine, long, deep
- Privacy:
 Limit access as de-identification increases
- Future: Big data partnerships to tackle big interdisciplinary education questions

Thank you!





Thanks to >200 researchers that have contributed!!

http://learnlab.org/DataShop

Ken Koedinger koedinger@cmu.edu

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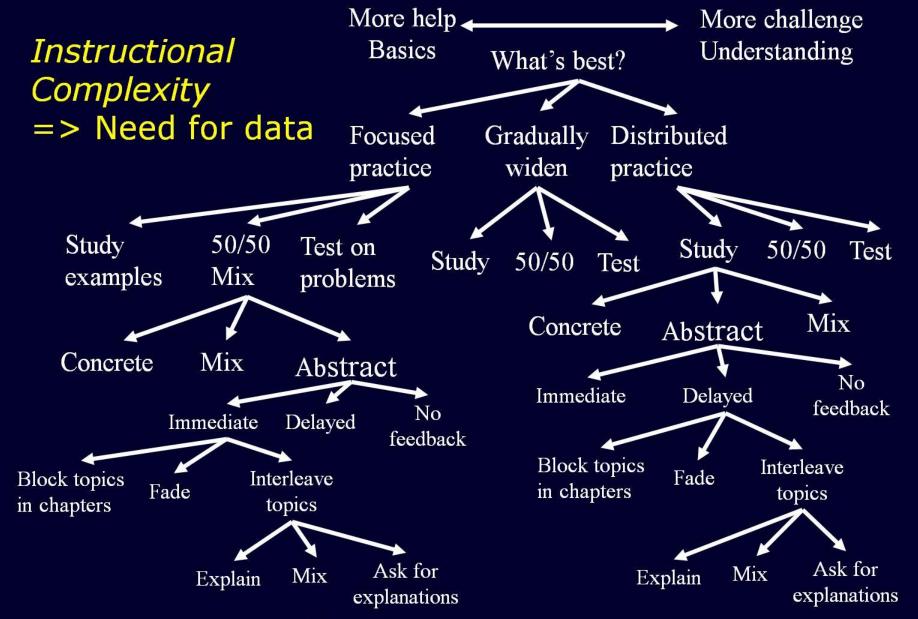
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Many other choices: animations vs. diagrams vs. not, audio vs. text vs. both, ...

Koedinger, Booth, Klahr (2013). Instructional Complexity and the Science to Constrain It. Science.

 $>3^{15*2} = 205$ trillion options!

DataShop IRB Procedures

Gail Kusbit, LearnLab Research Manager

As of 1/16/15, DataShop has

- 187 projects containing a total of 641 datasets
- 23 projects are public, 154 are private

Shareability Review Criteria

Data collection types

- 1. Not human subjects (data not originally collected for research purposes, e.g. course data)
 - the data is de-identified
- Study data collected under an IRB where consent not required
 - the data is de-identified
 - IRB approval letter
- 3. Study data collected under an IRB where consent required
 - the data is de-identified
 - IRB approval letter
 - Consent form
 - Non-prohibitive consent text

IRB Review Interface built by DataShop team and used by DataShop Research Manager

"Needs Attention" triggered when...

Researcher/data provider creates new project

 Researcher/data provider adds a new dataset to an "old" project after project had been designated "shareable"

 Researcher/data provider adds new data to an "old" dataset after its project had been designated "shareable"

Confirming dataset de-identification

For datasets not automatically de-identified by DataShop system, research manager...

- exports a sample of the dataset
- looks through 200 rows of data
- makes "good faith effort" to search for any identifiable information
 - if no identifying info found, RM manually changes "appears anonymous" to "yes"
 - if identifying info found, RM consults with DataShop personnel and data owner—dataset removed from DataShop

Additional IRB management features

- one IRB can cover multiple projects: IRB entry page gives PI or RM option of applying existing IRB to new project or adding a new IRB.
 - "All IRB" page gives RM a listing of all IRBs as well as listing of the projects associated with each IRB.

 one project can have multiple IRBs related to it: A project's IRB page shows all relevant IRB info w/links to documents

Non-exempt IRB Protocol Example

Protocol description:

 "Pilot studies, up to 30 paid students per year. Conducted at CMU to test our study materials before conducting the large-scale classroom studies."

Standard consent wording (permits sharing):

 By your child's participating, you understand and agree that the data and information gathered during this study may be used by Carnegie Mellon and published and/or disclosed by Carnegie Mellon to others outside of Carnegie Mellon.

Newer IRB-suggested consent wording (specific to DataShop, permits sharing):

 Your de-identified data may be stored indefinitely in the DataShop repository at Carnegie Mellon University. Only registered users of DataShop will have access to the data for analysis purposes.

Exempt IRB Protocol Example

Protocol description:

 "Students will either be completing the standard curriculum unit (already shown to improve learning) or the modified curriculum unit, which has been designed to be at least as good as the standard curriculum."

Protocol confidentiality/privacy wording:

 Carnegie Learning personnel will de-identify all student data before giving it to the research team. De-identified data will be stored on secure DataShop server, and may be shared with registered DataShop users for analysis purposes.

Count of project types in DataShop

- 187 projects total
- Projects subject to DataShop's 2012 IRB = 112
 - Not human subjects projects = 24
 - Exempt projects (consent not required) = 43
 - Non-exempt projects (consent required) = 21
 - Not specified (waiting for researcher) = 8
 - Misc (DataShop personnel testing, projectscreated but no datasets inside) = 16