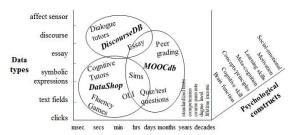
LearnSphere: Data-Driven Discovery and Innovation in Education

CMU: Ken Koedinger, John C. Stamper, Carolyn Rose MIT: Kalyan Veeramachaneni, Una-May O'Reilly Stanford: Candace Thille; U Memphis: Phil Pavlik

Big data in education *opportunity Problem*: Data in **separate silos**

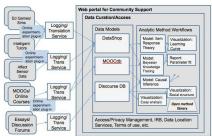
Click stream data in CMU's DataShop MOOC analytics in MIT's MOOCdb MOOC data in Stanford's DataStage Language & discourse data in CMU's new DiscourseDB



Data collection & analysis time scales

LearnSphere Solution

Web-based portal & workflow tool integrates DIBBs Facilitate discoveries not possible within silos



LearnSphere.org: Web-based Portal

Hub for sharing

- Learning data
- → Learning analytic methods
- Tools for generating data



LearnSphere's Workflow Authoring

Web-based workflow authoring

- → Method & data sharing & cross indexing
- → Emergent data standards from convergent method use

Easy for researchers, course developers, $\&\:$ instructors

- engage in learning analytics & ed data mining
- → without programming skills
- component implementations in Java, C, R, Python, Matlab



Discovery Example

Workflow analytics that bridge data silos from

→ tutor interaction, MOOC resource use and outcomes, & discussion boards

What student behaviors are associated with greatest learning?

- → 4 courses with 5M interactions from 12K students
- → Striking discovery: 6x better learning outcomes from active rather than passive learning
 - Active = answering questions with feedback
 - Passive = lecture watching or text reading

Developments & Innovations

Doubled data sets available to over 1,300

Developed DiscourseDB from scratch

New MOOCdb capabilities

Distributed version of DataShop demonstrated at Memphis Released workflow authoring tool

- → Workflow components contributed by many
- → Published results associated with analytics

Challenges & Future Directions

- 1. Uniformity-complexity challenge => emergent standards
 - → Broad R&D community => no single data schema
 - → Uniformity toward maximum reusability with
 - → flexibility in representations to adapt to user needs
- 2. Sharing-privacy challenge
 - → Maximize sharing of human data
 - without sacrificing student privacy
- 3. Sophistication-understanding trade-off
 - → Advance sophistication & variety of analytic DIBBs
 - → yet maintain understanding & trust
- 4. Flexible "need for speed"
 - → Some jobs impractical within default processing
 - → Transparent integration of cloud services needed

