LearnSphere: Infrastructure for Data-Driven Discovery & Innovation in Education

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DIBBs PI Meeting: Jan 11-12, 2017

Panel 3: Remaining Challenges & Future Directions

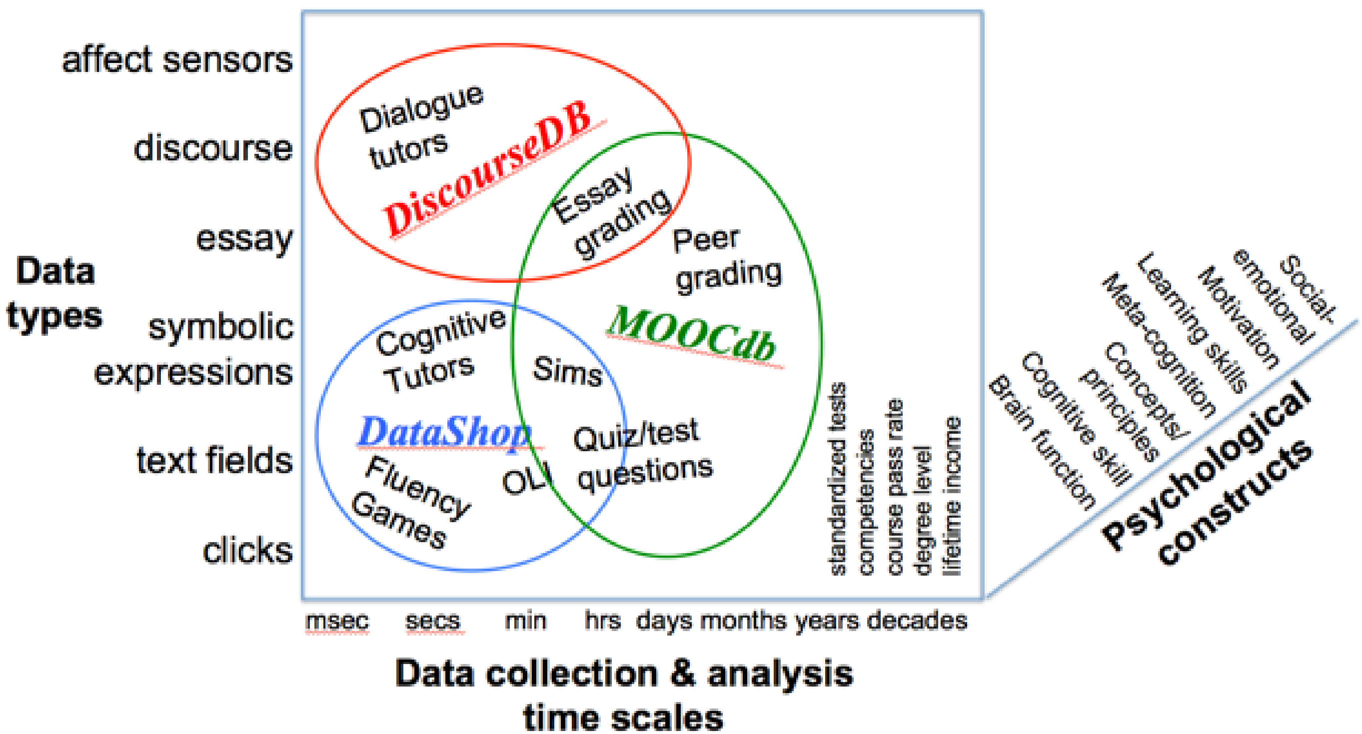
Big data in Education *Opportunity*
Problem: Data in **separate silos**

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



LearnSphere *Solution*

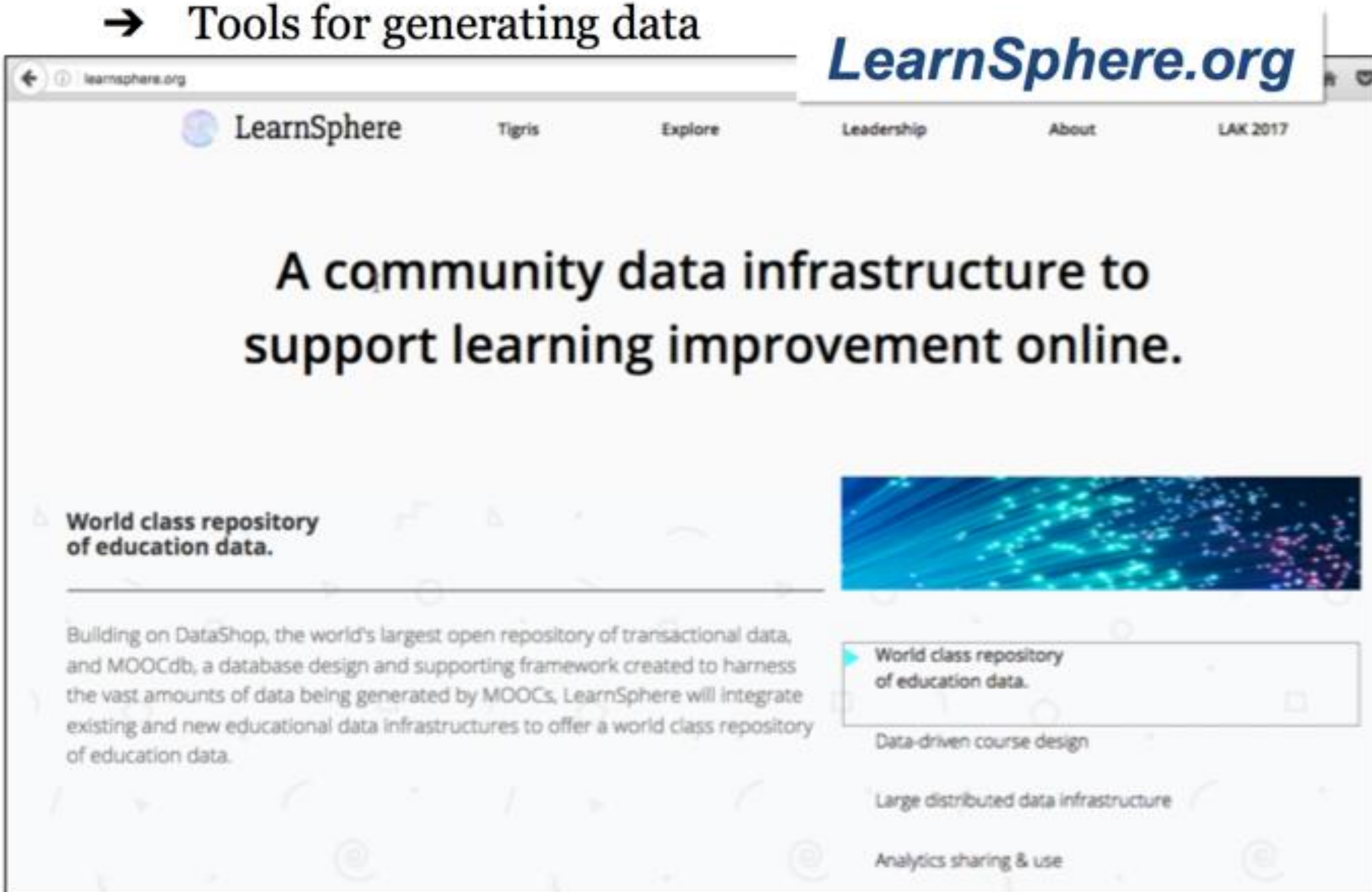
Web-based portal & workflow tool integrates DIBBs

Facilitate discoveries not possible within silos

LearnSphere.org: Web-based Portal

Hub for sharing:

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



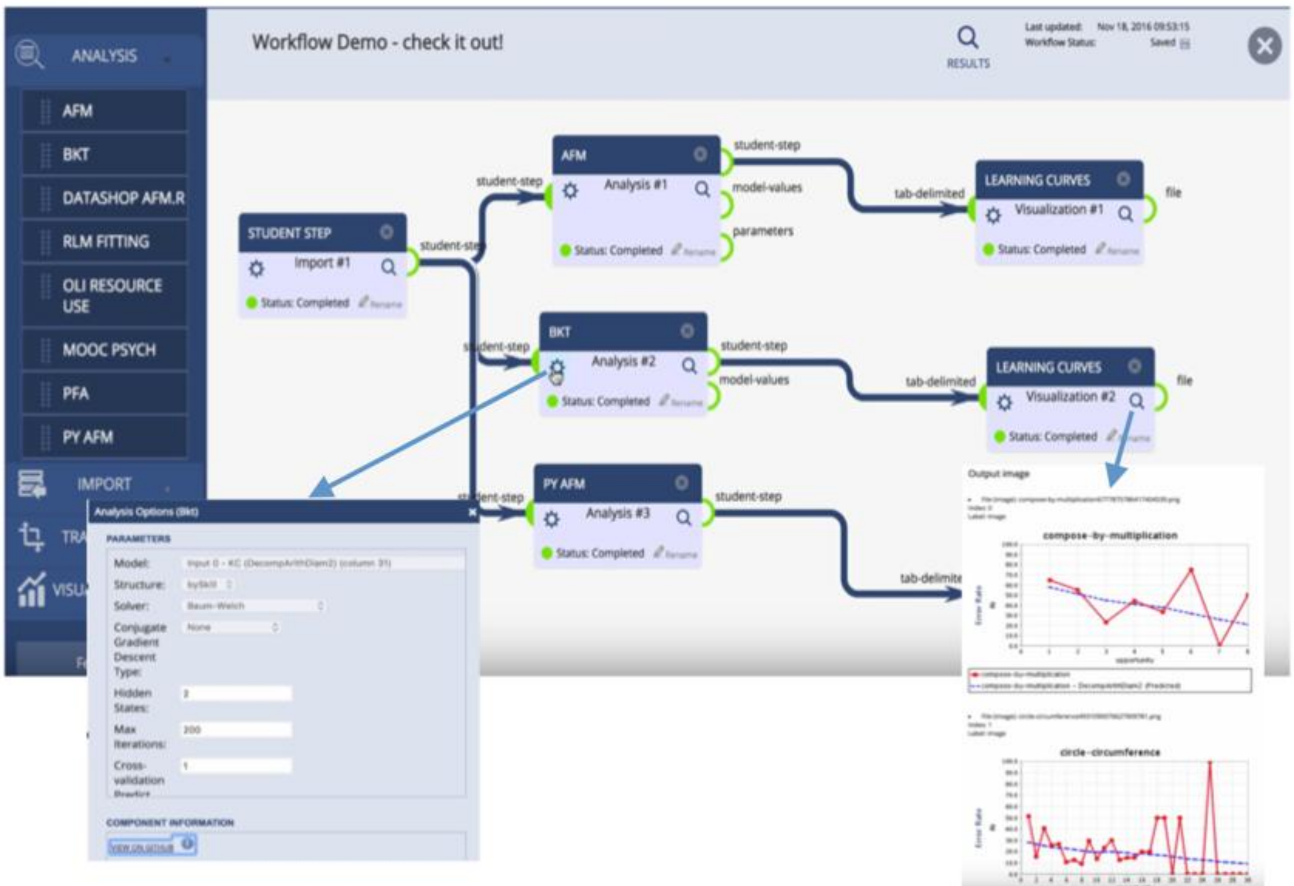
LearnSphere's Workflow Authoring

Web-based workflow authoring

- ➔ Method & data sharing & cross indexing
- ➔ **Emergent data standards** from convergent 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 3 sources:

➔ 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

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.*

Developments & Innovations

Doubled data sets available to over 1,300

Developed *DiscourseDB from scratch*

New MOOCdb capabilities

Distributed version of DataShop demonstrated at Memphis

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

Future Directions

- Computer science is part & parcel of doing science
  - Computational biology, computational chemistry, computational X …
- Publications are *not* just in English
  - Scientific insight is communicated through runnable models on available data