

Actionable Research through Learning Analytics

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"A new culture of learning needs to leverage social & technical infrastructures in new ways." John Seeley Brown







Talk Overview

- SoLAR community
- Learning Analytics basics
- Learning Analytics at University of Michigan
- Where do we go from here...?

Learning Analytics is...

"The measurement, collection, analysis and reporting of data about learners and their contexts for purposes of understanding and optimizing learning and the environments in which learning occurs."





SoLAR: International Community for LA

Research





Society for Learning Analytics Research (SoLAR)

Annual Conference

International Conference on Learning Analytics & Knowledge (LAK)

- Sydney, Australia March 5-9, 2018
- Phoenix, Arizona March 4-8, 2019

Summer Institute

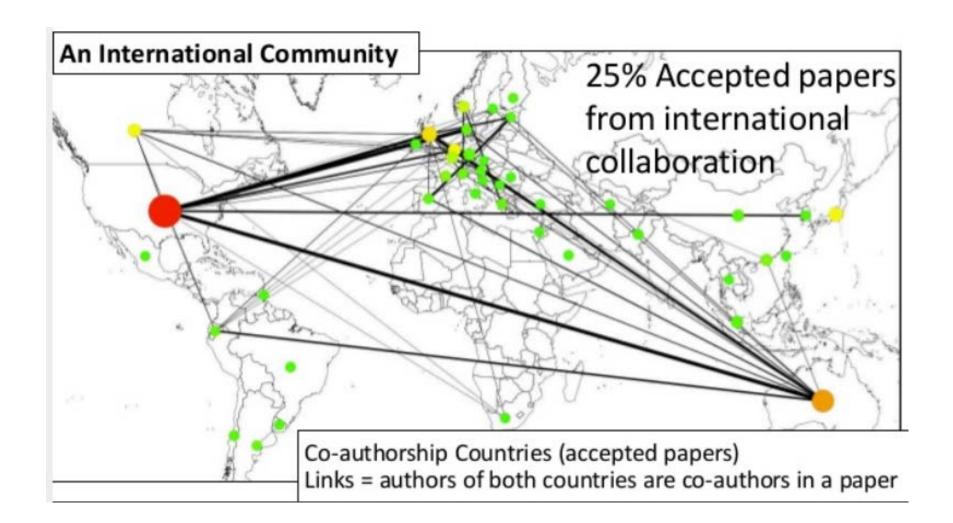
Learning Analytics Summer Institute (LASI)

Teacher's College, New York June 11-13, 2018

Journal

Journal of Learning Analytics

SCHOOL OF INFORMATION UNIVERSITY OF MICHIGAN



Use and Evaluation of Learning **Analytics Tools** (74)

Learning / Instructional Design (62)

Learning **Analytics** Infrastructure (50)

User Modelling / Adaptive Learning (47)

Feedback Systems (39) Self-Regulated Learning (36)

Retention / Students-at-Risk (31)

Educational Theory (25)

History / Future of Learning Analytics Discipline (23)

Adoption Strategies (21) Collaborative Learning (21)

Understanding Discourse (16)

Learning Analytics **Policies**

Emotions / Affective Learning (10)

Law and Ethics (8)

Cognition and Memory (8)

Topics

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Data Mining (63)

Inferential Statistical Analysis (49)

Qualitative Analysis (34)

Mixed Methods (31)

Statistical Modelling (46)

Visualisation Design and Evaluation (25)

User Interface Design and Evaluation (20)

Observational (16)

Natural Language Processing (23)

Network Analysis (14) Survey Design (9)

Multimodal Analysis (12)

Process Video Modelling

Methods

Case Studies (42)

Experimental Design (21)

HCI and Participatory Design (11)

Modelling / Classification (62)

Machine

Learning

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Q

Search Scholar

▼ English

Business, Economics & Management

Chemical & Material Sciences

▼ Engineering & Computer Science

Educational Technology

Health & Medical Sciences

Humanities, Literature & Arts

Life Sciences & Earth Sciences

GO LAK!

Physics & Mathematics

Social Sciences

Chinese

Portuguese

Spanish

German

Russian

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Top publications - Educational Technology Learn more

Publication	h5-index	h5-median
1. Computers & Education	88	121
2. British Journal of Educational Technology	48	66
3. The Internet and Higher Education	43	68
4. Journal of Educational Technology & Society	41	62
5. Journal of Computer Assisted Learning	40	63
6. The International Review of Research in Open and Distributed Learning	38	85
7. Educational Technology Research and Development	32	50
International Conference on Learning Analytics And Knowledge	32	49
9. Australasian Journal of Educational Technology	31	47
10. International Journal of Computer-Supported Collaborative Learning	28	38
11. IEEE Transactions on Learning Technologies	27	42
12. TOJET: The Turkish Online Journal of Educational Technology	26	48
13. TechTrends	26	40
14. Distance Education	25	47
15. Language, Learning & Technology	25	35



Learning Analytics Basics

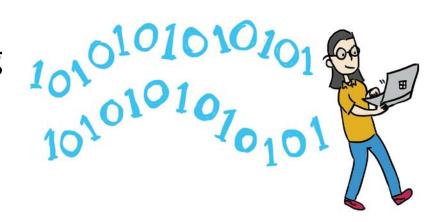


LA: Data Science for Education

We have been doing research on educational data for a long time...

What's changed?

- Theories about learning
- Pedagogy
- New data sources





Data-Rich Environment: Evidence of Learning

Process of learning: How we learn

Multi-modal records of student activity:
 clickstream from online tools, sensor data, eye tracking, library use, resources accessed, etc.

Products of learning: What we know

Discussion posts, blogs, tweets, hashtag use, etc.



Datasets & Sources

Uses data drawn from learning technologies and related information available in the **student** data warehouse and vendor tools:

- grades and student records,
- written evidence of learning (e.g. essays and assignments), and
- temporal interactions (e.g. engagement with course resources, textbooks, and tools)



Examples of LA Methods

Sequence Mining

RQ: How do course selections influence GPA?

Prediction Models

RQ: Among freshman entering with strong high school record (GPA > 3.8), who will do poorly (GPA < 2.0) at the end of their first year?

Clustering

 RQ: Given three categories – under achieving, over achieving, as expected – what categorizes the students who are under achieving?

Text Mining

 RQ: Can we classify students based on messages they contribute to a discussion forum?

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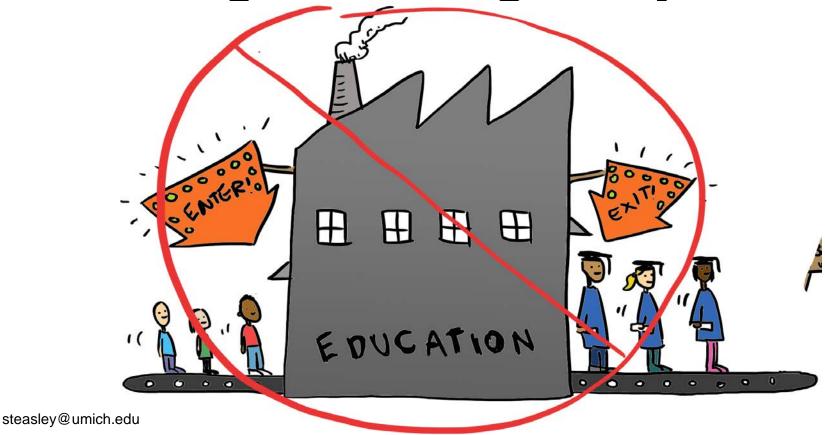
Potential Applications

- Predict student success
- Identify opportunities for intervention
- Determine what a learner does/does not know
- Monitor a student's behavior & engagement level
- Personalize the learning process
- Help instructors refine content
- Measure student improvement beyond test scores
- Improve student retention & completion

adapted from http://www.edudemic.com/big-data-education-2/

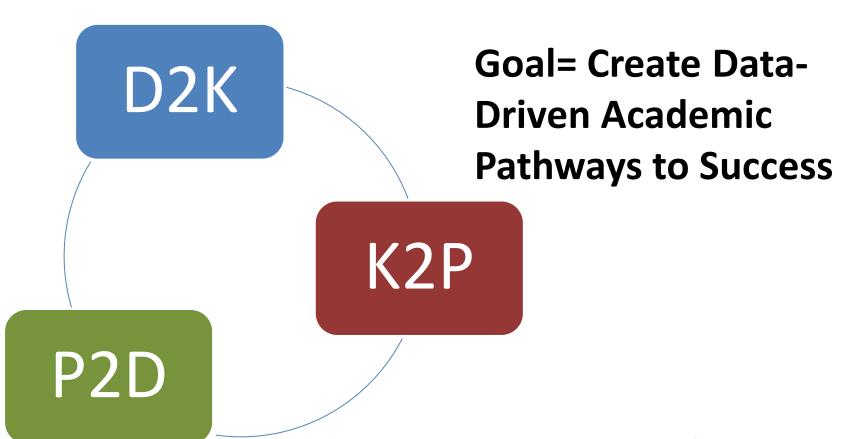


UM's Institutional Initiative to Leverage Learning Analytics





Actionable Research: Data to Knowledge to Practice





Learning Analytics @ UM

- Brief History
- Key Drivers
- Goals
- New tools and practices
- Where are we going

UM Context: Large Public Research-Intensive University



- 200 Years old
- 19 Schools and colleges
- 6,800 faculty
- 29,00 undergraduates; 15,700 postgraduates
- 9,200 total courses offered
- 110 courses have 200+ students enrolled [1/3 of all credit hours]



My Early LA Investigations @ UM

Supporting PhD student progress (2005)

Supporting faculty research collaboration (2006)

Social tagging (2007)

Supporting student collaborations (2007)

Understanding LMS use (2009)

"The pervasiveness of these systems [LMS] calls for larger studies across courses, disciplines, and institutions where the *lessons learned* can be generalized and more widely disseminated."

Brief History of LA @ UM

- Integrated student data warehouse established
- Individual faculty projects (e.g., my early work)
- Symposium on Learning Analytics at Michigan (SLAM)
- Provost-supported Learning Analytics Task Force
- Creation of Office of Academic Innovation
- Identified thrust area for new Michigan Institute for Data Science (MIDAS)
- Host SoLAR's learning analytics summer institute (LASI 2016 & 2017)



Goals for UM Learning Analytics Work: Learn from Every Student

Provide an integrated **student data ecosystem** for research leading to student success

Create **unique** a **test bed** for investigating student learning, including text processing and real-time applications

Protect **student privacy** while maximizing usefulness of data

Demonstrate value and scalability of existing and future high-value applications

Current UM Datasets & Sources for Learning Analytics

(circa 1996-present)

- Student Records
- Recruiting & Admissions
- Financial Aid / Student Financials
- College Resources Analysis System (CRAS):
 Collapsed Instructor & Course data
- Human Resources & Payroll
- LMS: CTools / Canvas
- Kaltura video content
- Lecture Capture







ABOUT | SUPPORTING STUDENTS

DATA & RESEARCH

BLOG | NEWS

LEARNING ANALYTICS DATA ARCHITECTURE (LARC)

DATA & RESEARCH

LEARNING ANALYTICS DATA ARCHITECTURE (LARC)

WHAT IS LARC?

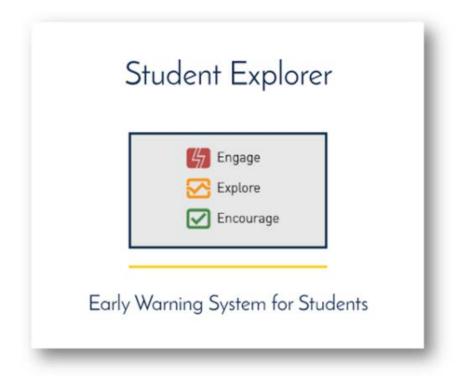
The Learning Analytics Data Architecture (LARC) Data Set is a research-focused data set containing information about students who have attended the University of Michigan since the mid-1990s. The data is meant to help answer typical learning analytics questions about students, their academic careers, and their class outcomes. The data is divided into that which is constant throughout a student's academic career (e.g., ethnicity, SAT test scores, high school GPA, and earned degrees), that which can change from term to term (e.g., academic level, academic career, term GPA, and enrolled credits), and that which can change from class to class (e.g., subject, catalog number, earned grade, etc.).

From Innovation to Scale

- Faculty innovators develop TEL tools
- Research teams test them (small scale)
- If effective, need to move from innovation to infrastructure (large scale)
 and
- Research teams evaluate commercial products



Supporting Academic Advisors







Teasley, Lonn, et al.

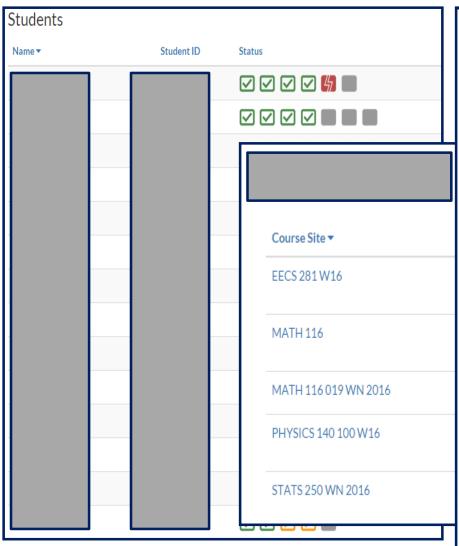


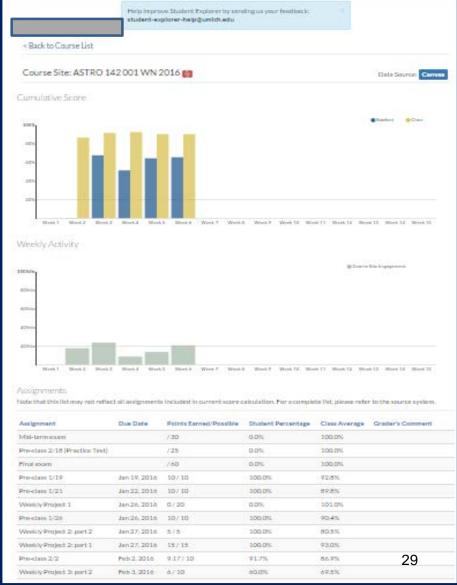
Student Explorer: Early Warning System

- User Centered Design: developed with academic advisors
- Uses real-time data from LMS
- Underlying algorithm calculates students' risk by norming grade and activity on a course-bycourse basis

- Began in 2010 with 4
 advisors in 1 program with
 data from 100 freshman
- Now 67+ advisors in 5
 programs with data from

 16,000+ undergrads
- Key tool for identifying struggling students before it's too late to intervene







Research Questions

 How do advisors use dashboard & how does advisor use affect student performance?

 How do students interpret dashboards & how does that affect their motivation?



Supporting Students





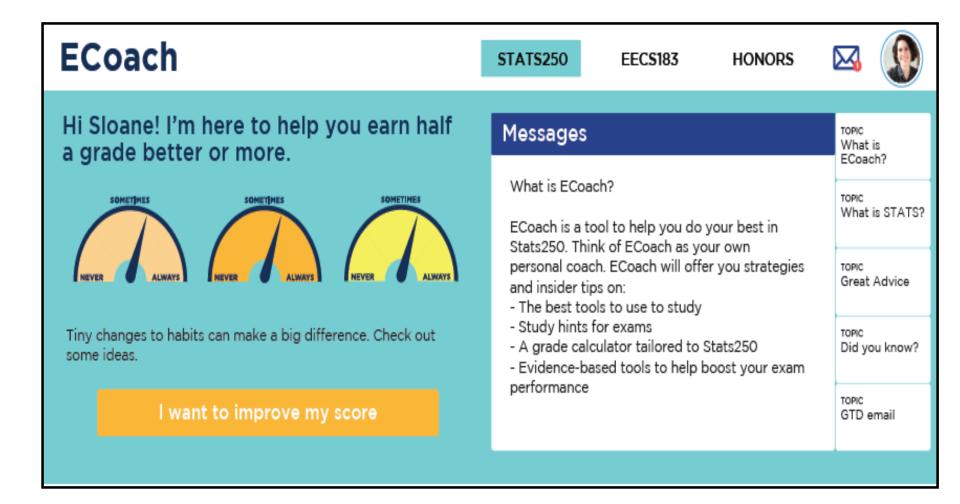
McKay, et al.

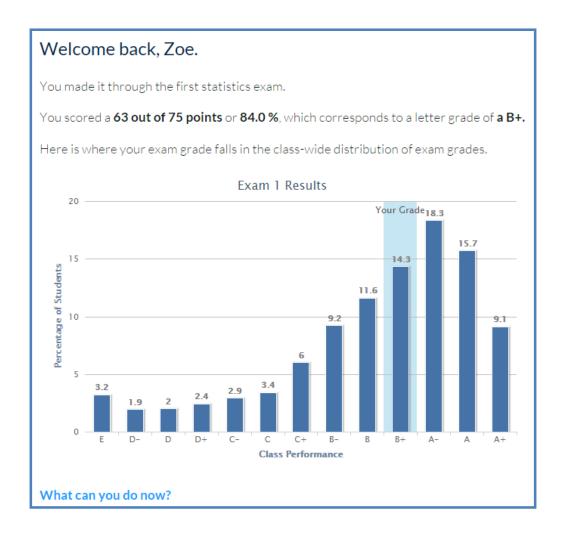


ECoach: Tailored Communication

- Built on digital health coaching system
- Uses real-time info about students to tailor feedback, advice, & encouragement
- Tailoring what to say and how to say it: testimonials from peers, behavior change experts

- Used since 2012 by 10,000+ students
- Delivered to every student in fall term
- Designing interventions to change the future for students







Research Questions

- Can techniques from health behavior interventions lead to changes in student behavior?
- Which are the important features of personalization to create effective feedback?



Supporting Faculty







Fishman, Holman, et al.



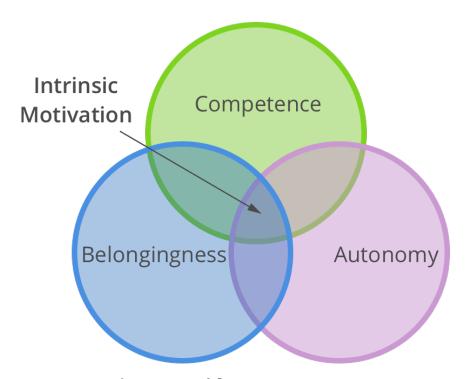
GradeCraft: Gameful Learning Management System

- An LMS with a couple of key changes
- Instructors design more assignments than students need to do, giving students autonomy over their work (within bounds)
- All students start with 0 points and earn up to the grade they want

- Grade Predictor tool to help students set goals
- Used since 2011 by 30 instructors, 10,000+ students in 58 courses
- Key tool for supporting autonomy and intrinsic motivation in the classroom



A Pedagogical Approach Inspired by Good Games



Based on Self-Determination Theory



Earn up



Freedom to Fail

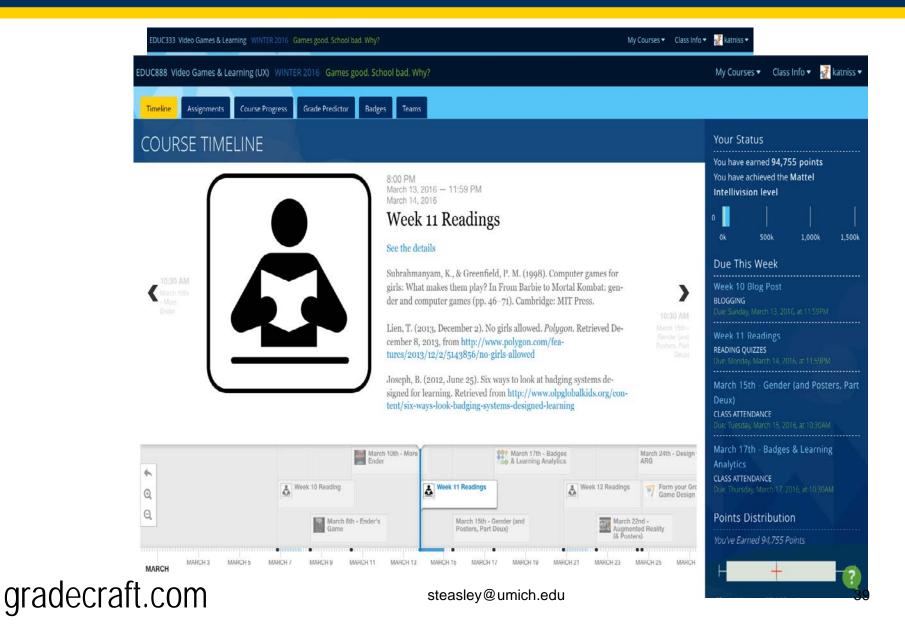


Increased Autonomy



Tangible Progress

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Research Questions

- How does assignment choice affect student success?
- How do students strategize about assignment selection based on their achievement orientation?
- How does course context affect student strategies?

http://gamefulpedagogy.com/



My Current Focus: Learner Dashboards

 Enables students to monitor their progress and compare their performance against that of their peers.

Goal = supports metacognition and self-regulation



Need for Research

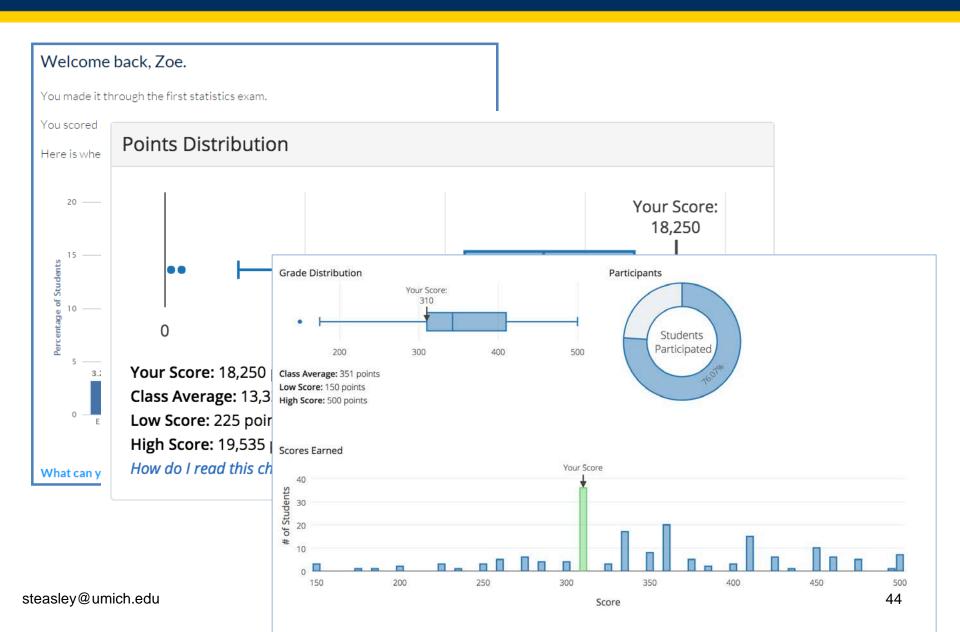
- Bodily and Verbert (2017) reviewed 93 studies of systems presenting some data to students:
 - Reported visualization design = 0
 - Did needs assessment = 6%
 - Did usability testing = 11%
 - Study effect on student behavior = 16%



Open Questions

- Are students able to interpret the information provided, and do they know what to do with it?
- Which students find this information motivating versus demotivating, and under which circumstances?



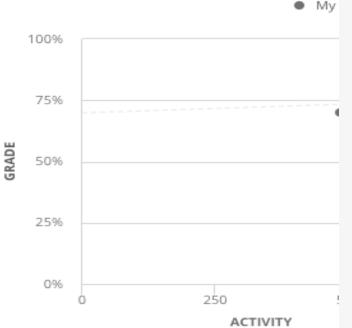


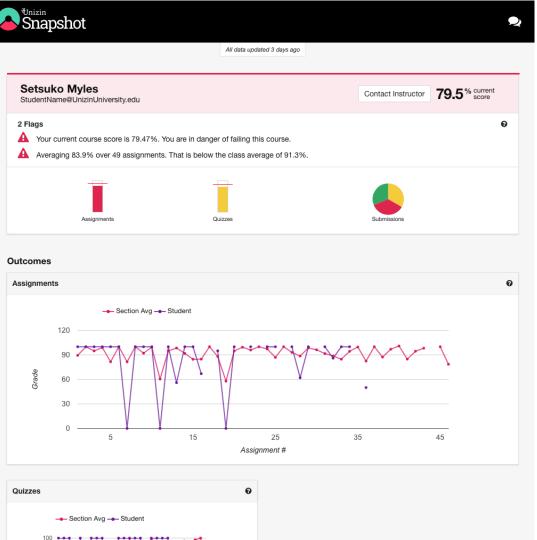
Gateway Course I

How Am I Doing?

You're doing really well in Gateway Cours Consider reaching out to another studen study help!

Current Class Status







Study 1

- We gave 1 undergrad course (Fall) and 1 Masterslevel course (Winter) access to Course Monitor dashboard as tool in Canvas
- Students could use it through whole semester
- Surveyed students at end of term about their overall assessment of the value of the information

We collected log data of use



Research Questions

- What are students' viewing preferences (i.e. for individual vs. comparative performance feedback)?
- How do students' use of the dashboard affect their assessment of their performance?
- Are there different effects of dashboard use on different kinds of students?



Survey Data

Study One (undergrads)	Mean	Study Two (masters)	Mean
Viewing my own performance on Course Monitor	2.75	Viewing my own performance on Course Monitor	2.64
Viewing my own performance on Course Monitor relative to the class average	3.25	Viewing my own performance on Course Monitor relative to the class average	3.29
Resulted in me feeling more positive about my performance in the course	2.13	Resulted in me feeling more positive about my performance in the course	2.57

0 = Not at all important, 1 = Slightly Important, 2 = Somewhat Important,

3 = Very Important, 4 = Extremely Important



Results







low frequency of use over term

comparative performance view was rated higher than just seeing own

reported **positive effect** on
students' good
about their
performance in
the course



Conclusions, so far...

- Most students found the dashboard visualizations informative and liked the comparative performance feedback
- Most students expressed interest in having such a dashboard available to them in theory, although most students didn't access it much in practice
- Caveats- limited sample of high achieving students in a competitive environment, & design issues with dashboard



What Can We Do Now?

- Build models of student behavior to diagnose students' academic challenges -> effective interventions before failure
- Design personalized learning trajectories that address the diversity of students & their preparation for learning at specific types of higher ed institutions
- Create interfaces for advisors, faculty & students to make data visible, understandable, and valuable
- Evaluate interventions, revise theory, re-design tools...



Data to Action

Students, advisors, faculty get the data. They decide what to do with it.

Experts get the data. They interpret and make decisions for students, advisors, faculty.

A spectrum of information agency...

Everyone gets data. Have experts help students, advisors, faculty interpret data.



Big Vision: Where Do We need to Go?

- Use institutional data to innovate teaching & learning
- Develop new models for effective instruction and fair assessment
- Create shared datasets that allow cross-institutional analyses
- Assume risks of exposing what does and doesn't work in higher ed - and for whom



Ethics of LA Data Use

- What kinds of data do we think is important to be collected about learners?
- What kind of data is unnecessary?
- What kind of control do we want to have over the learners' data?
- What kind of control do we want learners to have over their own data?
- What kinds of risks are we concerned about?
- Do we need policy about collection or use? Or both?



Many Thanks to:

LED Lab students
UM faculty & staff colleagues
SoLAR community

& my illustrator- Anders Finholt

