University Hall was constructed in 1871. This building featured an auditorium seating 3000. This at a time when total enrollment at the University was 1200 students. No small plans were made.
Birth of the industrial university

• In 1900, enrollment had tripled, to 3482, and the industrial era had begun
• In 1950, enrollment expanded by an additional factor of ten, to 43,683
• Michigan became the model of a modern public research university
• Indoor graduation had become impossible...
  1949 commencement on Ferry Field
Commencement, June 11, 1949 at Ferry Field
The 20th Century began with an industrial revolution. Public higher education exploded in scale and bureaucratized, adopting standardized tests, measuring outcomes in credit hours, GPAs, majors, and minors.

Since the 1970's U-M has worked hard to more deeply personalize education, with richer advising, freshman seminars, CSP, learning communities, and more.

Doing this at scale is difficult and costly. So what has been done reaches most students very thinly...
The 21st Century began with an information revolution. Public higher education has been slow to respond, but change has begun. Practically all information is online, classes are flipping, many educational activities are digitally mediated. The real revolution will come from personalization.
Personalizing education at scale

• We must be able to attend to every student:
  – As a student: we need to see what they do, assess what they know, represent their skills and accomplishments
  – As a person, with evolving background, interests, goals, identity, concerns, purpose, affect, well-being

• We must measure and report what matters: the elements of a liberal education
  – Intellectual breadth, disciplinary depth, range of experience, sustained engagement with desirable difficulties, networks of social and professional connection

• We must be able to act at scale:
  – Explore and understand, attend to everyone in real time, deliver actionable information to students, faculty, and staff
Learning Analytics @UM: 2009-2016

- Local faculty efforts:
  - Stephanie Teasley and the USE lab
  - Gus Evrard, LSA IT, and ART 1.0
  - McKay, Gerdes explore introductory physics

- An emerging conversation: SLAM - Symposium on Learning Analytics at Michigan

- Provost support faculty-led innovation: Learning Analytics Task Force: 3 yrs, $2 million
  - Continued SLAM
  - Grants program
  - LA Fellows program

- Now institutionalizing
  - DEI & many DIG projects
  - UMILA & IRIS
Today’s Seminar

• Aspects of personalized education
  – **Ethics**: what are we doing and why
  – **Measurement**: data collection and management
  – **Analysis**: modeling, extraction of meaning, exploration of how background and structures affect outcomes
  – **Action**: decision making, storytelling, creating the motivation for change

• Our goal: Meaningfully personalized education at Michigan in five years (not twenty!)
Ethics: What we’re doing and why
Ethical challenges

• What principles should govern the collection and use of data about individuals?
• Norms of consent, privacy, autonomy, responsibility?
• How does application of these principles change for students in our communities?

• Asilomar Convention:
  – 2014: Learning Research in Higher Education
  – Goal: to generate principles for ethical conduct of learning analytics to guide the creation of local policy

Second Asilomar meeting planned for June 2016: Learner Data and Records in the Digital Era
Six Asilomar principles

1. **Respect for the rights and dignity of learners**: transparency, protection of privacy
2. **Beneficence**: maximize benefits, minimize harm
3. **Justice**: benefit all, reduce inequalities
4. **Openness**: learning and research are public goods
5. **The humanity of learning**: insight, judgment, & discretion are essential, keep learning humane
6. **Continuous consideration**: ongoing, inclusive discussion of changing ethical circumstances
Applying these principles: “Predictive Modeling”

- Many early learning analytics applications use past performance of students to construct “predictive models”
- These models are really just reports of what’s happened in the past: they predict the future only if nothing changes
- How should we act when past students haven’t achieved their goals?
  - “Drown the bunnies”
  - Respond with new, personalized systems of support
- We learn from the past in order to change the future
Two Asilomar tenets for research

1. **Advance the science of learning for the improvement of higher education**: The science of learning can improve higher education and should proceed through open, participatory, and transparent processes of data collection and analysis that provide empirical evidence for knowledge claims.

2. **Share**: Maximizing the benefits of learning research requires the sharing of data, discovery, and technology among a community of researchers and educational organizations committed, and accountable to, principles of ethical inquiry held in common.
Academics and reputation

• Students/universities: an unusual relationship
  – Students want official validation of success
  – To increase value, they give up some control over this reputational record
    • Many rules about creation of the “permanent record”
    • Degree receipt (or not!) openly acknowledged
    • Transcript access, but not content, controlled by student
    • No ‘right to be forgotten’

The agreement between students and the institutions they attend presents an interesting, not yet fully explored topic for scholars of privacy and reputation.
Measurement:
Data collection and management
What do we measure?

• What we measure now:
  – Admissions information
  – Course taking & grades
  – Degrees & honors

• What we’re starting to record (explosive growth)
  – Process of learning: clickstreams, discussions, video, course structures
  – Products of learning: MC, forum posts, essays

• What we want to have:
  Detailed, evolving portraits of every student's background, interests, goals, and accomplishments

• These portraits should be used to offer admission, monitor progress, decide on graduation, and represent success
Cleaning & aggregation

• Many data sources
  – UM Data Warehouse: *hundreds* of organically evolving tables
  – LMS: CTools -> Canvas: course structures, authentic student work
  – Digitally mediated education: chat rooms, Google docs, Piazza
  – Non-academic sources: wearables, location...

• Gathering, digesting, and merging presents many challenges
  – Using identity while preserving privacy
  – Handling very diverse student portraits
  – Digesting multimodal data streams, extracting meaning
  – Handling incompletely defined data in real time
Just for student records, there are 157 pages of data description...
A partial solution LArc: Learning Analytics Data Architecture

A ‘public release’ model for cleaning research data – compare to data releases from open science projects like the Sloan Digital Sky Survey or the GAIA space mission.
Measuring learning in classes

• Grades: performance measures of unrecorded tasks, meant to estimate unknown outcomes, quantified on ill-defined scales

• We should be measuring learning – increases in well defined knowledge and skills – and focusing on individual growth over time

• **Direct**: pre and post testing aligned with learning goals. Good for foundational courses?

• **Indirect**: DS methods for extracting meaning from all student work
  – Simple: IRT, topic modeling and beyond
  – Complex: NLP, categorization by comparison
What we measure today

• A credit-hour/degree requirement economy
  – Credit-hour designations only loosely comparable
  – Categorical degree requirements can be met in highly various ways

• Performance measured only by grades, aggregated into GPA
  – Grades awarded vary 25% by field & course level
  – Students taking classes vary dramatically
Measuring what matters

• Liberal education is more than a list of classes and grades
  – Intellectual breadth
  – Disciplinary depth
  – Range of experience
  – Engagement & effort
  – Social & professional networks

• Important outcomes are long term – we need to see beyond campus

• Multidimensional portrait of student progress

• Multiple forms of commitment, success, risk, and failure encouraged and recognized

• Authentic goals reinforced and key outcomes noted

• ‘Success’ will be observed through growth, for both student and institution
How might we quantify intellectual breadth?

• One example: explore each student’s network of connection – Kar Epker’s senior thesis
  - Course co-enrollment: well measured, large bipartite network
    - Students connected by courses
    - Courses connected by students
• Better representations of interaction coming

• Simple measures:
  - How many connections?
  - What kinds of students?
  - How to weight, classify?

• Diversity of connection: compare interactions to random graph models
  - In degree: similar majors
  - Out degree: different

• Exposes isolation of majors, allows comparison of individuals within a major
(b) RPD between actual and expected weighted interactions of students segmented by major.

<table>
<thead>
<tr>
<th>Major</th>
<th>RPD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Music Theory and Composition</td>
<td>1.99</td>
</tr>
<tr>
<td>Physical Education Teaching</td>
<td>1.99</td>
</tr>
<tr>
<td>Dance, General</td>
<td>1.99</td>
</tr>
<tr>
<td>Technical Theatre/Theatre Design</td>
<td>1.99</td>
</tr>
<tr>
<td>Musical Theatre</td>
<td>1.99</td>
</tr>
<tr>
<td>Athletic Training/Trainer</td>
<td>1.98</td>
</tr>
<tr>
<td>Music History, Literature</td>
<td>1.98</td>
</tr>
<tr>
<td>Dental Hygiene/Hygienist</td>
<td>1.98</td>
</tr>
<tr>
<td>Geological/Geophysical Engineering</td>
<td>1.98</td>
</tr>
<tr>
<td>Jazz/Jazz Studies</td>
<td>1.98</td>
</tr>
<tr>
<td>Music Technology</td>
<td>1.98</td>
</tr>
<tr>
<td>Music, Other</td>
<td>1.97</td>
</tr>
<tr>
<td>Geological and Earth Sciences</td>
<td>1.97</td>
</tr>
<tr>
<td>Latin Language and Literature</td>
<td>1.97</td>
</tr>
<tr>
<td>Music Teacher Education</td>
<td>1.97</td>
</tr>
<tr>
<td>Sociology</td>
<td>1.57</td>
</tr>
<tr>
<td>Spanish Language and Literature</td>
<td>1.57</td>
</tr>
<tr>
<td>Multi-/Interdisciplinary Studies</td>
<td>1.56</td>
</tr>
<tr>
<td>Entrepreneurial and Small Business</td>
<td>1.56</td>
</tr>
<tr>
<td>General Studies</td>
<td>1.50</td>
</tr>
<tr>
<td>English Language and Literature</td>
<td>1.49</td>
</tr>
<tr>
<td>History, General</td>
<td>1.47</td>
</tr>
<tr>
<td>Engineering, General</td>
<td>1.44</td>
</tr>
<tr>
<td>Neuroscience</td>
<td>1.39</td>
</tr>
<tr>
<td>Biology/Biological Sciences, General</td>
<td>1.38</td>
</tr>
<tr>
<td>Physiological Psychology/Psychology</td>
<td>1.32</td>
</tr>
<tr>
<td>Economics, General</td>
<td>1.31</td>
</tr>
<tr>
<td>Political Science and Government</td>
<td>1.28</td>
</tr>
<tr>
<td>Experimental Psychology</td>
<td>1.22</td>
</tr>
<tr>
<td>Engineering, Other</td>
<td>1.17</td>
</tr>
</tbody>
</table>

![In-Connection Weighted RPD Distribution for Musical Theatre](image1)

Musical Theater

- Joint English/MT

![In-Connection Weighted RPD Distribution for Philosophy](image2)

Philosophy

- Philosophy Premed

![In-Connection Weighted RPD Distribution for General Studies](image3)

General Studies

- Transfer GS
Addressing the long term

• To fully understand our impact, to measure growth, we need to know
  – More about where students come from
  – More about what they do while with us
  – More about what they do after they leave us

• Exploring life-long impact of education: ISR, IRIS, connections to employment & beyond
  – Research questions, to take place in enclave
Envisioning the Future of the Research Enterprise

The Institute for Research on Innovation & Science (IRIS) is the global source for data to support fundamental research on the results of public and private investments in discovery, innovation, and education. It provides credible data and rigorous findings about the productivity and public value of the research enterprise to inform effective policy-making, support outreach, aid in research management, and expand the state of knowledge.

Learn More
The long term

What happens after college...

Fig. 6. Change in real wage levels of full-time workers by education, 1963–2012. (A) Male workers, (B) female workers. Data and sample construction are as in Fig. 3.

Analysis:
Modeling, extraction of meaning, exploration of how background and structures affect outcomes
Three examples:

1. Do living-learning programs work?
2. Are placement exams used well?
3. Are our classrooms equitable?
#1: Do living-learning programs work?

**Example: Health Sciences Scholars Program at Michigan**

- Live-in learning community
- Longitudinal data collected from 2004-2010
- One of several at Michigan, thousands of students

**RQ: How does participation in the learning community impact student outcomes?**

Our interest was looking especially at two risk groups:
- First in family to attend university
- Ethnic minorities

Background Research: Literature generally filled with “feel good” stories about learning communities, we wanted more quantified results.

Photo Credit: UM HSSP Program

Brooks, Chavez, Tritz, and Teasley, Learning Analytics & Knowledge, 2015

AAC&U Diversity, Helen Morgan, Jennifer Matlby, Christopher Brooks, March 2015, California
Quasi-Experimental Design

Our Method: Matched Samples

Step 1: Identify potential sources of bias in your population and determine how to measure them, such as:

- Achievement level of learners from student information systems
- Interest in the treatment through:
  - Applications to participate
  - Surveys on student outcome interests (e.g. CIRP)
  - Sign-on to tech-based treatments
- Demographics and other proxies for latent characteristics (e.g. first in family to attend school)

Step 2: Find the best matches for your sample in the general population
- Linear assignment problem (min-cost, max-flow), Hungarian method

Data elements matched on:
- ACT score (or converted SAT)
- Academic school enrolled in
- At risk support program enrollment (2)
- Year enrolled
- Honors enrollment status
- Credit hours achieved
- Citizenship
- Ethnic group (self-reported)
- Sex
- Previous research program experience
- Family income (bands)
- First in family to go to college
- Self-identification of being interested in pre-health programs

Brooks, Chavez, Tritz, and Teasley, Learning Analytics & Knowledge, 2015
HSSP significantly increased the likelihood of BS and advanced degrees for underrepresented and first-generation students.
Michigan 1:2:1 Introductory Chemistry Curriculum Model:

**Placement Analysis**

- **High School Chemistry**
  - AP scores of 3, 4, 5

- **Placement Exams**
  - above 70th percentile chemistry and 30th percentile math
  - below 70th percentile chemistry and/or below 30th percentile math

- **Chemistry 130**
  - Macroscopic Investigations and Reaction Principles (general chemistry) with Laboratory

- **Chemistry 210 & 215**
  - Structure and Reactivity I and II (organic chemistry) with Laboratory

- **Chemistry 230**
  - Physical Chemistry Principles and Applications
Regression Discontinuity


<table>
<thead>
<tr>
<th>Course</th>
<th>$RD$</th>
<th>$RD$-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organic chemistry</td>
<td>0.189*** (0.039)</td>
<td>0.246*** (0.056)</td>
</tr>
<tr>
<td>w/ covariates</td>
<td>0.142*** (0.040)</td>
<td>0.221*** (0.067)</td>
</tr>
<tr>
<td>Physical Chemical Principles</td>
<td>0.173*** (0.052)</td>
<td>0.342*** (0.094)</td>
</tr>
<tr>
<td>w/ covariates</td>
<td>0.169*** (0.052)</td>
<td>0.342*** (0.093)</td>
</tr>
</tbody>
</table>

*Note: $RD$ = displays results from primary linear model, $RD$-IV = displays results from regression discontinuity instrumental variable model. Standard errors are reported in parenthesis. $***p<0.001$ (two-tailed).*
#3: Are our courses equitable?
Gender and STEM performance

A Longitudinal Study of Engineering Student Performance and Retention.
III. Gender Differences in Student Performance and Attitudes

RICHARD M. FELDER*
Department of Chemical Engineering
GARY N. FELDER
Department of Chemical Engineering
MEREDITH MAUNEE
Department of Statistics
CHARLES E. HAMRIN, JR.**
Department of Chemical Engineering

The More Things Change, the More They Stay the Same? Prior Achievement Fails to Explain Gender Inequality in Entry Into STEM College Majors Over Time
Catherine Riegel-Crumb, Barbara King, Eric Grodsky and Chandra Muller
Am Educ Res J 2012 49: 1048 originally published online 24 February 2012
DOI: 10.3102/002831111245229

The online version of this article can be found at:
http://aer.sagepub.com/content/49/6/1048

The Determinants of Success in University Introductory Economics Courses
Gorden Anderson, Bwisee Benjamin, and

Factors that affect the physical science career interest of female students:
Testing five common hypotheses
Zahra Hazari,1,2,3,* Geoff Potvin,2,3 Robynne M. Lock,3 Florin Lung,4 Gerhard Sonnert,5 and Philip M. Sadler5
1Department of Teaching and Learning, Florida International University, Miami, Florida, USA
2Department of Physics, Florida International University, Miami, Florida, USA
3Department of Engineering and Science Education, Clemson University, Clemson, South Carolina, USA
4Department of Physics and Astronomy, Mississippi State University, Mississippi State, Mississippi, USA
5Science Education Department, Harvard-Smithsonian Center for Astrophysics, Cambridge, Massachusetts, USA
(Received 8 August 2012; revised manuscript received 28 June 2013; published 22 October 2013)
Gendered performance differences: different outcomes for students with the same background

<GPA – Grade> Male = 0.32
<GPA – Grade> Female = 0.59
GPD = 0.27
Large courses using timed exams for the majority of their grading.

Data from 2000 – 2012 for all ‘giant’ classes, with average enrollments over 400.
Data from 2000 – 2012 for all large introductory STEM lecture and lab courses

These performance differences remain when we account for all measures of background & preparation. The same patterns are observed on five CIC campuses.

Unexplained performance differences like this are signs of classroom inequity. We must act to address these disparate impacts.
Action:
Decision making, story telling, motivating change
Putting data to work

• **The next frontier**: use technology to put data in people’s hands. In doing this, we support decision making, trigger personal connections, motivate action, and guide behavior change.

• **DIG**: the UM Digital Innovation Greenhouse has been established to take good ideas developed on campus from innovation to infrastructure, personalizing education at scale.
DIG was born to solve a recurring problem

• Faculty innovators create IT tools which make education > personal, engaged, and life-long.
• Research teams test them, demonstrating effectiveness: they’re ready to spread!
• Then they hit the entrepreneurial “valley of death” between innovation and infrastructure
• Innovations need a nurturing place to mature and spread, both on-campus and off
53 Initiatives

Learning Experiences should be Personalized, Engaged, and Lifelong

DEI partnerships are Individualized, Creative, and Collaborative

Make an impact, Give Today

It takes a community. Your Email Join Newsletter
The DIG team

Innovators

Communities of Practice

Holly Derry

DIG Fellows

ITS Infrastructure teams
How we DIG

The University Community

Startups

UNIZIN

Innovators & pioneering adopters

Communities of practice: faculty, students, staff

University IT: support at scale

DIG team of Developers, U/X Designers, Behavioral Scientists

4/8/2016 Deans' Teaching and Learning Workshop
Since last May, DIG is real:
a place, a team of innovators
Students are our best creative engine: Fellows, Design Jams & Hackathons!
DIG projects:
A rapidly growing portfolio

Academic Reporting Tools
ART 2.0
Academic Data to Help Make Choices

Student Explorer
Early Warning System for Students

E Coach
Personalized Messaging to Students

GradeCraft
Gameful Pedagogy for Learning

M-Write
Writing-to-Learn Pedagogies at Scale

Policymaker
Role-Playing Simulations
Providing information to individuals

1. Learning about classes and more: ART 2.0
2. Supporting advising: Student Explorer
This summer, course cards will be joined by reports on courses of study (majors and minors) and people (students, faculty), along with tools for curriculum exploration...
Launched 3/23, growing fast!
Student Explorer: supporting advisors
Acting directly

ECoach: computer tailored electronic coaching for equity and student success
ECoach: computer tailored communication for student support and help with behavior change

Imagine a campus on which personalized, expert coaching is provided to every student connecting them to timely feedback, encouragement, and advice…

Welcome back, Zoe.

You made it through the first statistics exam.

You scored a 63 out of 75 points or 84.0%, which corresponds to a letter grade of a B+.

Here is where your exam grade falls in the class-wide distribution of exam grades.

What can you do now?

Review for Exam 2 = list of...
Exam Playbook: Scores & Reflection

Exam Information

Course: EECS183
Exam Date: Wednesday, March 23, 2016

Your Scores - Exam 2

- 102.0 on the Multiple Choice
- 102.0 on the Free Response
- 204.0 total, or 88.7%

Steps to take

Do the best you can on the final project...

- Start early.
- Read the spec very carefully. Then, read it again.
- Lay out your plan before you code.
- Create a battery of tests (because you don’t have autograder this time).
- Use Piazza and office hours to ask questions.
- Keep your team organized. Set meeting times, meet in person, keep notes, track people’s to-dos, and set deadlines.

My Resources

- Office hours held by a lecture instructor
- Exam review (see Course Schedule for day / time)
- Asking questions in class
- Office hours held by GSIs / IAs
- CodeLab exercises
- 183Study past exam questions
Expert tailored communication

- Built on CHCR digital health coaching heritage
- Use rich real-time info about students to tailor feedback, advice, encouragement
- Tailoring on both *what* to say and also *how* to say it: testimonials from peers
- Behavior change experts, social psychologists, experts from disciplines
- Used since 2012 by 10,000+ students
  - usage creates clear impacts on performance
- Preparing to reach every student in fall.
  - Designing interventions to change the future for students!
- Key tool for humane personalization: speak and connect
Data and the Future of Education

• We will have tools which expose information enabling everyone on campus to learn from the experience of all.
• We will be able to explore and represent what students and faculty do in richer, multidimensional ways, encouraging better experiences.

• UM is a giant laboratory for higher education!
• Teaching and learning will be evidence-based, consistently assessed, and continually refined.
• We’re hoping Michigan will become a center for using data to understand what higher education does for students and the nation.
The sheer amount of data that we generate in the course of our lives is growing exponentially as technology plays a larger and larger part in what we do every day. Nowhere is this fact more important than how information technology has become part of the basic infrastructure for education— in formal and informal settings, playing a role whether we are face-to-face with others or interacting solely online. The “data exhaust” that is generated by the systems used today to support how we teach and how we learn provides an unprecedented opportunity to better understand and support learning, and to question the impact of these technologies on individuals, institutions and culture. This effort, however, is necessarily interdisciplinary and requires the use of a diverse methodological toolset.
PLA MOOC Returns in July

Practical Learning Analytics

This MOOC offers a flexible, collaborative introduction to learning analytics in higher education. You'll learn by doing, using realistic data and code.

Starts on July 1, 2016

Enroll Now

About this course

Everyone involved in higher education has questions. Students want to know how they're doing and which classes they should take. Faculty members want to understand their students' backgrounds and to learn whether their teaching techniques are effective. Staff members want to be sure the advice they provide is appropriate and find out whether college requirements accomplish their goals.

What you'll learn

• About the landscape of learning analytics in higher education
Practical Learning Analytics: A Guide to Examining Student Data and Learning

How can we use data analysis to assess our teaching and student learning? How might you use learning analytics in your courses to help your students succeed? How have others used these tools? In this session, Dr. Timothy McKay will define learning analytics, give examples of how other faculty have used it, and explain what learning data and analysis tools are available. In addition Dr. McKay will discuss the benefits and concerns of learning analytics for faculty and departments.
Things to consider

• Get more practical – SLAM, LA Fellows, grants, DIG, ART for open LA, UMILA for the sensitive stuff, LED, DEI