LALink: Educational Data Science (Virtual) Demos

Christopher Brooks & George Siemens, University of Texas Arlington
Pete Smith, University of Michigan
Serdar Abaci, Joshua Quick & Katy Börner, IUB

CNS Talk, Social Science Research Commons, Woodburn Hall 200

October 17, 2016

Computed Using Data from Elsevier's Scopus

Learning Analytics

Empowering Teachers: How to make sense of the activities of thousands of students? How to guide them?

Empowering Students: How to navigate learning materials and develop successful learning collaborations across disciplines and time zones?

Empowering Researchers: How do people learn? What pedagogy works (in a MOOC) and when?

Empowering MOOC Platform Designers: What technology helps and what hurts?

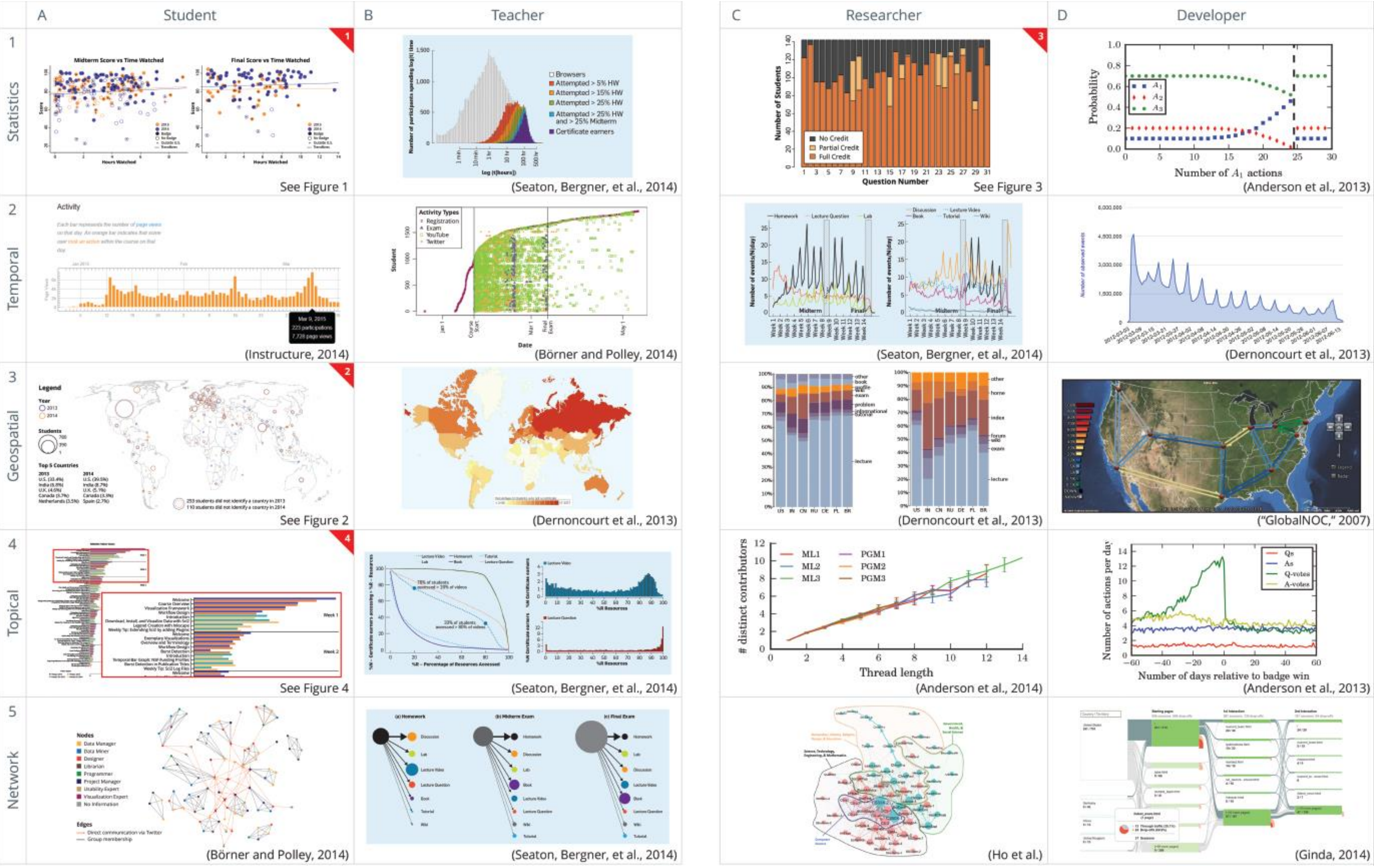

Figure 1: Analysis types vs. user needs.

Emmons, Light, and Börner. "MOOC Visual Analytics: Empowering Teachers, Students, Researchers, and Developers of Massively Open Online Courses". *Journal of the Association for Information Science and Technology (in press).*

Educational Data Science:
Precision Learning, Teaching, and Leadership

IU Emerging Area of Research Proposal

"We will develop, validate, and optimize models that explain and help predict the impact of different interventions on student success at IU and in life."

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Bloomington Assessment and Research

INDIANA UNIVERSITY
OFFICE OF THE VICE PROVOST FOR UNDERGRADUATE EDUCATION
Bloomington

The Team

- **Katy Borner**, Victor H. Yngve Distinguished Prof of Information Science, ILS, SOIC
- **Raymond Burke**, E.W. Kelley Prof of Marketing, KSB
- **Robert Goldstone**, Chancellor's Prof, Psychological & Brain Sciences, COAS
- **Dennis Groth**, Vice Provost for Undergraduate Education
- **Daniel Hickey**, Prof, Learning Sciences Program, SoE
- **Michael Kaganovich**, Prof of Economics, Economics, COAS
- **George Rehrey**, PI Consultant with IU’s CITL; Director of SOTL
- **Anastasia Morrone**, Prof of Educational Psychology, IUPUI School of Education; Associate Vice President for Learning Technologies, OVPIT; Dean of IT at IUPUI
- **Jennifer Meta Robinson**, Prof of Practice, Anthropology, COAS
- **Linda Shepard**, Senior Assistant Vice-Provost for Undergraduate Education; Director of Bloomington Assessment & Research
- **Timothy F. Slaper**, Indiana Business Research Center, IUB











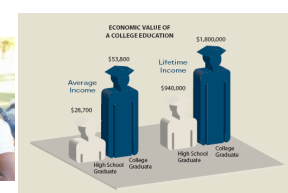
Big Questions

- What would college students, faculty, and other stakeholders do differently if they had easy, first-hand access to the data already created by college life in the information age?
- What wisdom about learning and life could students actualize from pathways visualized through documents, data, code, expertise, laboratory outcomes, class performance, and grades?
- What leverage points for learning could faculty discern and operationalize?
- What interventions should faculty/units/institutions implement for positive gains?

Changes in Higher Education

Today

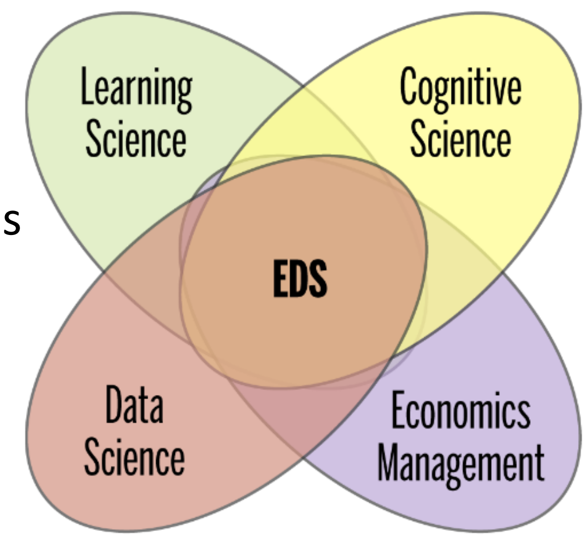
Tomorrow



Research Cores

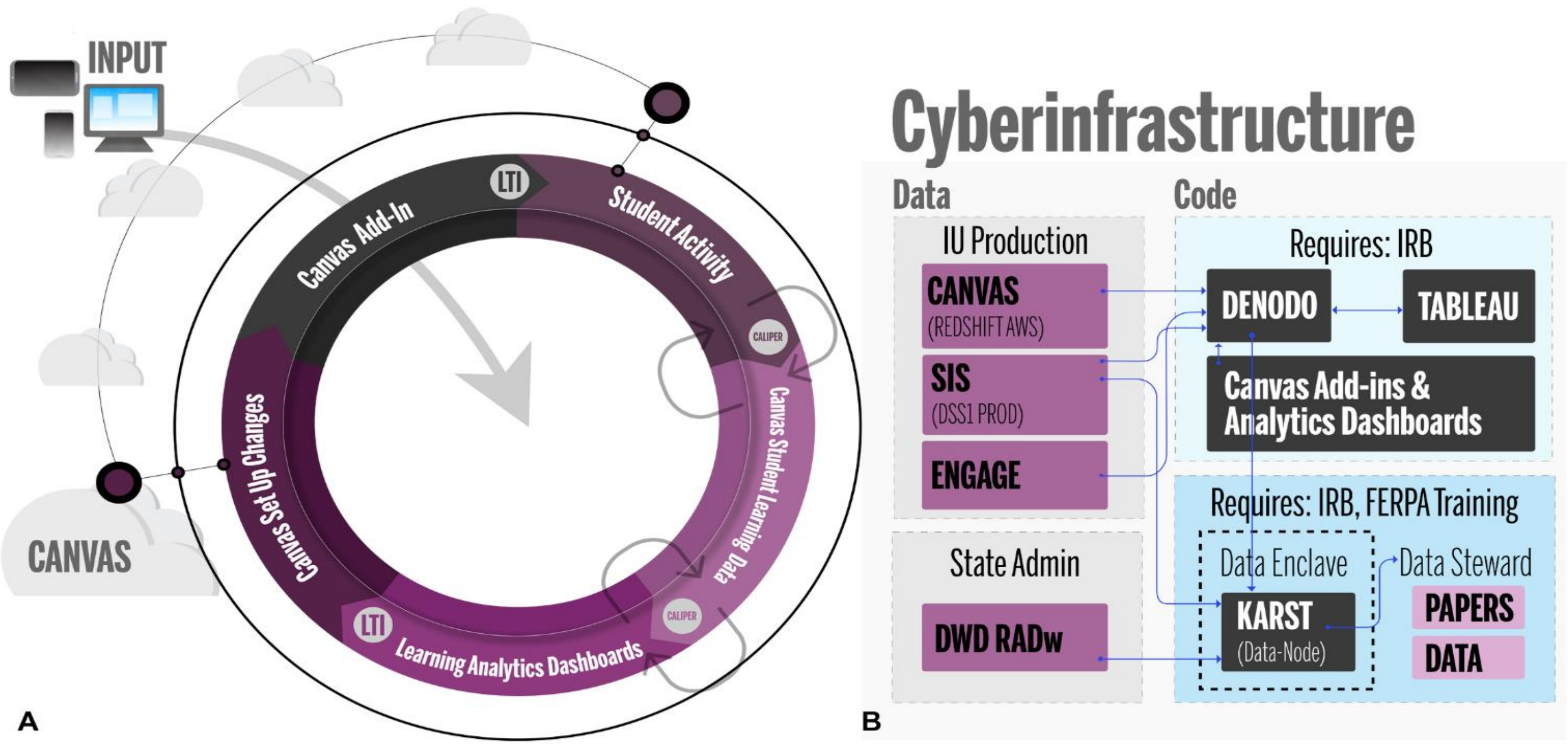
The team will perform cutting-edge, interdisciplinary research in **Educational Data Science (EDS)** at the intersection of four research areas:

- ***Cognitive Science > Classroom Experiments*** investigates the cognitive and social variables, patterns, and leverage points in learning and teaching.
- ***Learning Science > Student Support*** investigates the impact of curricular interventions on student success at IU and in life.
- ***Decision Science: Economics of Higher Education*** investigates the economic value of education across scales—from micro to macro. ***Management/Student Choice Research*** investigates the impact of incentives and educational product offerings on short-term and long-term decision making.
- ***Data Science > Learning Analytics*** performs research on data mining, modelling, and visualization techniques that increase "data (visualization) literacy" and data-driven decision making.



Cyberinfrastructure Core

- Implements novel means to provision sensitive data via secure data enclaves and federated Denodo virtualized databases.
- Develops novel functionality for existing learning management systems (LMS) such as Canvas using LTI and Caliper.
- Uses/extends Tableau to serve actionable dashboards for IU leadership.



Establishing EDS and Ensuring IU Leadership

Capitalizing on existing IU strengths:

- Student Learning Analytics (SLA) Fellows Program
- Scholarship of Teaching and Learning Program
- Learning Technologies, UITS
- Learning Science Research, PBS, COAS
- Cognitive Science Program, IUB
- Learning Sciences Program, School of Education
- Bloomington Assessment and Research (BAR) office
- Indiana Business Research Center, http://ibrc.indiana.edu
- Decision Support Initiative, http://dsi.iu.edu

Proactive collaborations with other institutions:

- Unizin—11-institution digital learning consortium, http://unizin.org
- Bay View Alliance—8-institution Student Learning Analytics (SLA) initiative

INDIANA UNIVERSITY

CENTER FOR INNOVATIVE TEACHING AND LEARNING

Office of the Vice Provost for Undergraduate Education / University Information Technology Services

Bloomington

IBRC

Bloomington Assessment and Research

Unizin

Digital Innovation Greenhouse at University of Michigan

Pete Smith, University of Michigan

The University of Michigan has engaged in a breadth approach to learning analytics, and is involved in scholarly activity in the field, applied technology development, and institutional infrastructure investment. In this talk, the rich ecosystem of educational innovation initiatives will be surveyed, with a particular focus on (a) investments in scholarly learning analytics work, including two $1.25M interdisciplinary learning analytics grants funded in part through the UM data science initiative, (b) activities in the Digital Innovation Greenhouse (DIG), which serves as an on-campus education technology accelerator to address this challenge (http://ai.umich.edu/about-ai/digital-innovation-greenhouse), and (c) institutional investment in Unizin and the development of a learning analytics architecture to enable data-driven rescission making.

UTA: Bridging Research and Practice

Christopher Brooks & George Siemens
University of Texas Arlington

Large scale data has resulted in increased interest in learning sciences and related research. Much of this research interest is coming from non-traditional education fields as physicists, biologists, and others begin to analyze the data generated by learners in online and blended environments. A second trend has been to incorporate the practices of business intelligence to improve how universities make decisions about student support, recruitment, and institutional resource allocation. In most universities, the research and the practice of analytics are treated as separate silos. At University of Texas Arlington, we have created an integrated model where our learning analytics research (LINK Research Lab) coordinates extensively with our University Analytics department. This discussion will focus on the components of an integrated research/practice system as well as the challenges and ongoing opportunities.

Learning Analytics Initiatives at Indiana University

Serdar Abaci and Joshua Quick, IUB

We will present the initial developments of learning analytics initiatives at Indiana University at an institutional level. We will also give an overview of our experience in processing, analyzing, visualizing, and interpreting the e-textbook reading behavior data that is available from the Unizin Engage e-text reader and discuss the research implications of studying instructional activity data from digital learning environments such as the Learning Management System (LMS).

Learning Analytics Innovation at the University of Michigan

Creating Scholarly, Practical, and Institutional Impact

Dr. Christopher Brooks
Research Assistant Professor, School of Information
Director of Learning Analytics & Research,
Office of Academic Innovation
University of Michigan
brooksch@umich.edu @cab938

U-M Approach To Learning Analytics

- Has a **scholarly** component...
  - a dozen faculty involved in grant writing, publishing, and graduate student mentorship in learning analytics
- Has a **practical** component...
  - building next generation tools and learning experiences for U-M learners based upon analytics and data
- Is an **institutional** activity...
  - driven at the highest levels (Provost) with service units in deep collaboration

Scholarly

- The Provost's Learning Analytics Task Force, Dr. Tim McKay (2012-2015)
- A significant community building activity through the **Student Learning and Analytics at Michigan** (SLAM) seminar series
- Increased involvement of U-M scholars with SOLAR
  - Dr. Stephanie Teasley, incoming President
  - Learning Analytics Summer Institute (LASI) 2016

Scholarly

- Continued nurturing of local community of scholars through Academic Innovation at Michigan (AIM) Analytics (2014-Present)
- Supporting next-generation learning analytics through the Michigan Institute for Data Science (MIDAS)
  - Two $1.25M interdisciplinary internal projects on learning analytics awarded for AY16
- Several external awards (NSF) to continue applied learning analytics projects (e.g. eCoach $1.9M)

Scholarly

- Broad array of topics and interests:
  - Predictive modeling of student success
  - Nudge interventions
  - Text and educaitonal discourse analysis (META, Mwrite)
  - Massive open online courses
  - Holistic modeling of students, psychological (affective) states
- Inter- and Multidisciplinary approach
  - Faculty from Information, CS, Education, Physics, Chemistry, English...

Practical

- Learning analytics are actively used to support academic innovation at U-M
- One place is through the Digital Innovation Greenhouse (Dr. Tim McKay)
  - Interesting model of institutional funded scholarly work turned institutional asset!
  - Educational technology incubation in higher ed
    - Academic Reporting Toolkit (ART) 2.0
    - Electronic Coaching (ECoach)
    - Advisor-facing Early Warning System (Student Explorer)

Practical

- ART 2.0
- Dr. Gus Evrard
- Dr. Chris Teplovs
- Data in agg from student course review

SI 365

Cyberscience: Computational Science and the Rise of the Fourth Paradigm

This course invites students to understand the ways in which data-rich, compute-intensive, collaborative research drives discovery in the natural and social sciences. Through readings, activities, and discussion with invited guests, students will gain an appreciation of the opportunities and challenges posed by the fast-growing, interdisciplinary subject of data science.

Advisory prerequisites:

Computing language course (e.g., EECS 183, 280, ENGR 101), Introductory statistics (e.g., Stats 250)

Credits:

3.00

Evaluation Data

Learn more about this evaluation data.

65% of respondents expressed a **strong desire** to take this course.

86% of respondents reported **learning a lot** from this course.

22% of respondents reported the workload as **heavy**.

Practical

- Simple data about the makeup of students in the course

Instructors

Who teaches the course?

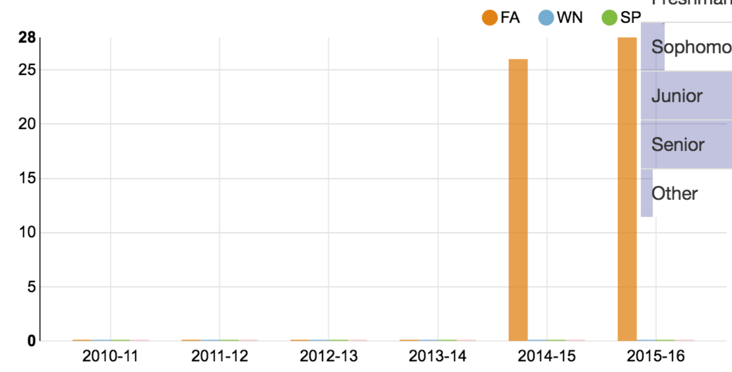
Show 10 **entries** **Search:**

Who	# Terms taught	Most recently
Evrard, August	2	Fall 2015

Showing 1 to 1 of 1 entries Previous 1 Next

Enrollment

When is it offered and how many people take it?



Level

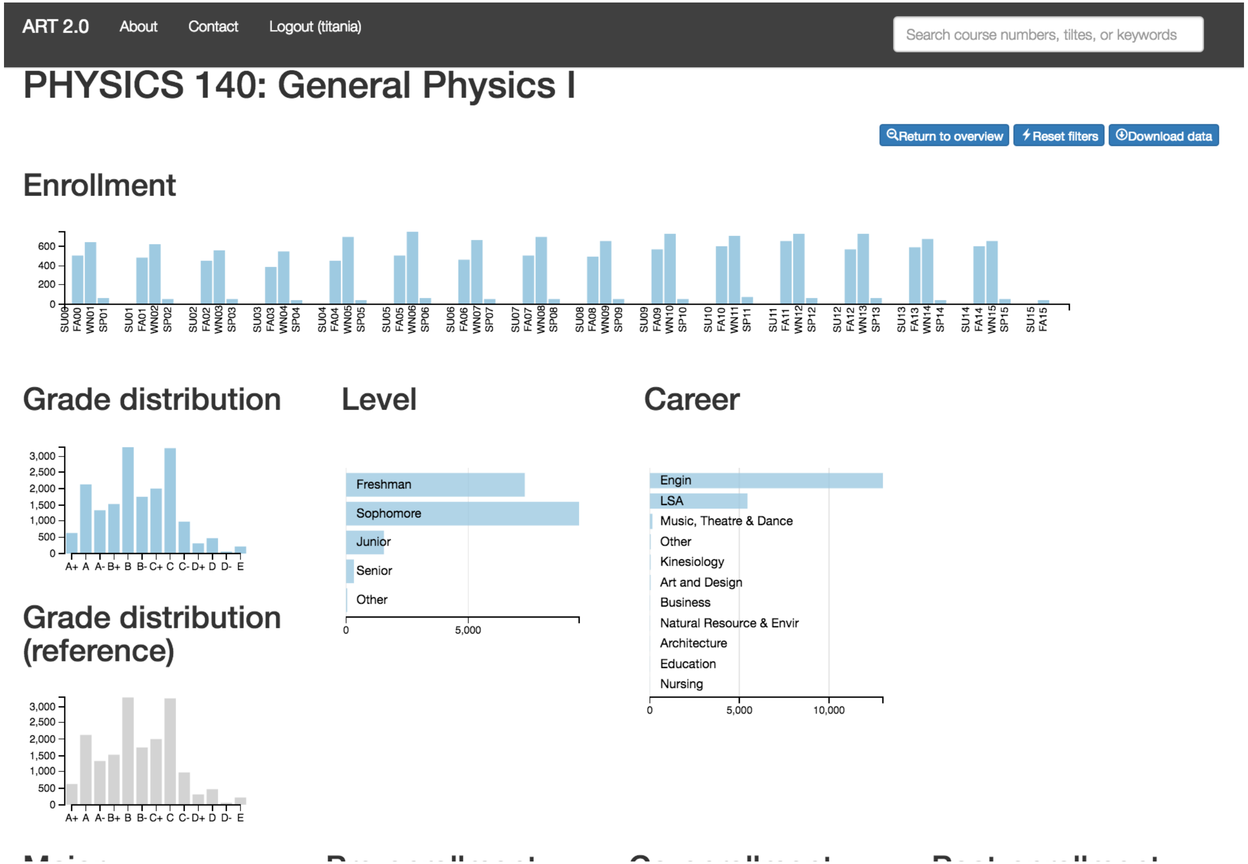
The year in school (based on credit hours earned) students were at the begining of the term in which they took this course.

Freshman	0%
Sophomore	4%
Junior	19%
Senior	76%
Other	2%

Christopher Brooks, University of Michigan @cab938 brooksch@umich.edu

Practical

- Explorable details about data about students in the course (for faculty)



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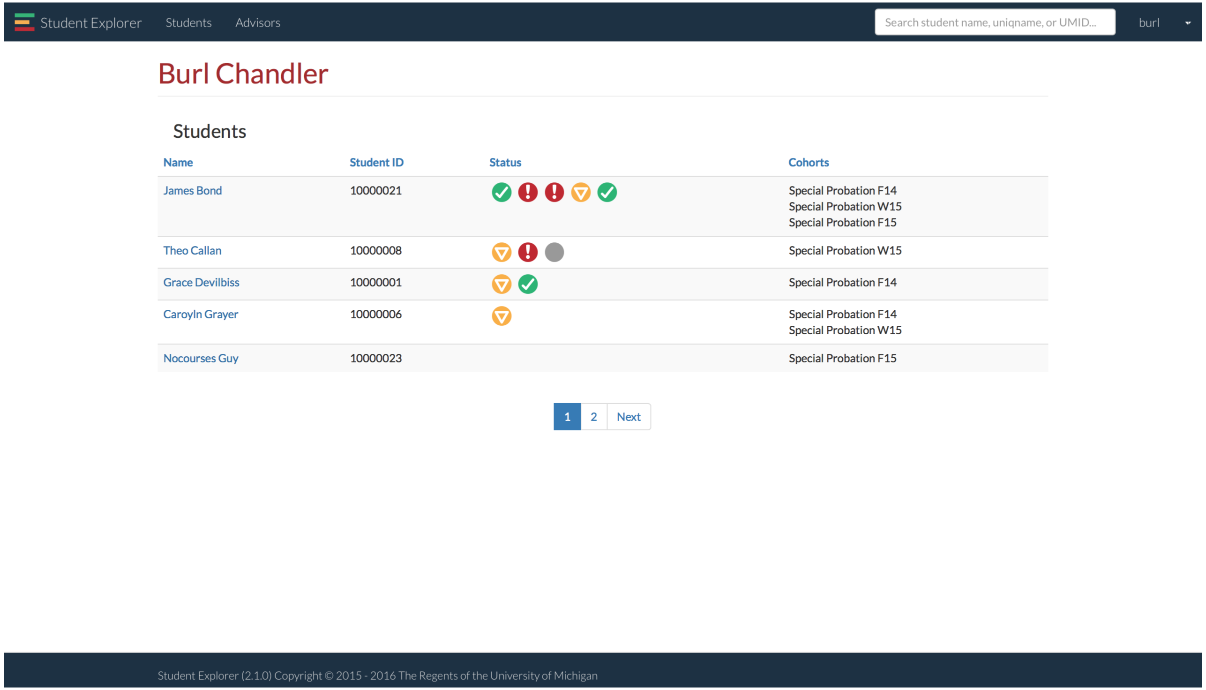
Student Explorer

- Kris Steinhoff, Dr. Steve Lonn, Dr. Stephanie Teasley

- At a glance early warning for advisors

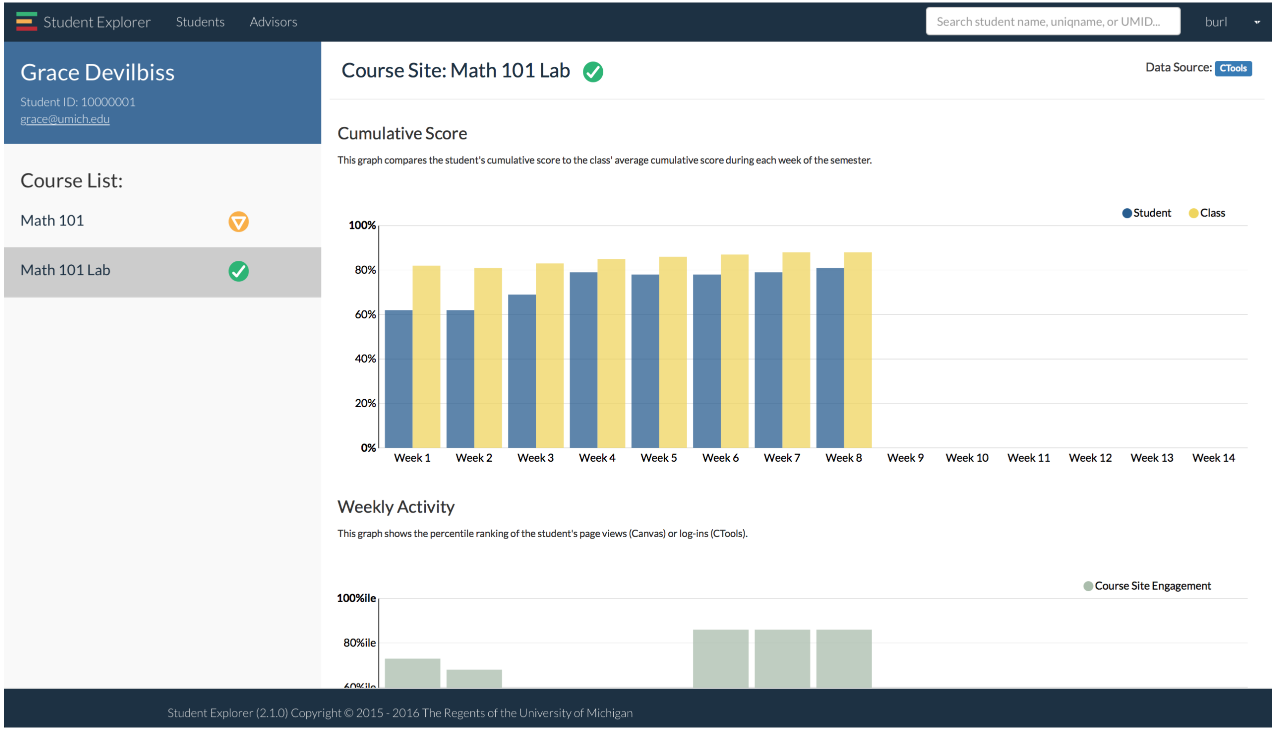


Christopher Brooks, University of Michigan @cab938 brooksch@umich.edu

SCHOOL OF INFORMATION
UNIVERSITY OF MICHIGAN

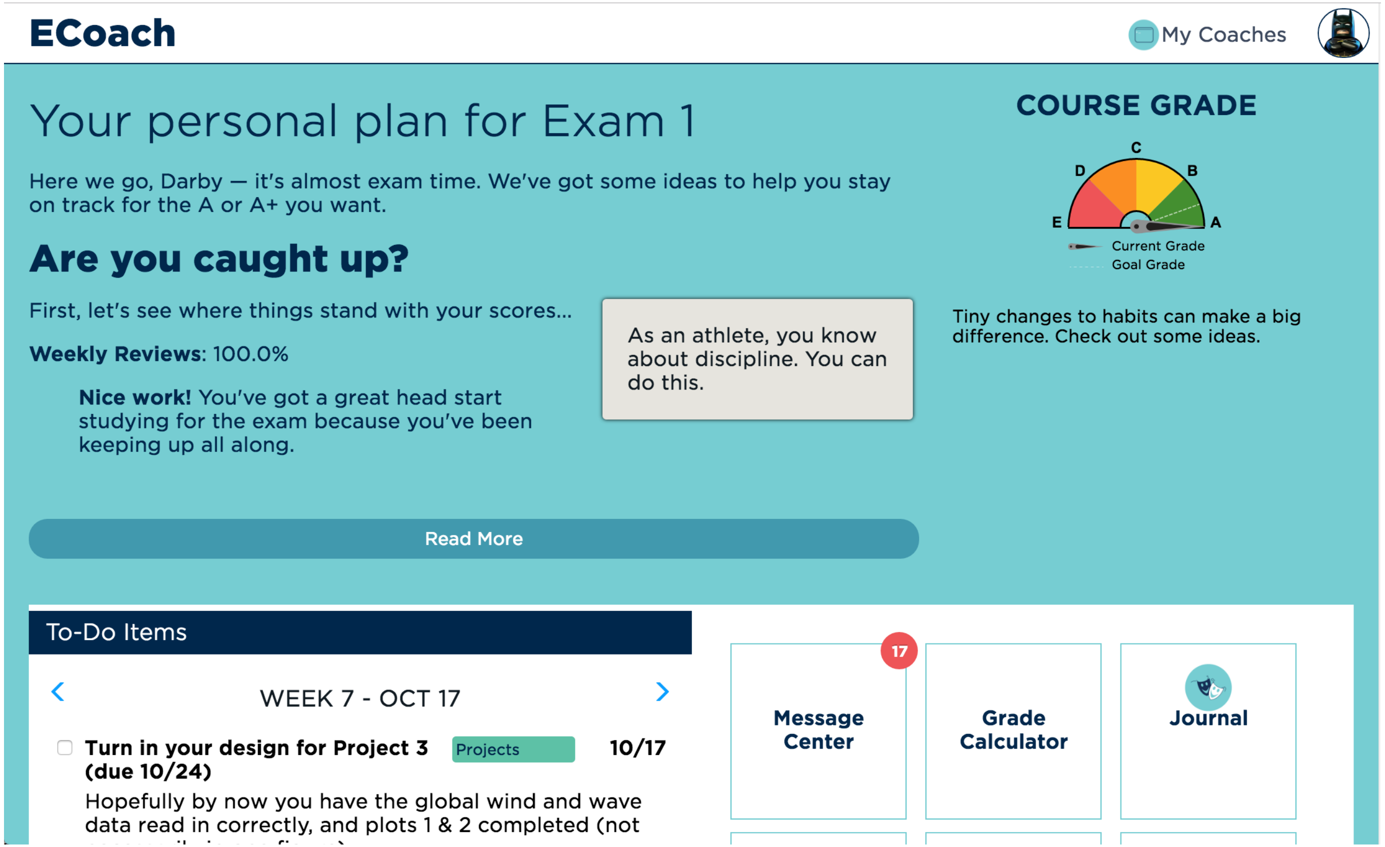
Student Explorer

- Behaviors of students in courses



ECoach

- Nudging students based on behavior and profiles
- Dr. Tim McKay



ECoach

ECoach My Coaches

SET YOUR GOAL

What grade are you aiming to get on your upcoming exam?

93

0 100

How motivated are you to get this grade?

Not At All — Extremely

1 2 3 4 5 6 7

How important is it for you to achieve this grade?

Extremely

6 7

ECoach My Coaches

CHOOSE YOUR TOOLS

Which resources will help you prepare for this exam?

Please take a moment to consider the types of questions that will be on the exam.

To achieve the grade that you want, what resources (listed below) do you think will help you prepare for this exam most effectively?

Practice exam questions (from Canvas)	ECoach
Private tutoring	Asking questions in lecture or lab
Office hours with a GSI	Office hours with a lecturer
Study group (or discussions with students)	Formula card
Textbook readings	Lab materials (ILPs)
Problem Roulette past exam questions	Past recommended HW problems
Video recorded lectures (on Canvas)	Past required HW problems

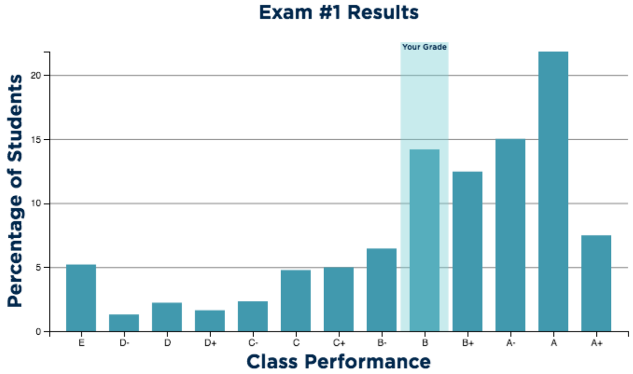
HOW ARE YOU FEELING?

Welcome back, Ben

You made it through the first statistics exam.

You scored a **61 out of 75 points** or **81.3%** which corresponds to a letter grade of a B

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



How do you feel about your grade on this Exam?

- I'm disappointed
- I feel ok about it

Institutional

- Creation of a unit affice and Vice Provost: Digital Education & Innovation, now the **Office of Academic Innovation**
- Compliments existing institutional assets
  - Not IT!
  - Not Teaching and Learning!
- Aim is to seed investment in new educational technologies, models, and methodologies
  - Technology incubation, academic innovation experimentation funding…

James Hilton
Vice Provost for Academic Innovation,Dean of Libraries

James DeVaney
Associate Vice Provost for Academic Innovation

Institutional Assets

- Extends beyond the immediate U-M environment with Unizin Consortium
- Strong support within IT unit on campus
  - Learning Analytics Architecture (LARC) dataset
  - Helping to develop IMS Caliper specification and implementations
  - New processes for data access (MOU, IRB)
- We take (1) cool, proven novel research and (2) scale it to the institution and then (3) share it in our broader consortium

Takeaway

- Learning Analytics at Michigan is
  - Scholarly
  - Practical
  - Institutional
- A broad array of actors doing many things, this summary just scratches the surface!

Christopher Brooks
Research Assistant Professor,
School of Information
Director of Learning Analytics and Research
Office of Academic Innovation

LINK Research Lab

Learning Innovation and Networked Knowledge

UNIVERSITY OF TEXAS ARLINGTON

Pete Smith
Chief Analytics Officer

George Siemens
Executive Director

linkresearchlab.org

Educational Data Science, Many Names

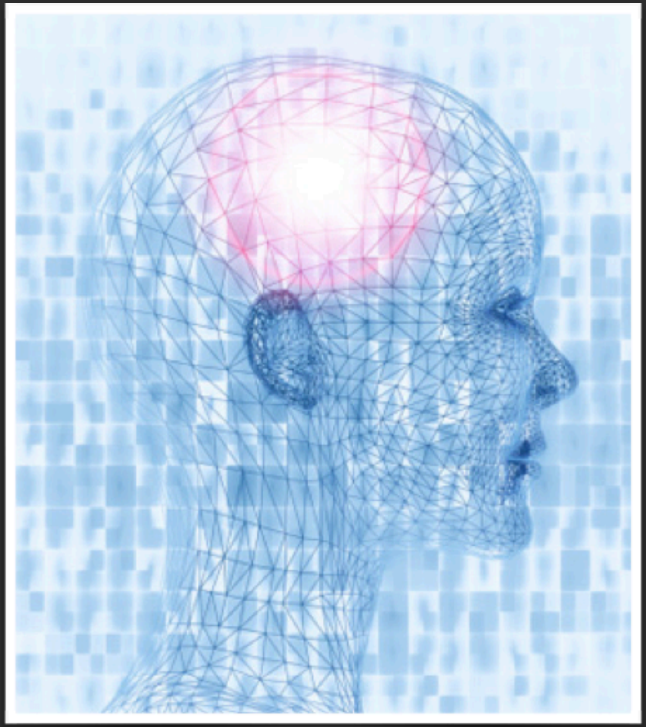
Educational Data Mining

Learning Analytics

“Big Data” in Education

And increasingly…

- Machine Learning
- Artificial Intelligence



Data-Enriched Educational Products

Online courses that enable the constant logging and tracking of learners through their clickstream data;

E-textbooks that can ‘learn’ from how they are used;

Adaptive learning systems that enable materials to be tailored to each student’s individual needs through automated real-time analysis;

As time goes on…

New forms of data analytics that are able to harvest data from students' actions, learn from them, and generate predictions of individual students' probable future performances;

Automated personal tutoring software that monitors students and gives constant real-time support and shapes the pedagogic experience.

—Mayer-Schönberger & Cukier (2014),

Learning with Big Data: The Future of Education

And emerging today…

New forms of data analytics that are able to harvest data from students' affective states, social and cognitive engagement;

More recently: machine learning drives AI tools such as chatbots, "smart" discussion fora, automated coaching, etc.

"Smart Campus UTA"

Behind it all…

…are models and “training data” for

- personal profiles
- e-curriculum pathways
- models of student activity, engagement, affective states
- models for natural-language interaction with learners

What data are feeding our models?

At UTA, primary sources are our Student Information System (SIS) and Learning Management System (LMS).

Additional Campus Systems: Student Affairs, Library, Housing and Food Services

Federation of data from neighboring two-year colleges is/will be taking place.

Expanding Geographical Context: Arlington and the DFW Metroplex as “Smart Cities”

UTA Experience

University Analytics

- New University Unit of 25 FTE
- Data Scientists for Data Mining, Analytics Across the Campus Academic and Business Enterprise

Learning Innovation and Networked Knowledge (LINK) Lab

- Research Facility of 24 including Faculty, Staff, Postdocs, and Graduate-level Researchers

UA Hardware and Toolsets

- Civitas Learning
  - Multivariate Modeling of Student Persistence, Graduation
  - IaaS around Student Data
- SAS
  - Visual Analytics
  - Enterprise Miner
  - Prediction Suite
  - Viya Machine Learning/Neural Network Modeling
  - 450 Core Server Farm (Planned)

UTA "Big Data Questions"

How will big data and new models provide a more complex understanding of the learner in higher education today?

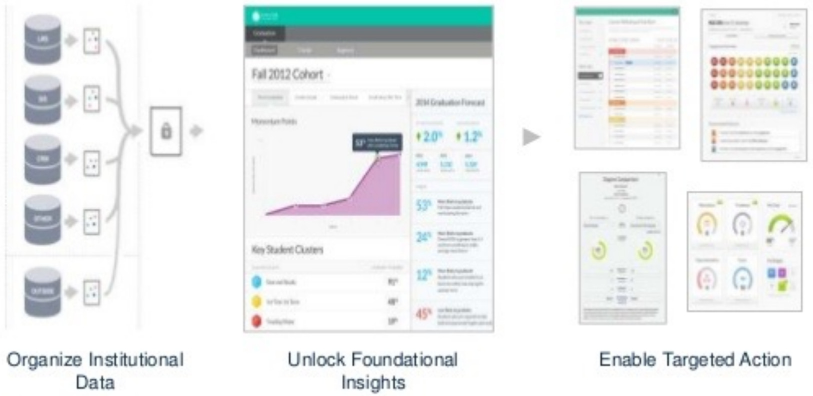
How can universities use big data to improve student success (retention and successful progress to graduation)?

Can higher education develop new, more multivariate models of student engagement? How might these models drive faculty, staff, and coaches to improve student cognitive and social presence in formal coursework?

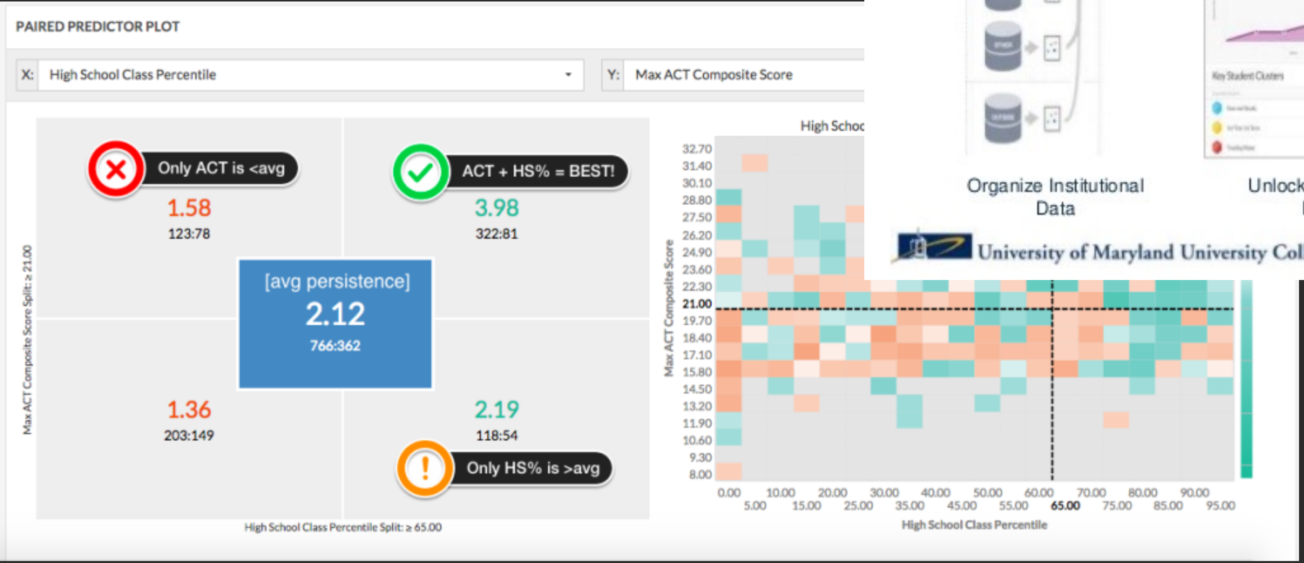
How can we better understand learners of diversity and personalize the educational experience for engagement and success?

About Civitas Learning

- Founded in 2011 by Charles Thornburgh and Mark Milliron
- Provides cloud-based predictive analytics applications for administrators, faculty, students, and advisors
- Helps answer the question of what's working, what's not working, for which students, at each point in their learning journeys



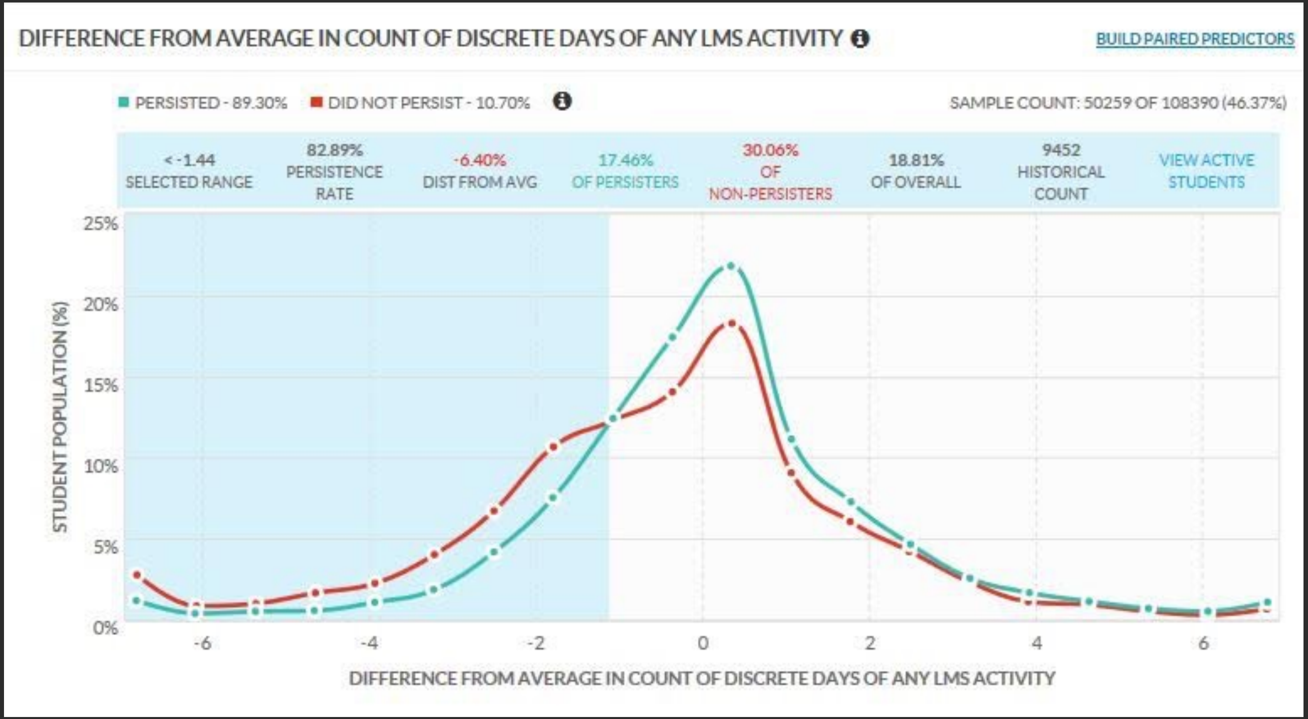
University of Maryland University College



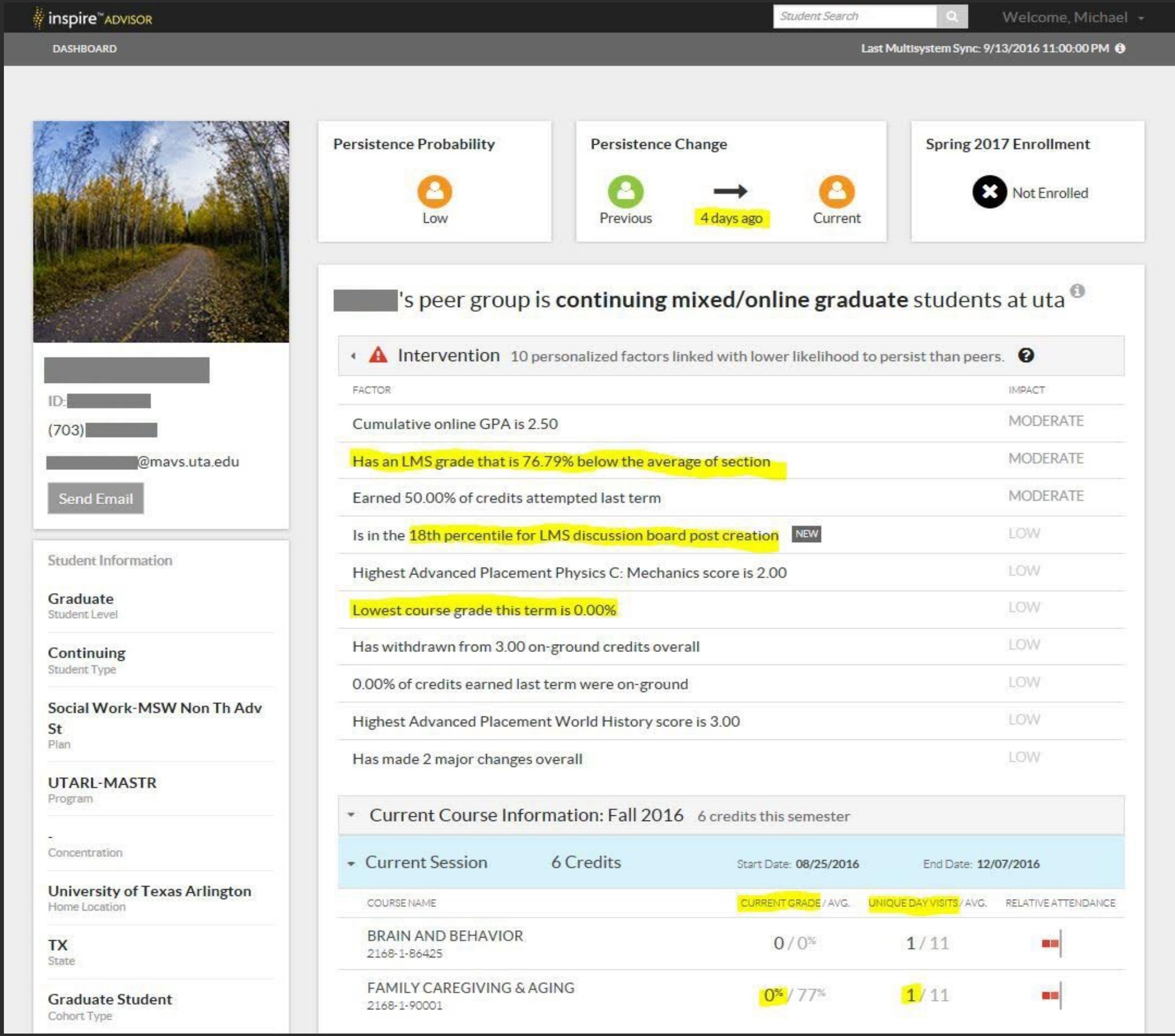
LMS Data in UTA/Civitas Model

Abc fact_web_activity **Civ Activity Type Id**	Abc fact_web_activity **Dim Date Id**	Abc fact_web_activity **Dim Enrollment Id**	Abc fact_web_activity **Dim Person Id**	Abc fact_web_activity **Dim Section Id**	fact_web_activity **Event Ts**	Abc fact_web_activity **Raw Activity Type Id**
announcement	42619	6469735	8052836	266752	9/7/2016 10:55:19 AM	COURSE_ACCESS_an...
announcement	42619	6469735	8052836	266752	9/7/2016 10:48:52 AM	COURSE_ACCESS_an...
announcement	42611	6415398	8814225	263394	8/30/2016 12:49:29 PM	COURSE_ACCESS_an...
announcement	42611	6415398	8814225	263394	8/30/2016 12:49:14 PM	COURSE_ACCESS_an...
announcement	42610	6446205	9265419	265888	8/29/2016 11:33:26 PM	COURSE_ACCESS_an...
announcement	42610	6446187	9035214	265888	8/29/2016 3:17:15 PM	COURSE_ACCESS_an...
announcement	42580	6354675	331765	261193	7/30/2016 12:41:45 PM	COURSE_ACCESS_an...
announcement	42580	6354675	331765	261193	7/30/2016 12:41:34 PM	COURSE_ACCESS_an...

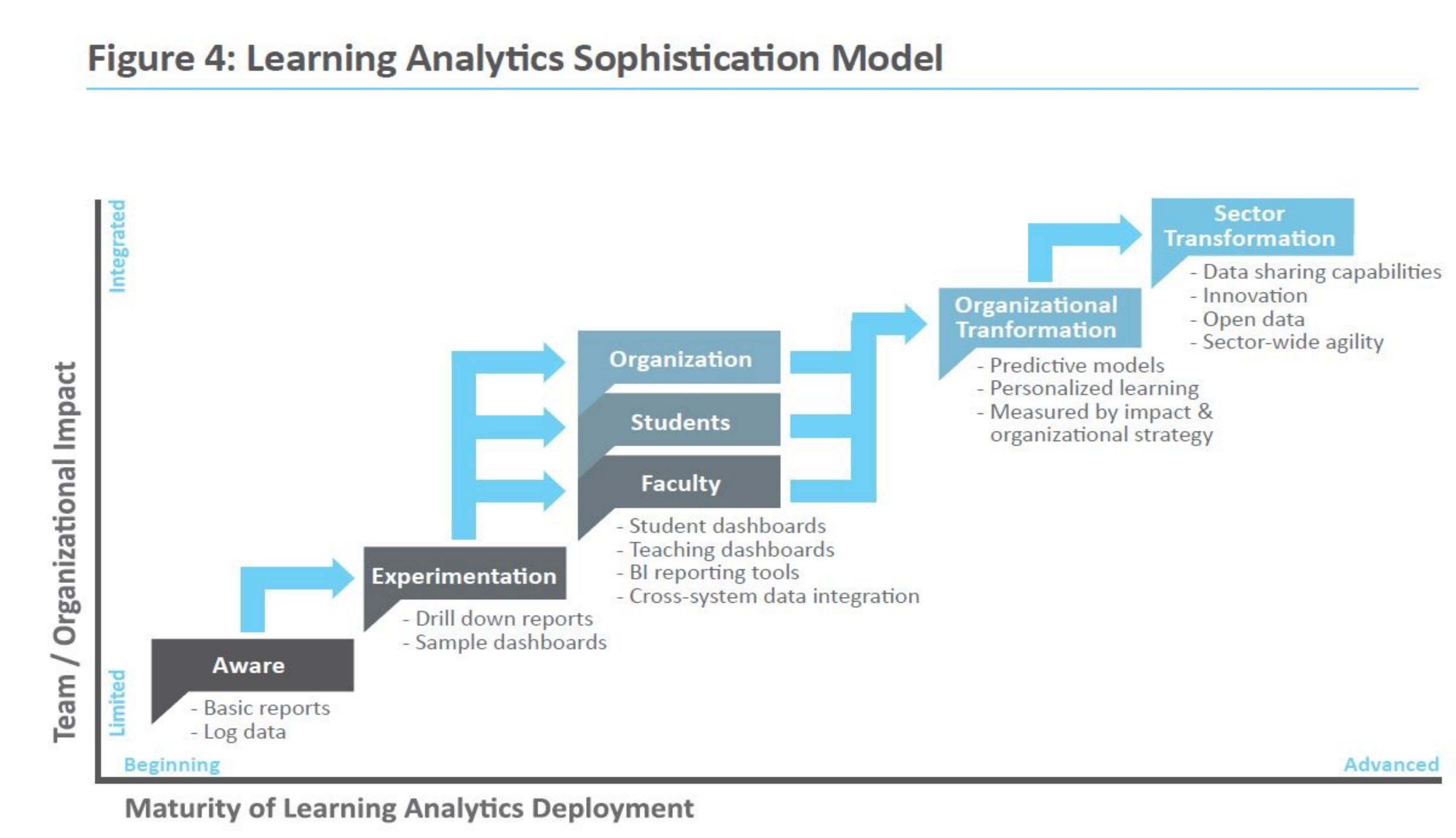
Sample Student Persistence Model Output



Sample Student Persistence Model Output



Learning Analytics Maturity Model



What does it mean to be human in a digital age?

Projects - dLRN

$1.6M Bill and Melinda Gates Foundation (PI)
linkresearchlab.org/dlrn

Projects - dLRN Conference

DIGITAL LEARNING
RESEARCH NETWORK

linkresearchlab.org/dlrn2015

Projects - Smart Science Network

SMART SPARROW

ASU online
ARIZONA STATE UNIVERSITY

$5.2M Bill and Melinda Gates Foundation (Co-PI)
linkresearchlab.org/research

Projects - BCC: Community and Capacity for Educational Discourse Research

$254K NSF (Co-PI)

linkresearchlab.org/research

Projects - BIGDATA: Collaborative Research

$1.6M NSF (Co-PI)

linkresearchlab.org/research

Projects - DALMOOC

linkresearchlab.org/dalmooc

Projects - Emerging Technologies and their Practical Applications in K12 Teaching and Learning MOOC

goo.gl/w9Bkdx

Projects - INTERlab

Interlab

interlab.me

Corporate Partnerships

aWEAR

Expanding data collection to include broadening scope of data collection

Holistic learning

Individual well-being

Preparing learners for the future of work and life

New Paradigm(s)

TABLE 1

A Typology of Educational Data Sources in Computer-Mediated Learning Environments

Data type	Mode of data collection	Assessment genres: Examples
Machine assessments	Computer adaptive testing	Select response assessments, quizzes (e.g., reading comprehension, grammar, vocabulary)
	Natural language processing	Automated essay scoring, feedback on language features
Structured, embedded data	Procedure-defined processes	Games, intelligent tutors
	Argument-defined processes	Rubric-based peer review of writing
	Machine learning processes	Semantic tagging and annotation, text visualizations, accepted textual change suggestions
Unstructured, incidental data	Incidental "data exhaust"	Keystroke patterns, edit histories, clickstream and navigation paths, social interaction patterns
	Dedicated devices for collecting unstructured data	Video capture, eye trackers, movement detectors

Cope & Kalantzis (2016), "Big Data Comes to School"

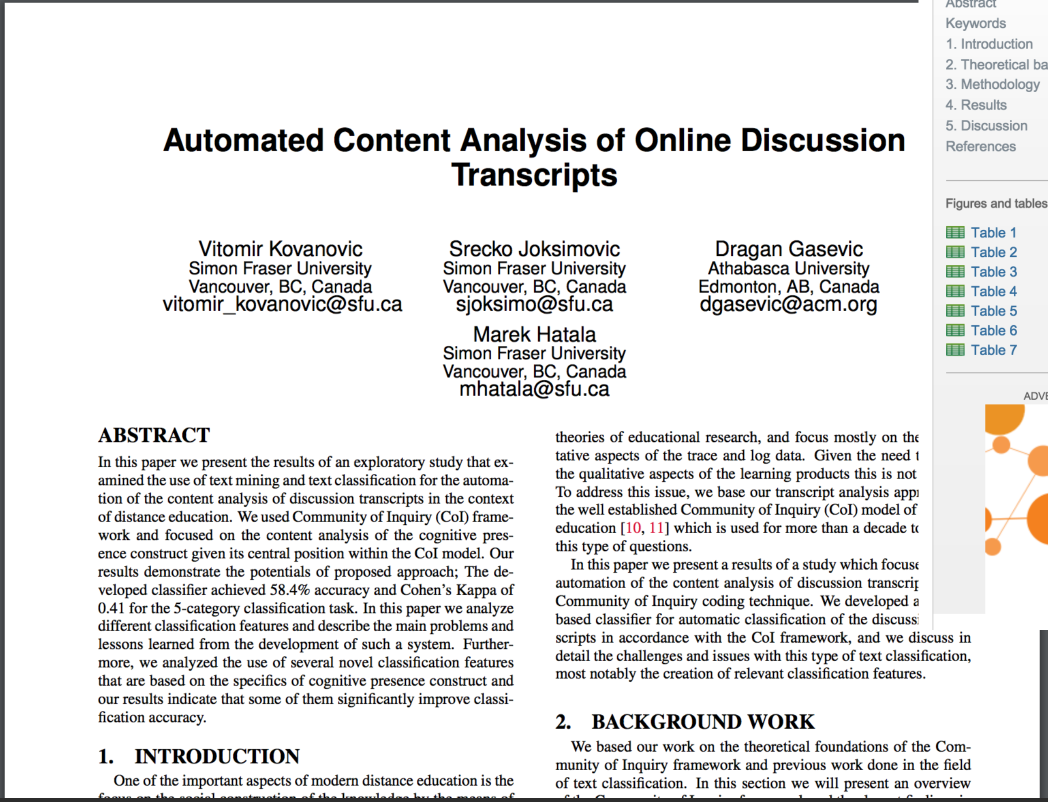
New Paradigm(s)

TABLE 3
Traditional Compared to Emerging Models of Research

Traditional research model	Emerging research model
Researcher as *independent observer*	Researchers recruit subjects as data collectors, *co-researchers*
Optimal *sample N* to produce reliable results	There is no marginal cost for *N* = *all*, and data are rich enough to support *N* = *1*
Practical limits to research perspective determined by the *scale of data collection*	*Multiscalar perspectives*, from *N* = 1 to *N* = all
Fixed time frames, long enough to demonstrate overall effect; longitudinal analyses expensive and thus infrequent	*Short time frames*, feeding small incremental changes back into the learning environment; *longitudinal time frames* as a consequence of data persistence
Standardization effects (fidelity, average effect)	Tracing *heterogeneity* in data, e.g., different paths in adaptive learning environments, salient activities of outliers
Causal effects: *overall*, for whole populations or population subsets	*Microgenetic* casual analysis, e.g., learning progressions for different students, differential effects traceable in varied learning paths
Relatively *separate quantitative and qualitative* research practices; *low significance of theory* in empirical analyses	*Integration of quantitative and qualitative* analyses; *increasing importance of theory* in data analyses

Cope & Kalantzis (2016), “Big Data Comes to School”

NLP Frontier



Automated Content Analysis of Online Discussion Transcripts

Vitomir Kovanovic
Simon Fraser University
Vancouver, BC, Canada
vitomir_kovanovic@sfu.ca

Srecko Joksimovic
Simon Fraser University
Vancouver, BC, Canada
sjoksimo@sfu.ca

Dragan Gasevic
Athabasca University
Edmonton, AB, Canada
dgasevic@acm.org

Marek Hatala
Simon Fraser University
Vancouver, BC, Canada
mhatala@sfu.ca

ABSTRACT

In this paper we present the results of an exploratory study that examined the use of text mining and text classification for the automation of the content analysis of discussion transcripts in the context of distance education. We used Community of Inquiry (CoI) framework and focused on the content analysis of the cognitive presence construct given its central position within the CoI model. Our results demonstrate the potentials of proposed approach; The developed classifier achieved 58.4% accuracy and Cohen's Kappa of 0.41 for the 5-category classification task. In this paper we analyze different classification features and describe the main problems and lessons learned from the development of such a system. Furthermore, we analyzed the use of several novel classification features that are based on the specifics of cognitive presence construct and our results indicate that some of them significantly improve classification accuracy.

1. INTRODUCTION

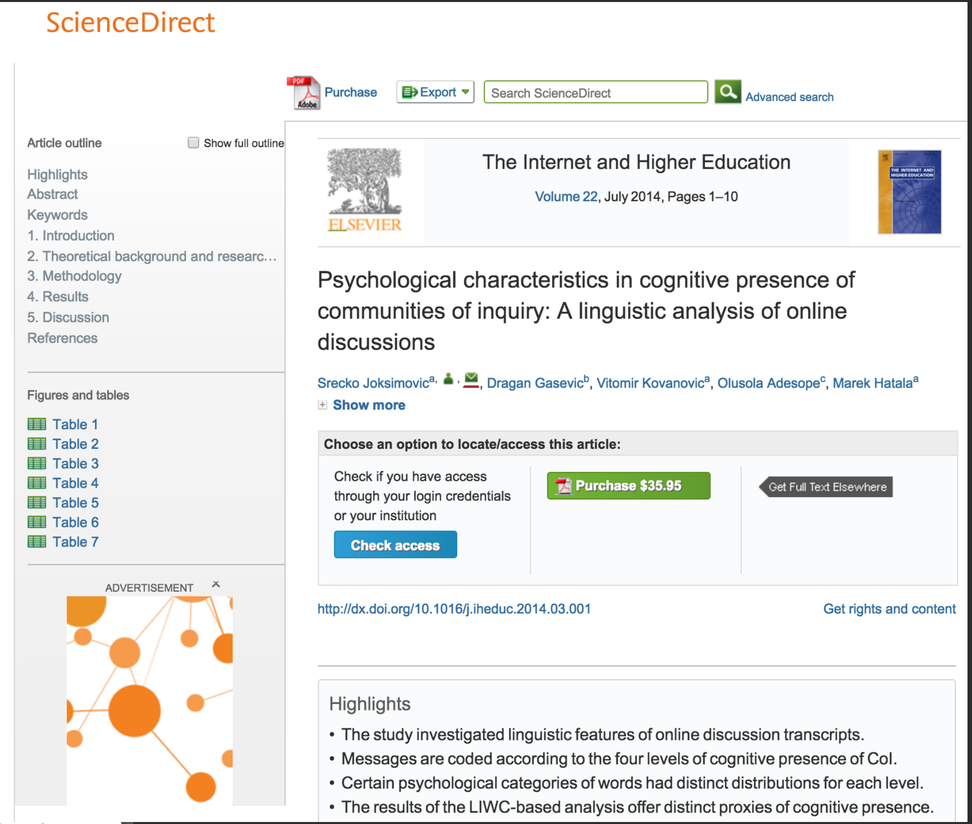
One of the important aspects of modern distance education is the

theories of educational research, and focus mostly on the tative aspects of the trace and log data. Given the need t the qualitative aspects of the learning products this is not To address this issue, we base our transcript analysis app the well established Community of Inquiry (CoI) model of education [10, 11] which is used for more than a decade t this type of questions.

In this paper we present a results of a study which focuse automation of the content analysis of discussion transcrip Community of Inquiry coding technique. We developed a based classifier for automatic classification of the discussi scripts in accordance with the CoI framework, and we discuss in detail the challenges and issues with this type of text classification, most notably the creation of relevant classification features.

2. BACKGROUND WORK

We based our work on the theoretical foundations of the Community of Inquiry framework and previous work done in the field of text classification. In this section we will present an overview



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ELSEVIER
The Internet and Higher Education
Volume 22, July 2014, Pages 1–10

Psychological characteristics in cognitive presence of communities of inquiry: A linguistic analysis of online discussions

Srecko Joksimovic[a], Dragan Gasevic[b], Vitomir Kovanovic[a], Olusola Adesope[c], Marek Hatala[a]

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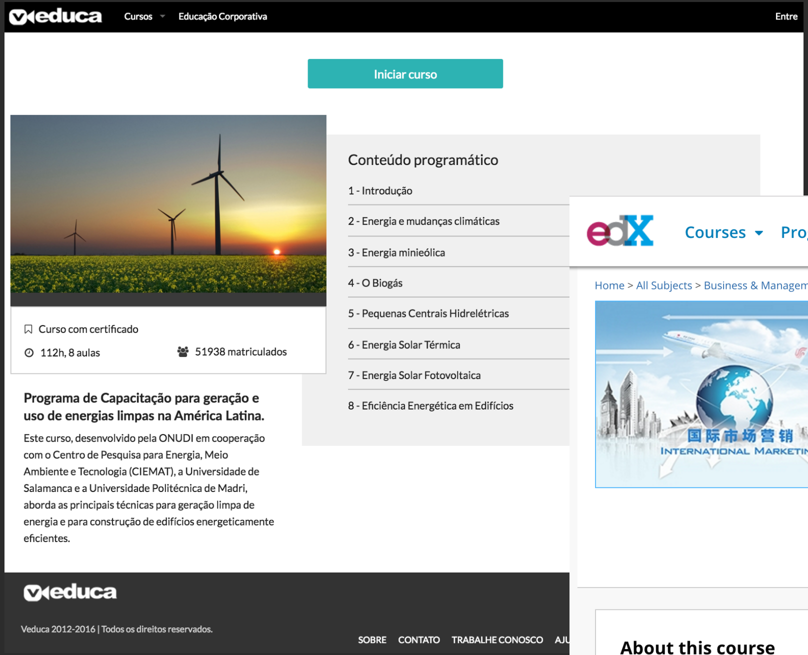
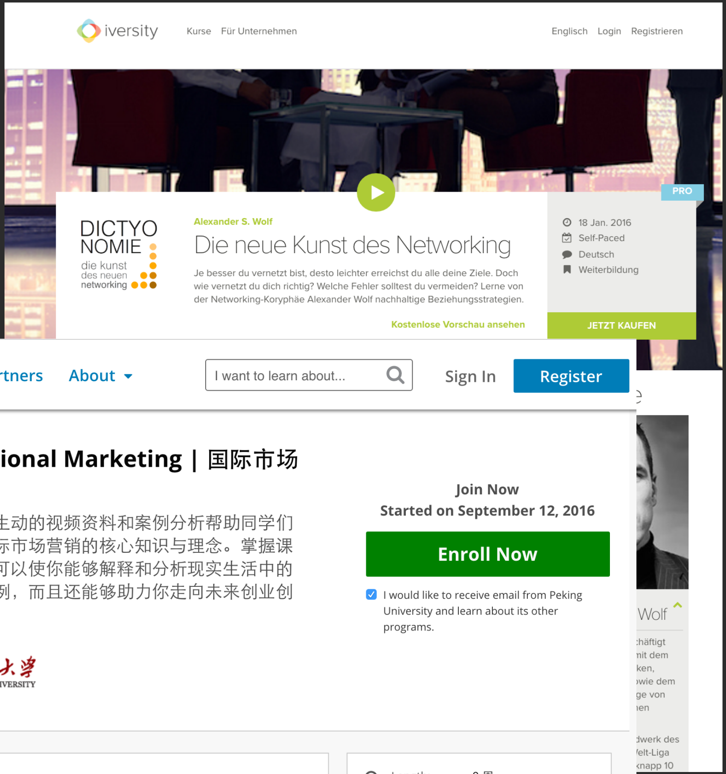
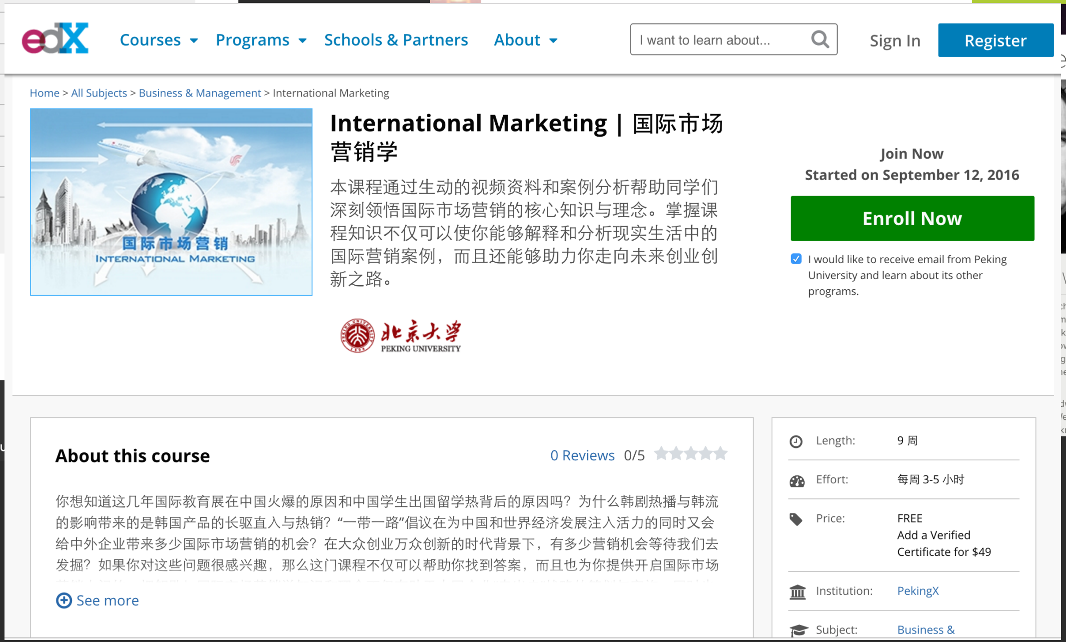
Highlights

- The study investigated linguistic features of online discussion transcripts.
- Messages are coded according to the four levels of cognitive presence of CoI.
- Certain psychological categories of words had distinct distributions for each level.
- The results of the LIWC-based analysis offer distinct proxies of cognitive presence.

Intercultural Frontier







Distributed Research Networks

Stanford

TC, Columbia

U of Edinburgh

Collaboration with UniSA

University of Penn

Knowledge is networked.

Learning is network formation.

Discovering connections and patterns is research.

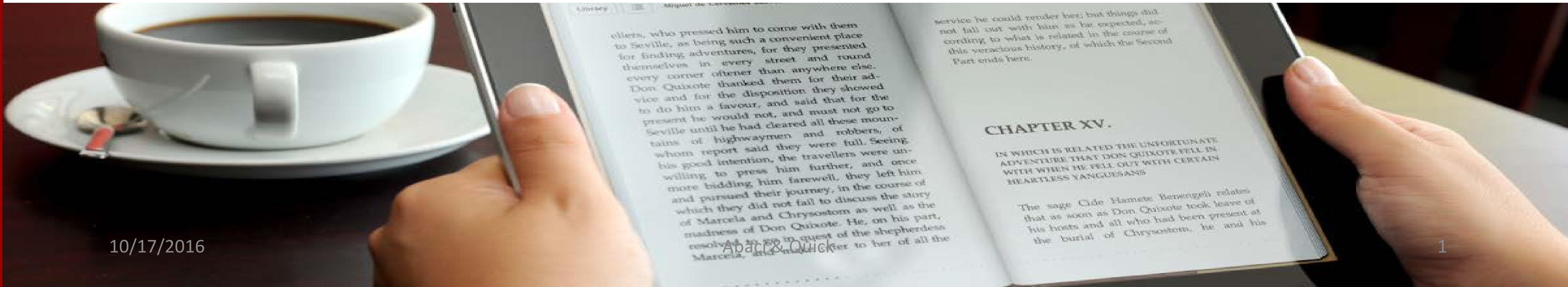
Making connections is innovation, creativity, and knowledge generation.

Institutional Analytics with the *Engage* Platform

Serdar Abaci, PhD
Educational Research and Evaluation Specialist

Joshua Quick
Graduate Research Assistant

UITS, Learning Technologies Division
Indiana University, Bloomington



IU eText Program

- Different business model for e-text adoption
  - Instructor adopts an e-textbook
  - E-textbooks are available 1st day of the class
  - On average, 60% savings in textbook cost
  - Students maintain access to e-texts
  - Students access all of their e-texts through single platform (Courseload – Now Unizin Engage)

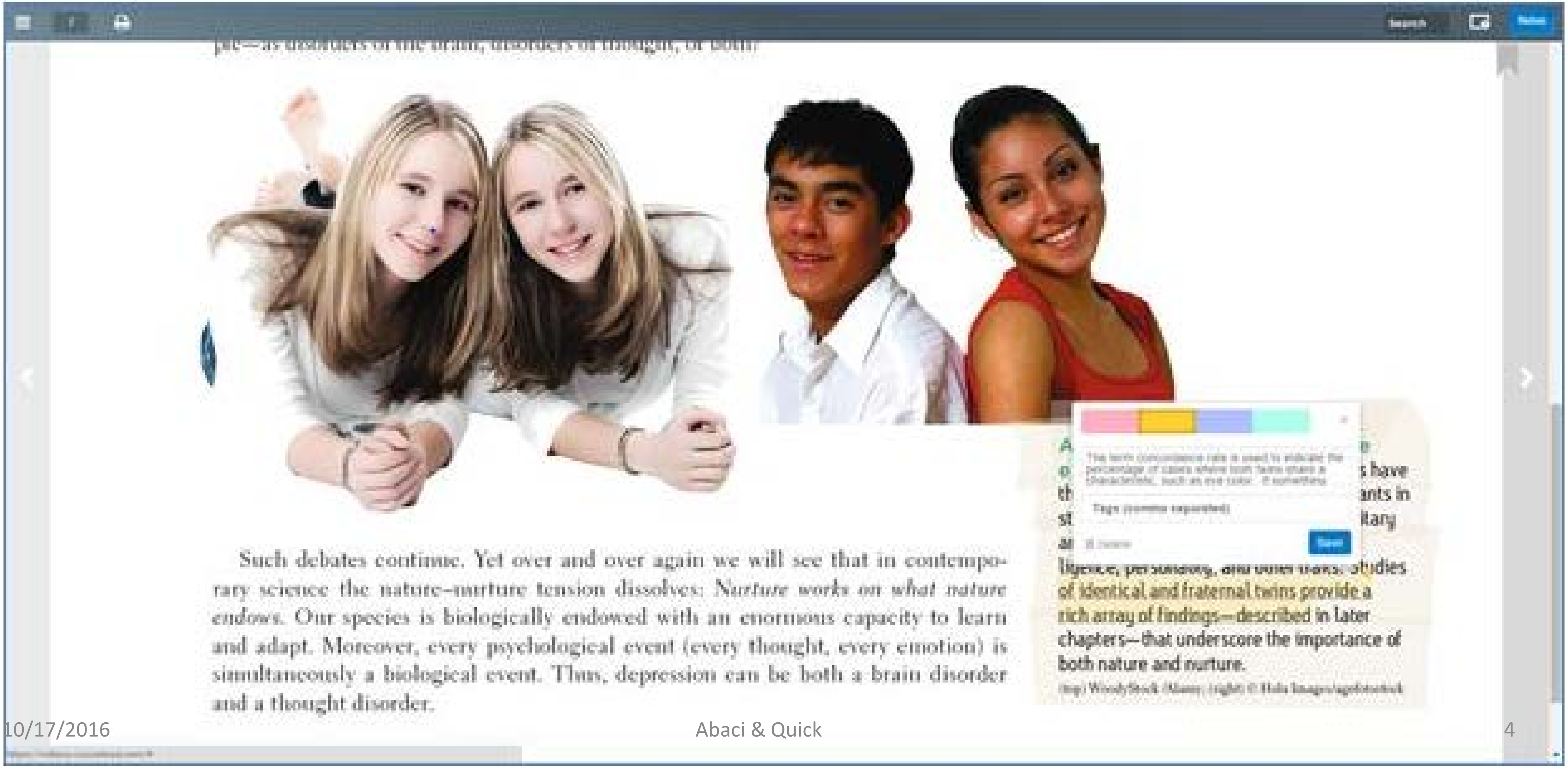
PILOT
2009-2011

FULL IMPLEMENTATION
SPRING 2012

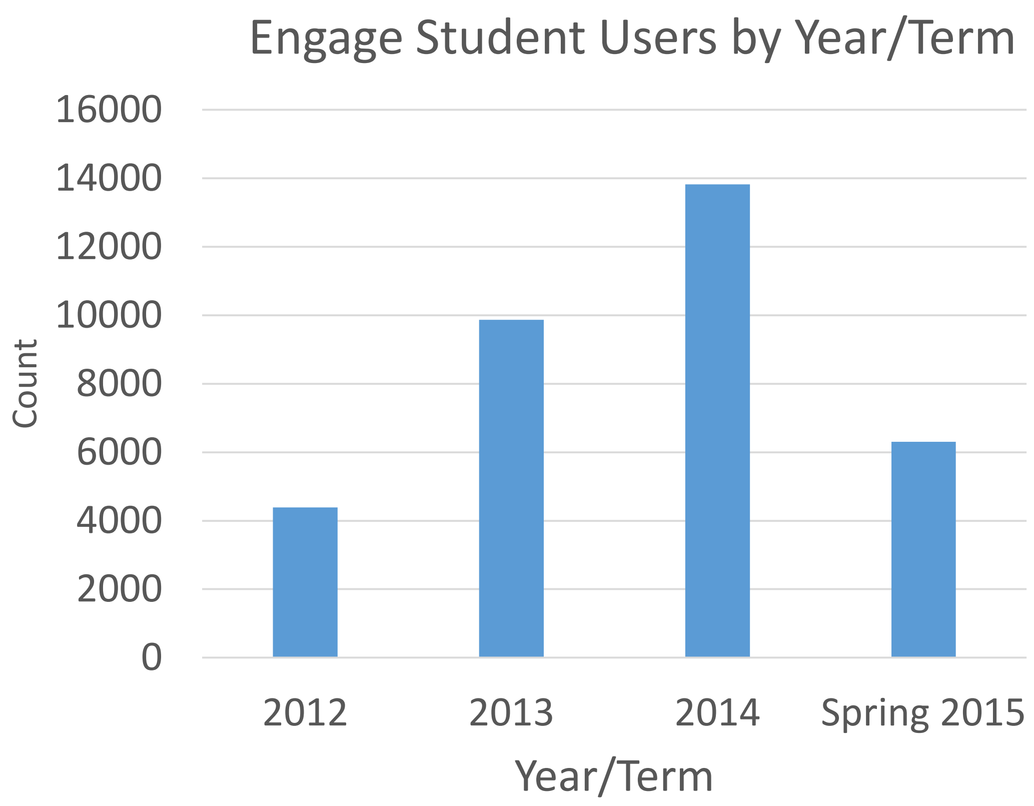
Engage Platform

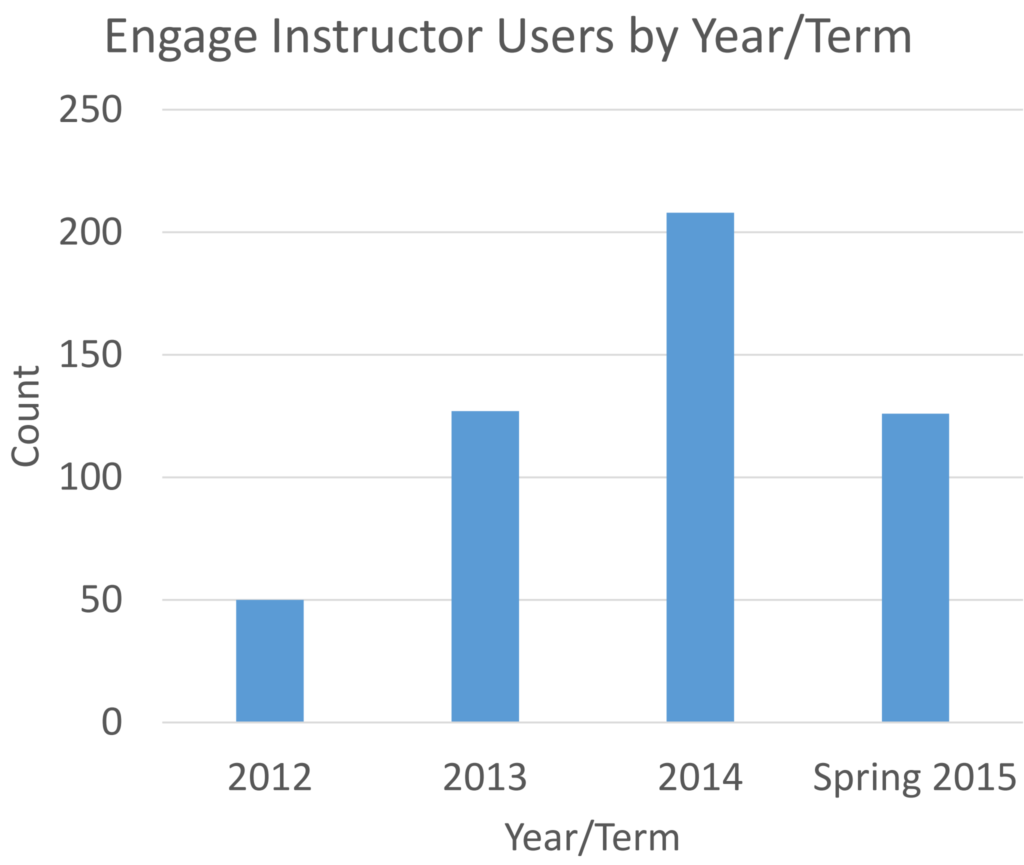
- Unizin online/mobile content delivery platform
- Enables students and instructors to read and annotate a shared document
- Allows for readily accessible feedback and collaboration
- Platform records these events and occurrences at institutional, course, and section levels

Engage eText Reading Platform Demo



2012-2015 Use





Student Use by Departments and Schools

Department/School	2012	2013	2014	Spring 2015
Business School	1732	4456	6856	4202
Economics Department	481	350	667	68
Journalism Department	174	388	425	0
School of Public & Environmental Affairs	75	266	222	110
School of Public Health	893	1661	1479	878
Statistics Department	0	735	1078	47

Initial Efforts

Source Data

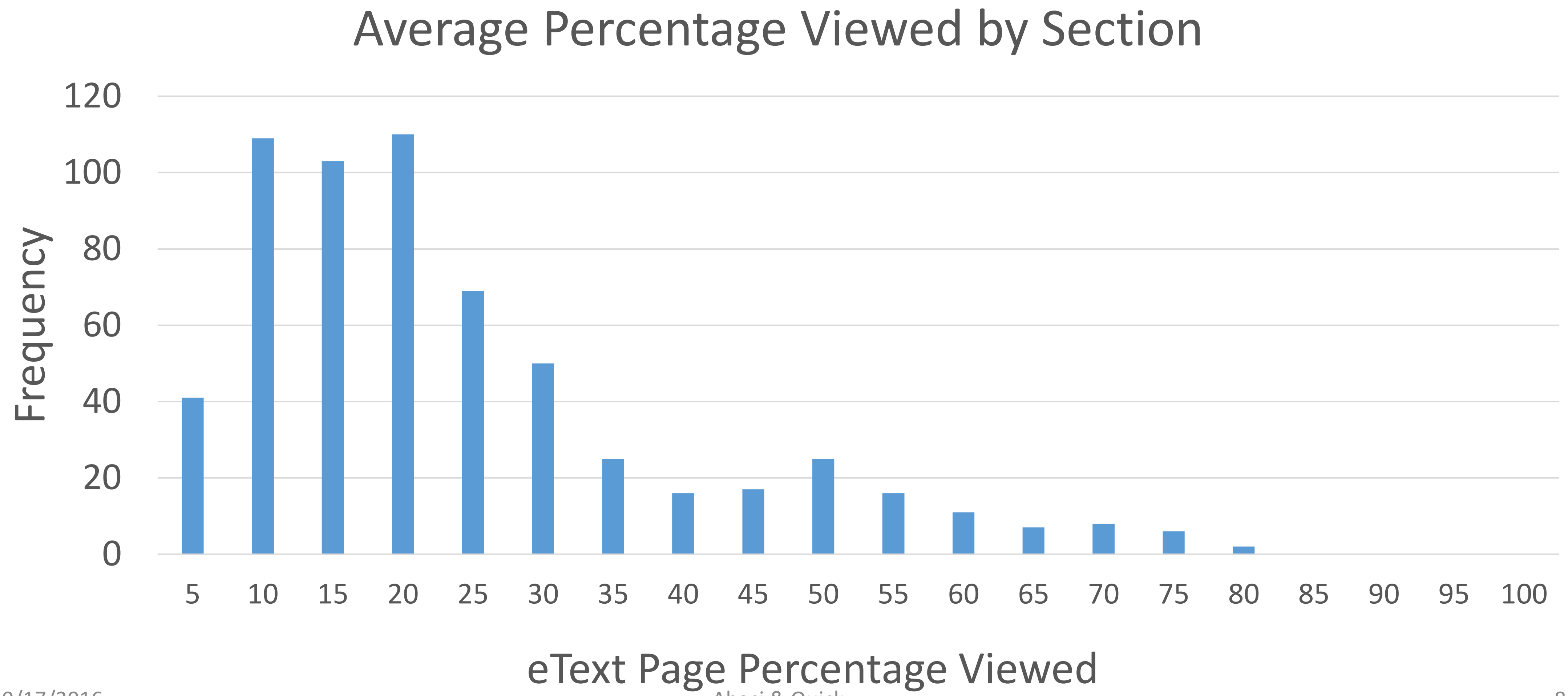
- # number of pages viewed
- Highlights
- Notes
- Questions

- Aggregated by section

Calculations

- % of page viewed → proxy for reading engagement with platform
- Measures of central tendency and deviation were taken.
- Distribution of these section level statistics were taken to identify higher use sections for exploratory analyses.

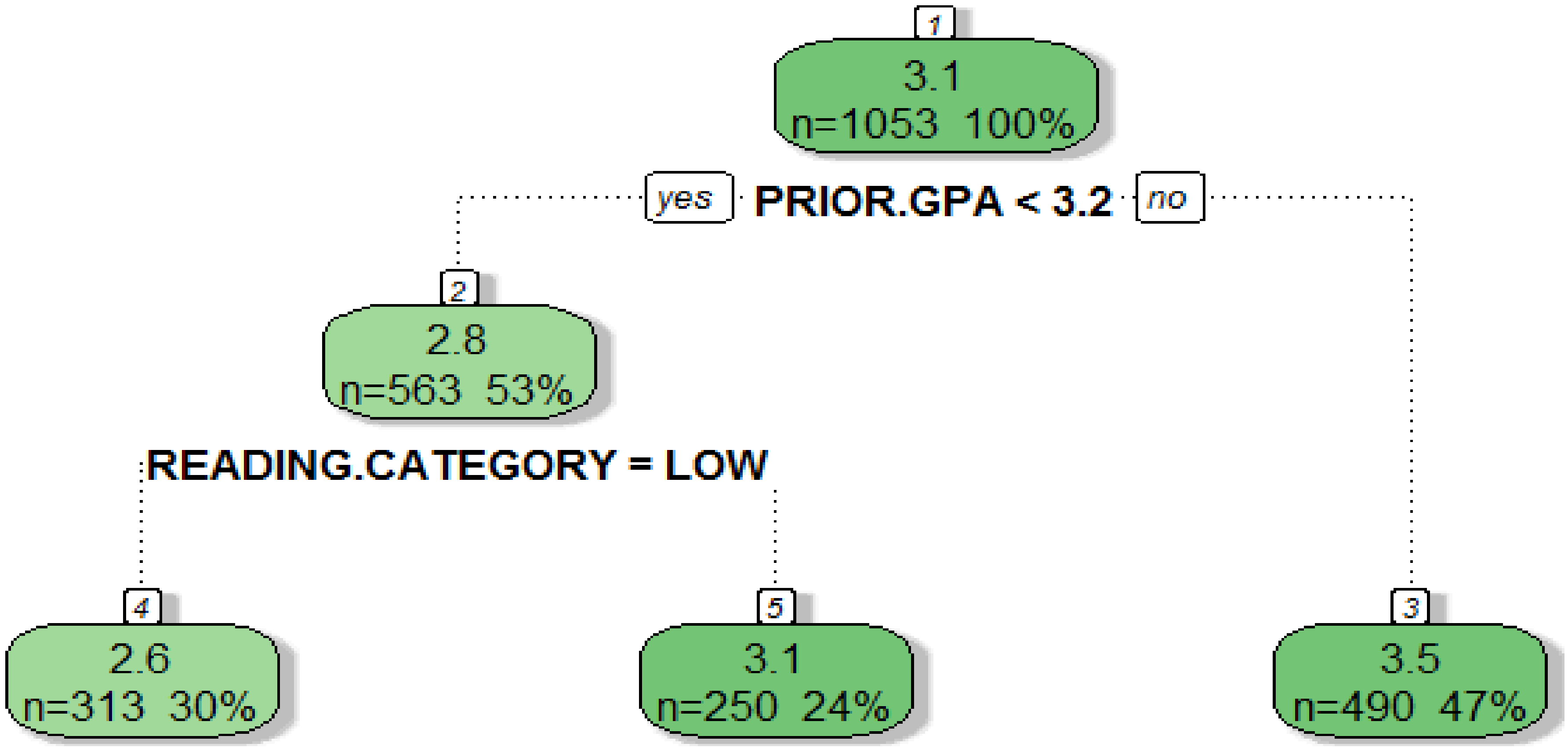
Existing Engagement Data



Exploratory Analytics

- Analysis is limited to Business School data (fall 2013)
- Instructors use of features is LOW
    - 0 → no use of features
    - 1 → any use of features
- Student page view
    - LOW → % of page view at or below section median
    - HIGH → % of page view above section median
- Students use of features
    - NONE → no use of a particular feature
    - LOW → use of a particular feature at or below section median use
    - HIGH → use of a particular features above section median use

Analytic Efforts



Challenges and Developments

- Low usage of interactive features
- Connecting to real-time Engage data
- Linking Engage data with other institutional data sources (e.g., SIS, LMS)

Future Directions

- Identifying eText usage patterns at departmental levels
- Identifying eText usage patterns at departmental levels across time
- Developing robust predictive models of eText usage and student engagement and achievement
- Text mining (i.e., Instructor and Student Notes)

Questions to Answer

- Does the level of content interaction predict the outcomes (learning, retention)?
- Does first day access to eText predict course outcomes?

Questions?

Thank You

- Serdar Abaci
  - sabaci@iu.edu
- Joshua Quick
  - jdquick@iu.edu