

Predictive Analytics in Higher Education

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EUNIS BITF Conference, March 7th 2014, Paris

TUM. Campus





TUM. Some numbers



13 Faculties

~ 400 Buildings

154 Studiengänge

~ **36 000** Students 33% female Students

20% int. Students

~ 500 Professors

~ 10 000 Staff members

13 Nobel Prizes

15 Leibniz-Prizes

4 Humboldt Professors

#53 2013 Academic Ranking of World Universities



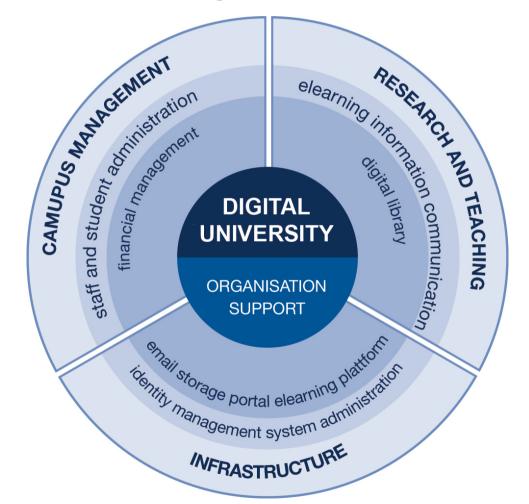


IT-Strategy: The Digital University

Leitmotif since 2002

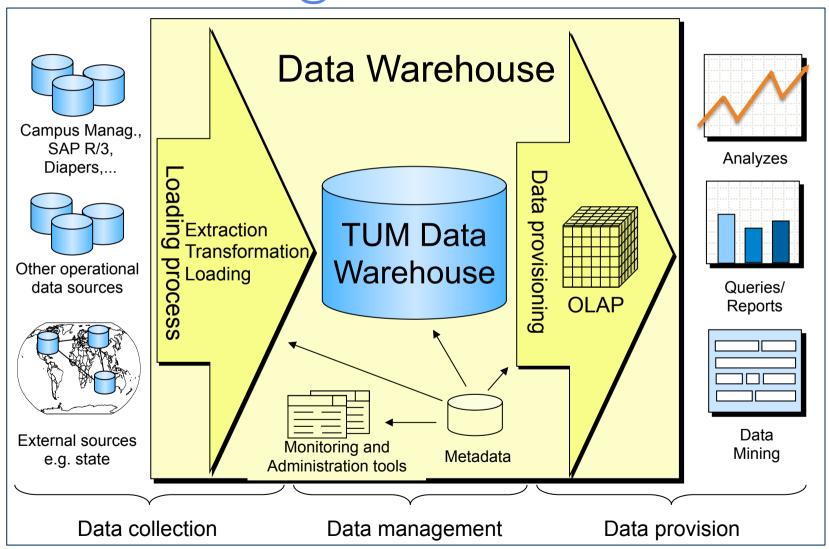
Completed IT-Projects:

SAP@TUM
IntegraTUM
elecTUM
mediaTUM
Data Warehouse
Corporate Design
CM@TUM





Data Warehouse: BW@TUM



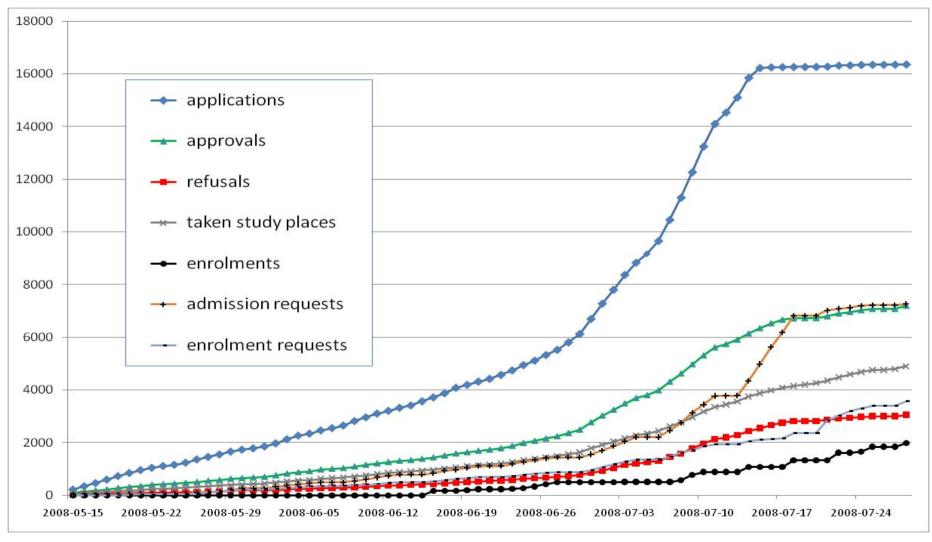


Data sources at TUM

Domain	InfoProvider	Operatives System
Staff	Personnel Administration	SAP R/3 HR
	Organization Management	SAP R/3 HR
Student & Exam Data	Students	TUMonline
	Tests / Exams	TUMonline
	Applicants	TUMonline
Accounting	Financial Planing	SAP R/3 FI
	Funds Management	SAP R/3 FM
	Controlling	SAP R/3 CO
Integrationdomain	various	various

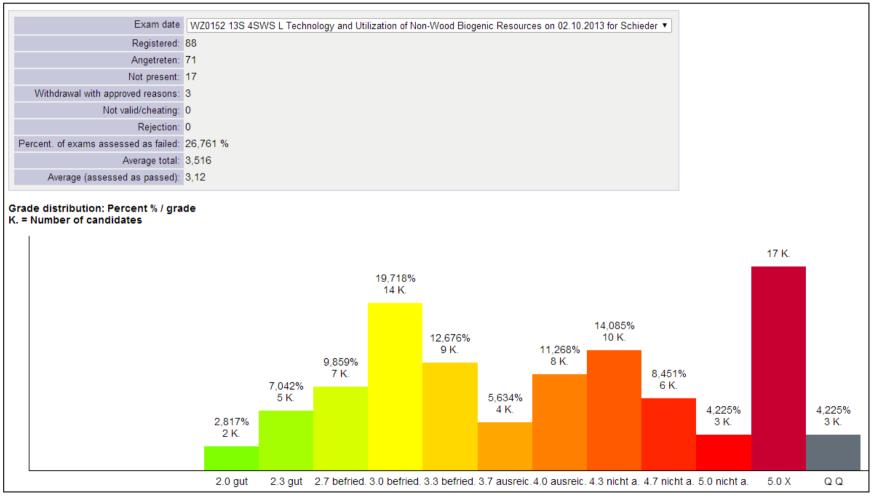


2008: Bachelor admission and enrolment statistic





Self-service rankings for students per test



How Target Figured Out A Teen Girl Was Pregnant Before Her Father Did





Every time you go shopping, you share intimate details about your consumption patterns with retailers. And many of those retailers are studying those details to figure out what you like, what you need, and which coupons are most likely to make you happy. <u>Target</u>, for example, has figured out how to data-mine its way into your womb, to figure out whether you have a baby on the way long before you need to start buying diapers.

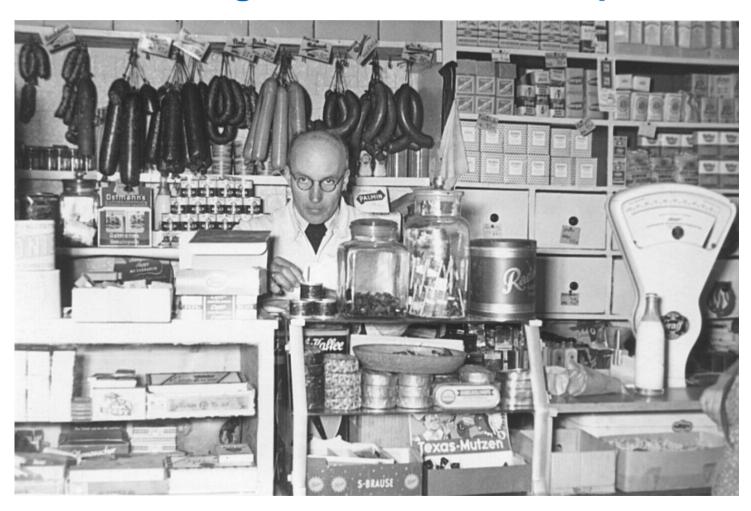


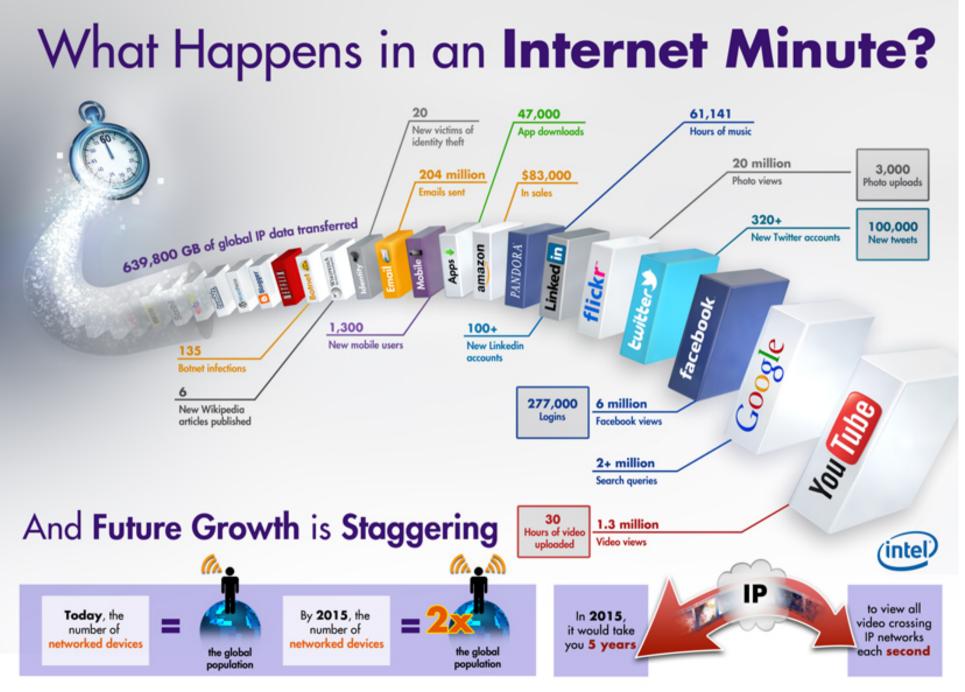
Charles Duhigg outlines in the <u>New York Times</u> how Target tries to hook parents-to-be at that crucial moment before they turn into rampant — and loyal — buyers of all things pastel, plastic, and miniature. He talked to Target

Pole's colleagues noticed that women on the baby registry were buying larger quantities of unscented lotion around the beginning of their second trimester. Another analyst noted that sometime in the first 20 weeks, pregnant women loaded up on supplements like calcium, magnesium and zinc. Many shoppers purchase soap and cotton balls, but when someone suddenly starts buying lots of scent-free soap and extra-big bags of cotton balls, in addition to hand sanitizers and washcloths, it signals they could be getting close to their delivery date.



New idea? No, e.g. former corner shops





Source: Intel. www.intel.com

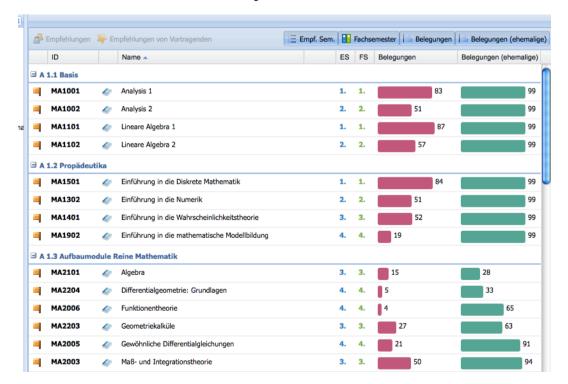


Academic & Learning Analytics

- Business Analytics for HEIs
- Goals, e.g. predicition of room allocation, study success, enrollment,

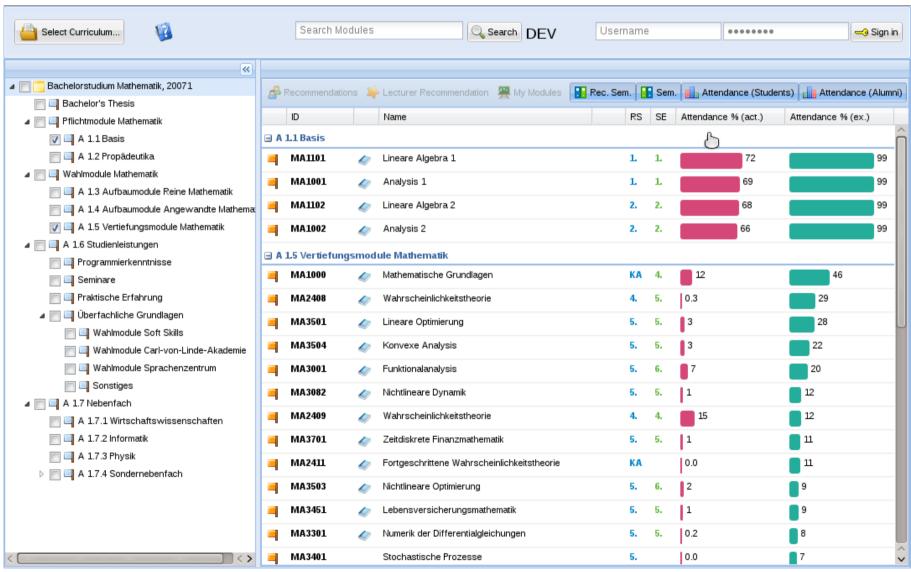
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Anzahl Belegung pro Wahlfach- modul	Anzahl Module MSc. Mech. Eng.	Anzahl Module BSc. Mech. Eng.	
> 401	0	6	
201 - 400	0	0	
51-200	0	8	
10-50	4	11	
2-9	90	18	
1	110	4	



First experiences. Modul assignments (1/2)



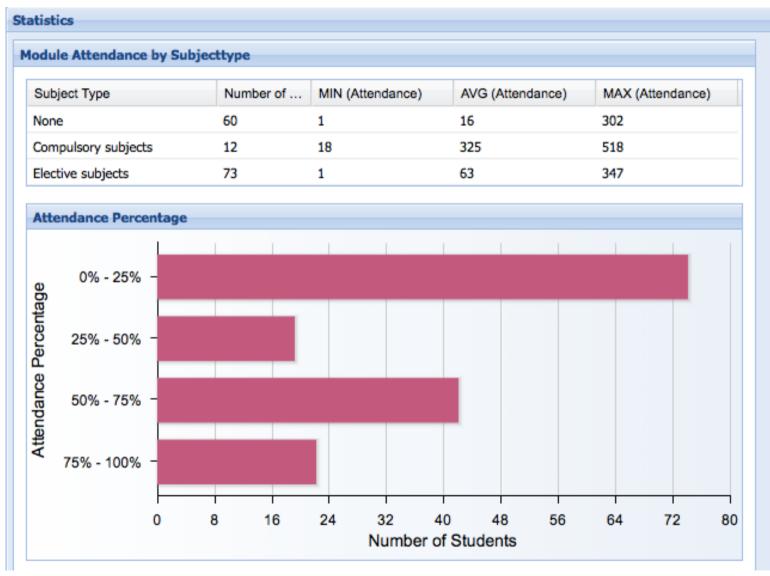


7.3.2014, Hans Pongratz

Source: A. Baumann, TUM





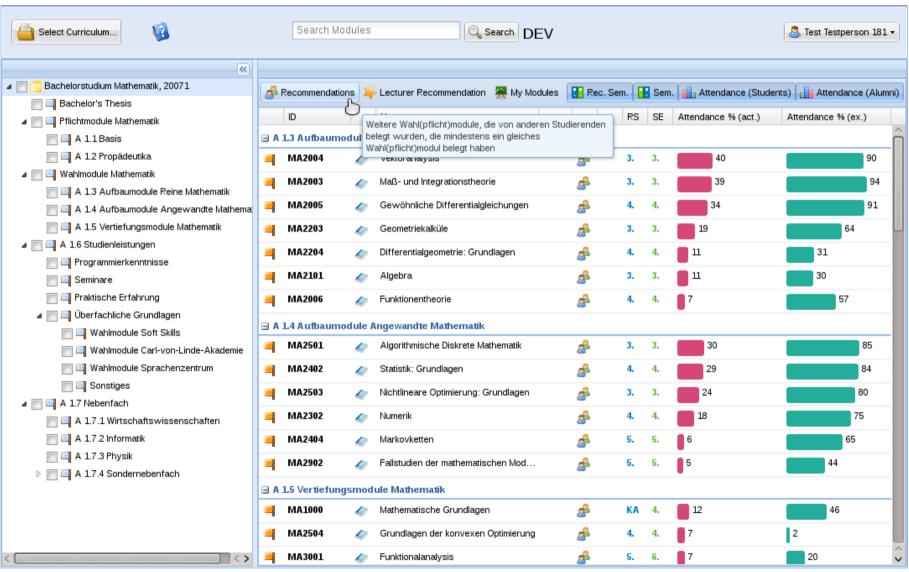


7.3.2014, Hans Pongratz

Source: A. Baumann, TUM

Frist experiences. Elective Modules





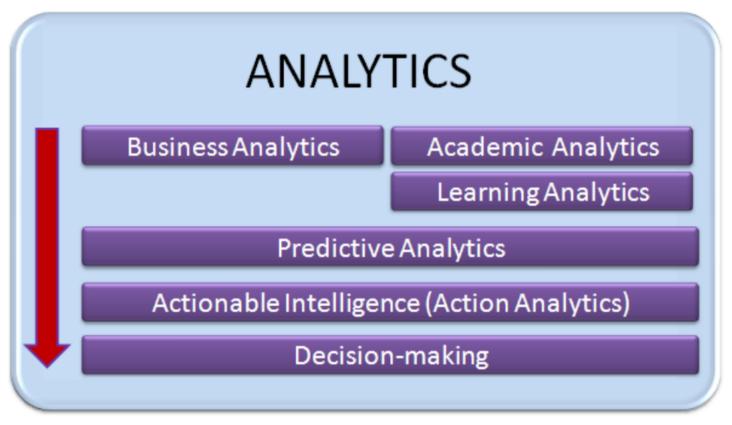
7.3.2014, Hans Pongratz

Source: A. Baumann, TUM



Conceptual Framework

Proposal by EDUCAUSE



Source: EDUCAUSE, http://net.educause.edu/ir/library/pdf/ELI3026.pdf



EDUCAUSE: Proposed Definitions

Term	Proposed Definition	Proposed Level of Focus	Sample Projects (see below for links)		
Analytics	An overarching concept that is defined as data-driven decision making (from Ravishanker).	All levels	 M-Reports Dashboard Learning and Career Outcomes 		
Academic Analytics	A process for providing higher education institutions with the data necessary to support operational and financial decision making (adapted from Goldstein and Katz).	Institution	 Effectiveness Sources Portal (ESP) Sponsored Project Excellence Achieved through Redesign (SPEAR) 		
Learning Analytics	The use of analytic techniques to help target instructional, curricular, and support resources to support the achievement of specific learning goals (adapted from Bach).	Department/ learner	Course SignalsCheck My Activity		
Predictive Analytics			 Student Success Plan Student Readiness Inventory 		

Source: EDUCAUSE, http://net.educause.edu/ir/library/pdf/ELI3026.pdf



Purdue University's Course Signals project

Examples & Projects (1/5)

Based on the dissertation of Dr. John Campbell a tool analyzes the learning behavior of students and can identify students who are not expected to successfully complete on the basis of their learning activity the course.

2009: first release

2010: "Users scored up to 26 % more As or Bs. Earned up to 12 % fewer Cs and up to 17 % fewer Ds & Fs".

2011: 7k of 20k student used tool

now: added value, e.g. Workshops,

Consultation, Advisors, ...



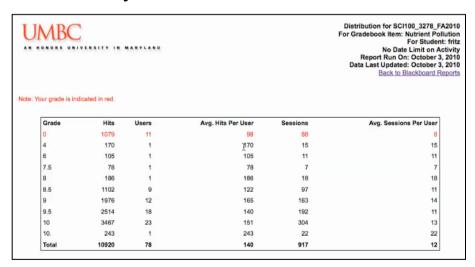
Further details: www.itap.purdue.edu/studio/signals/

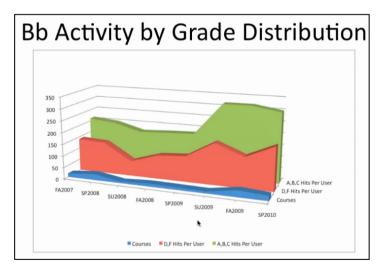


University of Maryland, Baltimore County (UMBC)

Examples & Projects (2/5)

"Check My Activity (CMA)" allows self-comparison between students with regard to their activity within the LMS and achieved course score.





Report Code is open, see "Get The Code"

Further details: www.umbc.edu/blackboard/reports



University of Kentucky: Academic Health student app

Examples & Projects (3/5)



KENTUCKY see blue.

WAKE UP! GET TO CLASS! III. AT&T TO

- Who sets alarms for themselves?
- Why not automatically set alarms for students around their schedule?
- Why not have automated wake-up calls?
- Why not suggest wake up times based on class attendance?
- Why not consider manipulation of reminders as a form of engagement?
- Can we ascertain student prospective memory capability and personalize based on it?

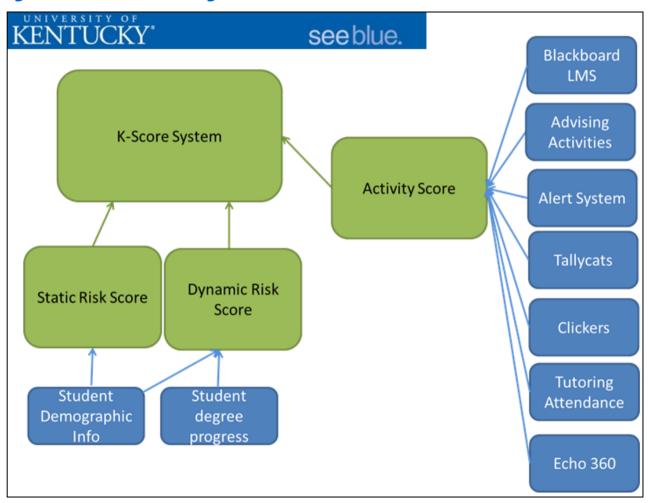


Source:

http://www.educause.edu/annual-conference/2013/improving-student-success-using-groundbreaking-analytics-and-fast₂₀ data-improve-student-retention



University of Kentucky: Framework



Source:

http://www.educause.edu/annual-conference/2013/improving-student-success-using-groundbreaking-analytics-and-fast₂₁ data-improve-student-retention



Overview: EDUCAUSE review Academic Analytics

Examples & Projects (4/5)

- Enrollment Predictive Modeling at Baylor University
- Predicting and Improving Student Retention at the University of Alabama
- Developing a Student Success Plan and Early Alert System at Sinclair Community College
- Connecting Resource Utilization, Risk Level, and Outcomes at Northern Arizona University

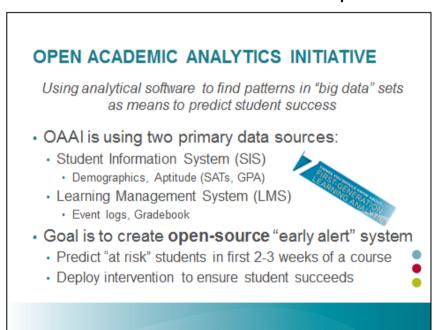
Further details: http://www.educause.edu/ero/article/academic-analytics-new-tool-new-era

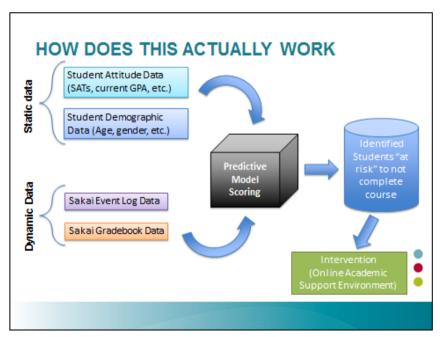


Open Academic Analytics Initiative (OAAI)

Examples & Projects (5/5)

Goal: open-source "early alert" system, which predicts "at risk" students within the first 2-3 weeks of a course and provides assistance for them.





Further details: www.educause.edu/events/educause-learning-initiative-2012-annual-meeting/open-academic-analytics-initiative-leveraging-openness-improve-learne



Open Academic Analytics Initiative (OAAI)

Examples & Proiects (5/5)

Finding #1: Imp
Our research show
To determine this
the control group
also included stud
receive an interve

	College	AAR run	# Students	Accuracy	FP Rate	Precision	Recall	
		AAR1	504	67.26%	35.36%	61.48%	70.54%	
	Savannah	AAR2	504	74.40%	32.50%	67.15%	83.04%	
12		AAR3	504	79.37%	18.21%	77.03%	76.34%	nt i
20		AAR1	502	61.95%	43.69%	47.41%	72.32%	ng t
Spring	Cerritos	AAR2	601	71.88%	27.49%	59.62%	70.78%	ard
S		AAR3	649	75.19%	25.12%	62.50%	75.76%	,
		AAR1	195	67.69%	40.48%	52.78%	82.61%	
	Redwoods	AAR2	195	78.97%	13.49%	72.58%	65.22%	
		AAR3	195	77.95%	14.29%	70.97%	63.77%	l

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		AAR3	195	77.95%	14.29%	70.97%	63.77%
	College	AAR run	# Students	Accuracy	FP Rate	Precision	Recall
		AAR1	425	68.47%	38.34%	58.19%	78.49%
	Savannah	AAR2	425	72.59%	30.04%	65.17%	76.16%
		AAR3	425	73.41%	26.88%	65.13%	73.84%
		AAR1	502	65.38%	32.35%	49.49%	61.01%
Fall 2012	Cerritos	AAR2	601	70.75%	27.78%	55.96%	67.92%
		AAR3	649	73.98%	24.51%	60.11%	71.07%
		AAR1	182	83.63%	16.52%	71.21%	83.93%
	Redwoods	AAR2	182	83.82%	16.52%	72.06%	84.48%
		AAR3	182	85.63%	13.04%	76.56%	83.05%
	NCAT	AAR1	719	64.12%	31.25%	26.53%	45.45%
		AAR2	719	71.07%	24.83%	35.29%	54.55%
		AAR3	719	75.10%	20.14%	40.82%	55.94%

Table 1 - Correlations between course grades and CMS

		Course Grade		
Undergradu	ate CMS	Marist	Campbell	
event free	quencies	Fall 2010	(2007)	
		N=18968	N=27276	
Sessions	Correlation	0.147	(no values	
	Significance	0.000(**)	· · · · · · · · · · · · · · · · · · ·	
Opened	N	11195	reported)	
Content	Correlation	0.098	0.112	
Viewed	Significance	0.000(**)	0.000(**)	
viewed	N	7651	19205	
Discussions	Correlation	0.133	0.068	
Read	Significance	0.000(**)	0.000(**)	
Reau	N	1552	7667	
Discussions	Correlation	0.233	0.061	
Posted	Significance	0.000(**)	0.000(**)	
rosted	N	1507	7292	
Assign.	Correlation	0.146	0.163	
Submitted	Significance	0.000(**)	0.000(**)	
Submitted	N	3245	4309	
Asssmts	Correlation	0.161	0.238	
Submitted	Significance	0.000(**)	0.000(**)	
Subilitted	N	1423	4085	

^(**) Significant at the 0.01 level (2-tailed) Marist data uses ratios over course mean instead of frequencies

Table 3 - Prediction analysis on spring and fall pilot data instead of frequencies https://confluence.sakaiproject.org/uownioau/attachinens//5671025/OAAI%20Final%20Progress

%20Report.pdf?version=1&modificationDate=1391705397000&api=v2



Talking about laws (1/2)

- EU Directive 95/46/EC on data protection
- EU Directive requires member states to achieve result by not dictating
- Terms and conditions

Personal data: any information concerning the personal or material circumstances of identified or identifiable natural person (concerned). Under personal data thus fall details of name, student number, degree, address, affiliations associations, email, etc. (http://www.bfdi.bund.de/bfdi_wiki/index.php/3_BDSG_Kommentar_Absatz_1_Beispiele)

Anonymized in the sense of the Bavarian Laws (quite similar to German & EU): Personal data will be considered anonymous if the data has been modified so that the reference to individuals cannot or only under extremely difficult conditions are restored (see also Article 4, Section 8 BayDSG, http://byds.juris.de/byds/009 1.1 DSG BY 1993 Art4.html)



Talking about laws (2/2)

<u>"Online as soon as it happens</u>", ENISA, p. 28, Whitepaper of the European Network and Information Security Agency, ISBN-13: 978-92-9204-036-9, February 2010

Member States shall provide that personal data must be:

- ✓ Processed fairly and lawfully.
- Collected for specified, explicit and legitimate purposes and used accordingly.
- ✓ Appropriate and relevant in relation to the purpose for which they are processed.
- ✓ Accurate and kept up to date.
- ✓ Kept no longer then the time necessary for the purpose for which they are processed (50).

Personal data can be processed if:

- ✓ The data subject has been adequately informed and has given unambiguously his consent for the collection and further use of his data.
- ✓ Processing is necessary to perform a contract having as a party the data subject or to enter into a contract requested by the data subject.
- ✓ A legal obligation requires the processing of personal data.
- Processing data is necessary in order to ensure the essential interests of the data subject;
- ✓ Processing is necessary to perform tasks of public interests or carried out by an official authority.
- ✓ The data controller has a legitimate interest in processing the personal data of the data subject; this interest, however, has to be necessary balanced with the right to privacy of the 7.3.2014 Hars Pongratz (51).





Questions to address & action items

- Root Questions vs. Research Approach
- Data sources
- Tools to use
- Anonymization of data
- Information about stored data
- Deleting stored data after X month/years
- Policy for data analytics?
- How gets access to data at which level?

Get in touch with data protection officer of your organization! Exchange ideas, tools, results, approaches! -> pongratz@tum.de ©