Using Predictive Analytics to Improve the Bottom Line

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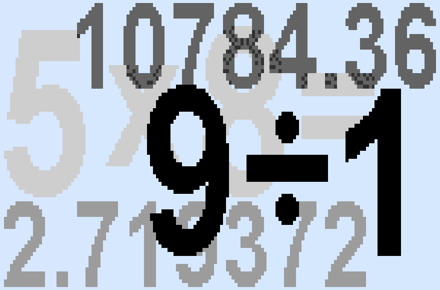

Serge Herzog, PhD
Director, Institutional Analysis
Consultant, CRDA StatLab
University of Nevada, Reno
Reno, NV 89557, serge@unr.edu

John Stanley, MEd
Institutional Analyst
University of Hawaiʻi at Mānoa
Honolulu, HI, jstanley@hawaii.edu

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Challenges for Institutional Research

- Compliance vs. Self-Improvement
- Developing a culture of evidence
- From reporting to analysis
- Converting results into ‘actionable’ statements
- From ‘data silos’ to integrated warehouse
- Leverage technology, stay abreast of tech
- Follow highest standards, best practices
- Know your customers, mission
- Empower staff, continuous honing of skills

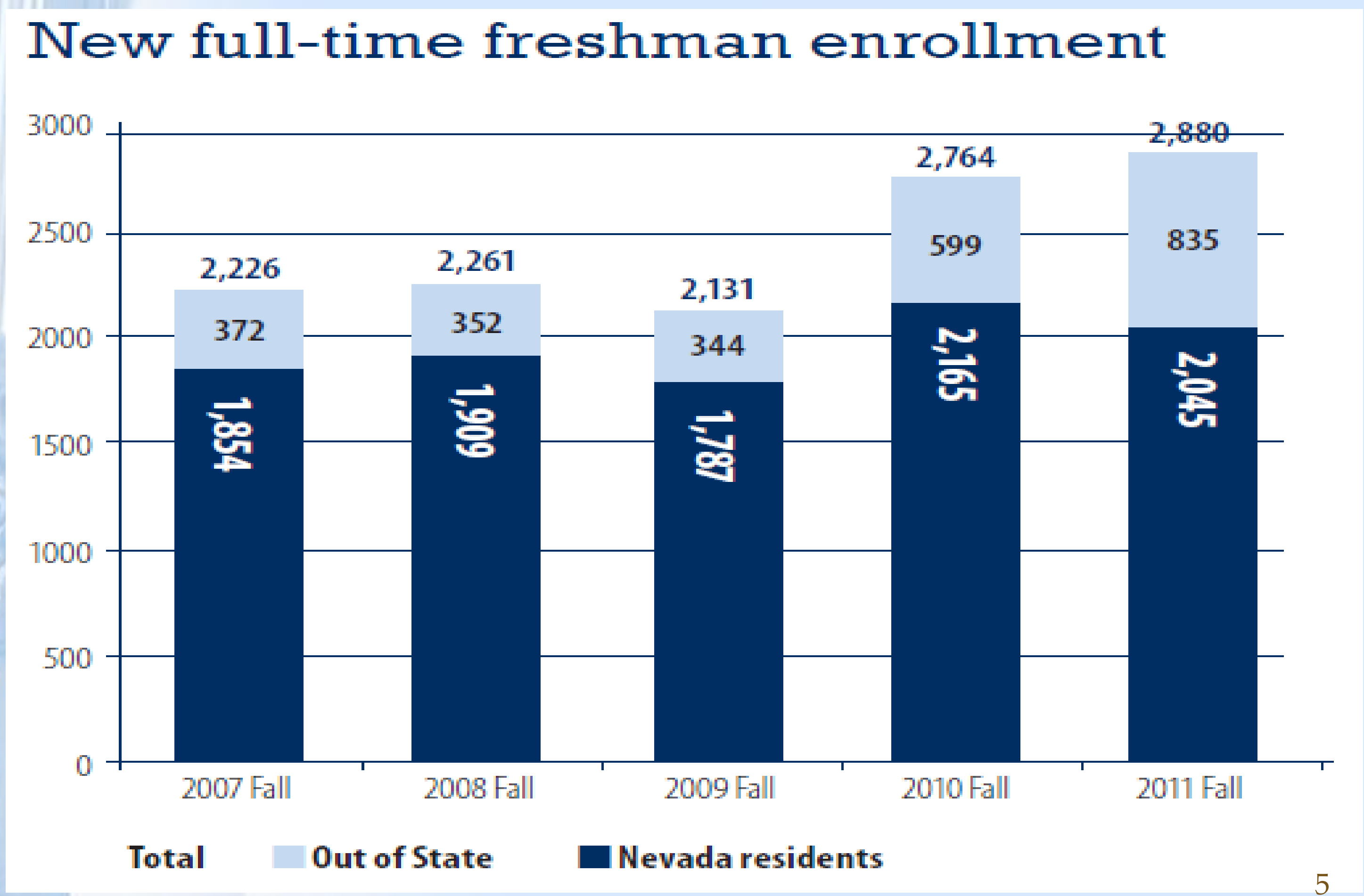
The Institutional Context

- Student success: a strategic imperative
- Performance-based state funding impending
- Dwindling state support for higher education
- Tuition-revenue maximization
- Reputation and marketing
- Effective senior-management support by IR
- K-16 Education Collaborative
  - High school transcript study
  - High school gateway curriculum
  - Reversing the tide of college remediation

The Institutional Context

	2009	2010	2011
Total Enrollment	**16,862**	**17,679**	**18,004**
Undergraduate	12,878	13,660	14,415
Graduate	3,294	3,248	2,935
First-Professional (Medical School)	241	246	249
Non-Degree	449	525	405
Ethnicity/Foreign Students			
American Indian/Alaskan	180	173	154
Asian American*			1,053
Asian/Pacific Islander	1,186	1,352	
Black, Non-Hispanic	448	500	547
Hispanic	1,390	1,617	1,970
Multi-Ethnic*			821
Pacific Islander*			39
White, Non-Hispanic	11,537	12,247	11,919
Foreign Students	671	632	594
Unreported	1,450	1,128	907

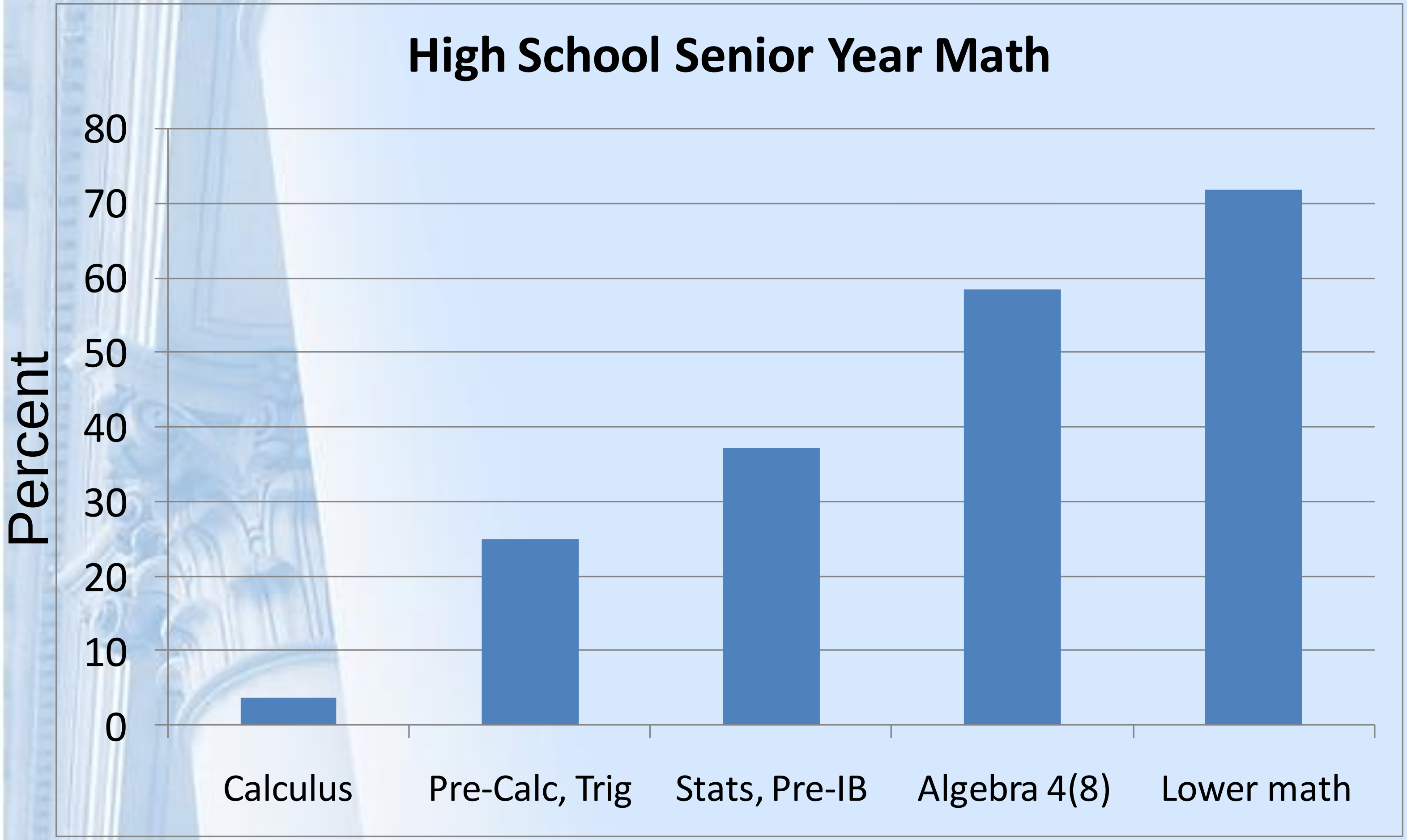
The Institutional Context



Examples of Actionable Findings

- Study abroad enhances academic performance
  - http://www.cis.unr.edu/IA_Web/research/USACConfOct2010.pdf
- Impact of classroom facilities/schedule on learning
  - Smaller rooms are preferable
  - After-2pm courses associated with lower performance
  - http://onlinelibrary.wiley.com/doi/10.1002/ir.224/abstract
- Student financial aid to maximize retention
  - Tuition discounts for middle-income students
  - More academic support for low-income students
  - http://www.uark.edu/ua/der/EWPA/Research/School_Finance/1802.html
- Effect of high school environment on freshmen success
  - http://www.uark.edu/ua/der/EWPA/Research/Achievement/1808.html

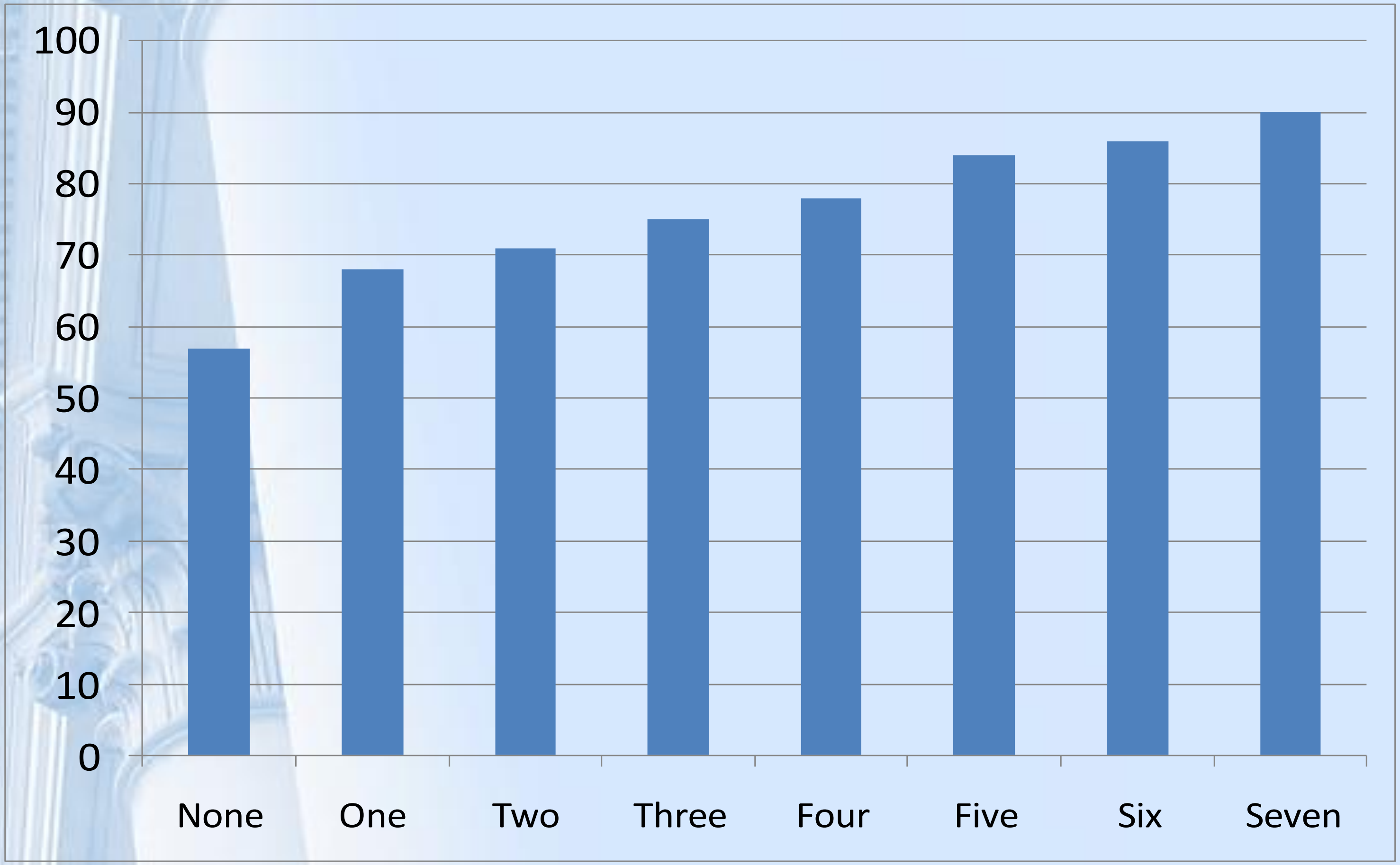
In Need of Math Remediation* at UNR



N = 41 495 408 982 218

* ACT math < 21 or SAT math < 500

First-Year Momentum* at UNR by AP Intensity



Number of AP Subjects in High School

*100-pt index of first-year GPA and completed credits

Student Success

Raising Graduation Rates

Comparing 4-year and 6-year-plus Graduates

*Opportunity cost of staying one more year in college = $32,000 in foregone earnings plus annual increase in tuition cost.**

HS GPA: 3.5 vs 3.2

ACT: 24.5 vs 22.2

First-Y GPA:

3.35 vs 2.71

CoreHum 201

Grade: 3.3 vs 2.6

MathGPA:

3.12 vs 2.4

Honors Courses:

14% vs 5%

Change in Major:

25% vs 55%

Capstone GPA:

3.5 vs 3.2

Avg annual remaining need: $2,610 vs $3,270

Final GPA:

3.4 vs. 2.9

Internship:

31% vs 24%

Difference in avg semester load: 3 credits

*Adjusted 2010-$. Source: Herzog, S. (2006). "Estimating Student Retention and Degree Completion Time." In J. Luan & C. Zhao (eds.), *Data Mining in Action*. NDIR, no. 131. San Francisco: Jossey-Bass, pp. 17-33.

Relevant Previous Research

- Caison, A. L. (2006). Analysis of institutionally specific retention research: A comparison between survey and institutional database methods. *Research in Higher Education 48(4): 435-451.*
- DesJardins, S. T. (2002). An analytical strategy to assist institutional recruitment and marketing efforts. *Research in Higher Education 43(5).*
- Herzog, S. (2006). "Estimating student retention and degree-completion time: Decision trees and neural networks vis-à-vis regression." In J. Luan & C. Zhao (eds.), *Data Mining in Action: Case Studies of Enrollment Management. New Directions for Institutional Research, no. 131. San Francisco, CA: Jossey-Bass.*
- Herzog, S. (2005). "Measuring determinants of student return vs. dropout/stopout vs. transfer: a first-to-second year analysis of new freshmen." *Research in Higher Education, 46(8): 883-928.*
- Morgan, S. P., & Teachman, J. D. (1988). "Logistic regression: Description , examples, and comparisons." *Journal of Marriage and the Family, 50(4): 929-936.*
- Pascarella, E. T., & Terenzini, P. T. (2005). *How College Affects Students: Volume 2, A Third Decade of Research. San Francisco, CA: Jossey-Bass.*

At-Risk Forecasting Model

- Identify at-risk freshmen students after initial matriculation for *early* intervention program
- Develop coefficients for predictors determining student fall-to-spring/fall dropout risk
  - Logistic regression model using historical cohorts as training dataset
  - Maximize prediction accuracy with balanced dataset
- Dropout risk scoring for new freshmen
  - Transformation of the logit(*p*) into probability scores
  - Decile grouping of scored students
  - Compare deciles with actual enrollment and other predicted enrollment (MAP-Works: http://www.unr.edu/mapworks)
- Reporting of dropout risk via secure online access

Data Description

- Data sources
  - Matriculation system (SIS legacy, Peoplesoft, DW)
  - MAP-Works
- Student cohorts
  - New full-time freshmen (excl. foreign students)
  - Fall entry ‘02-’09 for model dev. (training set, N=17,311)
  - Fall entry 2010 for model validation (holdout set, N=2,527)
- Data elements at start of first semester
  - Student demographics (age, gender, ethn/race, residency)
  - Academic preparation (high school GPA/test score index)
  - Financial aid profile (unmet need, Pell, loans, scholarships)
  - Credits enrolled, campus housing (y/n), athlete (y/n)
- Data elements after start of first semester
  - MAP-Works survey risk scores (Sep., Nov., Feb)

Data Management Tasks

- Exploratory data analysis
  - Variable selection (bivariate regression on outcome variable)
  - Variable coding (continuous/categorical/dummy in logit model)
  - Missing data imputation, constant-$ conversion (fin. aid data)
  - Composite variable(s)
    - Acad prep index = (HSGPA*12.5)+(ACTM*.69)+(ACTE*.69)
  - Variables excluded: college remediation, ACT/SAT test date
- Logistic regression model
  - Maximize model fit (-2LL test/score, pseudo R^2, HL sig.)
  - Create balanced sample in training dataset to optimize correct classification rate (CCR) for enrollees vs. non-enrollees (i.e. model sensitivity vs. specificity): all non-enrollees plus random sample of enrollees of ~ equal N)

Data Management Tasks

- Scoring of relative dropout/retention risk

$$p = \frac{exp^{(a+b_1x_1+b_2x_2+b_3x_3+b_4x_4\ldots.)}}{1+exp^{(a+b_1x_1+b_2x_2+b_3x_3+b_4x_4\ldots.)}}$$

Where: p = probability of enrollment/non-enrollment

exp = base of natural logarithms (~ 2.72)

a = constant/intercept of the equation

b = coefficient of predictors (parameter estimates)

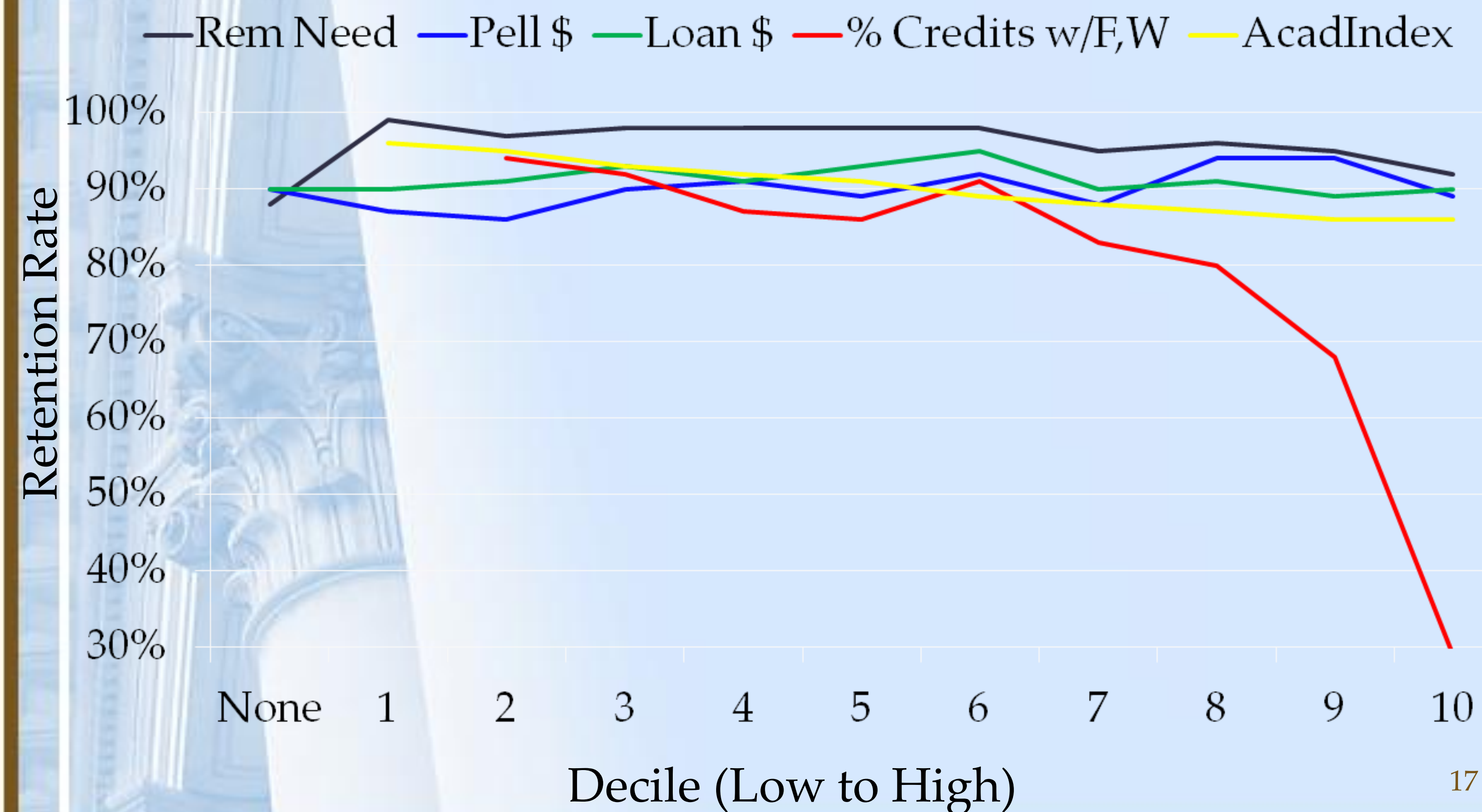
Approximation of *p*: (*p*[1-p]*b*)

Where: *p* = baseline probability of dependent variable

b = logit coefficient

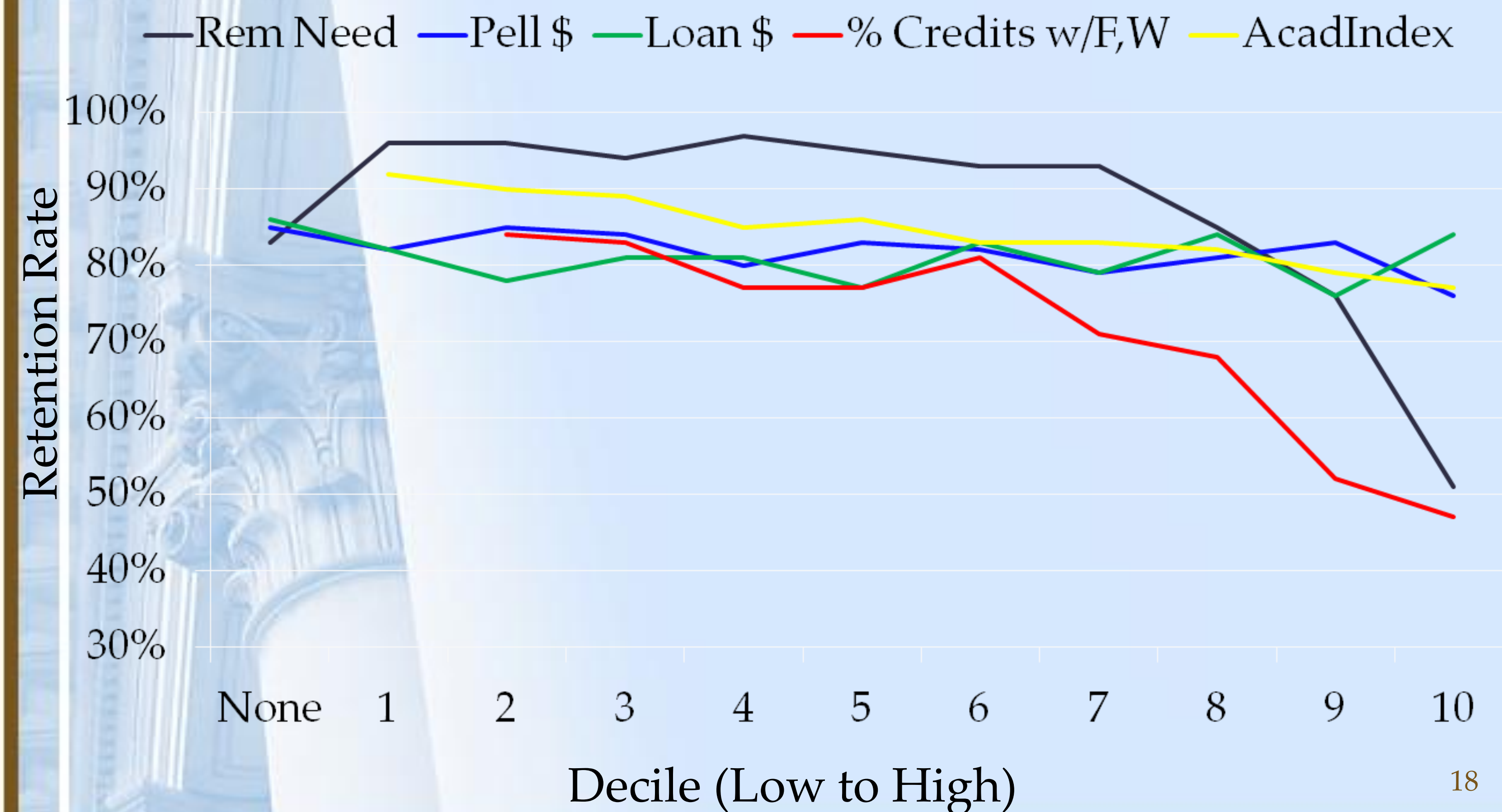
Selected Factors and Spring Retention

Fall Cohorts 2002-09 (N=17,311)



Selected Factors and 2nd Fall Retention

Spring-Retained Fall Cohorts 2002-09 (N=15,570)



Data Analysis

Balanced Model Classification Rates[a]

Observed		Predicted: Spring Retention: No	Predicted: Spring Retention: Yes	Predicted: Percentage Correct
Spring Retention	No	1122	302	78.8
	Yes	673	610	47.5
Overall Percentage				64.0

a. The cut value is .55; HL sig. = .364; Nagelkerke R-sq = .161

Model tries to maximize correct prediction of at-risk students (non-enrollees), so they can be focused on, without raising the chance of selecting non-risk students (i.e. beyond OR = 1 or CCR = 0.5).

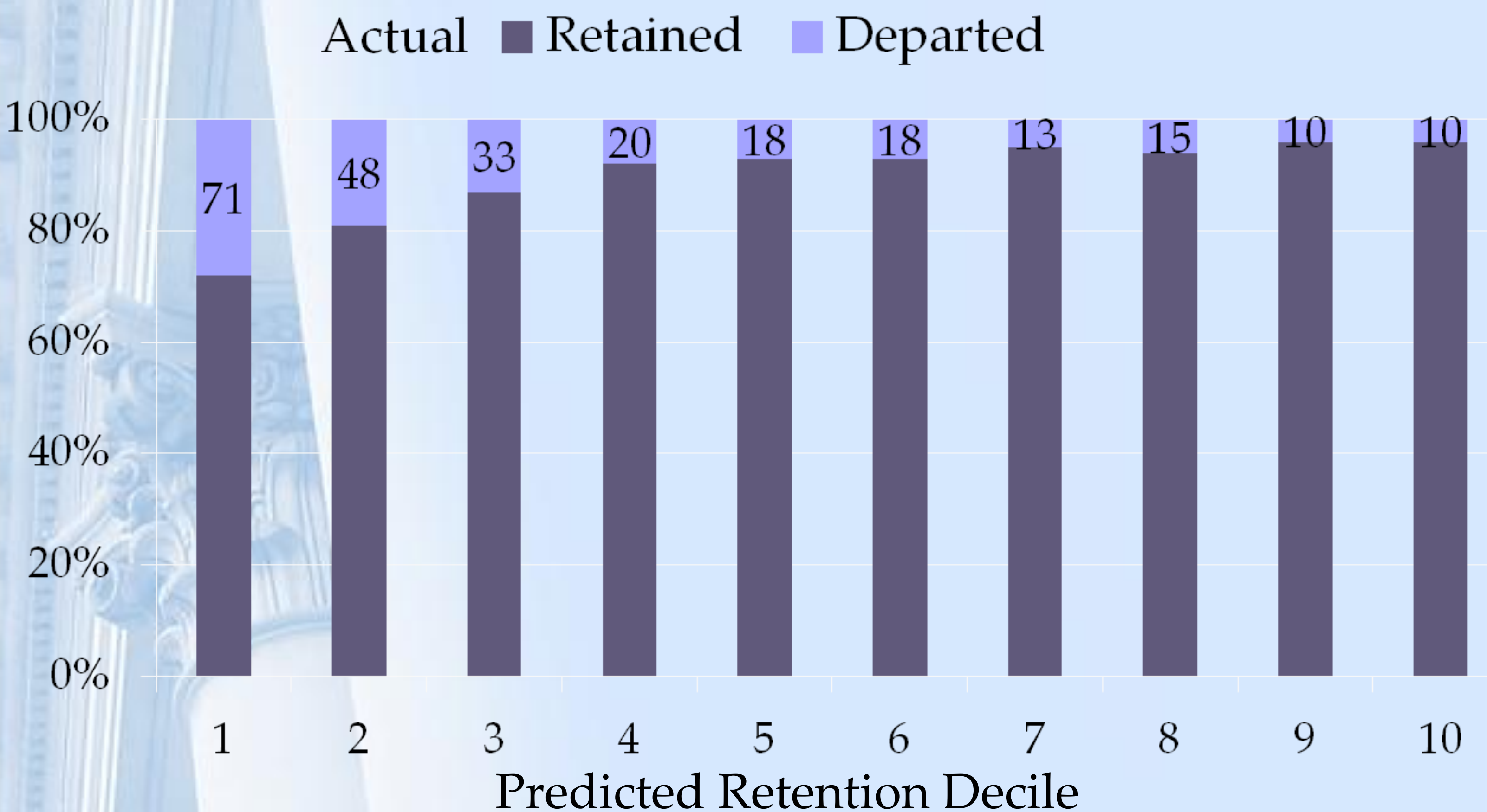
Data Analysis

Balanced Model Parameter Estimates

		B	S.E.	Wald	df	Sig.	Exp(B)
a	Age	-.038	.033	1.294	1	.255	.963
	Asian	.335	.161	4.305	1	.038	1.397
	Credits	.244	.026	87.958	1	.000	1.276
	ClarkRural	-.790	.106	55.783	1	.000	.454
	AIndex	.029	.005	29.534	1	.000	1.030
	LoanFlag	.284	.107	7.123	1	.008	1.329
	PellFlag	.145	.131	1.229	1	.268	1.156
	MillFlag	.596	.103	33.603	1	.000	1.815
	AthleteFlag	.814	.227	12.800	1	.000	2.256
	OnCampFlag	.596	.096	38.738	1	.000	1.814
	RemNeed$1K	-.015	.006	6.350	1	.012	.985
	Constant	-5.599	.803	48.632	1	.000	.004

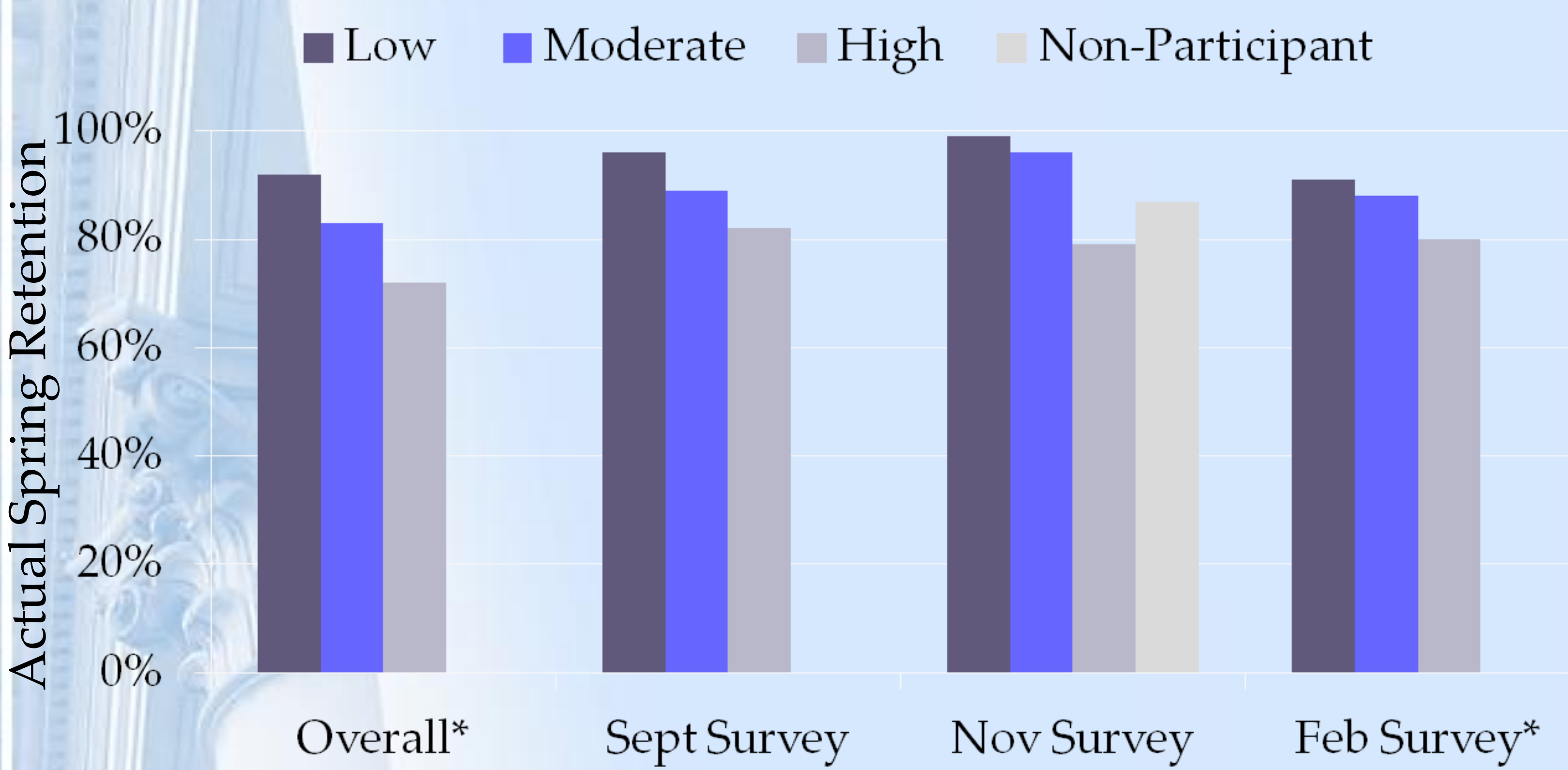
a. Single-step variable entry

Data Analysis



Spring Status of Fall 2010 Cohort

Data Analysis



Vendor Survey Risk Assessment, Fall 2010 Cohort

*Assesses fall 2011 dropout risk of spring-retained

Gauging Survey Value

	Baseline		MW Sep Survey		MW Nov Survey	
Predictors	*Wald*	*Sig.*	*Wald*	*Sig.*	*Wald*	*Sig.*
Age	2.1	*	2.4	*	2.2	*
Asian	0.5		0.1		0.0	
Credits Enrolled	5.3	***	5.5	***	6.1	***
ClarkRural	13.6	***	13.6	***	14.4	***
LoanFlag	1.4	*	0.7		0.5	
PellFlag	1.3	*	1.7	*	1.9	*
MillFlag	13.9	***	16.6	***	17.1	***
AthleteFlag	0.0		0.2		0.1	
HSGFlag	15.9	***	12.2	***	13.5	***
AcadIndex	7.1	***	1.5	*	0.9	
RemNeedFlag	2.4	*	2.6	*	2.8	**
MWR HI			9.9	***	23.5	***
MWR MO			4.1	***	11.1	***
LR test pass				yes		yes
Nagelkerke R^2		0.19		0.21		0.25
CCR of At-Risk		76.0%		75.6%		78.0%

Gauging Survey Value

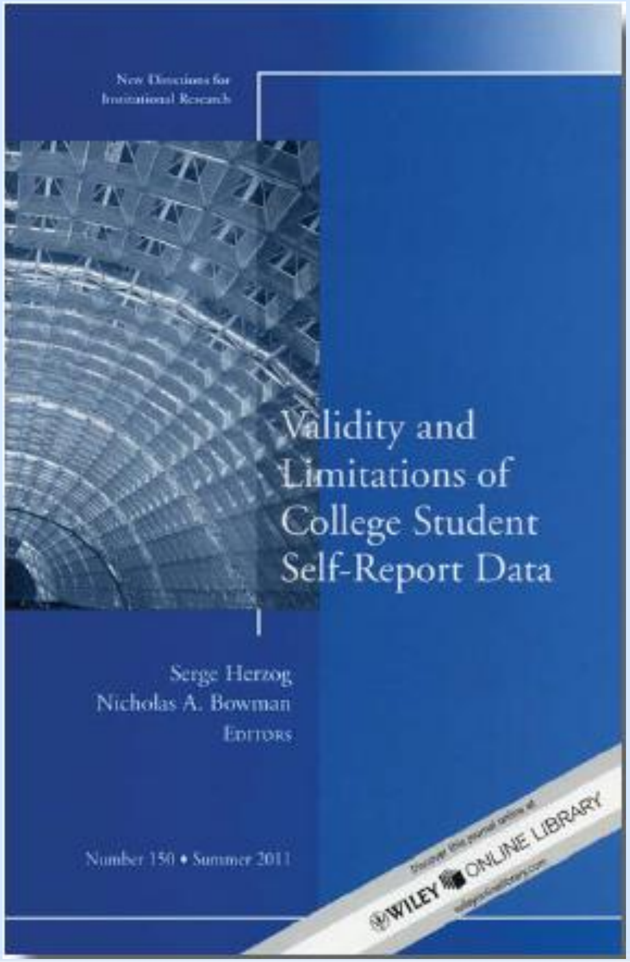
- A sustained 2% point rise in prediction accuracy over 5 years due to MAP-Works may translate into:
  - $237,500 in additional net revenue (5x1900x5x5) per cohort
  - Assuming no freshmen enrollment growth

But…

- Five-year cost of survey implementation
  - Product cost/fee, on-campus HR/IT investment
- Data not available until late in the semester!
- Balanced model (2002-10 data) yields 79% CCR for at-risk students, i.e. better than survey prediction
- Survey prediction furnishes no at-risk deciles

Value of Student Self-Reported Data for At-Risk Prediction

- Sources:
  - On-campus surveys
  - ACT Student Profile Q
  - SAT Student Descriptive Q
  - NSSE, CIRP (HERI-UCLA)
- Limitations:
  - Validity of acad exp questions
  - Convergent validity of construct
  - Cognitive vs. affective questions
  - Interpretive ambiguity
  - Mental recall
  - Vague quantifiers



Improving the Bottom Line

- Rise in freshmen retention by 4 percentage points due to better at-risk forecasting
  - AY 2010-11 *additional net tuition revenues* = ***$215,119*** (for 94 NV,19 WUE, excl OS students) for one cohort in one year, without OS $!
  - Downstream *cumulative additional net tuition revenues* result in $ millions!
- Incentive for student to speed up graduation
  - Opportunity cost per year in foregone earnings = ***$32,000*** per year (published constant 2010-$)

Sample Data for Advisors

- http://www.unr.edu/ia

R Number	Last Name	First Name	Email Addr	Age	College	Dept	Major	Dropout Risk Decile (10=highest; 1=lowest)	Relative Spring Retention %tile
				18	LBA	ART	BA-AHI	9	14.92
				18	LBA	ANTH	BA-AN	8	28.52
				18	LBA	ANTH	BA-AN	7	36.80
				18	LBA	ANTH	BA-AN	7	39.18
				18	LBA	ANTH	BA-AN	6	46.87
				18	LBA	ANTH	BA-AN	4	66.48
				19	LBA	ANTH	BA-AN	1	92.42
				18	LBA	ANTH	BA-AN	1	95.57

Sample Data for Advisors

- http://www.unr.edu/ia

Gender	Ethnicity	Credits	Resident	State/Cnty	HS GPA	ACTE	ACTM	Has Pell$ (1=yes)	Has Loan$ (1=yes)	Clark Cnty Resi (1=yes)
F	AS	12	NV	NWA	3.10	24	18	1	0	0
F	WH	15	NV	NCL	3.23	21	18	0	1	1
M	WH	16	WU	CA	3.19	23	20	0	0	0
M	WH	17	WU	OR	3.23	24	17	0	0	0
F	WH	16	NV	NWA	3.18	17	17	1	0	0
F	WH	15	NV	NDO	3.47	30	21	0	0	0
M	WH	15	NV	NWA	3.65	26	25	1	0	0
F	AS	16	NV	NCL	3.90	30	28	0	0	1

Impact of this At-Risk Forecasting Model

- *University Retention Rates Hold Steady As States Balance Access with Success.* Scripps Howard Foundation Wire, April 15, 2011.

- *Managing Talent: HCM and Higher Education.* Campus Technology Magazine, October 2010, Vol. 24 Number 2, pp. 36-42.

- *From Data to Information: Business Intelligence and Its Role in Higher Education Today.* University Business Magazine, January 2009, pp. 25-27.

- Consulting services to IR offices at institutions in Arizona, California, Hawaii, and Texas.

Predictive Analytics at U. of Hawaii

- New freshmen at the University of Hawai ʻi at Mānoa, Hawai ʻi's flagship public research university.
- 78% retention rate. 4 percentage points below peer group average. Rate flat for last 15 years.
- Excellent data storage, infrastructure, and IR reporting.
- Growing need to convert data results into actionable strategies.

Predictive Analytics at U. of Hawaii

- Relevant previous research has provided a suitable starting point for developing at-risk student forecasting model.
- Freshmen regression model has been well-received by campus stakeholders.
- Mānoa IR now moving from model building to implementation.
- IR and Advising staff from U. of Nevada-Reno travelled to Mānoa to share insights on implementing predictive analytics.

Takeaway from Collaboration

- Early-alert data key
- Identify results that are actionable.
- Support for student advising
- Involve colleges and departments.
- Ways to increase awareness of retention and graduation rates
  - Campaigns
  - Showing impact on the bottom line

Improving the Bottom Line at the University of Hawaii

- **388** freshmen from 2010 dropped out in year one.
- Retaining **26** students from 2010 would have improved Mānoa’s overall retention rate from 78.6% to **80%**.
- Additional Revenue from Tuition and Fees = **$259,920** (for 18 HI, 8 WUE, excludes OS).
- Are there 26 students in this group that we can help/retain?

Progress on Implementation at the University of Hawaii

- Currently doing:
  - Campus road show to share prediction model to stakeholders (including faculty and students).
    - Improved presentation for non-IR audience
  - Collaborating with student employment office to use data
    - Better marketing of on-campus job opportunities to freshmen
  - Integrating data with WASC and CCA reports
  - Mentioning odds ratios in campus campaigns and advertisements
  - Working more closely with College/Department personnel
  - Considering qualitative surveys to supplement quantitative data
  - Clarifying the role of analytics in MIRO’s mission and University’s strategic retention plan

Barriers to Implementation at the University of Hawaii

- Culture change
- Wary of misuse of data
- More accountability
- Faculty buy-in

Next Steps in Implementation at the University of Hawaii

- Beta-test with selected student advisors in spring 2013.
    - At-risk students monitored and called in for advising.
    - Decile data used to contextualize advising sessions.
- Collaboration with co-curricular office.
    - Enrolling in the First Year Experience class is a significant predictor in Hawai ʻi's model.
- "De-siloing" of data for analytical purposes.
- Continued relationship-building at the college level and beyond.
- Ride the analytics wave and maintain momentum.

Summary

- Predicting students at-risk
  - Keep prediction model parsimonious
  - Keep prediction data for student advising intuitive and simple (actionable)
  - Triangulate prediction data with multiple sources of information
  - Use prediction data as component part of student dropout-risk assessment
  - Follow ‘best practices’ in IR and keep abreast of changes in analytical and data reporting tools
- Using prediction data for student advising
  - Embrace the use of available data
  - Ensure users conceptually understand what’s behind the data
  - Use data as a complementary piece of information when advising students
  - Timing can be critical in terms of student intervention as well as maximizing advising resources
- Stay abreast of new research on predictive analytics:
  - E.g. “Analytics in Higher Education” by J. Bichsel, Educause, 2012

Link to presentation:

http://www.unr.edu/ia/research